Aspects of generation planning in competitive electricity markets

Bikal Kumar Pokharel

2005

Bikal, K. P. (2005). Aspects of generation planning in competitive electricity markets. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/4702>

<https://doi.org/10.32657/10356/4702>

Nanyang Technological University

Downloaded on 26 Apr 2023 18:02:50 SGT

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

**ASPECTS OF GENERATION PLANNING IN
COMPETITIVE ELECTRICITY MARKETS**

**BIKAL KUMAR POKHAREL
SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING
2006**

Aspects of Generation Planning in Competitive Electricity Markets

Bikal Kumar Pokharel

School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
Doctor of Philosophy

2005

Acknowledgements

My sincere gratitude to my supervisor Associate Professor Govinda Bol Shrestha for providing me an opportunity to work under him at Nanyang Technological University (NTU) and for his invaluable guidance during the entire course of my research that made this thesis possible.

Sincere thanks and gratitude is extended to Associate Prof Lie Tek Tjing, Nanyang Technological University, for his continuous support, suggestions and feedback. I would also like to thank Associate Professor Stein-Erik Fleten, Norwegian University of Science and Technology (NTNU), for data, helpful feedback and suggestions.

Acknowledgement is extended to Professor Choi San Shing, former head of the division-power engineering, for the opportunity given to pursue a research degree. Truly appreciated is the financial support granted by the Nanyang Technological University as postgraduate research scholarship.

I would also like to thank my colleagues and laboratory staff at the division of power engineering for interesting discussions and always providing a pleasant working atmosphere. Thanks also to many other friends and relatives for their support and encouragement and for making my stay in Singapore more enjoyable.

Finally, I would like to thank my family, in particular my mother Manju Pokharel and my father Ajaya K. Pokharel, who have been a constant source of inspiration throughout my academic career.

Table of Contents

Acknowledgements	i
Table of Contents	ii
Summary	vi
List of Figures	ix
List of Tables	xi
List of Symbols	xiii
List of Acronyms	xviii
1. Introduction	1
1.1 Motivation	1
1.2 Objectives	4
1.2.1 Generation Scheduling	4
1.2.2 Uncertainty and Risk Management	4
1.2.3 Bidding Strategies	5
1.3 Major Contributions	7
1.3.1 Medium Term Power Planning	7
1.3.2 Production Scheduling in Competitive Markets	8
1.3.3 Uncertainty Management in Generation Planning	10
1.3.4 Price Based Bidding Strategy	11
1.4 Thesis Outline	12
2. Background Literature	13
2.1 Overview of Deregulated Electricity Industry	13
2.1.1 Deregulation Process	14
2.1.2 Power Market Models	15

2.1.3	Classification of a Market	16
2.1.4	Continuous Changes in Market Structures and Rules.....	18
2.2	Generation Planning in Competitive Electricity Markets	21
2.2.1	Long Term Planning	21
2.2.2	Medium Term Planning	22
2.2.3	Short Term Planning	22
2.2.4	Real Time Optimization.....	23
2.3	Market Strategies in Competitive Markets	24
2.3.1	Generation Scheduling.....	26
2.3.2	Risk Management	36
2.3.3	Strategic Bidding in Competitive Market	40
2.4	Concluding Remarks.....	43
3.	Medium Term Power Planning	44
3.1	Introduction.....	44
3.2	NordPool	47
3.2.1	Financial Market in Nordpool.....	48
3.3	Problem Formulation	49
3.3.1	Expected Value Analysis	50
3.3.2	Forecasting.....	52
3.3.3	Scenario Tree	57
3.3.4	Stochastic Program with Recourse	59
3.3.5	Risk Averse Decision Maker	62
3.4	Medium Term Scheduling	63
3.4.1	Case Study.....	65
3.4.2	Results.....	65
3.5	Concluding Remarks.....	69
4.	Production Scheduling in Competitive Markets.....	71
4.1	Introduction.....	71
4.2	Unit Commitment in Competitive Markets	72
4.2.1	Traditional Power Markets.....	74

4.2.2	Price Based Unit Commitment (PBUC)	78
4.2.3	Scheduling of Individual Units	86
4.2.4	Price Based Self Commitment	90
4.2.5	Comparative Examples	94
4.3	Concluding Remarks	100
5.	Uncertainty Management in Generation Planning	102
5.1	Introduction	102
5.2	Risk Mitigation Using Forward Contracts	104
5.2.1	Expected Income Analysis	104
5.2.2	Significant Observations	111
5.3	Managing Price Uncertainty in Generation Scheduling	115
5.3.1	Modeling Parameters	117
5.3.2	Problem Formulation	121
5.3.3	Bidding Analogy	127
5.3.4	Numerical Examples	130
5.4	Concluding Remarks	138
6.	Price Based Bidding Strategy	140
6.1	Introduction	140
6.2	Bidding Framework	141
6.2.1	Price Uncertainty	141
6.2.2	Price Based Generation Scheduling	142
6.2.3	Problem Formulation	142
6.3	Bidding Strategy	146
6.3.1	Price Quantity Relationship	147
6.3.2	Formation of Bid Curve	149
6.3.3	Bidding Analysis	153
6.4	Numerical Example	153
6.5	Concluding Remarks	156
7.	Conclusions and Recommendations	157

