OPTIMAL BIDDING STRATEGIES FOR DAY AHEAD ELECTRICITY MARKET BY RISK CONSTRAINED STOCHASTIC PRICE BASED UNIT COMMITMENT

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ABSTRACT

OPTIMAL BIDDING STRATEGIES FOR DAY AHEAD ELECTRICITY MARKET BY RISK CONSTRAINED STOCHASTIC PRICE BASED UNIT COMMITMENT

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Optimum bidding curves for a generating company to take part in the day ahead energy market are developed throughout this thesis. Continuous aim of the generating company to maximize its profit will be partly fulfilled by optimizing its bidding in the market. Price uncertainty has always been a major issue for proper bidding and maximizing the payoff. In contrast with traditional Price Based Unit Commitment which is only dependent on a good forecast of energy prices, stochastic programming takes care of the price volatility by generating different possible scenarios using Monte Carlo Simulation method. Generating Company would be able to control his risk factor by indicating its risk tolerance in the model and trade some of the profit in favor of taking less risk. MATLAB platform is used to code the Mixed Integer Linear Programming model while CPLEX 9.0 solver engine is utilized to solve the optimization problem. Several case studies have been examined to show the validity of the model and the results have been interpreted to give more insight of the optimization solution.

Keywords: Stochastic Price Based Unit Commitment, Risk Constrained Programming, Monte Carlo Simulation, Bidding Curves, Day-Ahead Electricity Market, CPLEX

ÖZ

GÜN ÖNCESİ PİYASASI İÇİN RİSK DEĞERLERİNİ DİKKATA ALARAK OPTİMUM TEKLİF EĞRİSİ GELİŞTİRMESİ

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Bu tezde, elektrik üretim şirketlerinin gün öncesi elektrik piyasası için verdikleri fiat teklif eğrilerini optimum bir şekilde ve risk değerlerini göz önüne alarak verilebilmesine yönelik bir yöntem geliştirilmiştir. Piyasa mekanizmasının işlediği ülkelerde üretim şirketlerinin amacı kazançlarını maksimize etmektir. Geleneksel Birim Atama (Unit Commitment) yöntemleri, ancak saatlik bazdaki enerji fiatlarında önceki günlere göre değişimin yüksek olmadığı ve ertesi güne yönelik iyi fiat tahmini yapılması durumunda tatminkar sonuçlar verir. Bu tezde incelenen ve bir test sisteminde uygulanan yöntemde ise stokastic programlamadan faydalanarak, fiatlarda mümkün olabilecek oynaklıklar da modele eklenmiş olup, üretici şirket risk toleransını göz önüne alarak riskini kontrol edebilme imkanına sahip olabilmektedir.

Anahtar kelimeler: Stochastic Price Based Unit Commitment, Rik Sınırlı, Monte Carlo Metod, Teklif Eğerisi, Gün Öncesi Elektrik Piyasası, CPLEX

to Mehri, my endless love …

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
CL	Computational Learning
CVaR	Conditional Value at Risk
DP	Dynamic Programming
GA	Genetic Algorithm
GENCO	Generating Company
LR	Lagrangian Relaxation
MA	Model Based Adaptation Algorithm
MCP	Market Clearing price
MDP	Markov Decision Process
MFSC	Market Financial Settlement Center
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
MOLP	Multi Objective Linear Programming
NLDC	National Load Dispatch Center
NLP	Non Linear Programming
PAB	Pay-as-Bid
PBUC	Price Based Unit Commitment
QL	Q-Learning
SCB	Supply Curve Bidding
SDP	Stochastic Dynamic Programming
SFE	Supply Function Equilibrium
SILP	Stochastic Mixed Integer Linear Programming
SMIP	Stochastic Mixed Integer Programming
SNLP	Stochastic Non Linear Programming
SPBUC	Stochastic Price Based Unit Commitment
UP	Uniform Pricing
VaR	Value at Risk

NOMENCLATURE

n	Total number of units
Ns	Total number of scenarios
Nt	Total number of hours
i	Denote a unit
s	Denote a scenario
t	Hour index
pr_s	Probability of scenario s
ρ_{st}	Market energy price for scenario *s* at Hour *t* ($)
FP	Fuel price ($)
P_{ist}	Generation of unit *i* in scenario *s* at Hour *t* (MW)
SH_i	No load heat rate of unit *i* (Mbtu/h)
k	Segment index for a piecewise cost curve
$P_{k(ist)}$	Generation of segment k for unit *i* in scenario *s* at Hour *t*
m_k	Slope of segment *k* in piecewise cost curve
H_{ist}	Total heat rate of unit *i* in scenario *s* at Hour *t* (Mbtu/h)
$P_{min\ i}$	Minimum capacity of unit *i* (MW)
$P_{max\ i}$	Maximum capacity of unit *i* (MW)
I_{it}	Unit status indicator for unit *i* at Hour *t*
y_{it}	Startup indicator for unit *i* at Hour *t*
z_{it}	Shutdown indicator for unit *i* at Hour *t*
RU_i	Maximum ramp up rate for unit *i* (MW/h)
RD_i	Maximum ramp down rate for unit *i* (MW/h)
UT_i	Up time for unit *i* (Hour)
MU_i	Minimum up time for unit *i* (Hour)
TU_i	Number of hours unit *i* has been online initially
DT_i	Down time for unit *i* (Hour)

MD_i	Minimum down time for unit *i* (Hour)
TD_i	Number of hours unit *i* has been offline initially
TG_{ist}	Total generation of unit *i* in scenario *s* at Hour *t* (MW)
B_{it}	Bilateral contract of *i* in scenario *s* at Hour *t* (MW)
EPF	Expected payoff ($)
TP	Target Profit ($)
PF_{is}	Payoff of unit *i* in scenario *s* ($)
PF_s	Payoff of scenario *s* ($)
DR_s	Downside risk of scenario *s* ($)
EDR_{TP}	Expected downside risk of target profit *TP* ($)
ADR	Acceptable downside risk ($)

CHAPTER 1

INTRODUCTION

Power providers in a conventional monopolistic or vertically integrated electricity market usually try to reduce the expected costs as well as retaining a reasonable supply and demand security [1]. However, there is a gradual evolution of electricity markets towards a more liberalized or deregulated structures since the early 80s which is characterized by open competitive energy markets, unbundling electricity services, open access to the network and so on. In order to establish a competitive electricity market and enhance its overall efficiency, the re-structured market offers the opportunity for gaming on the market power. It also helps with the emergence of novel and modern technologies [2], [3]. The electricity "spot market" is identified as the market in which the electricity is purchased and sold at changeable prices, then delivered immediately or at a given moment. In such a market, participating companies usually face complicated situations due to lack of sufficient information regarding other competitors and market specific uncertainties.

Actual electricity market characteristics, such as lack of sufficient number of suppliers, long construction periods of power plants or large capital investment sizes, results in the deregulated electricity market to exhibit a behavior, similar to that of an oligopoly market [4]. Generally speaking, only a few dominating Generation Companies (GENCOs) serve a geographic area. Individual GENCOs have their own "market power" in such an oligopolistic market. This means that they can manipulate the market price via strategic bidding behavior [5]. This allows an opportunity for the GENCOs to increase their profits through strategic bidding. Therefore, it is possible for the GENCOs to maximize their profit by optimizing the bidding strategy in the deregulated electricity spot market, while keeping the associated risks to a minimum. The electricity market is a complex dynamic system with complicated interactions between its physical structures, market rules and all participating agents which face risks and uncertainties while maximizing profit [6], [7].

1.1. Objective

The objective of this thesis is to develop methods which provide the best bidding strategies for GENCOs in the day ahead electricity market. Such strategies should include all the risk and probability measures of GENCO's owner and market, respectively. Considering a GENCO having several power plant units at their disposal, one of the most crucial tasks and decisions is their bidding pattern and curves in the market for the following day. The most important factors which affect such a decision include:

i. Forecasted Market Price and its fluctuations
ii. Fuel Prices
iii. Cost Curves
iv. Risk Tolerance
v. Unit constraints

Considering all the above factors, the problem has been modeled and solved in MATLAB coding platform using CPLEX 12 as the solver engine.

1.2. Contribution

Bidding strategies of a GENCO is discussed throughout this thesis. Different risk tolerances have been studied and the final outcome incorporates the solutions to hourly bidding curves for the following day.

According to the data in the literature, there is no academically published article containing all the above factors in final solution which this thesis covers.

1.3. Motivation

With the development of electricity markets worldwide, private generating companies were no longer worried about system constraints nor its security. Maximizing the profit has become the main concern, hence different Price Based Unit Commitment (PBUC) formulations and solutions have been proposed in the literature and market price uncertainty has been a considerable issue ever since. In the present work, Stochastic Programming technique takes into account of such uncertainties by generating scenarios and solving the problem for each scenario. Furthermore, Monte Carlo simulations have also been applied to generate scenarios followed by scenario reduction techniques to reduce the number of scenarios to a level compatible with the available computational power.

1.4. Overview

As it is going to be discussed thoroughly in the following chapters, a detailed literature survey was done to understand the problem and get to know how far the new techniques have come to give the optimum solution.

The problem is formulated and modeled as a Mixed Integer Linear Programming. Coding of the problem is done in MATLAB with CPLEX 12 utilized as the solver engine. 1000 scenarios are produced by Monte Carlo simulation method using the estimated hourly market prices and their variances. Scenario reduction techniques have been applied afterward to reduce the number of the scenarios to 23.

Risk tolerance of the GENCO owner has taken into account in the model by introducing the risk as a constraint. The final solution for bidding strategy of the GENCO for the next day is then achieved by solving the problem again. Using two different methods to construct the bidding curve yields two different solutions according to the risk tolerance of the GENCO.

CHAPTER 2

LITERATURE SURVEY

There has been a massive transformation in the power industry over the last few years. Electricity has become a tradable commodity by market rule in a competitive environment rather than previously examined monopoly. The main idea behind this extensive change was to find an optimum resource allocation while achieving the least cost for consumers as well as maximum reliability. In order to achieve successful results within such changes, de-regulation has become an effective electricity trend mechanism for most countries.

New mathematical models, simulations and analysis have emerged as a result of these extensive changes in operational method of electricity industry. These methods are taking care of every aspect of electricity market; from profit maximization to anticipating market power exercise and possibility of arbitrage. Optimal bidding strategies have always presented an important issue for the generating companies in terms of their indisputable need to maximize payoff. Various techniques have been adopted and introduced to deal with such optimization problems.

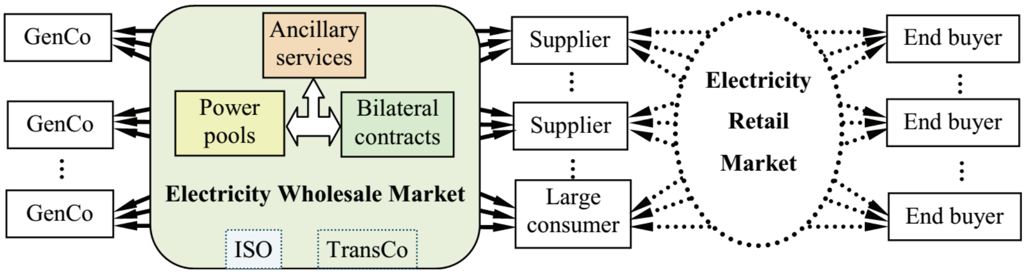

Fig 1 - general market structure of deregulated electricity markets

2.1. Bidding Strategies in the Electricity Market

Emerging spot market prices in some electricity markets in late 1980s brought up some new aspects of management, including market place, consumers, suppliers and administrative commissions [8] . Strategic bidding topic is addressed in [9] via proposing a dynamic programming approach towards optimal bidding strategy for England and Wales electricity market. This issue has gained considerable importance ever since and numerous methods and techniques have been implemented [5].

Proposed modeling techniques in the literature could be divided into four major groups, namely, Individual Optimization, Game Theory Models, Agent-based Models and combinatory models. These sections also consist of several sub-sections as illustrated in Fig 2.

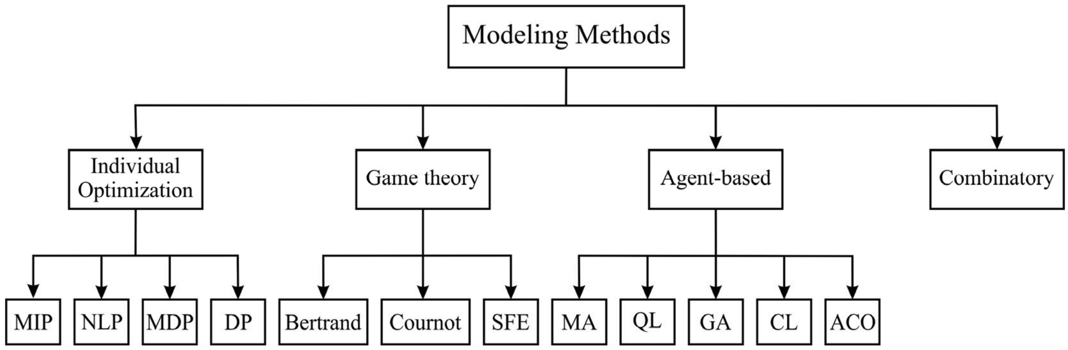

Fig 2 - Modeling methods for bidding electricity in the spot market

2.1.1. Individual GenCo Optimization

Optimal bidding strategy was first addressed as a classic Unit Commitment (UC) problem [10]. However, as the volatility of market prices and its crucial impact on the unit commitment result become obvious for market participants [11], new methods and techniques have been developed to deal with the price uncertainty to achieve more reliable outcomes. Most of the new techniques incorporate the stochasticity of the market variables into their models [12]. Application of stochastic programming in energy sector is thoroughly discussed in [13]. Variety of optimization methods are applied in the literature such as ILP[1], MILP[2], MOLP[3], NLP[4], DP[5] and MDP[6], all of which are considering the bidding strategy of only the generating company, regardless of other competitors in the electricity market.

---

[1] Integer Linear Programming
[2] Mixed Integer Linear Programming
[3] Multi Objective Linear Programming
[4] Nonlinear Programming
[5] Dynamic Programming
[6] Markov Decision Process

In [14], a stochastic mixed integer linear programming method is proposed to get the optimal bidding strategy for a price taking generating company while incorporating the price volatility.

Ni and Rourke had a stochastic mixed integer programming approach to formulate the price uncertainty while considering risk factors simultaneously. This model was solved by a combination of dynamic programming and Lagrangian relaxation methods [15].

Wen et al. applied a stochastic nonlinear programming method to devise optimum bidding curves in a sealed bid auction market. In the proposed method it was assumed that GENCOs are awarded the market clearing prices. It was also shown that MCP can be manipulated and increased by strategic bidding [16].

2.1.2. Game Theory Models

Game theory modeling takes other competitors' behavior into account to achieve optimal solution while analyzing economic equilibria. Generally, each participant decides on his strategy and then a profit will be calculated for each competitor by a payoff function and optimal solution will be achieved consequently by Nash equilibrium. According to Nash equilibrium model, no player can increase its payoff individually by having changed his own strategy and every participant will finally have the same strategy as the equilibrium [17].

Cooperative and non-cooperative competition levels are main parameters to classify game theory methods [18]. Based on the level of competition in the electricity market, three models are examined in the literature, namely, Bertrand, Cournot and Supply Function Equilibrium. In Bertrand model; being the most competitive one, capacity constraints are ignored and prices are considered as strategic variables for GENCOs while competing witch each other. On the contrary, in the Cournot models, capacities are strategic variables considering a price responsive demand. In this model, it is considered that MCP is obtained by aggregation of the supply-demand curve. In the Supply Function Equilibrium models however, simultaneous choice of supply functions determines the strategy of GENCO to compete in the market [19].

2.1.3. Agent-Based Models

In the new de-regulated electricity markets generating companies have to announce their bids to the market as power-price pairs and the whole market operates after aggregation of all generating companies to meet the demand requirements. This is a complex process which requires new and novel mathematical models as the conventional methods fail to solve the problem sufficiently. In the agent-based models, generating companies are considered as adaptive agents having their own strategies which they can improve by examining their behavior history. This approach has introduced new mathematical approaches [20]. The agent based models are typically composed of the following five steps:

1- Defining the questions to be solved
2- Model construction with an initial population of agents
3- Specifying the initial state of the model by definition of agents attributes and their framework within the electricity market
4- Having the model evolve over time without further intervention
5- Analyzing the simulation results and verifying the regularities observed in the data [21].

2.2. Scenario Generation

Comprehensive representation of price uncertainty is a necessary requirement for stochastic programming which is expressed by a multivariate continuous distribution. However, a stochastic model is based on discrete approximation of continuous distribution. Discretizing the continuous variables is a process known as scenario tree generation. In multistage scenario trees, new branches are introduced to the tree as the time periods go forward. The discretization of continuous distribution could result in an infinite number of scenarios, hence, the number of scenarios should be restricted such a way that it represents the uncertain variable as coherent as possible. The root node represents the initial value of the uncertain variable and further nodes down; represent the events of the world which are conditional at later stages. The arcs linking the nodes represent various realizations of the uncertain variables. An ideal situation is that a generated set of scenarios represent the whole universe of possible outcomes of the random variable [22].

Scenario generation techniques have been extensively studied in other areas such as financing and business planning [23]. While numerous scenario generation and reduction approaches have been studied in [24], and in the literature, power system application of such techniques have been rarely examined [25].

Various approaches exist in scenario generation for stochastic programming. Scenarios are usually produced by sampling historical time series or in some cases statistical models. These models include time series or regression models. Time series models were used in [26]. To generate scenarios for prices in electricity markets. In order to produce scenario trees available in the statistical properties of stochastic variables, nonlinear optimization was employed in [27].

2.3. Scenario Reduction

Numerical methods are used in solving applied stochastic programming models, such as in finance, production, energy, transportation etc. They are generally based on making approximations to the probability distribution using a finitely discrete probability measure. This approximation technique aims to facilitate solution of the base optimization problem by changing it to a finite-dimensional program. In order to prevent such optimization problems from being high dimensional, method of scenario reduction was applied in [22] which was further developed later in [23]. The mentioned scenario reduction methods are based on quantitative stability results for stochastic programs; utilizing the distances of probability distributions, while relying on Monge-Kantorovich mass transportation. Normally the scenario reduction problems are somewhat combinatorial models of k-median type and NP-hard. The forward and backward heuristics which has been discussed in [22] and detailed in [23] provide encouraging results regarding those models and are usually used in practical applications. In order to chance the constrained and mixed-integer two-stage stochastic programming models, the idea was extended recently in [24].

The most used scenario reduction technique in the data in the literature is based on defining the distance between two scenarios as the norm of a vector which can be calculated as the difference between the corresponding two scenario vectors. These include two realizations of the stochastic process which happen throughout the decision-making horizon.

2.4. Risk Constrained Programming

There are several methods in modeling of the risks related to a decision. One of the most common ways is using the mean-variance method, which is the standard model used in industry portfolio selection. In this approach, the risk is measured using the expected payment variance. A utility function is planned by affixing the expected payoff variance into the base expected payoff function. The aim of a decision maker is then to maximize its utility function. However, this method is very difficult to manage computationally in the case of stochastic integer program [25]. In order to analyze the bidding strategy risks, the value at risk (VaR) approach was applied in [26]. An open-loop solution, however, resulted in difficulty of modifications for the bidding strategy of a GENCO based on the risk level. Stochastic optimization techniques and real option models and were used to manage risk in [27]. A comprehensive review of risk evaluation approach in energy trading is discussed in [28].

CHAPTER 3

STOCHASTIC PRICE BASED UNIT COMMITMENT

An optimal bidding strategy has become a very imperative task for a GENCO to maximize its profit [26]. Several approaches for establishing bidding strategies were discussed in the previous chapter. Unit constraints are generally not considered in the formulation of those approaches. Neglecting those constraints would have a huge impact on the final results making it impractical. A well-defined Price Based Unit Commitment (PBUC) model is presented in this thesis which takes into account all unit constraints. However, the precision of market price forecast could have a direct impact on PBUC solution. Due to volatility of the electricity market, market price uncertainty is of a great importance. Stochastic Programming is known to be a proven method in overcoming such uncertainties. A scenario based stochastic model is used in this work to further develop the PBUC formulation incorporating the market dynamics into the model.

The methods used in this study are discussed in detail in the following sections.

3.1. Stochastic Programming

3.1.1. Introduction

One approach to model uncertainty involved in optimization problems is the utilization of stochastic programing. Typically, deterministic optimization problems are modeled with known parameters; however, realistic problems will most certainly include unknown parameters. Robust optimization is a method used to solve such problems when the parameters lie within certain bounds. The aim is then to find such a solution which satisfies feasibility across data domain as well as being somewhat optimal. Stochastic programming models are typically similar, with majority of them taking advantage of the predictability of data probability distributions. Generally speaking, such models are first formulated and then solved using an analytic or numerical method. The results of the analysis would then provide practical information to a decision-maker.

There are two basic types of stochastic programming discussed in the literature: Multi Stage programming and Two Stage programming. In multi stage programming, arrival of new information in every new step effect the model and the scenarios. Since in electricity market new data are completely unknown while doing the optimization, two stage programming is utilized here. This type of stochastic programming is discussed in the following section.