7.1	Conclusions	157
7.1.1	Medium Term Planning of Hydro Generators	157
7.1.2	Production Scheduling in Competitive Markets	158
7.1.3	Uncertainty Management	159
7.1.4	Bidding Strategy	160
7.1.5	Summary	160
7.2	Recommendations	162
	Author's Publications	164
	References	165
	APPENDICES	174
	APPENDIX A: Data for Hydro Plant for Medium Term Planning in Chapter 3	174
	APPENDIX B: Unit & Forecast Data for Production Scheduling in Chapter 4	175
	APPENDIX C: Scheduling Results from Chapter 4	180
	APPENDIX D: Plant Data and Forecast for Chapter 5 and 6	183
	APPENDIX E: Introduction to Utility Theory	184

Summary

In the competitive electricity market, profit driven generation companies (Gencos) need to make decisions on generation scheduling, contract evaluation, bidding strategies and risk management for various planning horizons. Power System planning tools are available for different planning levels. However, increasing uncertainty and continuously changing regulatory structure and trading rules have prevented, to a great extent, the use of such planning tools. Hence, new approaches for generation planning are being investigated to meet these requirements. In this research, various aspects of generation planning in short and medium term such as generation scheduling, contract evaluation, risk management and bidding strategies, are identified and investigated in the context of certain trading rules, types of market structures, types of generation units, contract availability, market uncertainties and risk preferences of the participants.

A medium term planning task in the form of a hydro scheduling problem to determine optimal bilateral contracts has been investigated in the context of a power market while considering major sources of uncertainties. The storability of water is accounted for by introducing successive periods and the uncertainty in the inflow and the market prices are represented through multistage scenario trees of probabilities at each period. A deterministic approach using expected values is extended to incorporate decision-making under uncertainty in the framework of a stochastic linear programming model with corrective recourse. The method is further extended for risk averse decision makers where the optimal portfolio is achieved by minimizing the variance subject to specified expected revenue resulting in a stochastic non-linear programming model. An improvement in the expected medium term profits has been achieved. It is also demonstrated that a larger short position with bilateral contracts does not always lead to a more stable income in presence of negative correlation between inflow and price.

Production scheduling in competitive markets, depend upon market structures, bidding rules, unit characteristics, generation capacity etc. The scheduling objective for competing Gencos is profit maximization and a Genco is not obligated to meet any

specific demand. Separate generation scheduling techniques are developed for two potential market scenarios that exist in different electricity markets. These price-based scheduling methods are further extended to solve self-scheduling problem with a hard demand constraint. Enumeration algorithms are used along with dynamic and quadratic programming for modeling and solution. It is shown that the change in the objective function and the demand constraint in the price based scheduling techniques can produce better schedules with higher profits. The performance of the self-scheduling techniques is found to be superior when compared to other methods reported in literature. Computation time is very low despite the use of computation-intensive methods. More importantly the implementation of the proposed scheduling methods indicate a way to manage various aspects of the scheduling problem in markets with different market structures and different trading rules. The need to understand the problem in hand and modify the existing methods to suit the market conditions is amply demonstrated.

The deterministic schedules based on forecasted prices may not be very meaningful unless the effects of uncertainty can be reflected in the outcome. Two different approaches for uncertainty management in the context of generation scheduling are proposed. The first approach uses the ‘maxmin’ criterion of decision-making for risk mitigation in a setting of a thermal generator that needs to investigate the influence of forward prices on hedging decisions. The analysis based on a simple two-stage model demonstrates the effect of contracts on income stability, which can be selected in accordance with the risk preference of the Gencos. The second approach presents a more comprehensive technique for uncertainty management based on utility theory to represent risk tolerance of a Genco. The optimal strategy is obtained through the coordination between generation scheduling and hedging decisions under price uncertainty. It is demonstrated how both generation quantity and short-term forward contracts can be adjusted as a means of hedging against price uncertainty.

Bidding is the means of achieving the desired daily schedules in competitive markets. Therefore, design of effective bids is critically important for successful operation of Gencos. The bidding strategy of a Genco will depend on its objectives, the market rules

and the market conditions. A technique of designing bids for a price taker Genco operating in a system that requires separate bids for individual generating units is presented in chapter 6. The bidding curves are developed by extending the generation scheduling technique. Generation schedules obtained for a large number of price scenarios created using Monte Carlo simulation are utilized to formulate effective bids.