3.1.2. Two Stage Stochastic Programming

Two-stage stochastic formulation, which is widely used in stochastic programming, considers optimal decisions based on real-time data and is not related to future observations. Below is the general formulation of a two-stage stochastic programming problem:

$$\min_{x \in X} \left\{ g(x) = \mathrm{f}(\mathrm{x}) + \mathrm{E}\left[Q(x,\xi) \right] \right\} \qquad (1)$$

Where $Q(x,\xi)$ is the optimal value of the second-stage problem:

$$\min_{y} \left\{ q(y,\xi) \mid \mathrm{T}(\xi)x + W(\xi)y = h(\xi) \right\} \qquad (2)$$

Classical two-stage linear stochastic programming problems can be modelled as

$$\begin{aligned} \min_{x\in\mathbb{R}^n} \quad & g(x) = c^T x + E\left[Q(x,\xi)\right] \\ \text{subject to} \quad & Ax = b \\ & x \geq 0 \end{aligned} \tag{3}$$

Where $Q(x,\xi)$ is the optimal value of the second-stage problem:

$$\begin{aligned} \min_{y\in\mathbb{R}^m} \quad & q(\xi)^T y \\ \text{subject to} \quad & T(\xi)x + W(\xi)y = h(\xi) \\ & y \geq 0 \end{aligned} \tag{4}$$

It should be noted that $x \in \mathrm{R}^n$ is the first-stage decision variable vector, $y \in \mathrm{R}^m$ is the second-stage decision variable vector, and $\xi(q,T,W,h)$ is the second-stage problem data. A "here-and-now" decision X has to be made before realization of the uncertain data ξ, which is viewed as a random vector, is known. After a realization of ξ becomes available in the second stage, the behavior is optimal by solving an appropriate optimization problem [29].

At the first stage, we optimize (minimize in the above formulation) the cost $C^T x$ of the first-stage decision plus the expected cost of the (optimal) second-stage decision. We can view the second-stage problem simply as an optimization problem which describes our supposedly optimal behavior when the uncertain data is revealed, or we can consider its solution as a recourse action where the term Wy compensates for a possible inconsistency of the system $Tx \leq h$, and $q^T y$ is the cost of this recourse action.

The considered two-stage problem is linear because the objective functions and the constraints are linear. Conceptually, this is not essential and one can consider more general two-stage stochastic programs. For example, if the first-stage problem is integer, one could add integrality constraints to the first-stage problem so that the feasible set is discrete. Non-linear objectives and constraints could also be incorporated if needed. A sample scenario tree for two stage stochastic programming is shown in Fig 3.

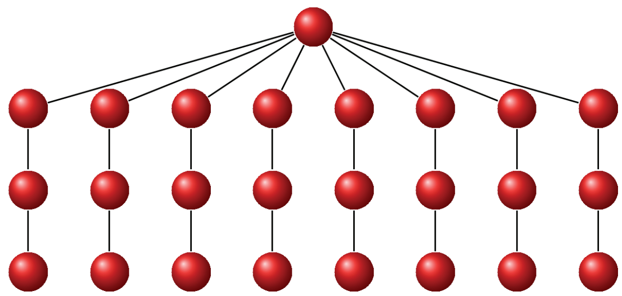

Fig 3- Fan type scenario tree for two stage stochastic programming

3.2. Scenario Generation

Using an expert opinion in prediction of future behavior could be a practical method in constructing scenarios. The number of constructed scenarios, however, should be kept low to maintain computability of the deterministic equivalent with available computational power. It is generally accepted that an optimal solution obtained by considering a number of scenarios would result in more adaptability than in the case considering a single scenario.

There are various approaches in generating scenarios for stochastic programming. These scenarios are commonly generated by sampling historical time series or statistical methods such as regression models. In this thesis, Monte Carlo simulation method is used to generate the scenarios.

The Monte Carlo method provides approximate solutions to a variety of mathematical problems by performing statistical sampling experiments on a computer. This method is directly applicable to problems with inherent probabilistic structures. The Monte Carlo method requires that the physical (or mathematical) system be described by Probability Density Functions (PDF). Simulation can proceed by random sampling from these PDFs, and necessitates a fast and effective way to generate random numbers, uniformly distributed on the interval [0, 1]. The outcomes of these trials are accumulated or tallied. Many simulations are performed and the desired result is taken as an average or expectation over all the trials.

Market Prices and their variance are supposedly calculated by artificial neural network. With the hourly prices and their variances at hand, Monte Carlo simulation is executed 1000 times with an even distribution of probabilities, meaning each scenario has a probability of 1/1000.

Monte Carlo Simulation is performed using FrontLine Systems® solver engine in Excel software. A set of thousand scenarios is a considerably large set to deal with by stochastic programming. Hence, scenario reduction techniques are applied to reduce the number of scenarios.

3.3. Scenario Reduction

Scenario reduction aims to exclude scenarios that have a very low probability and then to parcel remaining similar scenarios. Scenario reduction algorithms determine a subset of scenarios and calculate probabilities for new scenarios such that the reduced probability measure is closest to the original probability measure in terms of a certain probability distance between the two measures [22], [23].

Scenarios are shown as dots and also in a tree shape in Figs 4 and 5. It can be seen that large number of scenarios in Fig 5 which are scattered all over the space could be bundled and arranged as it is shown in Fig 6. Furthermore, by eliminating the most unlikely scenarios, the number of scenarios would be reduced significantly in order to make the stochastic program feasible to solve.

The same method has been utilized in this thesis to overcome the complexity of solving a huge problem. By eliminating the scenarios which include at least one element of 4% or less probability, a total of 23 scenarios have been maintained for the stochastic program. Reduced scenarios are presented in details in Appendix B.

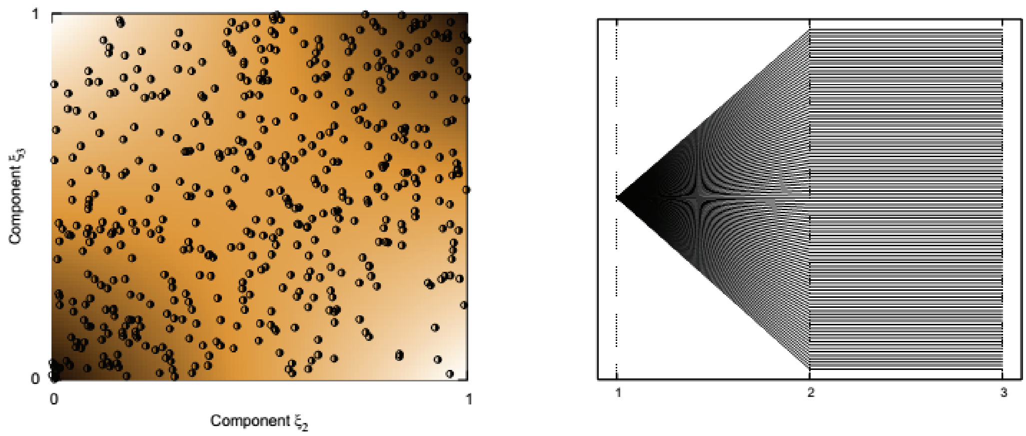

Fig 4 - Original Scenarios – No reduction has been applied

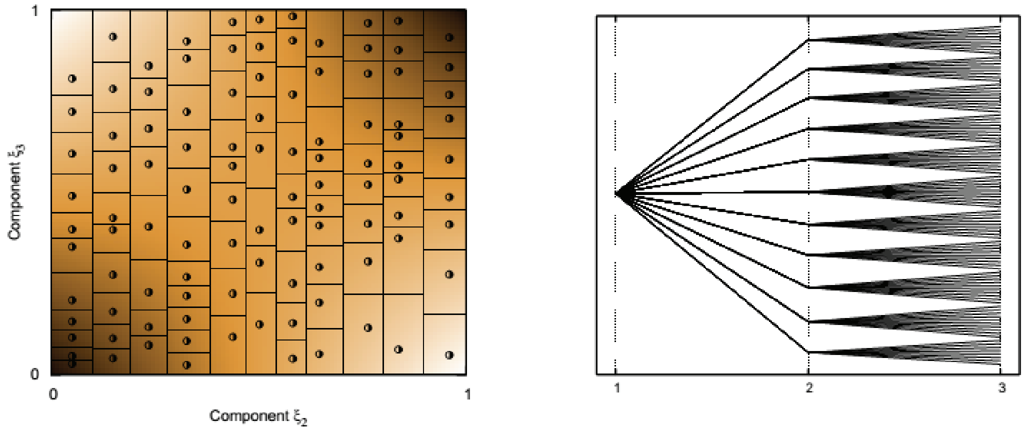

Fig 5 – results of scenario reduction technique

3.4. Objective Function

The proposed method could be run for simultaneous bidding strategies in energy and ancillary services markets. But since ancillary services markets are cleared after the day-ahead energy market, it would be more appropriate to run the model again for ancillary services markets separately. The exact prices of day-ahead energy market would guarantee a better result for ancillary services markets.

A generation company is seeking to have the maximum payoff as:

max :

$$\sum_{i=1}^{n}\sum_{s=1}^{Ns}\sum_{t=1}^{Nt} pr_s * \rho_{st} * \mathrm{P}_{its} - \left[pr_s * \mathrm{FP} * \left[SH_i * \mathrm{I}_{its} - \sum_{k=1}^{Seg} P_k(i,t,s) m_k(i) \right]\right] \qquad (5)$$

This objective function is basically an optimization of classic revenue – cost problem.

3.4.1. Problem Formulation

3.4.1.1. Unit Cost Function

A piecewise convex function is needed for MILP programming instead of conventional quadratic cost function. Heat rate function of each unit has been divided into 4 pieces in this thesis. Such a piecewise function is modeled by linear programming as follows:

$$H_{ist} = SH_i + \sum_k P_k(i,t,s)m_k(i)$$
$$P_{i,t} = \sum_k P_k(i,t,s)$$
$$P_{\min_i} \le P_k(i,t,s) \le P_{\max_i} \quad (6)$$

where,

SH_i : No load heat rate when the unit is committed

A sample 4-segment piece-wise linear function is shown in Fig 6.

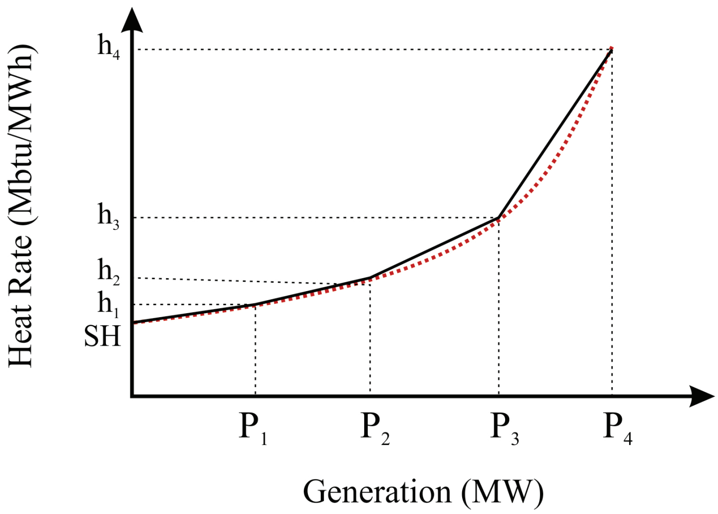

Fig 6- sample 4-segment piece-wise linear function

3.4.1.2. Unit Production Capacities

To keep the generation of unit within its minimum and maximum limits, the following constraint should be taken into account:

$$\begin{aligned}
&\mathit{If}\ I_{it} = 0,\ \text{then}\ P_{its} = 0 \\
&\mathit{If}\ I_{it} = 1,\ \text{then}\ P_{\min_i} \le P_{it} \le P_{\max_i} \\
&\text{so} \\
&P_{\min_i} I_{it} \le P_{its} \le P_{\max_i} I_{it}
\end{aligned} \qquad (7)$$

3.4.1.3. Unit Status Indicators

Startup/shutdown indicators are useful tools to represent minimum up/down time constraints. The startup and shutdown indicators are defined by:

$$\begin{aligned}
&\mathit{If}\ I_{it} = 1\ \mathit{and}\ I_{i,t-1} = 0,\ \mathit{then}\ y_{it} = 1\ \mathit{and}\ z_{it} = 0 \\
&\mathit{If}\ I_{it} = 0\ \mathit{and}\ I_{i,t-1} = 0,\ \mathit{then}\ y_{it} = 0\ \mathit{and}\ z_{it} = 0 \\
&\mathit{If}\ I_{it} = 0\ \mathit{and}\ I_{i,t-1} = 1,\ \mathit{then}\ y_{it} = 0\ \mathit{and}\ z_{it} = 1 \\
&\mathit{If}\ I_{it} = 1\ \mathit{and}\ I_{i,t-1} = 1,\ \mathit{then}\ y_{it} = 0\ \mathit{and}\ z_{it} = 0
\end{aligned} \qquad (8)$$

where,

I: Unit Status

y: Startup Indicator

z: Shutdown Indicator

3.4.1.4. Ramp Up/Down Constraints

From one time period to the next, a unit cannot increase its output above a maximum increment, which is called the ramping up limit. Similarly, a unit cannot decrease its output above a maximum decrement, which is called the ramping down limit. Also it is assumed that, the output of a unit right after it is started up is its minimum capacity and the output right before it is shutdown is also its minimum capacity.

For the ramp up:

$$\begin{aligned}
y_{it} = 1 &\rightarrow P_{it} - P_{i,t-1} = P_{\min_i} \quad \because \quad P_{it} = P_{\min_i} \;\&\; P_{i,t-1} = 0 \\
&\text{if } I_{it} = I_{i,t-1} = 0 \rightarrow P_{it} - P_{i,t-1} = 0 \\
y_{it} = 0 &\rightarrow \text{if } I_{it} = 0 \;\&\; I_{i,t-1} = 1, \text{ then } P_{it} - P_{i,t-1} < 0 \\
&\text{if } I_{it} = I_{i,t-1} = 1 \rightarrow P_{it} - P_{i,t-1} \leq RU_i
\end{aligned} \qquad (9)$$

hence, $\mathrm{P}_{it} - P_{i,t-1} \leq y_{it} * P_{\min_i} + (1 - y_{it}) RU_i$

where,

RU_i : Maximum Ramp Up Limit of Unit i

For the ramp down:

$$\begin{aligned}
z_{it} = 1 &\rightarrow P_{i,t-1} - P_{it} = P_{\min_i} \quad \because \quad P_{i,t-1} = P_{\min_i} \;\&\; P_{i,t} = 0 \\
&\text{if } I_{it} = I_{i,t-1} = 0 \rightarrow P_{i,t-1} - P_{it} = 0 \\
z_{it} = 0 &\rightarrow \text{if } I_{it} = 1 \;\&\; I_{i,t-1} = 0, \text{ then } P_{i,t-1} - P_{it} < 0 \\
&\text{if } I_{it} = I_{i,t-1} = 1 \rightarrow P_{i,t-1} - P_{it} \leq RD_i
\end{aligned} \qquad (10)$$

hence, $P_{i,t-1} - P_{it} \leq z_{it} * P_{\min_i} + (1 - z_{it}) RD_i$

where,

RD_i : Maximum Ramp Down Limit of Unit i

In conclusion, ramping limits of units are modeled as:

$$\begin{aligned}
P_{it} - P_{i,t-1} &\leq y_{it} * P_{\min_i} + (1 - y_{it}) RU_i \\
P_{i,t-1} - P_{it} &\leq z_{it} * P_{\max_i} + (1 - z_{it}) RD_i
\end{aligned} \qquad (11)$$

3.4.1.5. Minimum Up/Down time

Minimum up time constraint implies that a unit must stay in operation for a certain number of hours before it can be shut down. Likewise, minimum down time constraint implies that a unit must remain down for a certain number of hours before it can be brought online.

When a unit is initially in operation for less than the minimum up time, it needs to stay in that operation mode for some hours, which is defined as the difference between the minimum up time and the initial operating hours. In general, for the purpose of the unit commitment formulation, this value is limited by zero and maximum hours for scheduling. The model is as below:

$$UT_i = \max\left\{0, \min\left[Nt, (MU_i - TU_{i0}) * I_{i0}\right]\right\} \quad (12)$$

where,

UT_i : Up time for unit i

MU_i : Minimum up time for unit i

TU_{i0} : Number of hours unit i has been online initially

A unit's minimum up time constraint is modeled as follows. Equation 13a indicates that if a unit is initially in operation for less than minimum up time, it has to stay in operation for the remaining required hours. Once a unit is started up, if the number of remaining hours (the difference between maximum hours for scheduling and the current time) is larger than the minimum up time, equation 13b indicates that the unit has to stay up for at least the minimum up time hours; otherwise, equation 13c indicates that the unit cannot change its operating status for the remaining hours.

$$\sum_{t=1}^{UT_i}(1-I_{it})=0$$

$$\sum_{l=t}^{t+MU_i-1} I_{il} \geq MU_i y_{it} \qquad \forall t = UT_i+1,...,Nt-MU_i+1 \qquad (13a,b,c)$$

$$\sum_{l=t}^{NT}(I_{il}-\text{y}_{it})\geq 0 \qquad \forall t = Nt-MU_i+2,...,Nt$$

Similarly, if a unit is down initially, equation 14 defines the difference between the minimum down time and the initial down hours, which is limited by zero and maximum hours for scheduling.

$$DT_i = \max\left\{0, \min\left[Nt, (MD_i - TD_{i0})*(1-I_{i0})\right]\right\} \qquad (14)$$

where,

DT_i : Down time for unit i

MD_i : Minimum down time for unit i

TD_{i0} : Number of hours unit i has been offline initially

A unit's minimum down time constraint is modeled as follows. Equation 15a indicates that if a unit is initially down for less than minimum down time, it has to stay off for the remaining required hours. Once a unit is shutdown, if the number of remaining hours (the difference between maximum hours for scheduling and the current time) is larger than the minimum down time, equation 15b indicates that the unit has to stay off for at least the minimum down time hours; otherwise, equation 15c indicates that the unit cannot change its operating status for the remaining hours.

$$\sum_{t=1}^{UT_i}(1-I_{it})=0$$

$$\sum_{l=t}^{t+MD_i-1}(1-I_{il})\geq MD_i z_{it} \qquad \forall t = DT_i+1,...,Nt-MD_i+1 \qquad (15\ a,b,c)$$

$$\sum_{l=t}^{NT}(1-I_{im}-z_{it})\geq 0 \qquad \forall t = Nt-MD_i+2,...,Nt$$

3.4.1.6. Energy Bilateral Contracts

In order to take into account the existing bilateral contracts, we have to add this constraint to the model as well:

$$TG_{its} - P_{its} = B_{it} \quad (16)$$

3.4.1.7. Non-decreasing Conditions

Each GENCO is required to submit a monotonically increasing bidding curve for the participation in the electricity market. An example of such a bidding curve is provided in Fig 7.

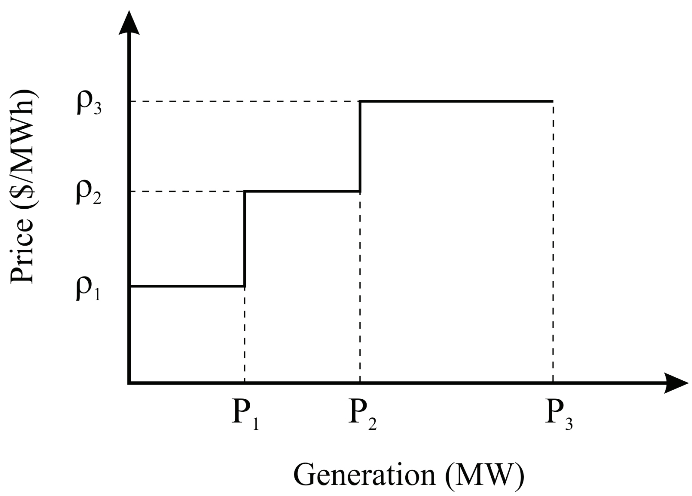

Fig 7- Monotonically increasing bidding curve

This non-decreasing constraint should be enforced to reassure the ever increasing condition while constructing the bidding curves. For every scenario and each consecutive hour, the following condition should be always satisfied:

$$[\rho_{st}(n)-\rho_{st}(n')]*[P_{ist}(n)-P_{ist}(n')]\geq 0 \qquad (17)$$

CHAPTER 4

RISK CONSTRAINED PROGRAMMING AND BIDDING CURVE CONSTRUCTION

The stochastic model of price based unit commitment discussed in Chapter 3 is a risk-neutral model, optimized to give the maximum payoff. In case of a GENCO concerning about the risk he may take, risk factors should be introduced to the formulation of the problem.

4.1. Modeling the Risk

4.1.1. Coverage of Target Profit

Having obtained the solution of the stochastic model, the Expected Payoff (EPF) of the model is then calculated as the multiplication of probability of each scenario and its payoff for every unit, as represented below:

$$EPF = \sum_{i=1}^{Ng} \sum_{s=1}^{Ns} pr_s * PF_{is} \qquad (18)$$

A GENCO is bound to set himself a Target Profit (TP) which is less than, or at least, equal to EPF. If GENCO's target profit is greater than the Expected Payoff of the solution, the program will stop without a solution indicating "The Target

Profit is NOT feasible". In order to facilitate a tighter decision making values, unit based target profit selection is modeled to enable a GENCO with large number of units to choose individual target profit for its units rather than a single target profit for all units.

4.1.2. Meeting the Expected Downside Risk

If in a scenario payoff is less than chosen target profit, there is a risk associated with that scenario called downside risk. Otherwise, there is no risk involved in that scenario.

Downside risk of a scenario for GENCO is calculated as:

$$PF_s = \sum_{i=1}^{Ng} PF_{is}$$
$$DR_s = \begin{cases} TP - PF_s, & \text{if } PF_s \le TP \\ 0, & \text{if } PF_s > TP \end{cases} \tag{19}$$

And the expected downside risk (EDR) for the chosen target profit would be the aggregation of all scenarios considering their probabilities:

$$EDR_{TP} = \sum_{s=1}^{Ns} pr_s * DR_s \tag{20}$$

GENCO should choose how much risk he is willing to take while covering his target profit. That acceptable risk is defined as Acceptable Downside Risk (*ADR)*.

If $ADR < EDR_{TP}$, the model is run for several loops; as explained below, until it reaches the acceptable downside risk, without short falling the target profit. In this process, program will stop indicating that the target profit and corresponding downside risk is not feasible whenever expected payoff is below the target profit.