List of Figures

Figure 2.1 Electricity wholesale market before 2003 in Singapore.....	20
Figure 2.2 Electricity wholesale market after 2003 in Singapore.....	21
Figure 2.3 Electricity market models [13]	25
Figure 3.1 NordPool generations	48
Figure 3.2 Time periods.....	50
Figure 3.3 Sketch in principle: Short-term variable costs in NordPool [3]	53
Figure 3.4 Variation in reservoir level and spot price over several years.....	53
Figure 3.5 Scenario tree	57
Figure 3.6 Power production and useful inflow over a typical year [19]	64
Figure 3.7 Revenue comparisons for risk neutral and expected value cases	67
Figure 3.8 Revenue comparisons for risk neutral and risk averse producers	68
Figure 4.1 Stages in dynamic programming for PBUC	81
Figure 4.2 Selective enumeration process	82
Figure 4.3 Flow chart showing the solution procedure for ‘PBUC’	84
Figure 4.4 Stages in dynamic programming for Scheduling of Individual Units.....	88
Figure 4.5 Power dispatch for single unit for forecasted price	90
Figure 4.6 Power dispatch for change in price	92
Figure 4.7 Effect of self-commitment on target dispatch of ‘PBUC’	95
Figure 4.8 Possible combinations of 3 units	99
Figure 5.1 Stages in the market.....	104
Figure 5.2 Maximum/minimum profit for different risk preference & forward prices	111
Figure 5.3 Effect of spot price variance on quantity forward	112
Figure 5.4 Comparison of hedged and unhedged situation.....	113
Figure 5.5 Hedging ratio and forward price.....	113
Figure 5.6 Optimal minimum profit.....	114
Figure 5.7 Comparison of optimal minimum income.....	115
Figure 5.8 Lognormal distribution.....	119
Figure 5.9 Blocks of contracts	125
Figure 5.10 Optimal generations for different risk attitudes.....	135
Figure 5.11 Comparisons for risk averse Genco.....	137

Figure 5.12 Comparisons for risk seeking Genco.....	137
Figure 5.13 Sets of optimal contract solutions for case 3	138
Figure 6.1 Bidding curve	144
Figure 6.2 Price distributions for discrete quantities	147
Figure 6.3 Cumulative profit distributions for discrete quantities	148
Figure 6.4 Determining ON/OFF price.....	151
Figure 6.5 Cumulative profit distributions for small price intervals	152
Figure 6.6 Price and quantity bid based on profit weight	153
Figure 6.7 5-Step bid curves for 24 periods for unit 1	155
Figure E.1 Risk aversion and certainty equivalence [106]	185

List of Tables

Table 2.1	Generation scheduling practices in different electricity markets.....	32
Table 3.1	Periods under consideration.....	55
Table 3.2	Forecasted inflow.....	55
Table 3.3	Forecasted price	55
Table 3.4	Comparison for the case when price forward is equal to the expected mean .	66
Table 3.5	Comparison for the case when price forward is average of expected prices ..	66
Table 4.1	Profit comparison for four systems.....	97
Table 4.2	Cost comparisons for 10 and 110 unit system [94] (Appendix B)	98
Table 4.3	Cost comparisons for 10 and 40 unit system [96]	98
Table 5.1	Unit 1 optimal schedules variations.....	120
Table 5.2	Comparison in fitness value for unit 2.....	131
Table 5.3	24-hours schedules from utility functions for various risk attitudes for UC1, UC2.....	132
Table 5.4	Comparison in fitness value for unit 2.....	132
Table 5.5	Four cases under study.....	133
Table 5.6	Profits and contract comparisons for UC1, UC2 and UC3.....	134
Table 5.7	Contract size and uncertainty.....	136
Table 6.1	Price distributions	148
Table 6.2	Comparison of expected profits with price uncertainty.....	156
Table 6.3	Comparison of profits for expected mean price.....	156
Table A.1	Specifications of hydro power plant	174
Table A.2	Price details (Chapter 3).....	174
Table A.3	Inflow details (Chapter 3)	174
Table B.1	Characteristics of 10 unit system [94].....	175
Table B.2	Characteristics of 110 unit system [94].....	175
Table B.3	Characteristics of 10 unit system [96].....	177
Table B.4	Characteristics of 40 unit system [96].....	178
Table B.5	Price forecast for 24 hours	179
Table B.6	Load for 24 hours	179

Table B.7	Spinning reserve for 24 hours	179
Table C.1	UC plan for 10 unit system [94] ('Scheduling of Individual Units')	180
Table C.2	Self commitment schedule for 10 unit system [94] ('PBUC')	180
Table C.3	Self commitment schedule for 10 unit system [96] ('PBUC')	180
Table C.4	Self commitment for 110 unit system [94] ('Individual Units')	181
Table C.5	Self-commitment for 40 unit system [96] ('Individual Units')	182
Table D.1	Characteristics of two units [94]	183
Table D.2	Price forecast [67] and standard deviations for 24 hours	183

List of Symbols

Chapter 2

δ	Angle associated with bus voltage, V
θ	Angle associated with admittance matrix
a_i, b_i & c_i	Cost coefficient of unit i
$C_i(G_i)$	Unit cost characteristic of the generating unit i
FP	Forecasted price
F_t	Forward price
G_i	Real power generation by unit i
$G_{i,j}$	Power flow from bus i to bus j
i	Index of a generating unit ($i \in 1, 2, \dots, NT$)
J	System cost
MDT_i	Minimum down time of unit i
MUT_i	Minimum up time of unit i
NG	Set of all generating units including generator on slack bus.
NL	Number of P-Q buses.
NT	Number of thermal generating units
PD	Real power demand
P_{Loss}	Transmission Loss
Q	Reactive power generation
QD	Reactive power demand
Q_{ft}	Quantity forward
Q_{sT}	Spot quantity
RDN_i	Ramp up rate of unit i
RUP_i	Ramp down rate of unit i
SD_i	Shutdown cost of unit i

SR	Spinning reserve
S_T	Expected spot price at delivery time T
ST_i	Startup cost of unit i
t	Time period ($t \in 1, 2, \dots, T$)
T	Total number of periods
USD	Unit shutdown state ($1 = Shutdown, 0 = No Shutdown$)
UST	Startup state ($1 = Startup, 0 = No Startup$)
V	Bus voltage
W	Unit status ($1 = Running, 0 = Off$)
$Y_{i,j}$	Element of bus admittance matrix

Chapter 3

$E(Rev)$	Expected revenue based on the expected price and inflow
G_t	Generation in period (MWh)
G_t^s	Corrective recourse action taken for generation in each period for scenario s after the price and inflow (the uncertainties) are observed
I_t	Expected inflow in period t (MWh)
n	Number of periods
P_{ft}	Forward price for the bilateral contract in period t (NOK/MWh)
P_{st}	Expected average spot price in period t (\$/MWh)
P_{st}^s	Spot price associated with scenario s
Q_{bt}	Bilateral contract signed for period t (MWh)
R_t	Revenue in each period (NOK)
SP_t	Spillage in period t (MWh)
SP_t^s	Recourse action taken for spillage in each period for scenario s , after the price and inflow are observed

t	Time period
W_t	Water reservoir level in period t (MWh)
Y_t	Sales / purchase in the spot market in period t (MWh)

Chapter 4

δ_i	Cold startup cost of unit i
σ_i	Hot startup cost of unit i
τ_i	Unit cooling time constant of unit i
$a_i, b_i \& c_i$	Cost coefficient of unit i
$C_i(G_i)$	Cost of Producing G_i Units Of Power
$G_i^{\max}$	Generation upper limit of unit i
$G_i^{\min}$	Generation lower limit of unit i
$G_{i,t}$	Generation in period t by unit i (MWh)
i	Index of thermal units ($i \in 1, 2, \dots, NT$)
J	Total system cost
MDT_i	Minimum down time of unit i
MUT_i	Minimum up time of unit i
n	Stage number in dynamic programming
N	Total no of stages in dynamic programming
NT	Number of thermal generating units
PD_t	Power demand at time t
PN	Number of periods in each stage n
PS_t	Expected average spot price forecast in period t (\$/MWh)
R_t	Reserve requirement in each period t (\$)
$SD_{i,t}$	Shutdown cost of unit i in time t
$ST_{i,t}$	Startup cost of unit i in time t

t	Time period ($t \in 1, 2, \dots, T$)
T	Total number of periods
$T_{i,t}^{off}$	Time unit i is in OFF state at time t
$T_{i,t}^{on}$	Time unit i is in ON State at time t
USD	Unit Shutdown State ($1 = shutdown, 0 = no shutdown$)
UST	Startup State ($1 = startup, 0 = no startup$)
W	Unit status ($1 = running, 0 = off$)