In order to get to our acceptable downside risk level, the scenario with the lowest payoff is first determined. Then, the Hour with the least payoff within that scenario should be determined and penalized in a way that in the next model run, the unit is forced to be off. This penalizing is performed by multiplying the corresponding energy market price for that Hour with a very small number (in this case, 0.0001). The program is then executed for that unit again and the acceptable risk and target profit are checked. The model will continue to run until it reaches a solution within the boundaries, otherwise it will stop indicating the infeasibility of chosen target profit and risk level.

The following procedure is developed to risk-constrained the problem:

1) Solve the stochastic price based unit commitment problem.
2) Calculate the expected payoff and corresponding expected downside risk.
3) If the target profit is higher than *EPF,* Stop. Selected target profit is unreachable.
4) If $ADR \geq EDR_{TP}$, stop and present the unit commitment schedule and construct the bidding curves. Otherwise go to step 5.
5) Penalize the Stochastic model objective function with multiplying the energy price of the Hour which has the least payoff at lowest payoff scenario by 0.0001.
6) Go to step 1.

Obviously, taking less risk would decrease the expected payoff, but that is the price GENCO is willing to pay in order to reduce his risk level.

The schematics of the flowchart of the whole optimization process are summarized as below:

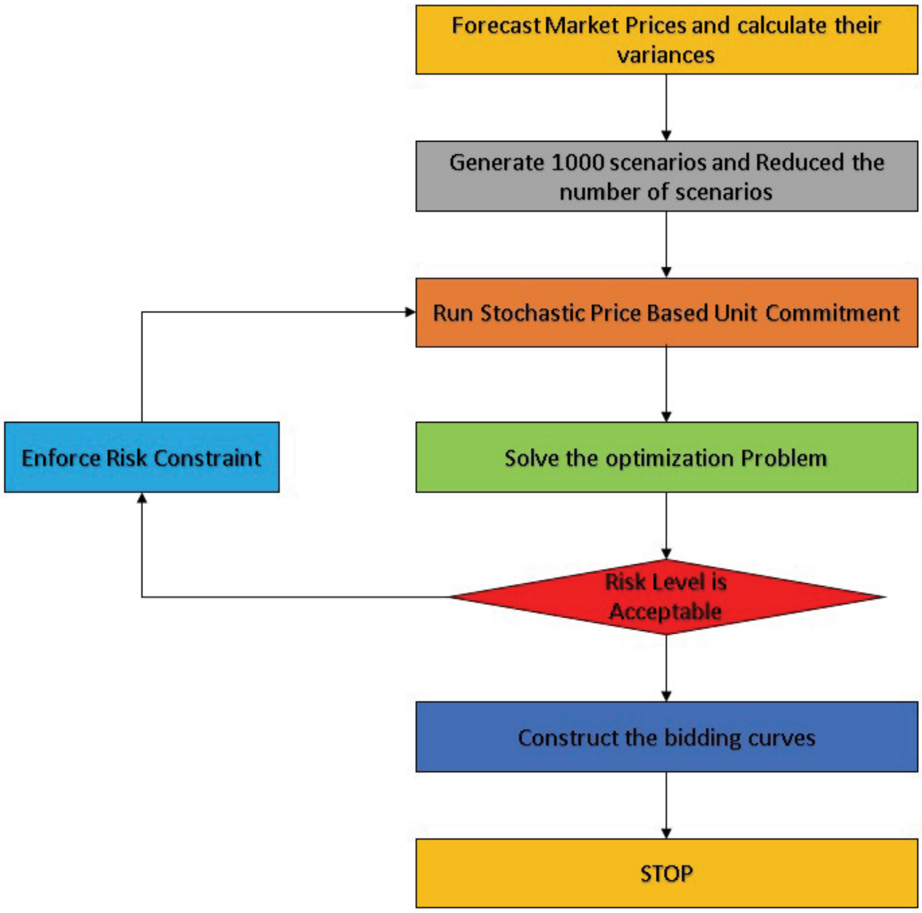

Fig 8- Flow Chart of the Optimization Pocedure

4.2. Constructing Bidding Curves

The problem solution presents hourly non-decreasing price and quantity pairs. A sample for a unit is shown in Fig. 10 in which there is a large jump from the second pair to the third. In such cases, there are two possible ways of constructing a continuous bidding curve as shown in Fig. 11.

The first method is to use the lower generation and upper price of two continuous points in order to obtain a new price and quantity pair and then to connect all the price and quantity pairs to devise the bidding curve. By applying this method, the unit may lose some revenue if the market price is between $18/MWh and $25/MWh since the unit will only be awarded 60 MW.

This is a conservative way of constructing bidding curves. The second method is to use the upper generation and lower price of two continuous points to obtain new price and quantity pairs. This would be a risky method as a unit may incur losses if the market price is between $18/MWh and $25/MWh and the awarded generation is 100 MW. Based on the two methods, another method is presented here to construct the bidding curves. If there is big jump between different steps of bidding curves, that jump could be divided into smaller parts which have a stepwise increases between them. So the new bid curve will be less risky and present a better results in the competition between GENCO and other bidders.

After diving the points in bidding curves, these points can be treated differently by applying either methods in order to get a conservative or risk seeking bidding strategy.

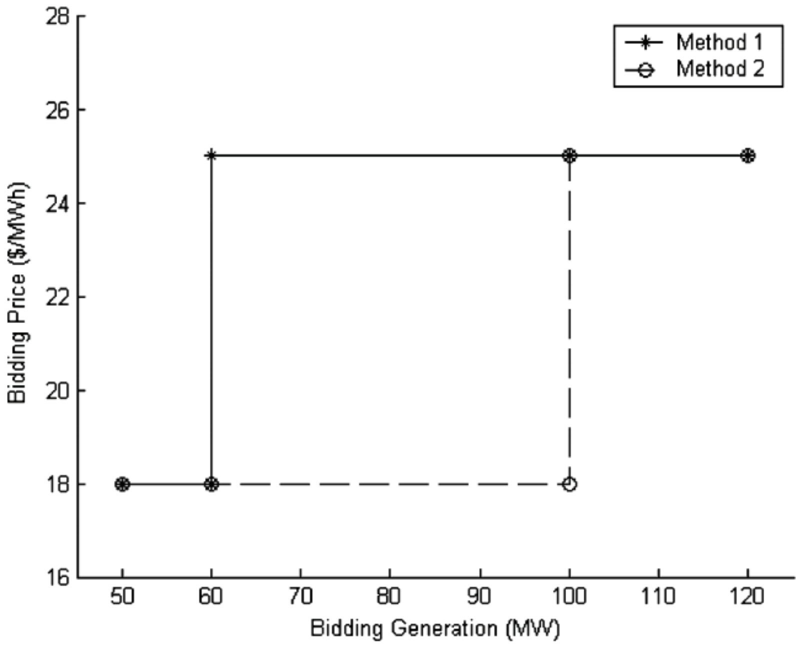

Fig 9- Two basic method for constructing the bidding curve

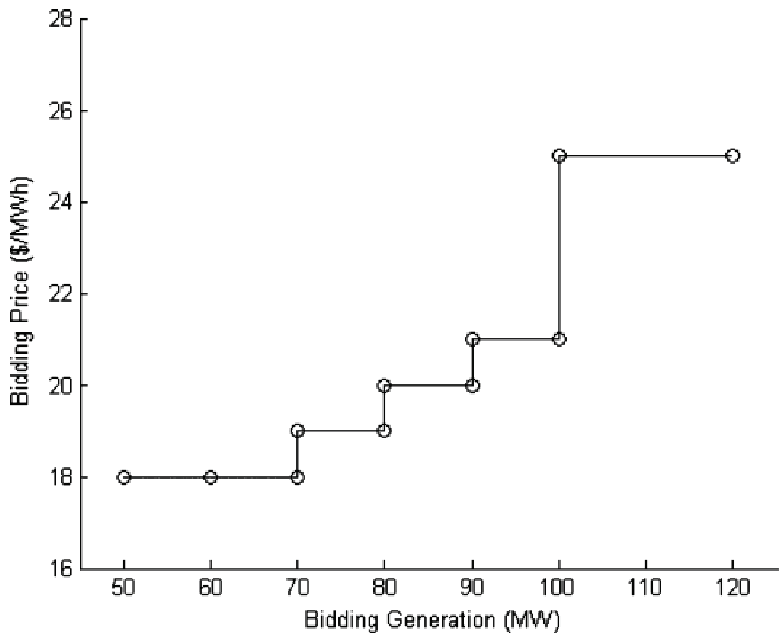

Fig 10 - Method 3 for bidding curve construction

CHAPTER 5

CASE STUDIES AND NUMERICAL EXAMPLES

A GENCO owning 20 thermal units is considered for simulations and demonstration of proposed method. The unit's data and market energy prices are presented in Appendix A. Market prices are considered to have a normal distribution.

The problem is modeled and coded in MATLAB R2013a-32bit. CPLEX9.0 solver engine is utilized to solve the optimization problem on a personal computer with Intel Core™ $i5_{vPro}$ CPU and 4 GB of memory.

5.1. Case 1- Simple PBUC with Deterministic Data

In this case, the predicted energy prices are considered as the real time prices and simple Price Based Unit Commitment (PBUC) program is preformed to get the unit commitment schedule for units. Some insight is given by performing the simple PBUC for comparison of the results with the Stochastic PBUC.

GENCO will just bid his optimum solution as one block for the day-ahead energy market and no bidding curve is presented. This kind of bidding involves a huge risk, since a GENCO might have to shut down all units in a particular Hour if the market price is below his offer. However, if GENCO manages to precisely estimate the market prices, the optimum solution is achieved by simple PBUC and GENCO would make a profit of 47227.5$.

Unit schedules are presented in Table 1 and offered power and price pair for the day-ahead market is as shown in Fig 11:

Table 1- Hourly schedule for the deterministic case- Case1

Unit	Hours (1-24)
Unit 1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 0 0
Unit 2	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 0 0
Unit 3	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 0 0
Unit 4	0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 0 0
Unit 5	0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 6	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0
Unit 7	0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 8	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 0 0
Unit 9	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 0 0
Unit 10	0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 0 0
Unit 11	0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 12	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0
Unit 13	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0
Unit 14	0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 15	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0
Unit 16	0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 17	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0
Unit 18	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0
Unit 19	0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 20	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

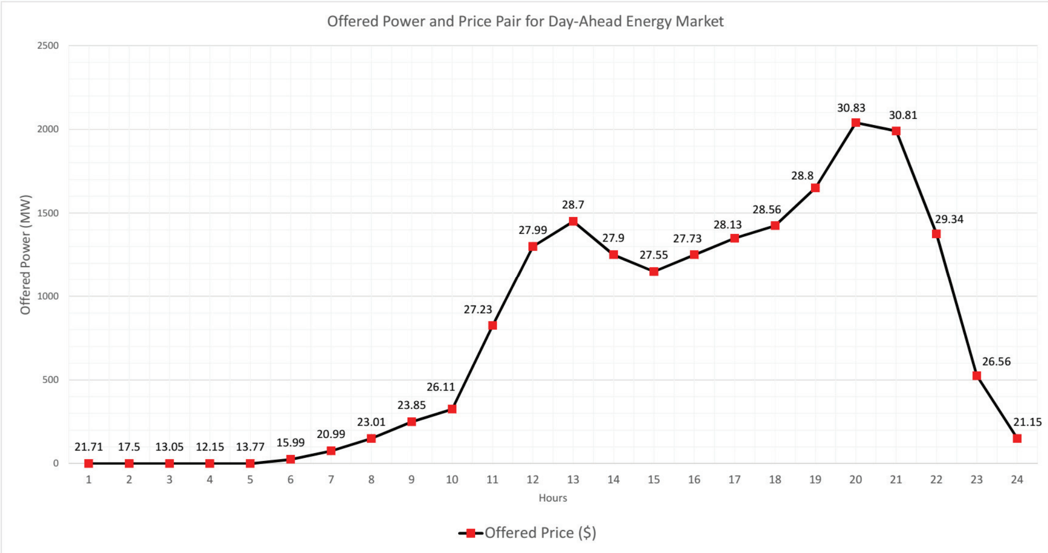

Fig 11- Power-price pair bids for day-ahead energy market in Case1

5.2. Case 2- Risk Neutral Stochastic PBUC

Since market prices could never be estimated precisely, stochastic programming method is a proven tool to deal with uncertainty of input data in an optimization problem. In order to obtain a data set to represent the stochasticity of the volatile variable, Monte Carlo method is utilized to generate random numbers taking into account the estimated data and their variances. The bigger data set results in better solution. Unfortunately, solving an optimization problem with huge amount of data would not be computationally affordable and would require longer simulation time. To avoid such unfeasibility and yet come up with an acceptable solution, scenario reduction techniques are applied to reduce the number of generated scenarios, while maintaining its characteristics as a representation of uncertain variable.

In this case, 1000 scenarios are generated using Monte Carlo Simulation method, with each scenario having the same 1/1000 probability. Scenario reduction technique is then applied to reduce the number of scenarios. Finally, 23 scenarios are left which will represent the stochasticity of the problem. Results and bidding curves are revealed as the outcome of the developed program and then bidding curves are processed using the same technique discussed in 4.2.

Table 2 shows the 24 Hour unit schedule for all units. Expected payoff of each unit is also presented in Table 3. The total expected payoff indicates that GENCO might be able to have a higher profit, if the market prices are higher than the ones that estimated.

Table 2- Unit Status for Case 2

Unit	Hours (1-24)
Unit 1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 2	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 3	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 4	0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 5	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 6	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 7	0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 8	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 9	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 10	0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 11	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 12	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 13	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 14	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 15	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 16	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 17	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 18	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 19	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 20	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Table 3 – Expected payoff for Case 2

Unit No	Expected Payoff $	Unit No	Expected Payoff $
1	196.96	11	4361.34
2	196.96	12	207.54
3	196.96	13	207.54
4	4146.41	14	3482.12
5	4657.43	15	207.54
6	209.04	16	3482.12
7	14979.46	17	207.54
8	196.96	18	207.54
9	196.96	19	3482.12
10	3267.22	20	17864.84
SUM	61954.60 $		

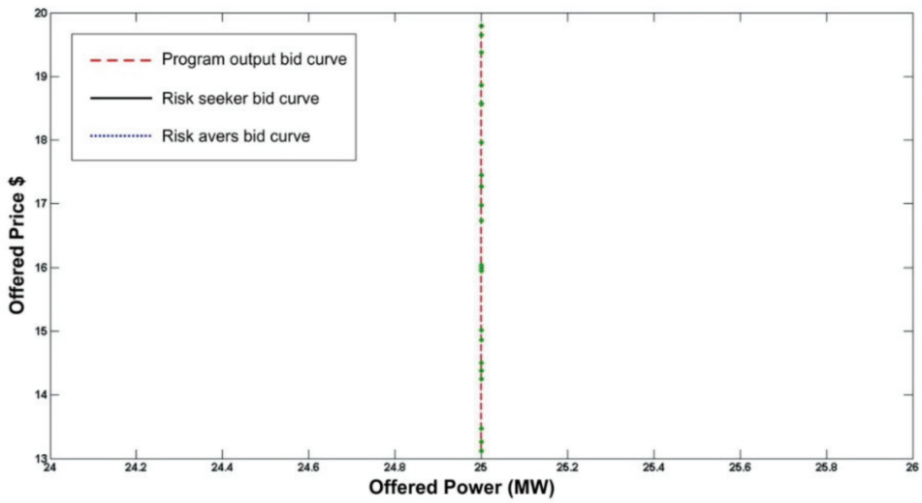

Fig 12- Case 2, bidding curve for Hour 6

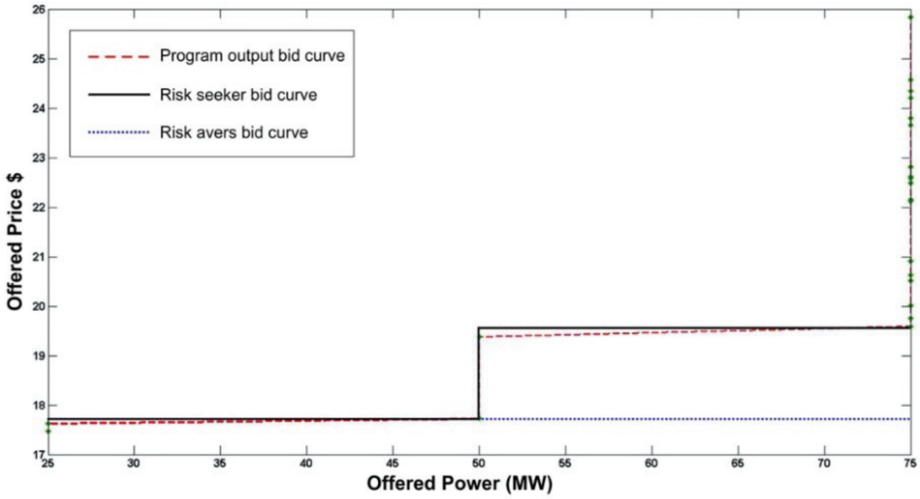

Fig 13- Case 2, bidding curve for Hour 7

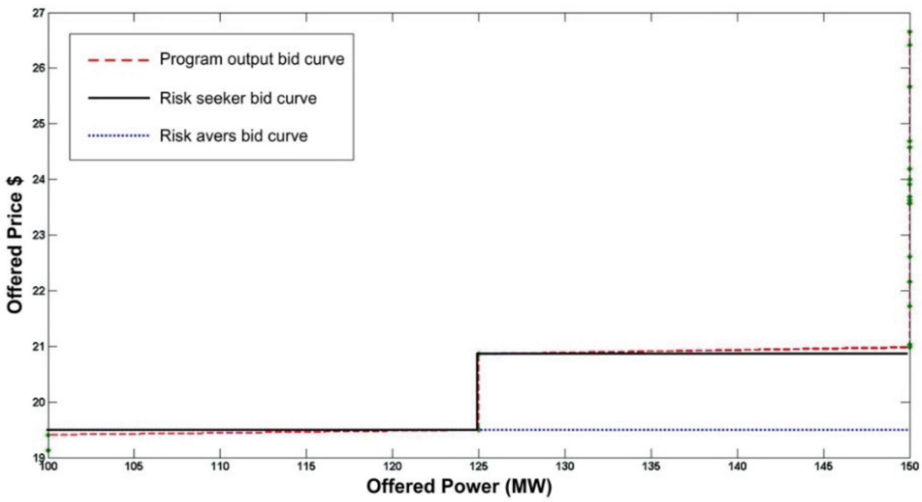

Fig 14- Case 2, bidding curve for Hour 8

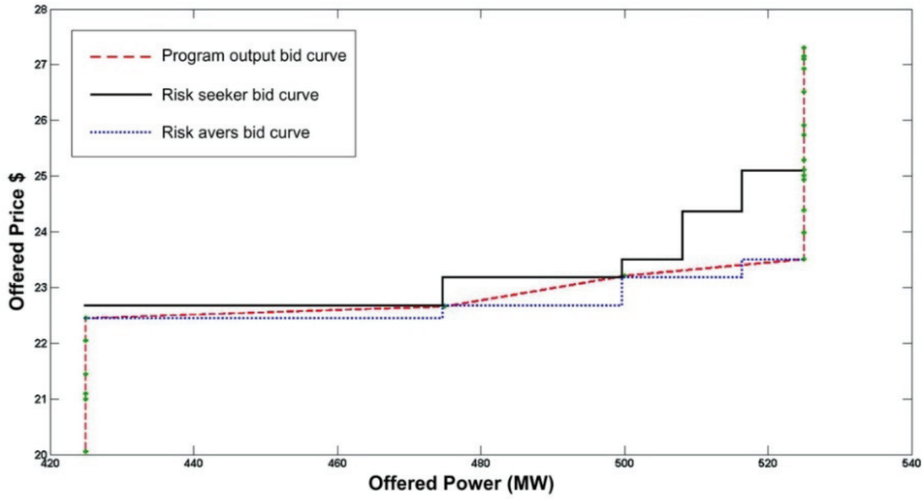

Fig 15- Case 2, bidding curve for Hour 9

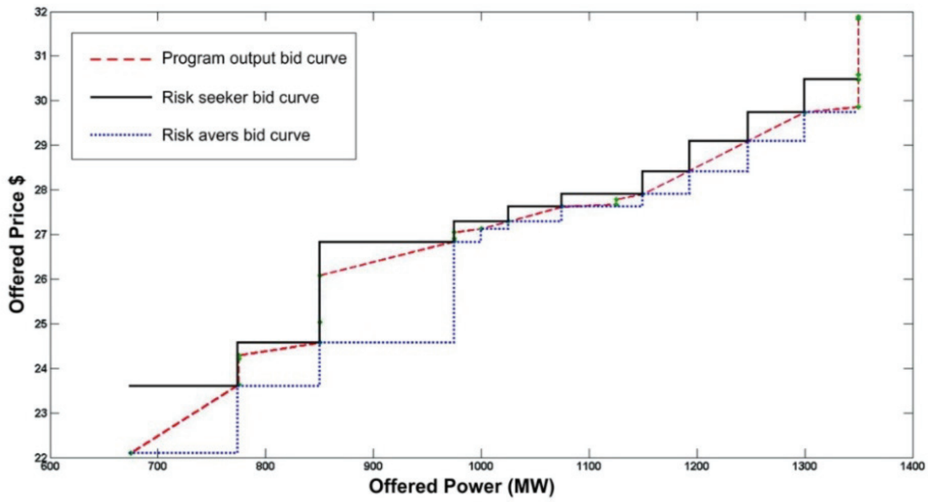

Fig 16- Case 2, bidding curve for Hour 10

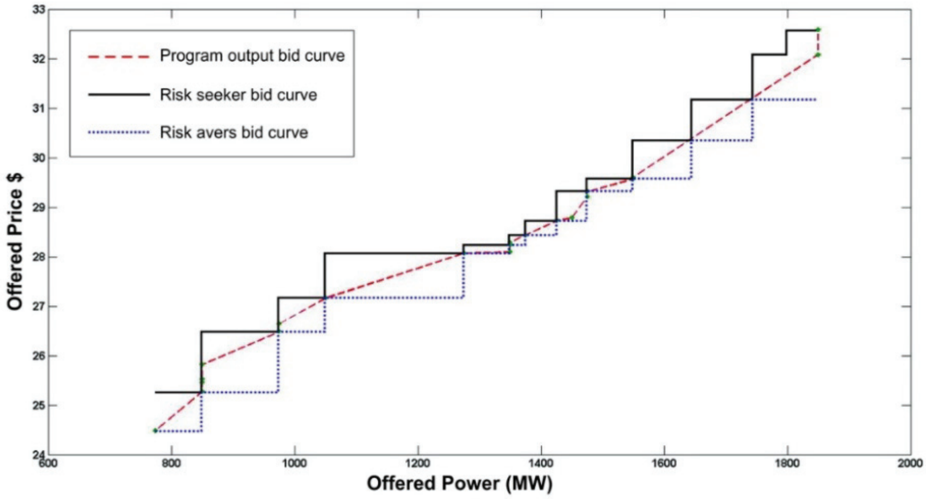

Fig 17- Case 3, bidding curve for Hour 11

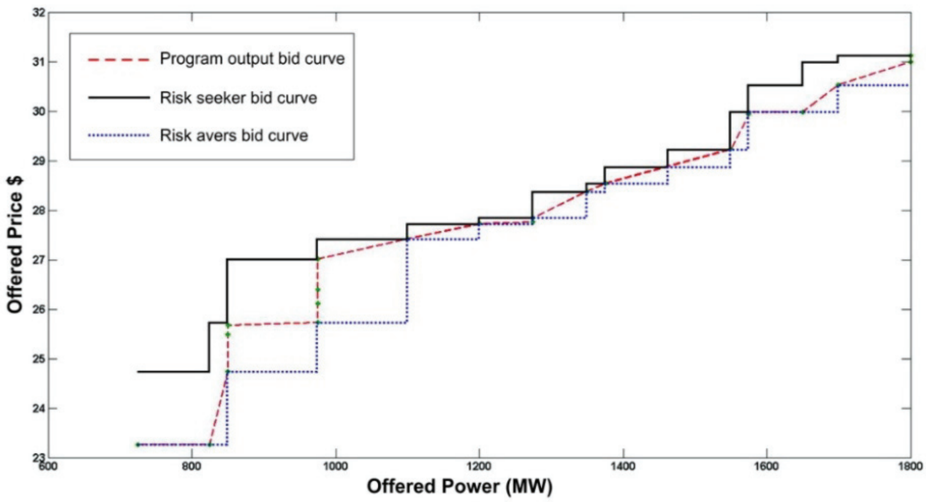

Fig 18- Case 2, bidding curve for Hour 12

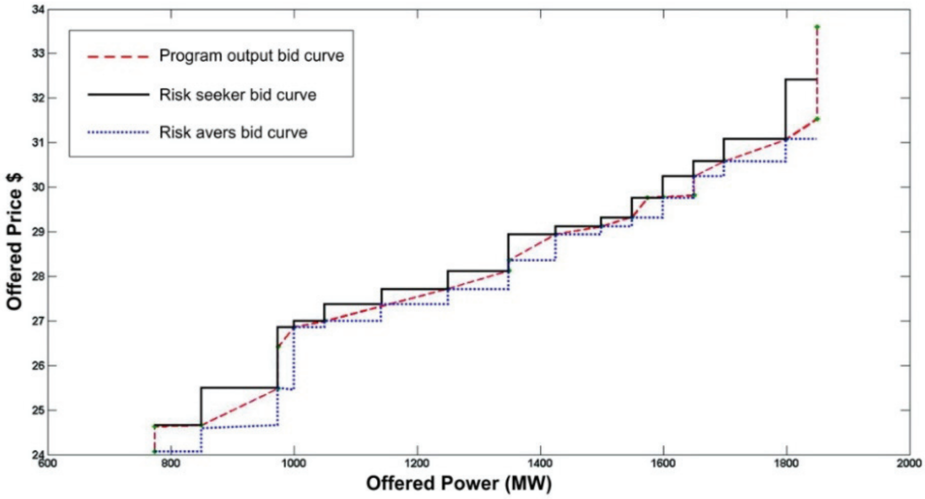

Fig 19- Case 2, bidding curve for Hour 13

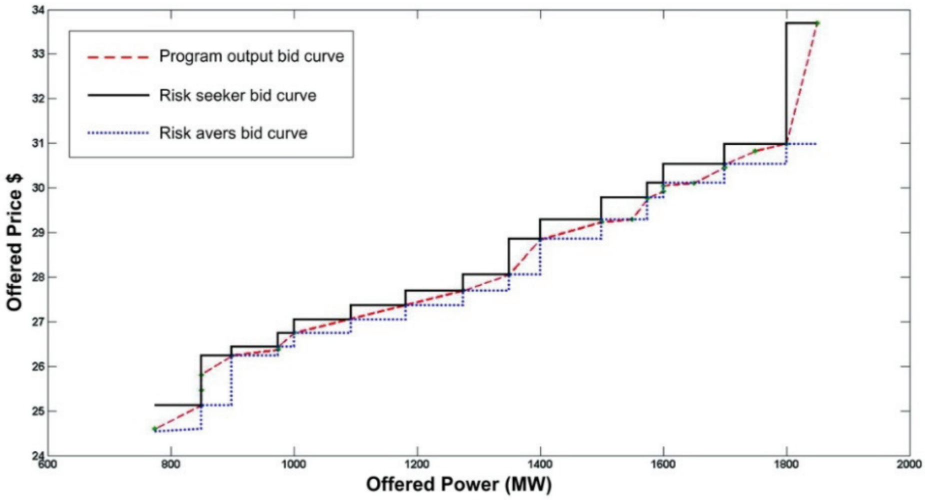

Fig 20- Case 2, bidding curve for Hour 14

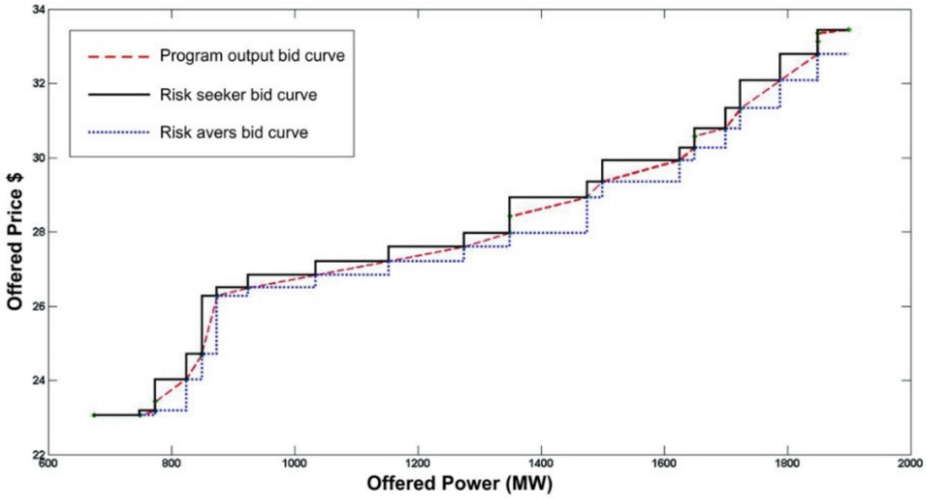

Fig 21- Case 2, bidding curve for Hour 15

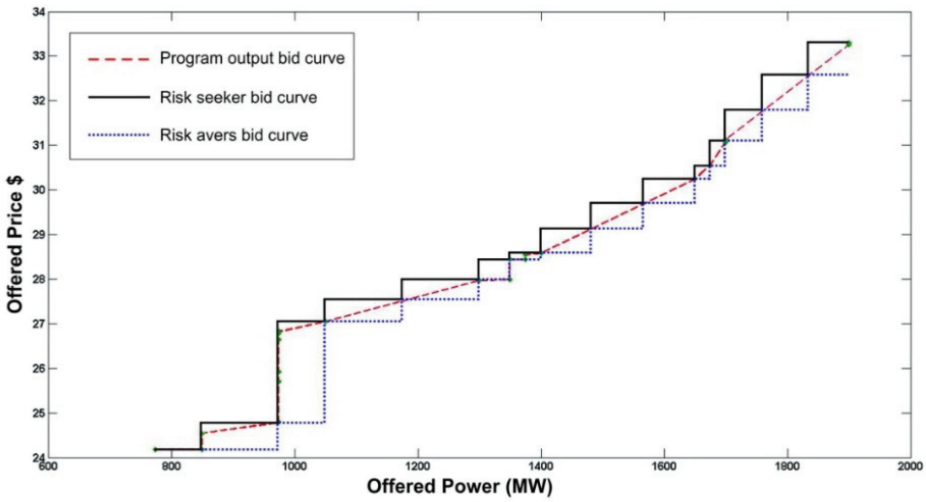

Fig 22- Case 2, bidding curve for Hour 16

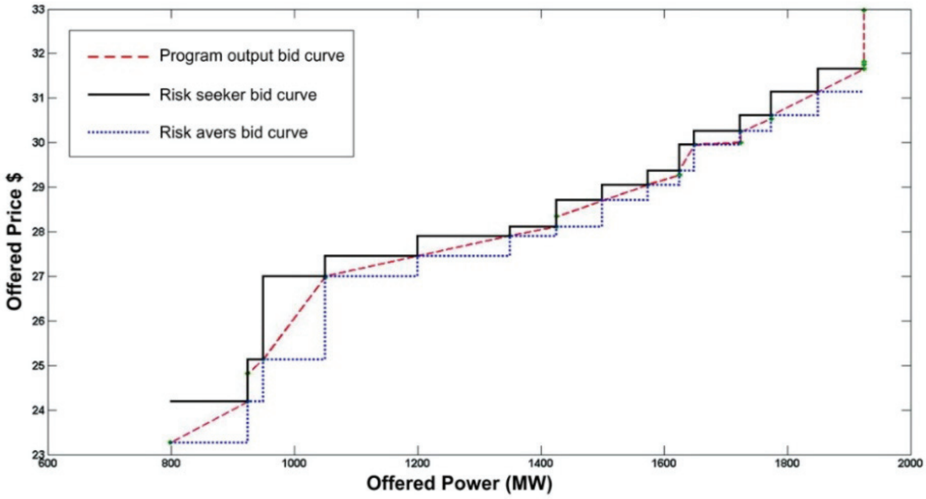

Fig 23- Case 2, bidding curve for Hour 17

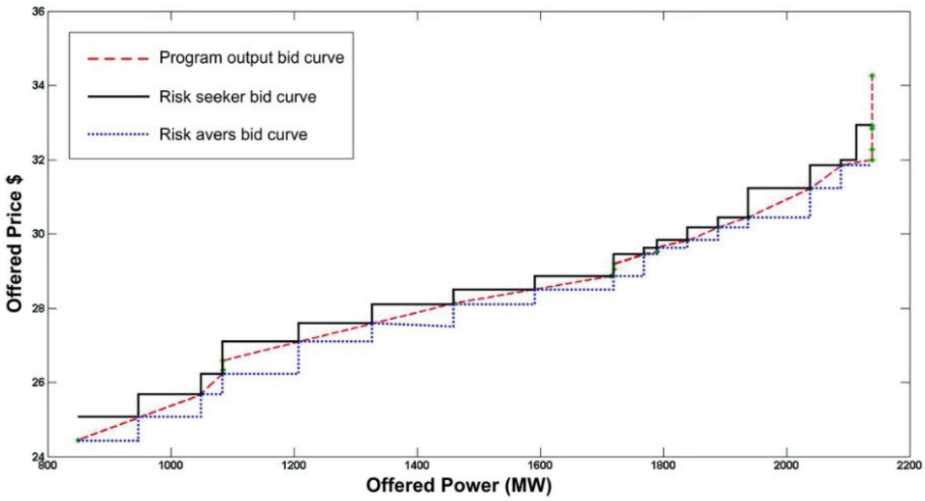

Fig 24- Case 2, bidding curve for Hour 18

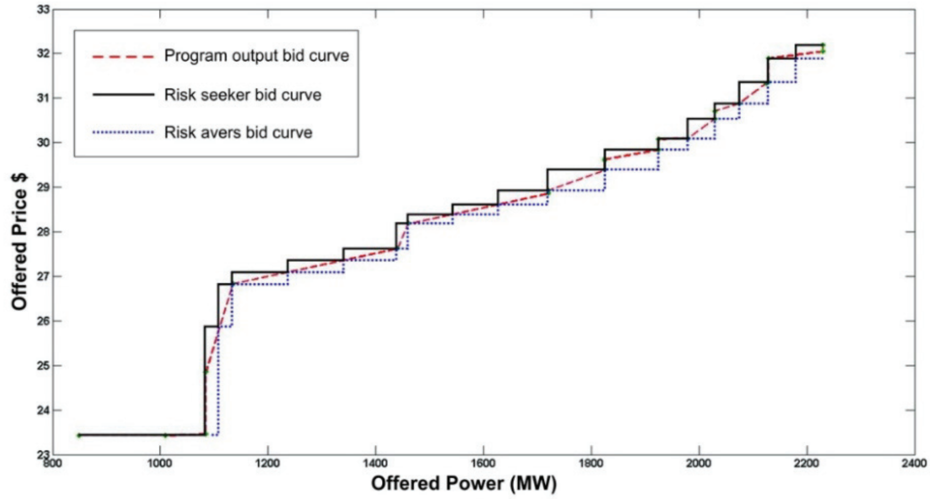

Fig 25- Case 2, bidding curve for Hour 19

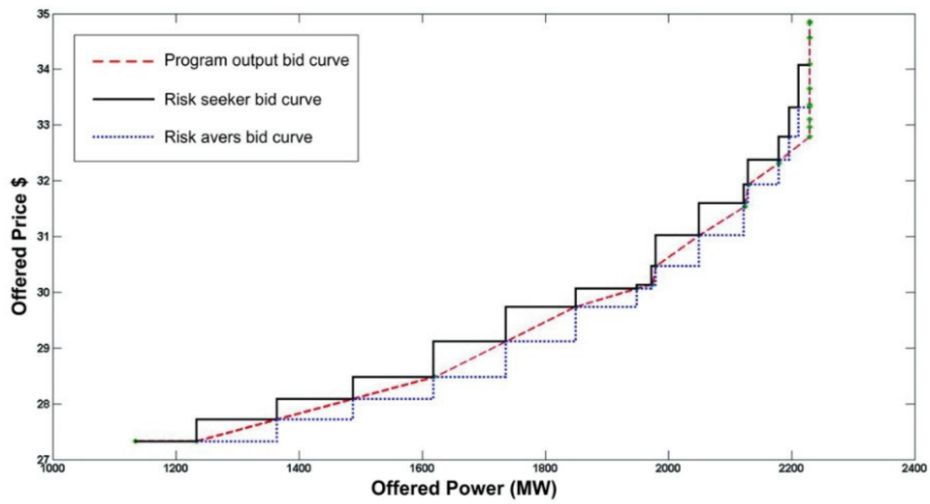

Fig 26- Case 2, bidding curve for Hour 20

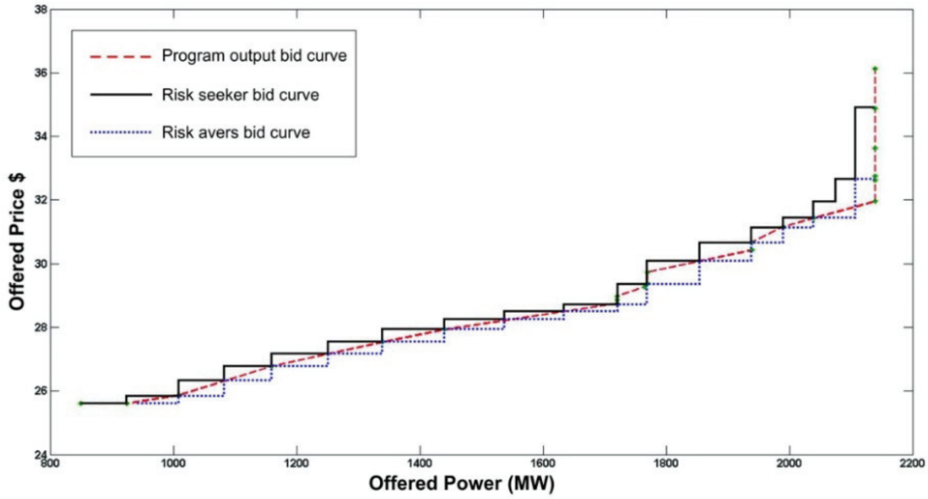

Fig 27- Case 2, bidding curve for Hour 21

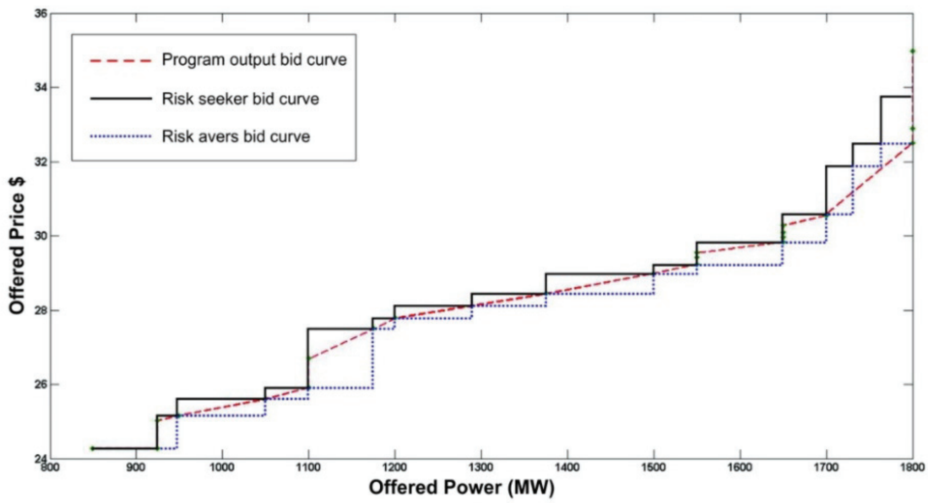

Fig 28- Case 2, bidding curve for Hour 22

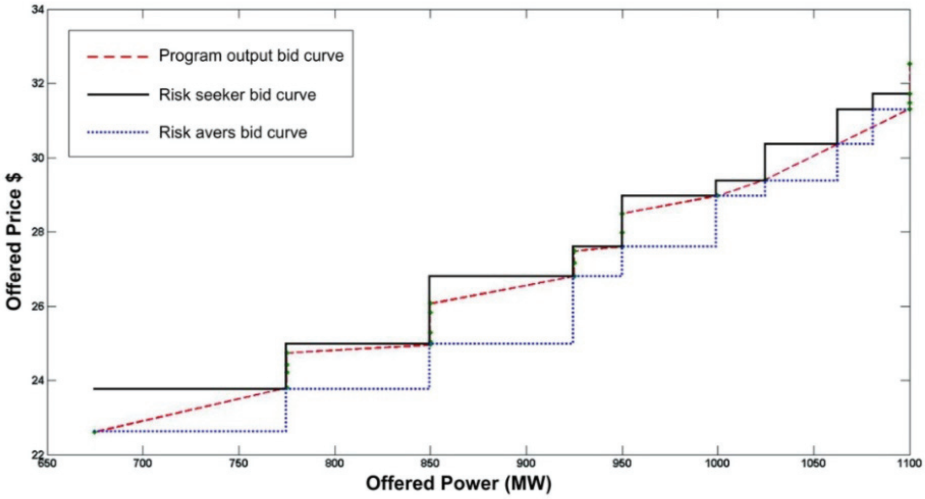

Fig 29- Case 2, bidding curve for Hour 23

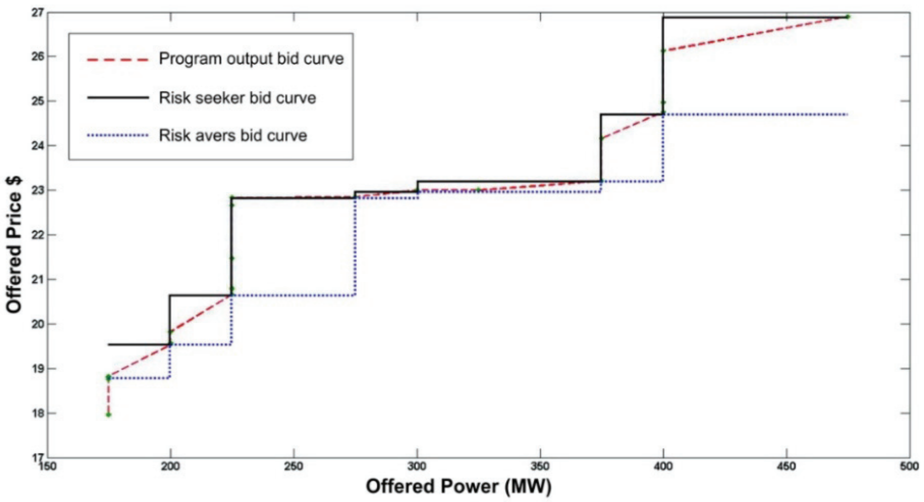

Fig 30- Case 2, bidding curve for Hour 24

5.3. Risk Constrained Stochastic PBUC

In order to investigate the impact of risk constraints in the proposed model, two different possible attitudes of a GENCO are considered; the first one being a tightly constrained owner with a big target profit and small risk tolerance and the other with a bit looser risk constraints.