Chapter 5 and 6

σ_s	Standard deviation of the spot price
A_{iv}, B_{iv}	Constants of inverse demand function where A_{iv} is greater than c_1
c_1	Cost coefficient of producer 1
$E(S_T)$	Expected value of the spot price
Q_T	Total quantity produced by all producers (MWh)
h_f	Hedging ratio
B	Bidding Blocks ($B \in 1, 2, \dots, NB$)
$B(HL)$	Block of contract with length of HL hours
BI	Block index of contract $B(HL)$
F_t	Forward price at time t for delivery at time T (\$/MWh)
HL	Length in hours of a block of contract
$PB_{B,t}$	Bid Price for Block B
Pen_t	Penalty function at time t
$PR_{s,t}$	Price corresponding to scenario s
$prob_{t,s}$	Probability associated with scenario s
Q_1	Quantity produced by producer 1 (MWh)
Q_{ft}^I	Quantity forward by producer 1 at time for delivery in Time T

Q_{sT}^I	Spot quantity produced by producer 1 at time T (MWh)
$QB_{B,t}$	Bid Quantity for Block B
QF_t	Quantity forward in time t
Q_{T-1}	Total quantity produced in the market minus the quantity produced by producer1
r	Risk preference.
s	Index of a scenario ($s = 1, 2, \dots, S$)
S	Total number of price scenarios
S_T	Spot price at time t for delivery at Time T (\$/MWh)
U	Utility function
W_{pen}	Weight of the penalty function
UB	Bid Status ($1=selected, 0=Not Selected$)
Y_t	Sales / purchase in the spot market in period t (MWh)

List of Acronyms

AI	Artificial Intelligence
ANN	Artificial Neural Network
Disco	Distribution Company
ED	Economic Dispatch
EMA	Energy Market Authority
Genco	Generation Company
GA	Genetic Algorithm
GRNN	Generalized Regression Neural Network
ISO	Independent System Operator
MC	Marginal Cost
MCP	Market Clearing Price
MDT	Minimum Down Time
Mm ³	Million cubic meters
MUT	Minimum Up Time
MWh	Megawatt hour
NEM	New Electricity Market
NOK	Norwegian Kroner
NY	New York
NZEM	New Zealand Electricity Market
OPF	Optimal Power Flow
PBUC	Price Based Unit Commitment
PX	Power Exchange
PJM	Pennsylvania-Jersey-Maryland
Transco	Transmission Company
UC	Unit Commitment

1. Introduction

1.1 Motivation

Restructuring of the electricity industry in many parts of the world has established competitive markets where Gencos compete to sell electricity. The scheduling of a Genco's units are mainly determined by the spot market schedule from the market clearing along with the necessary provisions for their long and medium term contract commitments. These are dependent on the market-clearing price, which is dynamically determined every period. The generation scheduling in competitive market is therefore price based and exposed to a high degree of uncertainty.

Under perfect competition, marginal cost bidding would have been a dominant strategy for each power producer and social welfare maximization would be achieved at market equilibrium. However, the actual characteristics of power networks make it difficult to achieve a perfectly competitive electricity market. Limited number of suppliers in the electricity market, transmission bottlenecks creating isolated markets that are substantially smaller than the physically connected power network, very little demand elasticity, and non-storability of electricity requiring real time balance between demand and supply to keep the grid stable have made the behavior of the electricity market quite complex. This has made the restructuring of the electricity industry a much greater challenge than was inferred from the experience with natural gas, airlines, telecommunication etc [1]. As a result, electricity markets with varying structures and market rules, which are still evolving exist in various parts of the worlds.

In the last 15 years of deregulation, the electricity market has gone through a series of changes in market rules and regulations to make the market competitive so as to provide equal opportunities for the market participants and to make sure that the security of the system is not compromised. For instance, the conversion of the pool that required compulsory participation, in UK, to a pool that only required participants who have not

Chapter 1 Introduction

entered into bilateral contracts to participate, gives some indication about the ongoing changes in the market structure. Unlike the stable market in the past, Gencos in competitive markets now have to adapt quickly to the changes in market structures in order to survive and remain profitable.

Among the challenges faced by Gencos, uncertainty in price has been the most critical as price has direct impact on the profit earned. Due to this uncertainty, the degree of risk has increased manifolds in competitive markets. To combat risk, tools of risk mitigation are available in various forms viz.- forward contracts, futures contract, options, etc. And with the availability of these tools with different characteristics, the modeling of electricity markets has become even more complex for Gencos. Despite the availability of these tools, Gencos are still exposed to considerable risk due to unpredictability in price in the face of unexpected events. For instance, due to severe drought during 2002/2003 in Norway (where 99% of the generation is hydropower), the average system price never returned to the same levels of 2001 or before. In the drought period, the Gencos who had signed bilateral contracts in large quantities had to buy from the market at a very high price to meet the contract obligations resulting in a loss. Also, Gencos who had already entered into bilateral contracts for the period after the drought, say 2004/2005, based on earlier lower price expectations had to continue their supply at a cheaper rate despite the higher average price in the aftermath of the drought. This indicates that suppliers are exposed to the market risks and have to decide on how much energy to sell in the spot market and how much to sell in the forward market in order to minimize risk and maximize profit.