The units with expected profit less than target profit are shut down completely and the ones with risk tolerances higher than expected, are optimized to reach the acceptable risk level meeting the required target profit expectations. In this process, the scenario which violates the risk level is selected, and the Hour which has the minimum payoff would be penalized by multiplying its energy price with a very small number (0.0001). This forces the model to reach new optimized solution which the low payoff Hour being eliminated. The model continues to run until the constraints are met.

The data of their expectations and risk tolerances are presented in Table 4.

5.3.1. Case 3- Tightly Risk Constrained GENCO

In this case, a GNECO with high target profit and very low risk tolerance is considered. Since the target profit for units 2, 12, 14 are below the minimum expected payoff, they have been shut down. As for units 13 and 20, indicated risk levels could not be obtained while covering the target profit, and consequently those units have been shut down as well.

Table 4- Risk Constraints of GENCO

Unit No	Expected Payoff	EDR	Target Profit	EDR	Target Profit	EDR
Unit 1	196.96	117.08	180	45	170	50
Unit 2	196.96	117.08	200	50	170	50
Unit 3	196.96	117.08	180	45	170	50
Unit 4	4146.41	8.41	3100	20	4000	20
Unit 5	4657.43	47.99	3700	30	3700	30
Unit 6	209.04	135.25	190	100	190	100
Unit 7	14979.46	0	14000	100	14000	100
Unit 8	196.96	117.08	190	60	170	60
Unit 9	196.96	117.08	190	60	170	60
Unit 10	3267.22	63.72	2100	25	3000	25
Unit 11	4361.34	196.29	4000	100	4000	100
Unit 12	207.54	153	240	80	180	60
Unit 13	207.54	153	200	60	200	60
Unit 14	3482.12	260.38	3600	150	3000	100
Unit 15	207.54	153	200	80	200	80
Unit 16	3482.12	234.56	3000	140	3000	140
Unit 17	207.54	153	200	80	200	80
Unit 18	207.54	153	200	80	200	80
Unit 19	3482.12	160.54	2800	80	2800	80
Unit 20	17864.84	233.84	15000	100	12000	100

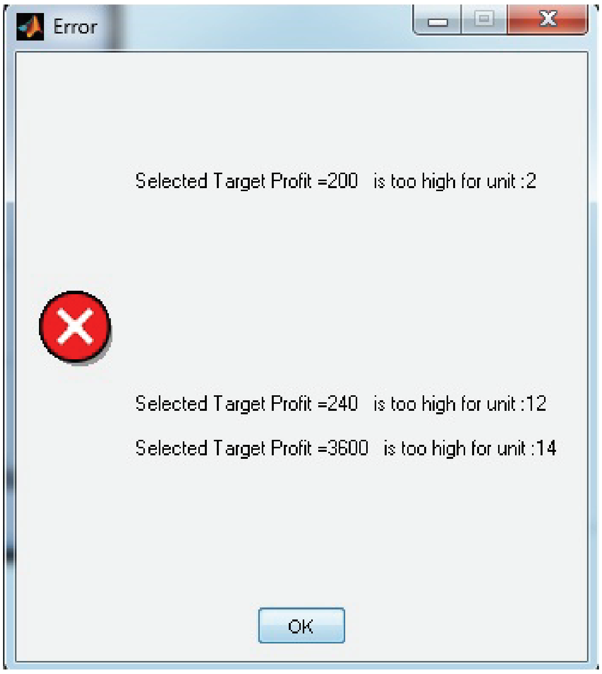

Fig 31- Program Output for Non Feasible Target Profit- Case 3

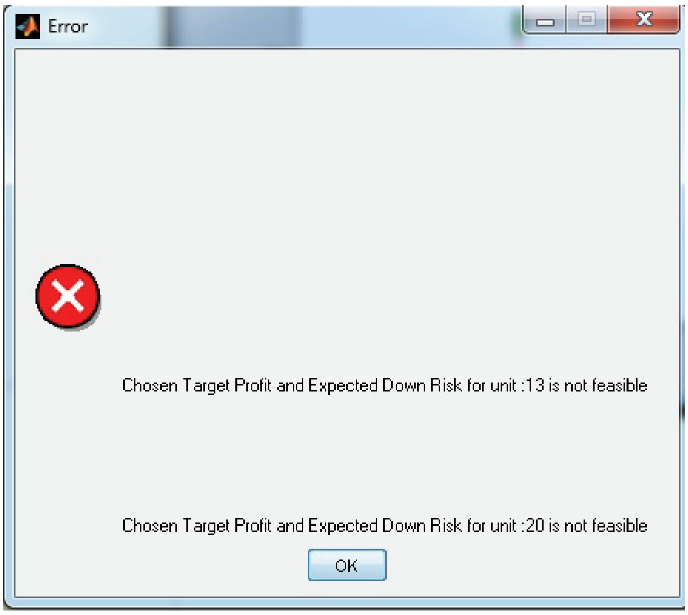

Fig 32- Program Output for Non Feasible Risk Tolerance- Case 3

These constraints results in decreasing the expected risk of GENCO by decreasing its expected profit to 41924.75$. Solutions and unit status are presented in Table 5 and 6. In Table 7, the different outputs with the risk neutral case are marked in red.

Table 5- Expected Profit and Risk Results for Case 3

Unit No	Target Profit	EDR	Expected Profit	EDR
Unit 1	180	100	196.96	55.39
Unit 2	200	115	-	-
Unit 3	180	100	196.96	55.39
Unit 4	3100	45	4146.41	8.41
Unit 5	3700	70	4657.43	47.99
Unit 6	190	230	209.04	48.33
Unit 7	14000	600	14979.46	0
Unit 8	190	140	196.96	117.08
Unit 9	190	140	196.96	117.08
Unit 10	2100	55	3718.52	0
Unit 11	4000	230	5839.19	226.68
Unit 12	240	185	-	-
Unit 13	200	140	-	-
Unit 14	3600	345	-	-
Unit 15	200	185	207.54	153
Unit 16	3000	320	3482.12	234.56
Unit 17	200	185	207.54	153
Unit 18	200	185	207.54	153
Unit 19	2800	185	3482.12	160.54
Unit 20	15000	230	-	-

Table 6- Unit Status for Case 3

Unit	Hours (0-24)
Unit 1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 2	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ***0 0 0 0 0 0*** 0 0
Unit 3	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 4	0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 5	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 6	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 7	0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 8	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 9	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 10	0 0 0 0 0 0 0 0 0 ***0 0 0 0 0 0*** 1 1 1 1 1 1 1 1 0
Unit 11	0 0 0 0 0 0 0 0 ***0 0 0 0 0 0 0*** 1 1 1 1 1 1 1 1 0
Unit 12	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ***0 0 0 0 0 0*** 0 0
Unit 13	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ***0 0 0 0 0 0*** 0 0
Unit 14	0 0 0 0 0 0 0 0 ***0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0***
Unit 15	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 16	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 17	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 18	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 19	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 20	0 0 0 0 0 0 0 ***0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0***

5.3.2. Case 4- Loosely Risk Constrained GENCO

In this case, a GENCO with looser risk constraints is considered in which, target profits are all less than the expected payoff of units and hence, no unit is forced to shut down completely. This has resulted in expected payoff of 55702.5$ which is higher than the previous case. It is again shown that taking more risk will increase the expected payoff. The results are presented in the following tables. In Table 7, the results which differ from the ones in Table 6 are marked in red.

Table 7- Expected Profit and Risk Results for Case 4

Unit No	Target Profit	EDR	Expected Profit	EDR
Unit 1	180	90	196.96	51.97
Unit 2	200	90	196.96	51.97
Unit 3	180	90	196.96	51.97
Unit 4	3100	45	-	-
Unit 5	3700	70	4657.43	47.99
Unit 6	190	230	209.04	48.33
Unit 7	14000	600	14979.46	0
Unit 8	190	140	196.96	51.97
Unit 9	190	140	196.96	51.97
Unit 10	2100	55	-	-
Unit 11	4000	230	5839.19	226.68
Unit 12	240	140	207.54	44.83
Unit 13	200	140	-	-
Unit 14	3600	230	3373.32	218.84
Unit 15	200	185	207.54	153
Unit 16	3000	320	3482.12	234.56
Unit 17	200	185	207.54	153
Unit 18	200	185	207.54	153
Unit 19	2800	185	3482.12	160.54
Unit 20	15000	230	17864.84	122.77

Table 8- Unit Status for Case 4

Unit	Hours (0-24)
Unit 1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 2	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 <u>**1 1 1 1 1 1**</u> 0 0
Unit 3	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 4	0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 5	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
Unit 6	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 7	0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 8	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 9	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 10	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 <u>**0 0 0 0 0 0 0 0**</u> 0
Unit 11	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 0
Unit 12	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 <u>**1 1 1 1 1 1**</u> 0 0
Unit 13	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Unit 14	0 0 0 0 0 0 0 0 <u>**1 1 1 1 1 1 1 1 1 1 1 1 1 1 1**</u> 0
Unit 15	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 16	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 17	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 18	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
Unit 19	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit 20	0 0 0 0 0 0 0 <u>**1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1**</u>

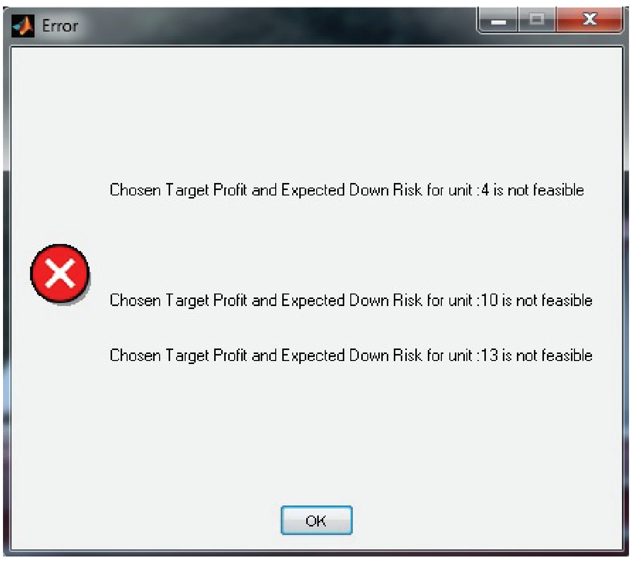

Fig 33- Not feasible units in Case 4

All the bidding curves of the risk constrained cases (Case 3 and 4) are presented in Appendix C.

5.4. Discussion on results

If the estimated prices happened to be the market clearing prices GENCO would have to schedule its units according to power price bid he has won. a sample of winning power-price bid is shown in Fig 32.

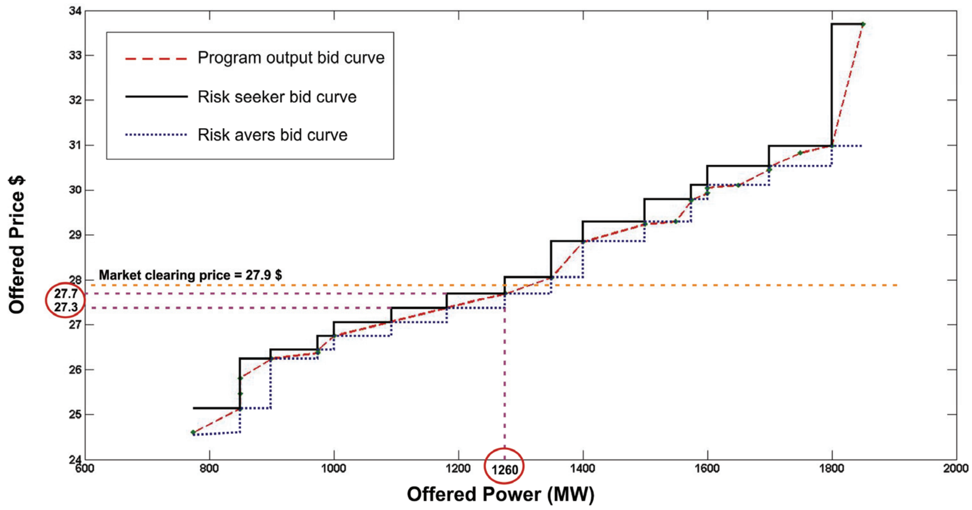

Fig 34- power-price winning bid for Hour 14

GENCO have to do a classic unit commitment problem to optimize its units scheduling while meeting the promised power for every Hour. The results of such a unit commitment for each case are presented in tables 9, 10, 11.

Table 9- Risk seeker winning price power pairs – case 2

	Risk Seeker		**Risk Averse**	
Hour	**Price**	**Power**	Price	Power
6	14	25	14	25
7	19.9	75	17.6	75
8	21	150	19.5	150
9	23.5	510	23.5	525
10	25	850	25	980
11	27.2	1050	27.2	1260
12	27.9	1180	27.6	1180
13	28.1	1350	28.5	1420
14	27.9	1260	27.5	1260
15	27.5	1280	27.3	1280
16	27.5	1160	27.5	1280
17	28	1430	28	1520
18	28.5	1580	28.5	1700
19	28.8	1700	28.8	1800
20	30.5	1950	30.5	2050
21	30.8	1930	30.8	1980
22	29.3	1540	29.3	1640
23	25	850	25	920
24	20.7	220	20.7	270
Total Revenue		563773.5		596536.5
Total Cost		523256.9		557810.7
Profit		40516.63		38725.82

Table 10- Risk seeker winning price power pairs – case 3

	Risk Seeker		**Risk Averse**	
Hour	**Price**	**Power**	Price	Power
6	14	25	14	25
7	19.6	75	17.7	75
8	21	100	19.5	100
9	21	250	21	250
10	24.6	450	24.3	450
11	26.5	550	26.5	600
12	27.8	600	27.8	700
13	27.8	600	27.8	650
14	27.7	600	27.7	650
15	27.5	600	27.5	650
16	26.5	750	26.5	800
17	28	1050	27	1120
18	28.5	1180	28.5	1280
19	28.5	1200	28.5	1300
20	30.5	1540	30.5	1620
21	30.5	1520	30.5	1570
22	29.3	1170	29.3	1260
23	25	650	25	700
24	20.8	150	20.8	200
Total Revenue		365381		389965.5
Total Cost		328516.9		354176.6
Profit		36864.14		35788.89

Table 11- Risk seeker winning price power pairs – case 4

	Risk Seeker		**Risk Averse**	
Hour	**Price**	**Power**	Price	Power
6	14	25	14	25
7	19.6	75	17.7	75
8	21	150	19.5	150
9	23.6	425	23.3	425
10	24.5	500	24.5	620
11	26.5	620	26.5	720
12	27.5	800	27.5	850
13	27.5	710	27.5	800
14	27.9	800	27.6	800
15	27.5	800	27	800
16	26.5	720	27	820
17	27.9	1120	28.1	1180
18	28.5	1230	28.5	1320
19	28.8	1390	28.8	1420
20	30.6	1520	30.6	1550
21	30.4	1460	30.1	1460
22	29	1160	29	1160
23	24.9	370	26	620
24	20.8	200	20	200
Total Revenue		392849		416780
Total Cost		355453.4		380108.2
Profit		37395.6		36671.77

Table 12 – Comparison of different case studies results

Case	EPF $	Achieved Profit $	Expected Risk $	Value of perfect information $
Deterministic	47227.5	47227	0	0
Risk Neutral	61954.6	40516	2691.3	6110.9
Loosely Constrained	55702.5	37395	1823.3	9831.9
Tightly Constrained	41924.7	36868	1530.4	10363.1

CHAPTER 6

CONCLUSION AND FUTURE STUDIES

Optimum bidding curves for a generating company to take part in the day ahead energy market are developed throughout this thesis. Continuous aim of the generating company to maximize its profit will be partly fulfilled by optimizing its bidding in the market. Price uncertainty has always been a major issue for proper bidding and maximizing the payoff. In contrast with traditional Price Based Unit Commitment which is only dependent on a good forecast of energy prices, stochastic programming takes care of the price volatility by generating different possible scenarios using Monte Carlo Simulation method. Generating Company would be able to control his risk factor by indicating its risk tolerance in the model and trade some of the profit in favor of taking less risk. MATLAB platform is used to code the Mixed Integer Linear Programming model while CPLEX 9.0 solver engine is utilized to solve the optimization problem. Several case studies have been examined to show the validity of the model and the results have been interpreted to give more insight of the optimization solution.

1000 scenarios are generated in the presented model by Monte Carlo simulations and then reduced to 23 scenarios using scenario reduction techniques. If there is no risk constraints involved in the model, the solution presents hourly bidding curves for GENCO, aiming to maximize its expected payoff.

Risk constraints could also be handled in the presented model as well. GENCO decides on his target profit and acceptable downside risk and the model gives the optimum solution to meet those constraints. Case studies and their results shows that GENCO could reduce its risk level by reducing its expected payoff.

Two different approaches for a GENCO is studied in this thesis; one with tight risk constraints and the other with looser constraints. Results show that the more risk taken, the higher expected payoff will be.

Using the developed technique here, GENCO have a better chance to maximize its profit while controlling the amount of risk he is willing to take. This achievement is easily gained by a fairly accurate price forecasting in a reasonable time.

It should not be forgotten that this technique does not account for other participants' behavior and it is a single GENCO optimization method. In order to achieve higher levels of optimality and risk reduction and even exercising market power, gaming theory and agent based models could also be integrated.

In order to hedge against high risk levels associated with several hours and scenario, some mechanisms such as intelligent bilateral negotiations and wind and renewable energies incorporations could also be examined and studied.

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APPENDIX A

DATA FOR CASE STUDIES

Table 13- Units data

Unit no	P min MW	P max MW	Min ON Hour	Min OFF Hour	Ramp UP MW/h	Ramp Down MW/h	IniT Hour	Fuel Type	Fuel Price $/Mbtu
1	5	30	1	1	15	15	1	Gas	1
2	5	30	1	1	15	15	1	Gas	1
3	5	30	1	1	15	15	1	Gas	1
4	150	300	4	4	150	150	1	Coal	1
5	100	300	4	4	150	150	1	Coal	1
6	10	30	1	1	15	15	1	Gas	1
7	25	100	5	5	50	50	1	Coal	1
8	5	30	1	1	15	15	1	Gas	1
9	5	30	1	1	15	15	1	Gas	1
10	100	300	4	4	150	150	1	Coal	1
11	100	350	4	4	175	175	1	Coal	1
12	8	30	1	1	15	15	1	Gas	1
13	8	30	1	1	15	15	1	Gas	1
14	25	100	5	5	50	50	1	Coal	1
15	8	30	1	1	15	15	1	Gas	1
16	25	100	5	5	50	50	1	Coal	1
17	8	30	1	1	15	15	1	Gas	1
18	8	30	1	1	15	15	1	Gas	1
19	25	100	5	5	50	50	1	Coal	1
20	50	250	4	4	125	125	1	Coal	1

Table 14-Quadratic Heat Rate curve Coefficients

Unit no	cf (Mbtu/h)	bf (Mbtu/MWh)	af (Mbtu/MWh2)
1	31.67	26.24382	6.97E-02
2	31.67	26.24382	6.97E-02
3	31.67	26.24382	6.97E-02
4	6.78	25.3875	0.010875
5	6.78	24.8875	0.010875
6	31.67	26.24382	6.97E-02
7	10.15	17.82	0.0128
8	31.67	26.24382	6.97E-02
9	31.67	26.24382	6.97E-02
10	6.78	25.8875	0.010875
11	32.96	26.76	0.003
12	31.67	26.24382	6.97E-02
13	31.67	26.24382	6.97E-02
14	10.15	24.82	0.0128
15	31.67	26.24382	6.97E-02
16	10.15	24.82	0.0128
17	31.67	26.24382	6.97E-02
18	31.67	26.24382	6.97E-02
19	10.15	24.82	0.0128
20	28	22.3299	2.40E-03

Table 15- Piecewise Linear Heat Rate Constants

Unit no	Number of piece wise segments	Power Range seg 1	Mbtu/ MWh	Power Range seg 2	Mbtu/ MWh	Power Range seg 3	Mbtu/ MWh	Power Range seg 4	Mbtu/ MWh
1	4	10	26.94	10	28.33	5	29.38	5	30.07
2	4	10	26.94	10	28.33	5	29.38	5	30.07
3	4	10	26.94	10	28.33	5	29.38	5	30.07
4	4	150	27.01	50	29.19	50	30.28	50	31.36
5	4	150	26.51	50	28.69	50	29.78	50	30.86
6	4	10	26.94	10	28.33	5	29.38	5	30.07
7	4	25	18.14	25	18.78	25	19.42	25	20.06
8	4	10	26.94	10	28.33	5	29.38	5	30.07
9	4	10	26.94	10	28.33	5	29.38	5	30.07
10	4	150	27.51	50	29.69	50	30.78	50	31.86
11	4	150	27.21	100	27.96	50	28.41	50	28.71
12	4	10	26.94	10	28.33	5	29.38	5	30.07
13	4	10	26.94	10	28.33	5	29.38	5	30.07
14	4	25	25.14	25	25.78	25	26.42	25	27.06
15	4	10	26.94	10	28.33	5	29.38	5	30.07
16	4	25	25.14	25	25.78	25	26.42	25	27.06
17	4	10	26.94	10	28.33	5	29.38	5	30.07
18	4	10	26.94	10	28.33	5	29.38	5	30.07
19	4	25	25.14	25	25.78	25	26.42	25	27.06
20	4	100	27.56	50	22.92	50	23.16	50	23.41

Table 16- Market Energy Prices and Their Variances

Hour	Energy Price ($/MWh)	Variance of energy price
1	21.71	10.86
2	17.5	8.75
3	13.05	6.53
4	12.15	6.08
5	13.77	6.89
6	15.99	8
7	20.99	10.5
8	23.01	11.51
9	23.85	11.93
10	26.11	13.05
11	27.23	13.62
12	27.99	14
13	28.7	14.35
14	27.9	13.95
15	27.55	13.77
16	27.73	13.86
17	28.13	14.06
18	28.56	14.28
19	28.8	14.4
20	30.83	15.41
21	30.81	15.4
22	29.34	14.67
23	26.56	13.28
24	21.15	10.58

APPENDIX B

GENERATED SCENARIOS

Monte Carlo simulation method is applied to generate scenarios for stochastic programming. 1000 scenarios are generated using energy market prices and their variances. Since a 1000-scenario problem is considerably large for Personal Computers to handle, the number of scenarios should be reduced significantly.

Scenario reduction technique is applied such that the remaining scenarios still present a good estimation and representation of the stochasticity of the market prices.

Eliminating scenarios which have at least one element with a probability of less than 4%, the number of scenarios are reduced to 23.

Microsoft Office Excel program is utilized to deal with data processing. Monte Caro simulations are performed by FrontLine Solvers™ add-on for Microsoft Excel.

The reduced scenarios are presented in the following tables.

Table 17- Hourly Market Prices for Scenarios 1 to 8

	S1	S2	S3	S4	S5	S6	S7	S8
H1	20.08	18.06	24.73	21.79	18.06	20.31	20.43	19.59
H2	16.25	14.57	18.06	18.89	18.1	19.21	20.97	16.17
H3	13.12	10.51	11.88	15.29	16.12	13.23	10.9	13.15
H4	9.71	9.59	11.46	13.55	9.59	12.58	14.41	11.48
H5	13.44	11.98	16.57	13.03	13.68	13.79	15.96	16.44
H6	16.97	13.12	18.86	18.56	13.12	16.73	15.01	19.79
H7	25.84	17.47	17.47	22.48	20.63	22.15	17.62	22.59
H8	23.69	19.13	21.04	22.16	26.65	24	19.41	24.19
H9	21.1	20.06	22.66	23.21	26.93	25.74	24.94	23.51
H10	24.21	22.1	30.58	27.04	31.88	29.74	24.29	27.13
H11	25.46	24.49	29.6	28.78	25.27	32.08	28.72	28.09
H12	27.76	23.26	24.74	30.53	25.48	26.39	25.73	27.84
H13	31.08	24.07	27.72	28.36	29.79	30.59	24.07	29.33
H14	29.92	24.6	25.12	29.23	25.47	26.44	29.29	27.7
H15	23.43	23.06	31.33	28.93	26.48	30.27	24.68	23.18
H16	27.05	24.18	33.26	28.54	26.63	27.97	24.54	31.07
H17	30.62	23.27	31.82	29.06	28.34	30	30.25	30.54
H18	29.45	24.45	32.27	29.19	29.51	32	28.86	31.85
H19	29.39	23.43	29.62	28.86	23.43	30.88	32.05	29.84
H20	33.65	27.33	30.47	31.93	34.09	31.6	30.14	34.57
H21	36.12	25.61	26.78	31.96	28.97	29.37	32.76	29.27
H22	25.16	24.27	30.59	30.28	29.42	28.99	29.54	30.55
H23	32.52	22.61	31.48	27.48	31.72	25.27	28.49	29.41
H24	21.47	17.97	24.76	20.78	18.76	19.82	22.85	18.8

Table 18- Hourly Market Prices for Scenarios 9 to 16

	S9	S10	S11	S12	S13	S14	S15	S16
H1	21.8	26.44	19.31	22.53	18.25	21.43	19.76	25.65
H2	19.49	16.04	15.3	16.02	14.57	18.62	19.47	16.84
H3	10.59	12.17	11.95	10.51	11.31	12.6	11.58	16.47
H4	12.47	15.38	13.82	14.06	12.9	12.25	12.03	11.95
H5	15.61	15.14	12.27	12.11	14.7	14.02	11.98	12.18
H6	16.03	14.38	18.57	14.86	17.27	15.94	17.44	19.37
H7	19.38	22.12	24.21	24.34	20.52	23.66	19.75	20.91
H8	22.61	24.58	20.86	23.56	20.98	21	23.57	24.69
H9	25.01	27.16	25.12	23.99	20.06	20.99	25.29	22.45
H10	31.84	27.62	26.84	29.86	27.79	23.63	24.57	22.1
H11	28.28	28.07	26.64	25.82	32.58	28.23	29.31	26.48
H12	23.26	26.11	28.54	28.53	25.67	29.98	27.42	31
H13	29.12	31.53	29.83	30.25	33.6	26.99	26.86	29.81
H14	30.53	28.84	29.76	30.83	25.81	26.37	26.74	28.05
H15	30.78	29.93	32.79	33.13	33.44	24.04	23.06	27.59
H16	24.79	30.55	28.58	25.92	24.54	26.82	28.43	33.3
H17	24.82	28.11	25.13	23.27	29.38	27	29.29	31.75
H18	29.63	30.46	26.25	26.59	32.91	24.45	29.83	34.26
H19	29.59	28.93	31.36	26.83	30.54	24.86	27.62	30.71
H20	31.54	32.97	32.32	29.74	31.02	32.79	33.1	34.86
H21	27.93	31.16	28.75	32.62	31.97	25.87	27.53	31.43
H22	26.69	28.44	29.96	34.98	27.5	25.91	29.23	24.27
H23	27.6	24.21	26.8	27.15	24.74	28.97	25.04	26.06
H24	22.65	26.13	24.16	17.97	19.57	24.97	20.79	18.83

Table 19- Hourly Market Prices for Scenarios 17 to 23

	S17	S18	S19	S20	S21	S22	S23
H1	23.91	18.46	23.2	22.55	21.6	20.6	26.22
H2	18.43	15.98	21.71	20.67	20.28	20.52	18.82
H3	12.48	16.52	15.04	11.9	10.61	14.14	15.41
H4	11.67	9.76	12.84	13.29	12.28	12.63	14.49
H5	15.93	16.68	14.78	16.96	12.9	14.01	17.85
H6	14.24	15.99	17.96	13.47	14.5	13.26	19.64
H7	22.61	17.72	19.59	20.01	24.57	23.79	22.81
H8	26.42	23.91	19.13	21.72	19.5	25.67	23.62
H9	27.1	26.52	22.05	27.3	25.91	21.44	24.39
H10	25.03	27.68	27.29	30.47	26.08	26.9	27.9
H11	27.16	25.53	24.49	29.2	29.57	28.43	29.31
H12	28.38	29.98	29.93	27.72	27.01	31.12	29.23
H13	28.94	24.63	29.77	24.66	28.13	25.48	26.42
H14	29.78	30.11	30.05	26.24	30.99	33.69	30.46
H15	33.35	24.74	27.97	26.28	28.41	29.35	30.58
H16	25.7	28.43	30.25	31.13	26.77	24.18	27.99
H17	29.95	32.97	31.66	24.19	26.97	27.91	29.27
H18	29.04	26.34	25.68	30.17	28.13	31.23	32.83
H19	28.18	30.1	31.89	32.19	23.46	31.34	30.08
H20	28.48	32.36	27.33	33.33	34.83	33.37	30.07
H21	33.64	34.87	25.61	30.42	30.68	29.73	28.86
H22	32.5	25.6	32.9	27.78	30.09	25.02	29.84
H23	25.82	24.95	27.99	22.61	24.41	23.8	31.31
H24	20.66	26.9	22.83	23	23	19.54	23.21