Planning decisions of Gencos also depend on the characteristics of generation units. For hydro producers, despite low generation cost, the availability of water is limited and depends on the seasonal inflow conditions. Gencos have to manage the available water optimally as water can be stored to some extent in the reservoirs and hence can be used in different periods. In case of thermal generators, cost of generation has significant impact on decision-making. If the startup time and startup cost of the generating units are very

high, producers have to decide between shutting off the unit and running at a minimum level despite bearing loss during some of those operating periods.

Thus, the task of generation planning for a Genco has been very different from that of the traditional utility, which used minimization of total system operation cost as the basis of generation planning. The increasing uncertainties and fundamental structural and regulatory changes have made the diverse task of generation planning problem very challenging and complex in the competitive markets. A review of recent developments in this field is provided in chapter 2.

Long-term planning and medium term planning mainly involves decisions on contracts and generation scheduling months and years in advance. Short-term plans constitute daily/weekly decisions on unit commitment, short-term contracts and bidding strategies. Planning models that exist for each of these planning horizons generally address a particular aspect of the planning problem in isolation. The growing importance of trading and coordination among various planning problems therefore requires market participants to reorganize their planning process with respect to new trading opportunities. The ongoing liberalization process with regular changes in market structures and trading rules have so far made it difficult to formalize concepts for energy trading. While the basics behind the existing tools and approaches used to address the planning problems may be helpful, it is felt that new approaches are necessary to address the need of the evolving markets. For instance, deterministic techniques that only rely on prognosis techniques and individual assessments of future developments can hardly address increasing uncertainties. This indicates that the existing planning techniques, even the relevant one, need to be suitably extended to address the needs of competitive markets. These techniques should provide power producers effective generation planning tools to achieve a proper tradeoff between the objectives of maximizing the profit and minimizing the risk while considering their risk preferences under price uncertainty. This may be achieved by: 1) modifying and extending the existing models to reflect the market changes, 2) combining different models and 3) developing new models. While doing this, technical

aspects of the generation planning as well as the regulatory requirements must be satisfied to address the new market conditions.

1.2 Objectives

The broad objective of this research is to study various aspects of generation planning strategies and to develop planning approaches for power producers in competitive electricity markets. The following tasks are the major objectives.

1.2.1 Generation Scheduling

The change in the objective from cost minimization in the traditional market to profit maximization in the competitive market has meant that the well-established traditional power-scheduling problem should now be addressed with a different approach to suit the competitive objective while doing short term, medium term and long term planning. For this purpose, the traditional and the existing power scheduling models have to be studied and new models should be developed to accommodate the competitive goals. The specific objectives in this respect are:

- To investigate and develop medium term power scheduling approach to analyze bilateral contracts that will help Gencos to develop optimal contracts.
- To investigate and develop short-term generation scheduling techniques that will address unit commitment and self-commitment problems for competitive Gencos participating in a deregulated market for a given market structure and market rules.

1.2.2 Uncertainty and Risk Management

In addition to the various uncertainties that existed in the traditional power system operational planning (viz.- fuel price uncertainties, demand uncertainties etc), deregulation has introduced more uncertainty, e.g. energy price. It is imperative that these

uncertainties are suitably incorporated in the generation planning problem that corresponds to the structure of the market.

Similarly, a power producer can be risk averse, risk neutral or risk seeking. Therefore planning approaches should be able to incorporate the willingness of the Gencos to take risk in determining generation commitments accordingly. Thus the objective in this regard is to investigate the source of uncertainty and find suitable ways to represent them in generation planning tasks, which will be helpful to formulate risk management strategies for competitive Gencos depending on their risk preferences and market behavior.

1.2.3 Bidding Strategies

To determine a good bidding strategy is probably the most important task in competitive markets as it is through bids that the Gencos can achieve their generation targets in the spot market. The modeling approaches for bidding can vary depending upon the market rules (e.g. step function / piecewise linear curve), generation unit characteristics (e.g. thermal, hydro, nuclear) etc. In addition bidding strategies can be influenced by market uncertainties, contract obligations and market predictions. The objective in this respect is to analyze the impact of price uncertainty on generation schedules and investigate the possibility of formulating optimal bidding strategies as an extension to the generation scheduling problem.

While considering these aspects of generation planning, approaches for coordinating operational and financial decisions in the competitive market can differ substantially in different planning horizons.