APPENDIX C

BIDDING CURVES FOR CASES 4 and 5

C.1. Bidding Curves for Case 3

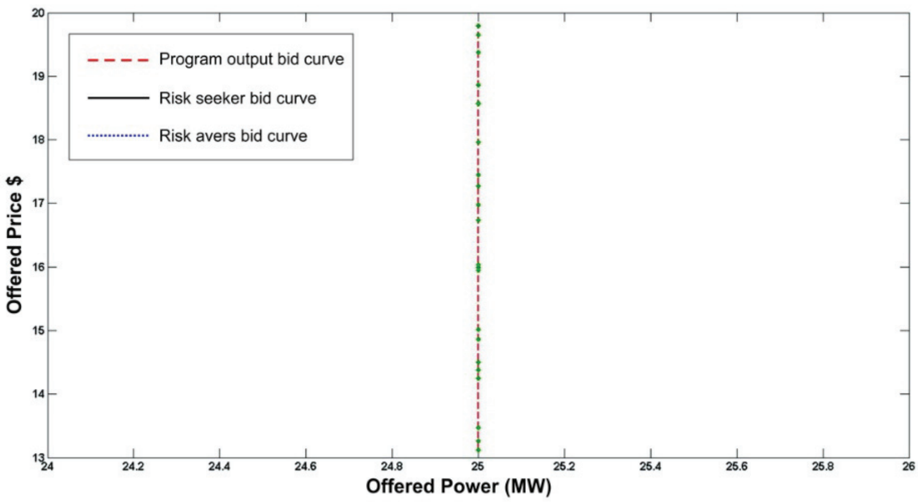

Fig 35- Case 3, bidding curve for Hour 6

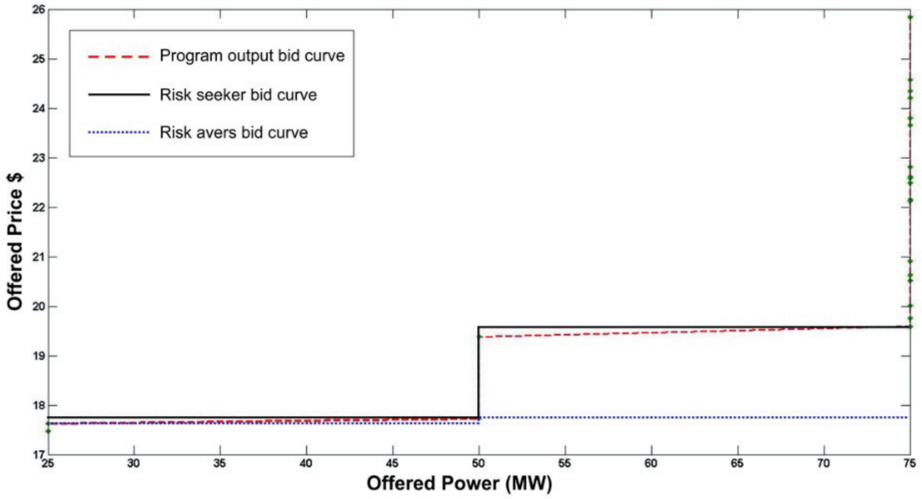

Fig 36- Case 3, bidding curve for Hour 7

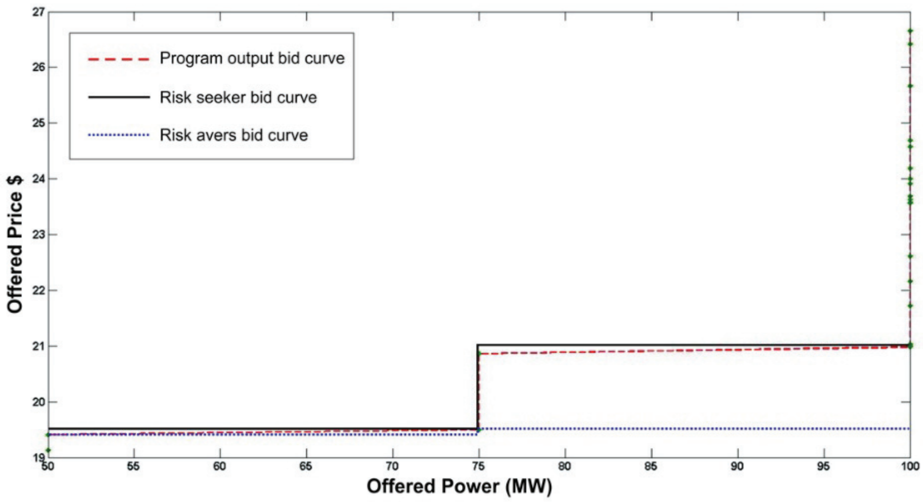

Fig 37- Case 3, bidding curve for Hour 8

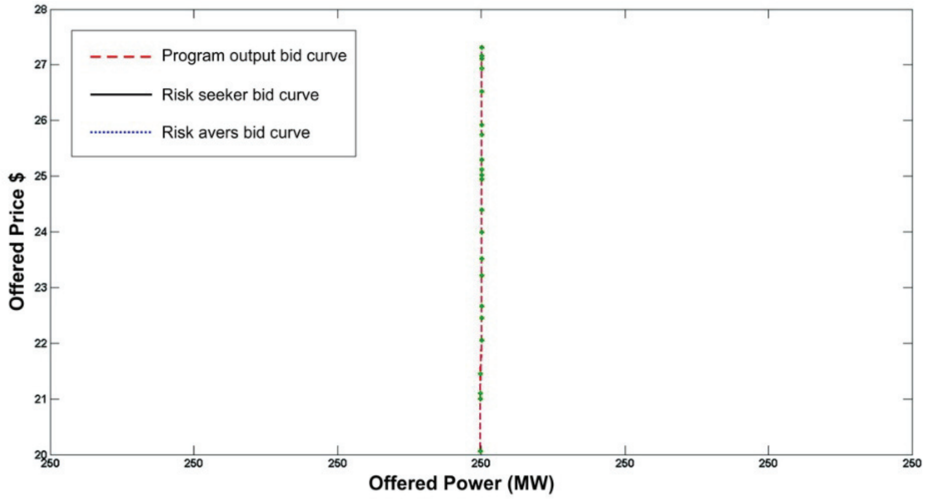

Fig 38- Case 3, bidding curve for Hour 9

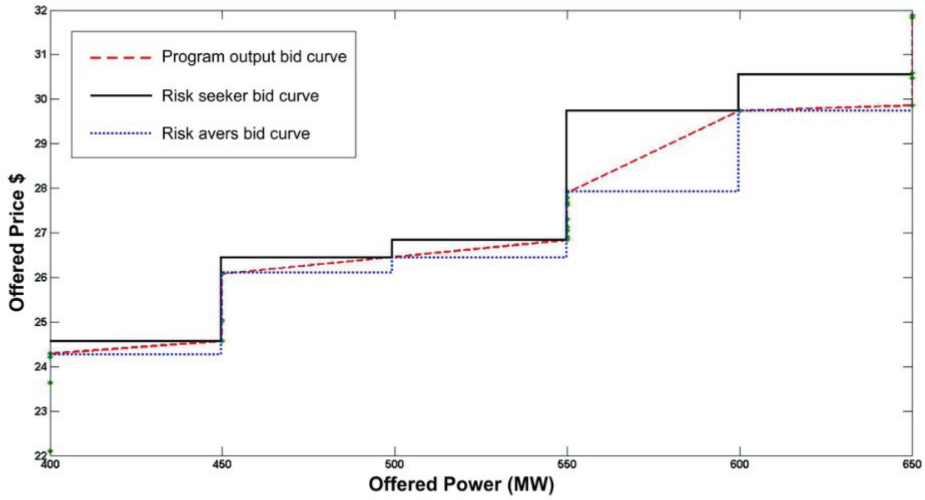

Fig 39- Case 3, bidding curve for Hour 10

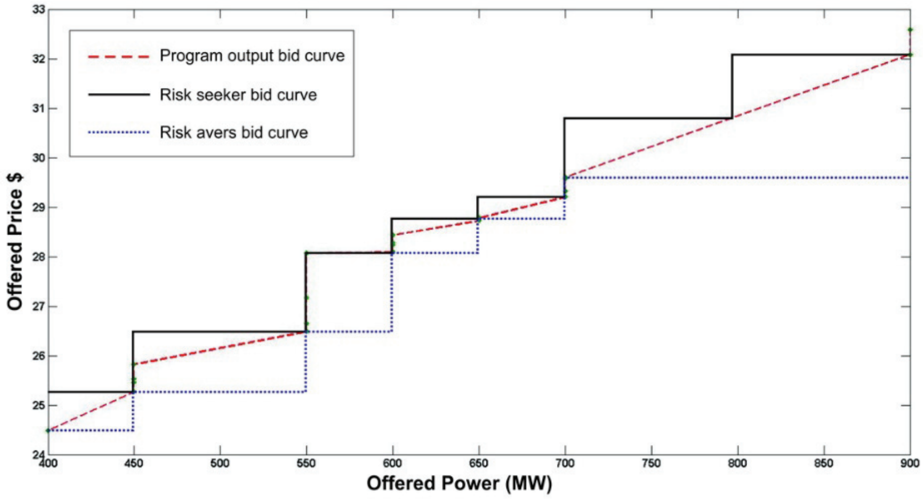

Fig 40-Case 3, bidding curve for Hour 11

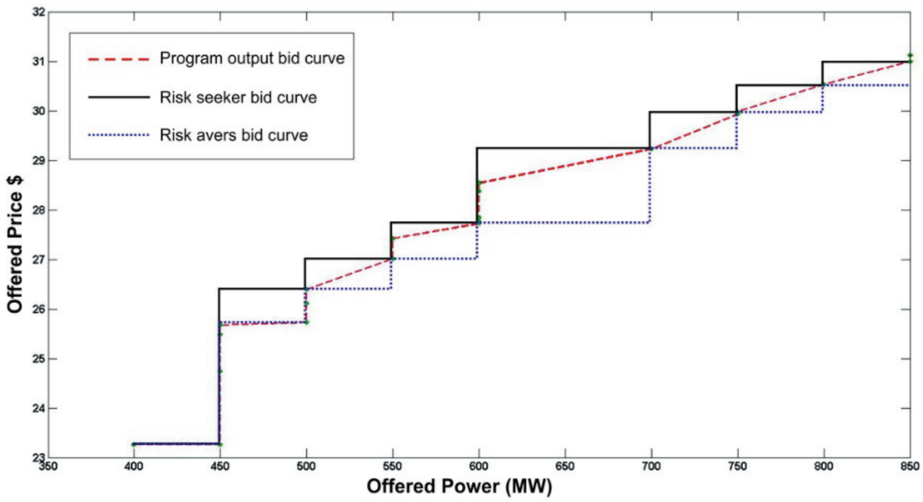

Fig 41-Case 3, bidding curve for Hour 12

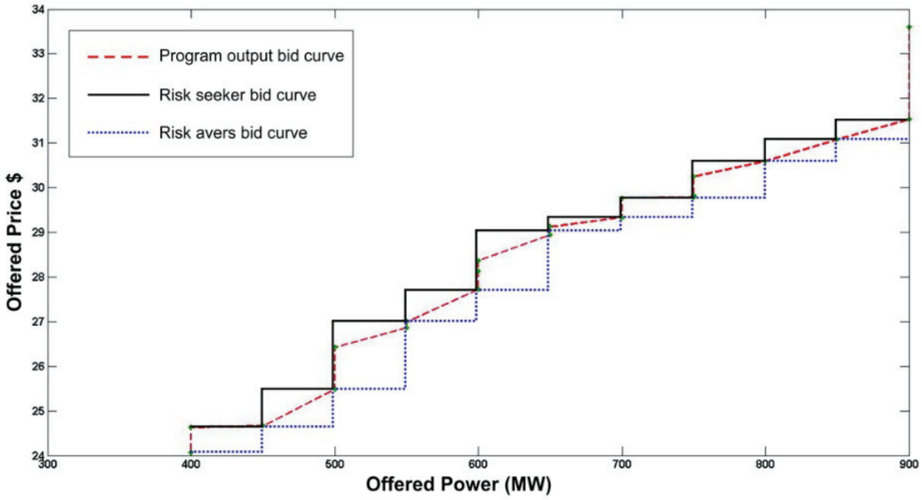

Fig 42-Case 3, bidding curve for Hour 13

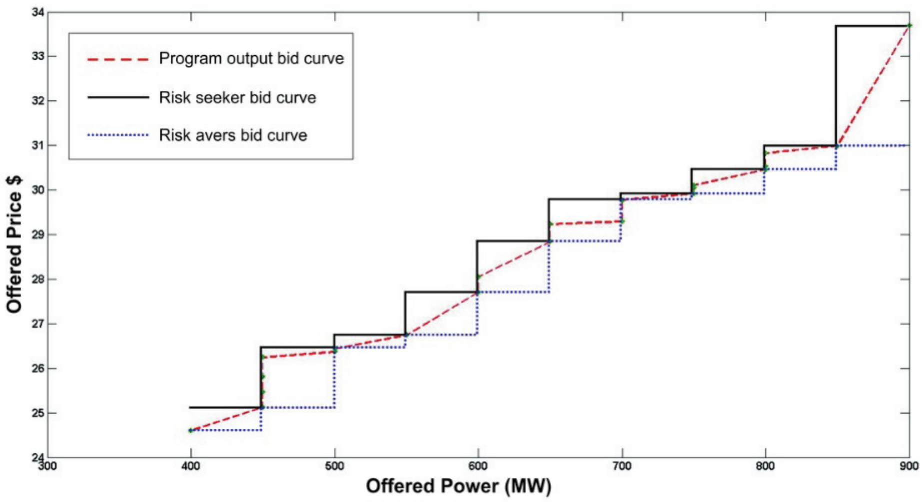

Fig 43-Case 3, bidding curve for Hour 14

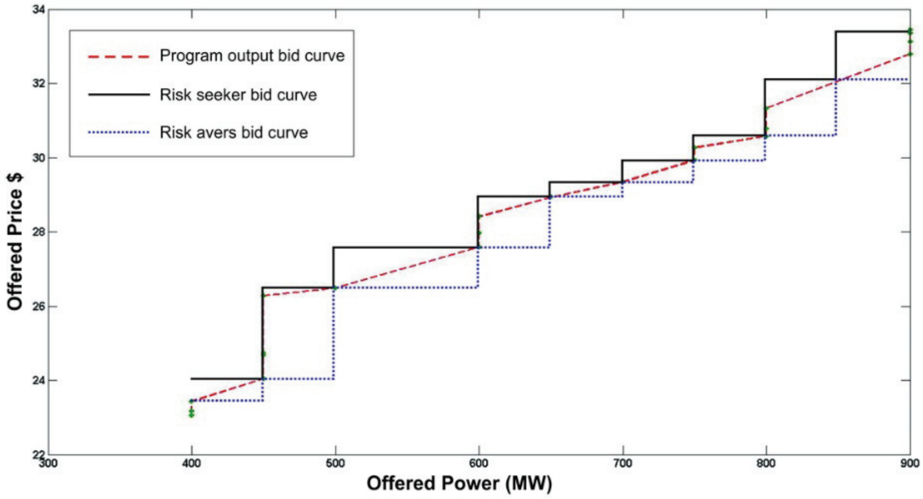

Fig 44-Case 3, bidding curve for Hour 15

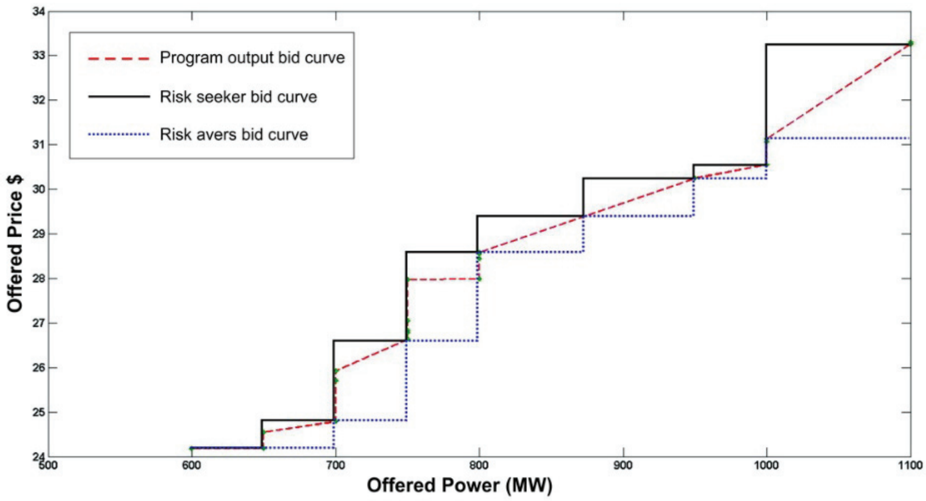

Fig 45-Case 3, bidding curve for Hour 16

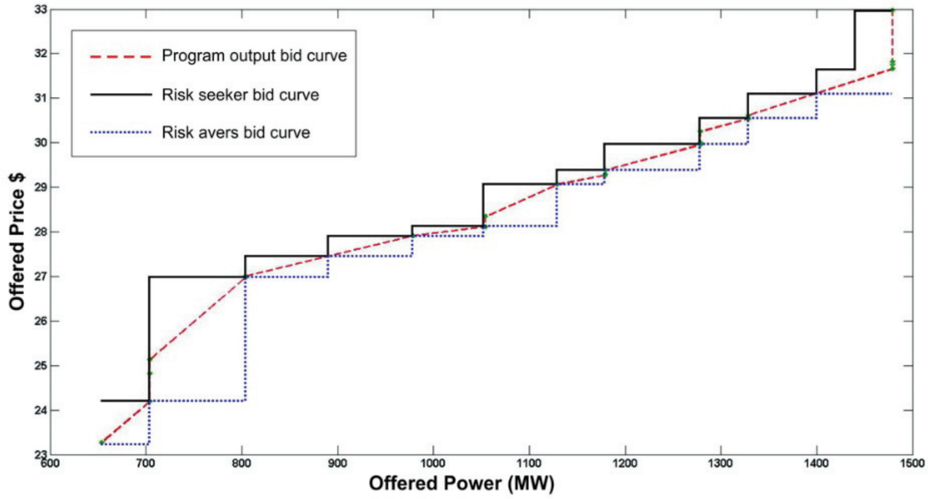

Fig 46-Case 3, bidding curve for Hour 17

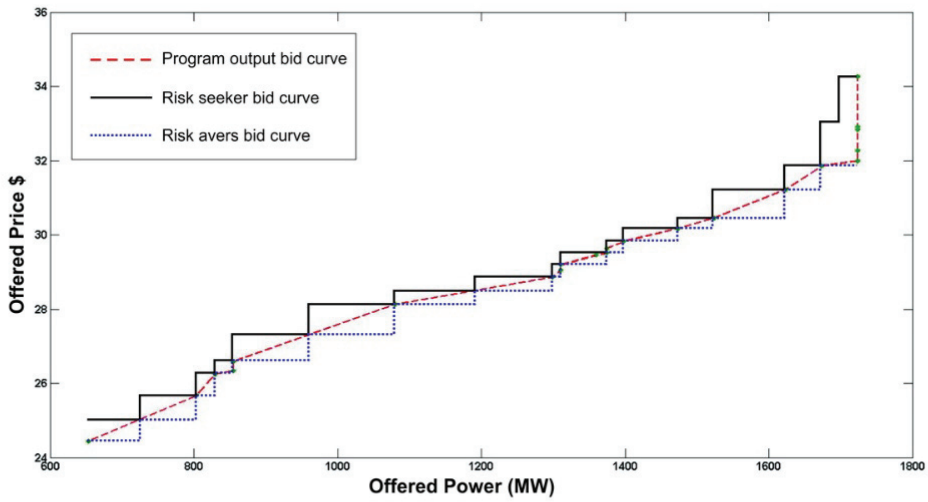

Fig 47-Case 3, bidding curve for Hour 18

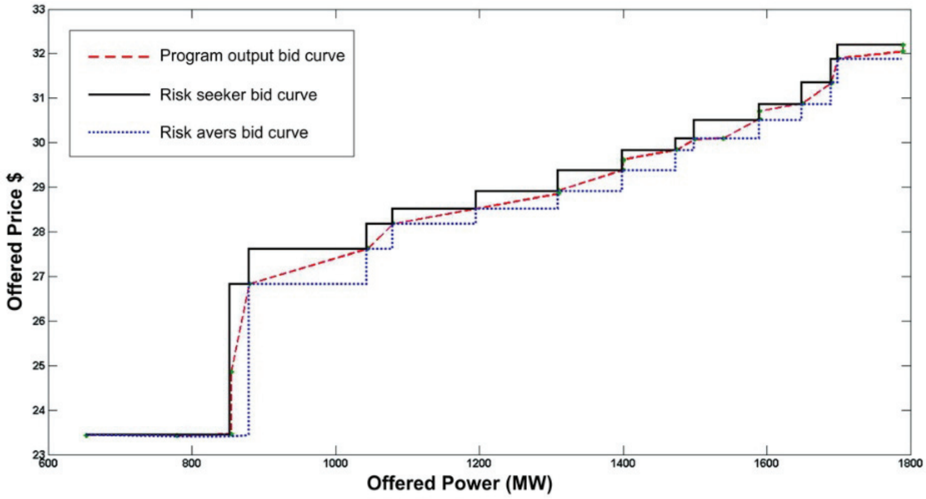

Fig 48-Case 3, bidding curve for Hour 19

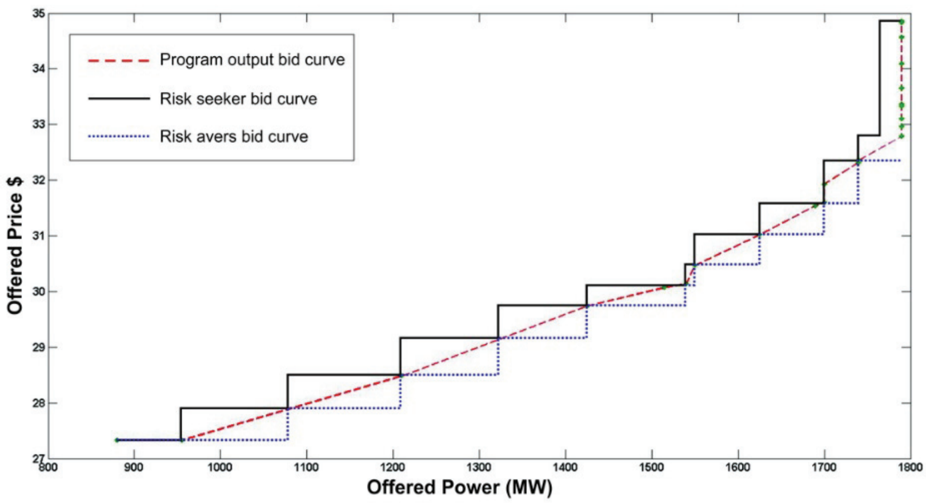

Fig 49-Case 3, bidding curve for Hour 20

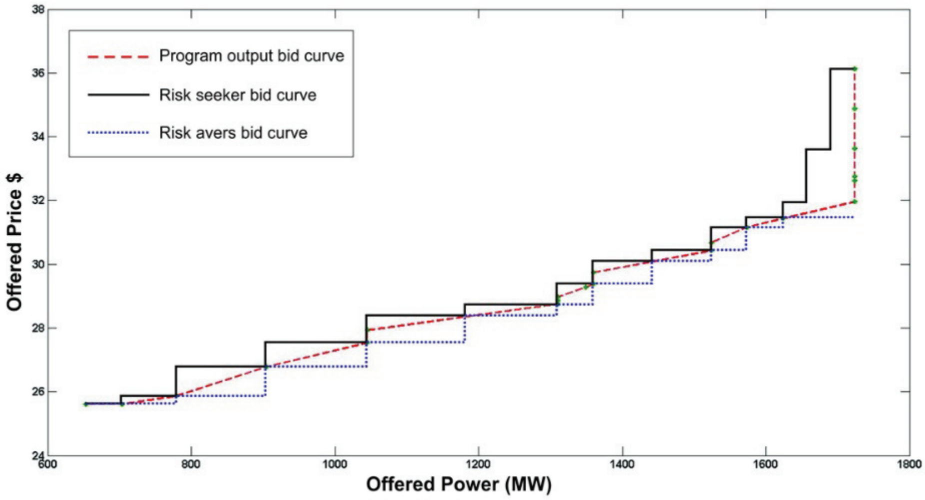

Fig 50-Case 3, bidding curve for Hour 21

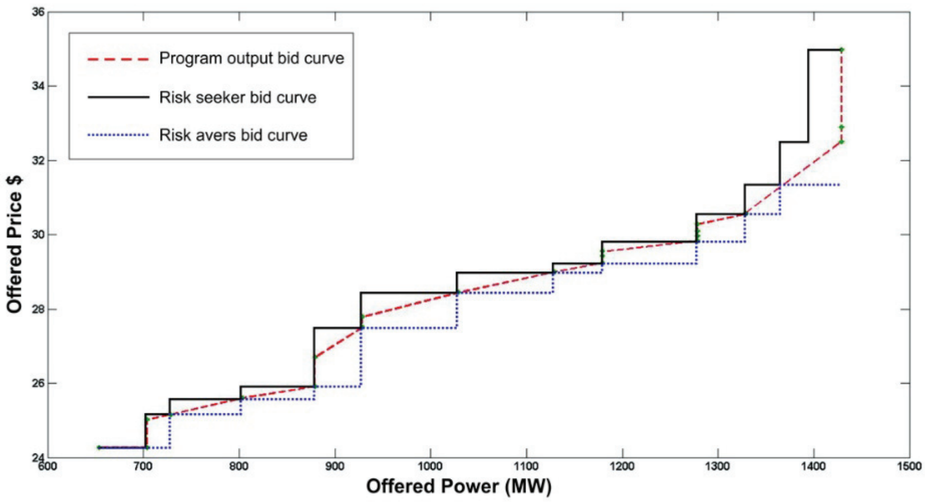

Fig 51-Case 3, bidding curve for Hour 22

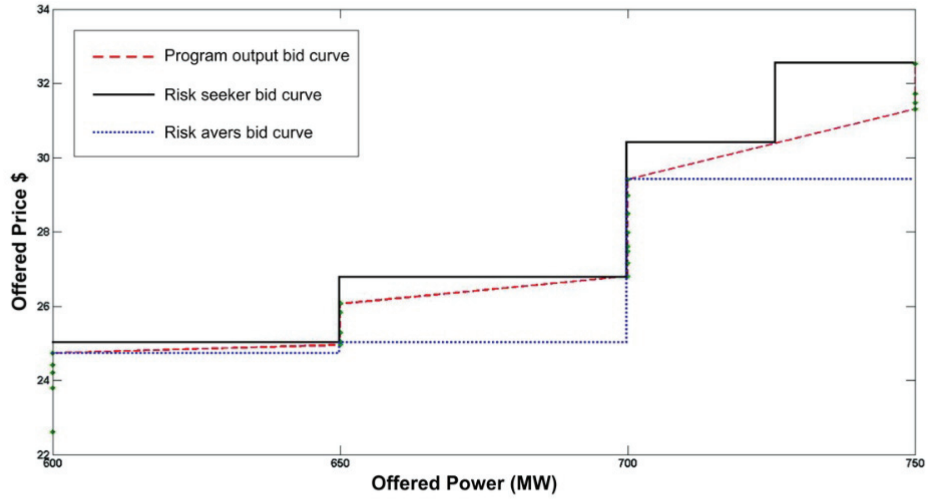

Fig 52-Case 3, bidding curve for Hour 23

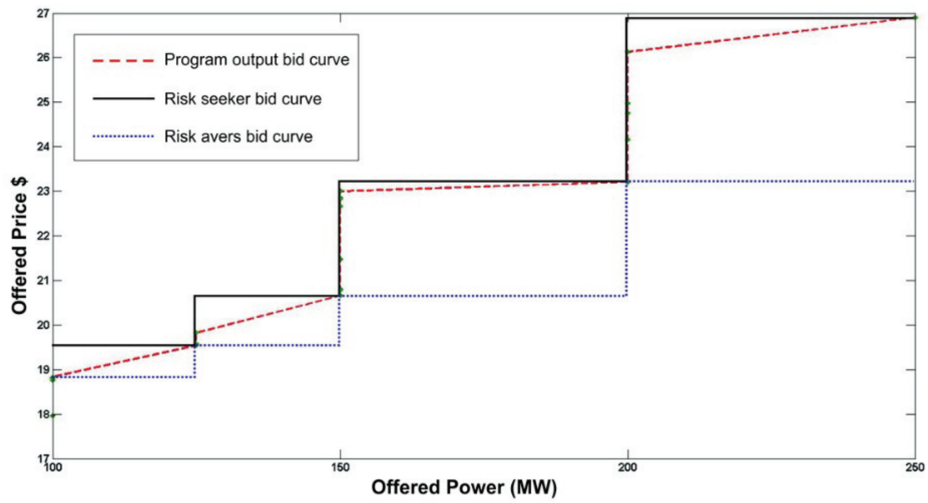

Fig 53-Case 3, bidding curve for Hour 24

C.1. Bidding Curves for Case 3

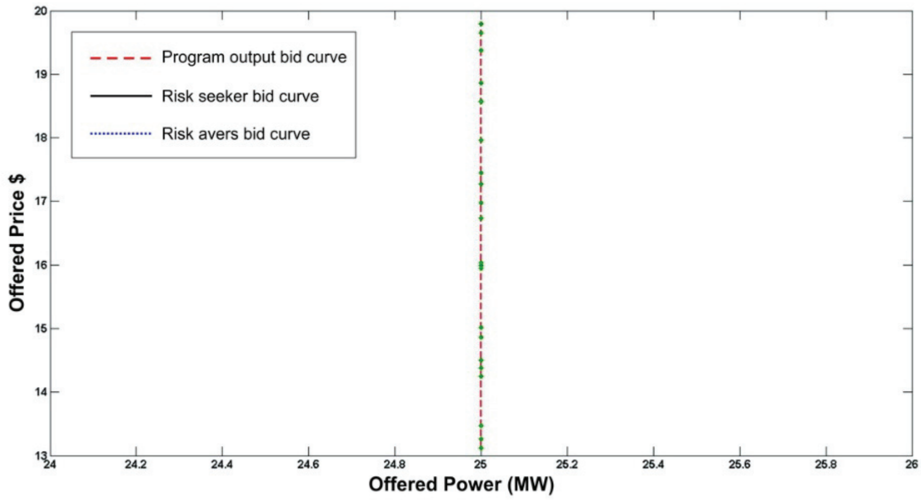

Fig 54-Case 4, bidding curve for Hour 6

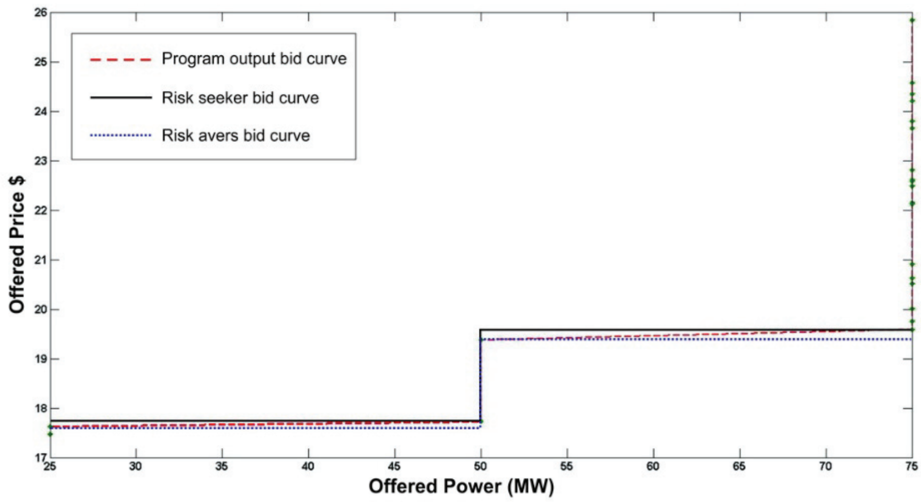

Fig 55-Case 4, bidding curve for Hour 7

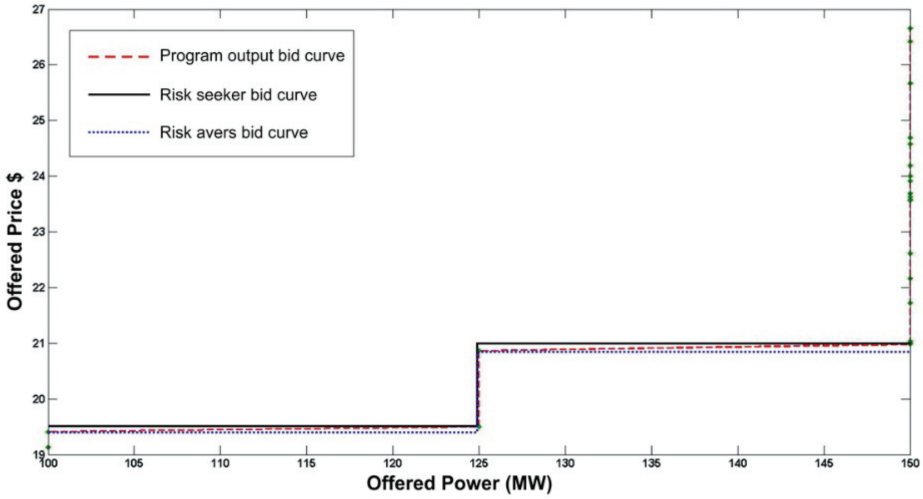

Fig 56-Case 4, bidding curve for Hour 8

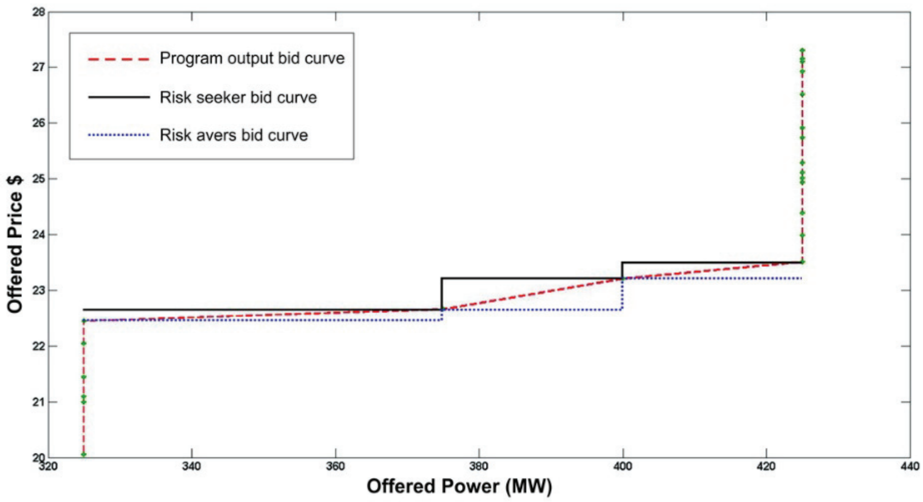

Fig 57-Case 4, bidding curve for Hour 9

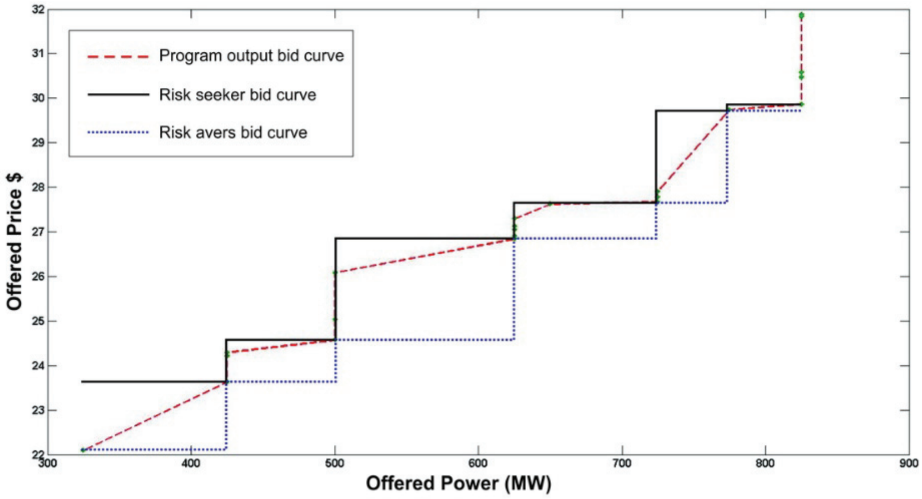

Fig 58-Case 4, bidding curve for Hour 10

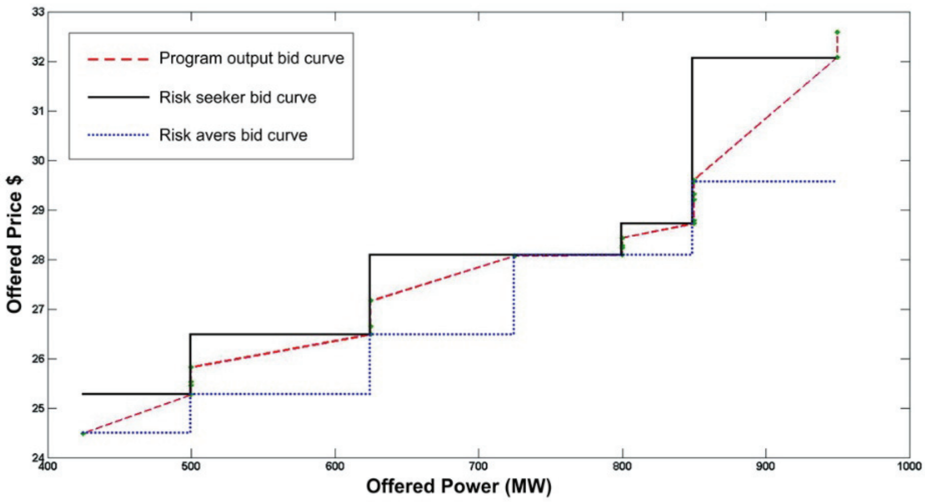

Fig 59-Case 4, bidding curve for Hour 11

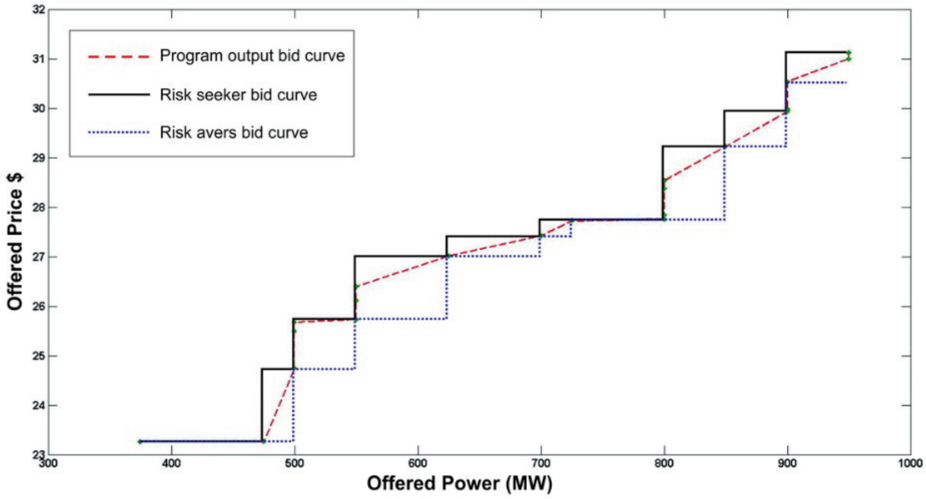

Fig 60-Case 4, bidding curve for Hour 12

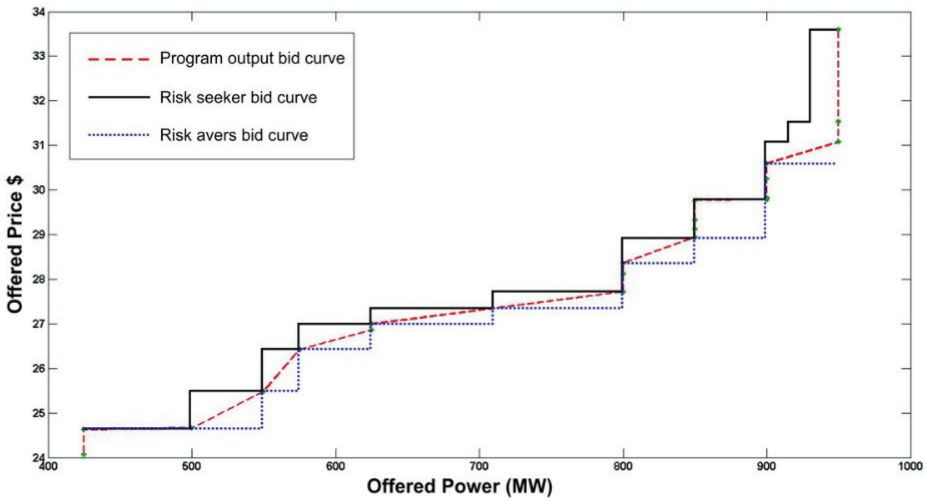

Fig 61-Case 4, bidding curve for Hour 13

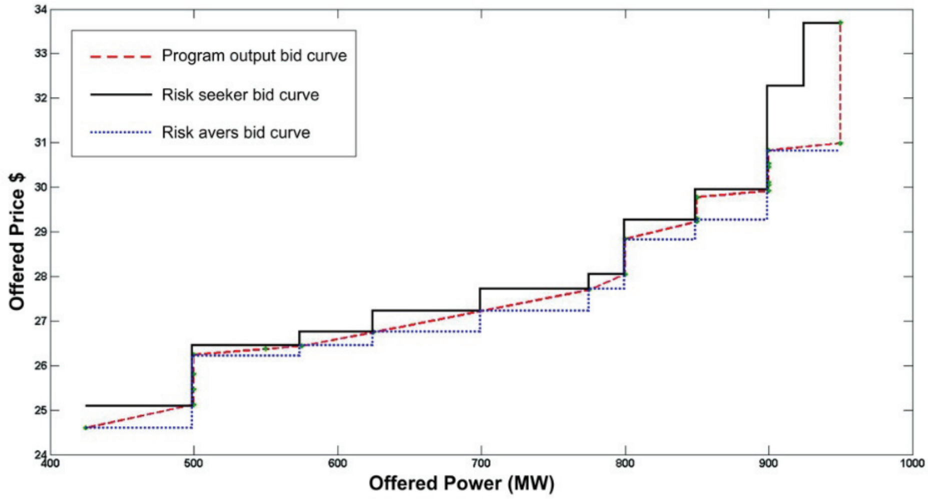

Fig 62-Case 4, bidding curve for Hour 14

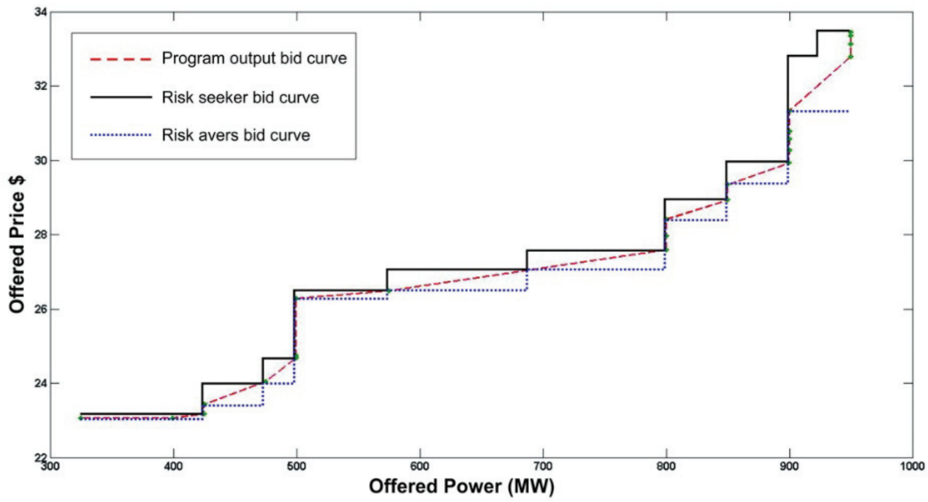

Fig 63-Case 4, bidding curve for Hour 15

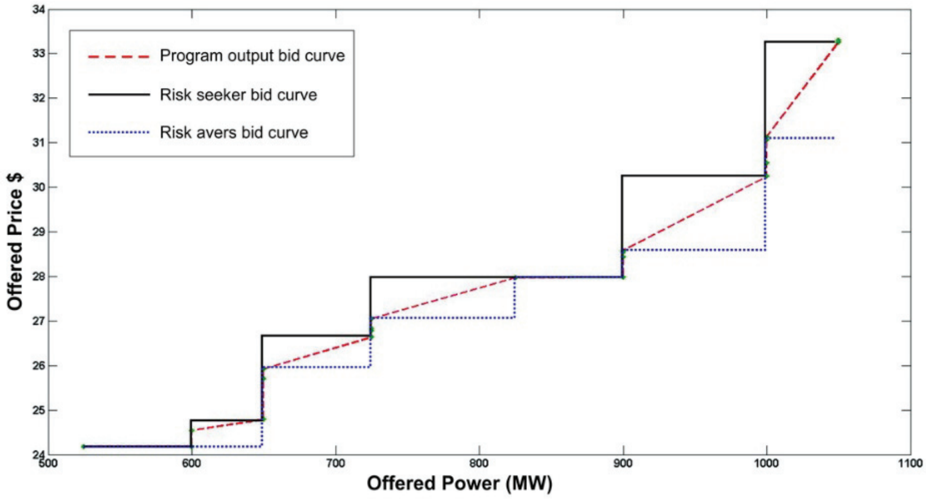

Fig 64-Case 4, bidding curve for Hour 16

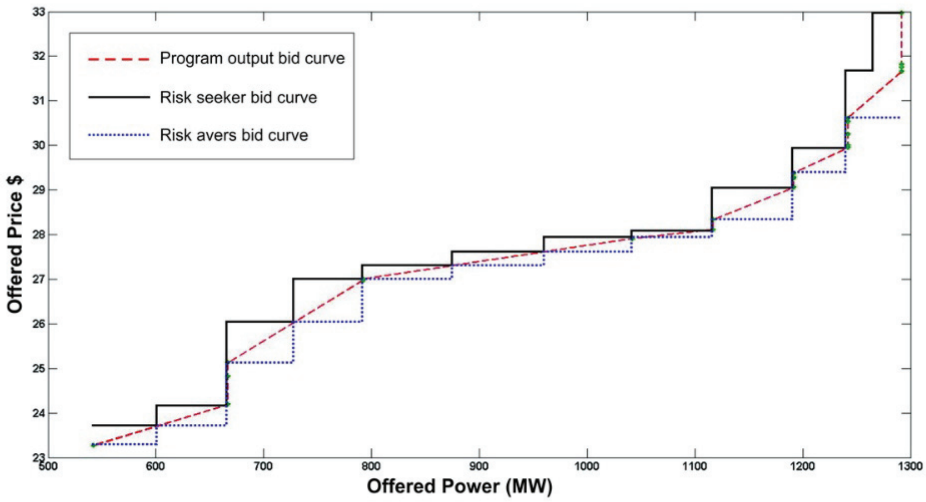

Fig 65-Case 4, bidding curve for Hour 17

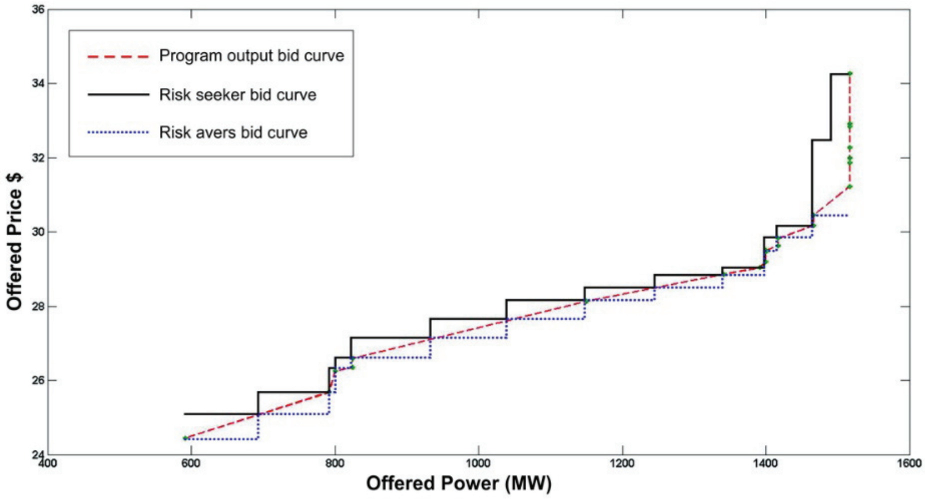

Fig 66-Case 4, bidding curve for Hour 18

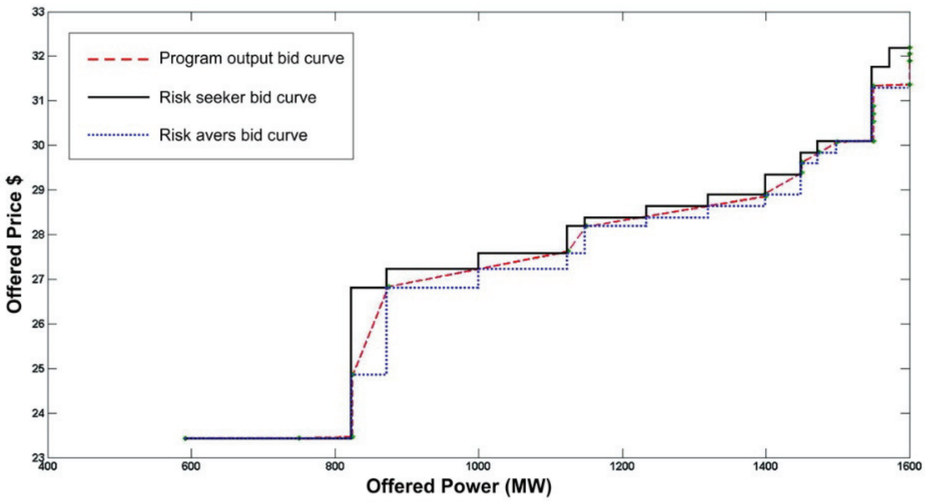

Fig 67-Case 4, bidding curve for Hour 19

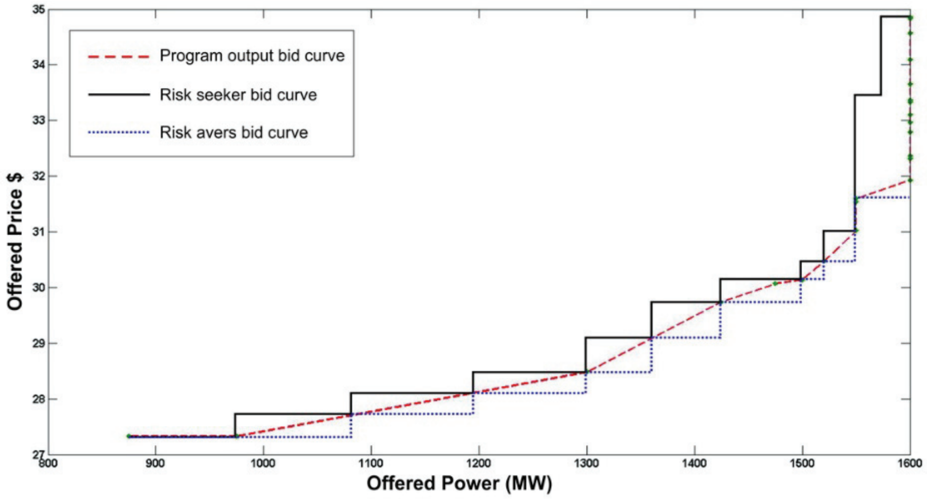

Fig 68-Case 4, bidding curve for Hour 20

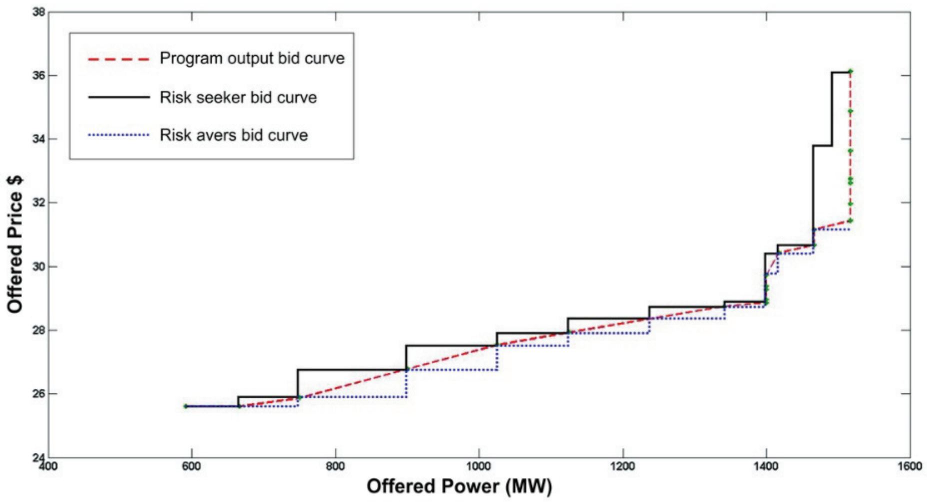

Fig 69-Case 4, bidding curve for Hour 21

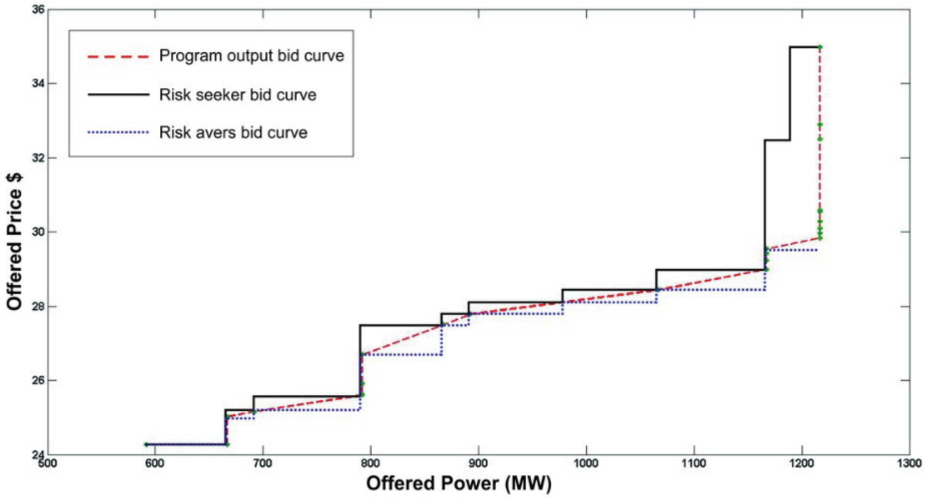

Fig 70-Case 4, bidding curve for Hour 22

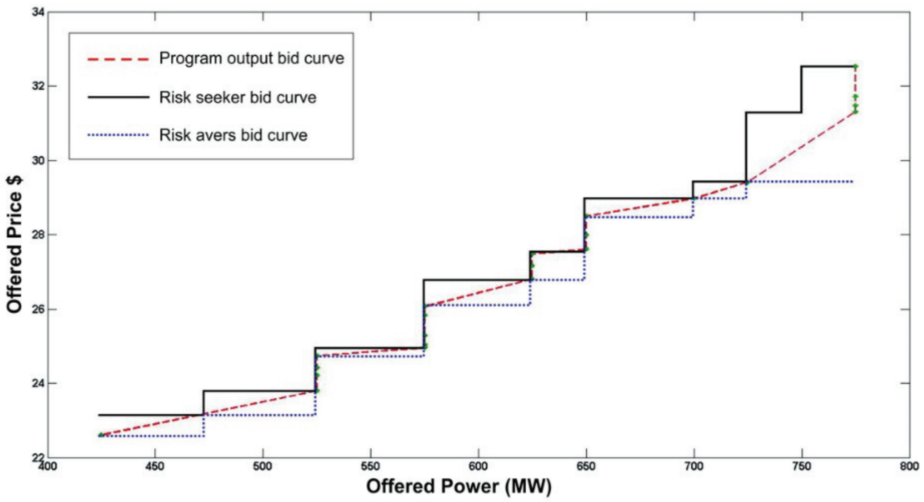

Fig 71-Case 4, bidding curve for Hour 23

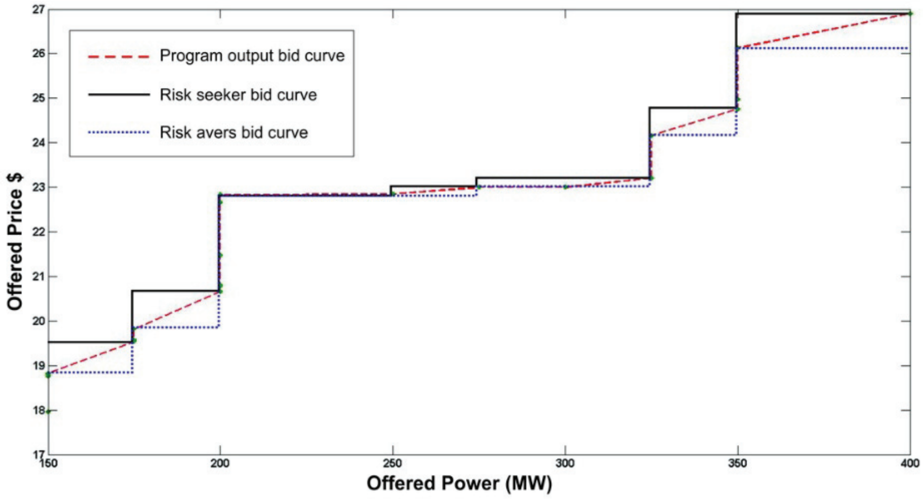

Fig 72-Case 4, bidding curve for Hour 24