A) Issues in the Medium Term Planning Horizon

In the medium term, usually with the planning horizon up to 1 year, acquisition and use of contracts mostly traded bilaterally, is of major concern to power producers due to high price volatilities in competitive markets. This planning problem becomes more complex for finite resource generation like hydropower as it involves additional decision on the optimal use of water in the reservoirs. Inflow uncertainty and its negative correlation with price complicate the problem further. The objective in the medium term planning problem is to represent the market uncertainties, investigate its impact on bilateral contracts and generation schedules in order to determine proper contracts to match the risk preference of the Gencos.

B) Issues in the Short Term Planning Horizon

In short term planning horizon, where usually a period of less than a month is considered, the aspects of generation planning mainly constitute generation scheduling, short-term contract decisions and bidding strategies. The objective here is to investigate the impact of price uncertainties, risk preference of Gencos and market rules on these aspects of generation planning.

1.3 Major Contributions

Approaches to several aspects of generation planning in competitive electricity market have been developed and illustrated with examples. The approaches developed use various known tools such as scenario analysis, dynamic programming etc to modify and extend the generation planning goals to meet the demands of competitive markets.

1.3.1 Medium Term Power Planning

An optimal management of hydropower resources on a medium term in the presence of bilateral contracts under price and inflow uncertainty is investigated in the context of a price-taking hydropower Genco. The stochastic nature of price and inflow is represented in a scenario tree of probabilities. In the proposed method, the deterministic approach is extended to incorporate corrective recourse actions taken on probable fluctuations of spot prices and water inflows to optimize the expected revenue of combined assets in spot market and bilateral contracts. It is seen that the proposed model is more appropriate for risk-neutral producers whose optimal portfolio is simply the one with maximal expected revenue. For risk-averse producers, the technique is extended to adjust the contract position where the optimal portfolio achieved has minimum variance from the specified expected revenue. Stochastic linear and non-linear programming is used as a framework for modeling and solution. The technique is verified for the medium term scheduling of a hydropower Genco based on the historical data of NordPool.

The developed stochastic approach is clearly seen to represent the market uncertainty better when compared to the deterministic model. More interestingly, it is observed that the higher volume of bilateral contract (short position) does not necessarily mean more stable or higher income as the interactions of various uncertainties affect the overall decision.

1.3.2 Production Scheduling in Competitive Markets

The task of unit commitment (UC) has become more complex in the competitive market as the actual generation is not known until the market is cleared. Hence, the existing approaches should be modified based on market structures, bidding rules, size of Gencos, presence of market power, etc. to address the UC problem. It is also worth noting that continuous improvement in technology has meant sharp decrement in the computational time and hence the increased prospects of using methods associated with dimensionality and higher solution time like dynamic programming, enumeration and other heuristic techniques. The UC problem has been analyzed in three different contexts.

A) Price Based Unit Commitment (PBUC)

It is seen that the Gencos demand, despite being flexible in the competitive market, can be governed by many other factors such as 1) market rules for vesting contract requirement imposed on Gencos that forces them to produce above certain percent of their generation capacity, 2) internal company policy or management decisions to maintain the generation level approximately at a certain level so that the market share is maintained above a certain percent or within a certain range, and 3) the contract obligations already signed determining the approximate demand level. In addition, the Gencos may often be able to forecast their expected demand within a certain tolerance using their experience and knowledge of the market behavior. The PBUC technique is developed specifically for such Gencos. Forecasted price is incorporated in the redefined profit-maximizing objective. An enumeration algorithm is used to search for the best commitment solutions within the targeted range of demand in each stages of dynamic programming.

B) Scheduling of Individual Units

In some electricity markets, it may be necessary to develop UC for individual units and then combine these individual schedules to optimize the scheduling of the whole group of generators, if possible. Examples of such scenarios may be 1) markets that require the

Gencos to bid for each individual generator rather than for a group of units, or 2) if Gencos have insignificant market power (i.e. if they are relatively small compared to the rest of the market), where a price taker assumption would be valid and the operation of one generator can be assumed to be independent of the others. A price-based approach to optimize Gencos profit for such individual units over a period of time is developed. The proposed technique utilizing a modified dynamic programming technique is shown to be effective in identifying optimal solution in a very short time. It is observed that while scheduling individual units, the dimension of the scheduling problem is significantly reduced. This reduction allows Gencos to develop on their own, simple techniques capable of giving global solutions instead of using more complex and expensive commercial software.

C) Self-Commitment: An Extension

In some markets, once the bids are cleared, the Gencos can again carryout self-commitment to obtain optimal decisions for the scheduled demand. In these cases, the demand constraints may become relevant again and there may be scope to optimize the schedule of all the Gencos units as a group. This makes the UC problem similar to the traditional power systems. To address such situations, a technique is proposed that uses price as a guideline and adjusts the price fictitiously in each period by increasing or decreasing it until the demand condition is satisfied. The proposed approach clearly depicts how slight modification and extension to the existing techniques can solve different aspects of scheduling problems.

The proposed production scheduling approaches, which have been tested for several systems reported in the literature, confirmed that the change in the objective to profit maximization and flexibility in demand constraint have a clear impact on profits earned by the Gencos. Superior performance of the proposed self-commitment techniques is demonstrated through comparative examples from reported works. It is noteworthy that these techniques that employ enumeration and dynamic programming, both of which are techniques associated with ‘the curse of dimensionality’, needs significantly reduced

computational time indicating the increased scope of search methods previously associated with larger solution time and considered not practical for a number of real time applications.

1.3.3 Uncertainty Management in Generation Planning

Generation scheduling, bidding strategy and hedging are very important in making planning strategies in competitive electricity market but have been in general addressed independently. Price based generation scheduling approaches can be used to plan in advance on how to use their available capacity but the targets can only be achieved through proper bidding techniques. Gencos apply hedging strategies to manage their exposure to price volatility but the contracts signed can have influence on generation scheduling criteria and bidding strategies. Additionally, the volatile price that has direct impact on the profits earned must be properly represented. Two different approaches are developed to address these aspects of generation planning.

The ‘maxmin’ criterion of decision-making with the objective of maximizing the minimum expected income of a producer for an acceptable level of risk is proposed. The mean value of price forecast that indicates the most probable spot price at a future time is taken as the reference price for risk-averse decisions. . A simple two-stage model is proposed to study the relation between the risk behavior and the appropriate contract price. This approach can help identify the appropriate level of bids on the forward market to fit the risk behavior. It is shown how a risk averse producer can choose a smaller but more certain profit while a risk seeker can opt for a potentially larger profit which can vary significantly.

The real market presents a more complex problem, which can hardly be represented by the two-stage model. Hence, to address a more complex short term planning problem, a technique based on Genetic Algorithms is initially proposed to highlight the need of proper representation of price uncertainty rather than relying on simple bid curves while

making bidding strategies. A method based on utility theory that incorporates the risk preference of the Gencos is developed to hedge against market risk. The short-term contracts (e.g. day contracts) that have almost never been mentioned in literature are used as a hedging tool in the planning problem. The generation scheduling problem is coupled with the hedging problem to determine the optimal level of generation and the optimal short-term contracts to hedge against price uncertainty. In short, the model proposed incorporates price uncertainty, generation scheduling and risk tolerance of the Gencos in the overall decision-making process. The effectiveness of the proposed model is demonstrated through simulation studies. It illustrates how generation and forward contracts should be managed based on the risk preference of the participants while implementing short term planning decisions.

1.3.4 Price Based Bidding Strategy

Bidding strategies of Gencos differ depending upon the size of the Gencos, the efficiency, the operating cost, the flexibility of the generating units, the level of competitiveness in the market, the presence of market power etc. A new approach is developed for building an optimal bid curve under price uncertainty for a price taker Genco participating in markets that require the Gencos to submit bids for individual generating units separately. This technique uses a generation scheduling technique of individual units for modeling and solution. Price uncertainty is incorporated using Monte Carlo simulation. Simulation results are presented to show that this approach leads to higher expected profits for Gencos. The results also confirm that using simple two-step bids reported in literature give suboptimal solutions when compared to a number of bid steps developed using the proposed approach. It is seen that the bidding method is simple yet effective.

1.4 Thesis Outline

This thesis is organized as follows:

Chapter 1	Motivation, objectives and contributions of this dissertation were presented in this chapter.
Chapter 2	describes background literature of the traditional market and the deregulated market focused on issues related to generation planning.
Chapter 3	focuses on the power scheduling solutions in the hydro dominated Norwegian electricity market in a medium term.
Chapter 4	presents two different price based generation scheduling methods and self-commitment methods in view of different market conditions that exist in deregulated markets.
Chapter 5	proposes two different uncertainty management approaches in a short term planning horizon.
Chapter 6	presents a method of using price based generation scheduling to develop bidding strategies under price uncertainty.
Chapter 7	ends the thesis with conclusions and recommendations.

2. Background Literature

2.1 Overview of Deregulated Electricity Industry

Traditionally, the electric power industry consisted of utilities that were state/government-regulated vertically integrated monopolies having the overall authority over all activities in generation, transmission and distribution of power within its domain of operation. Such utilities were obliged to provide electricity to everyone in the region. It was not necessary to segregate the costs incurred in generation, transmission and distribution. Therefore utilities often charged their consumers an average tariff rate depending on their aggregated cost during a period as per the rate of return regulation authorized by the regulating body. In such utilities, the basic objective of the operator was to minimize the total system cost while satisfying all associated system constraints. In addition, the vertically integrated utilities also had a centralized system of long term planning. All activities such as long term generation and transmission expansion planning, medium term planning activities such as maintenance, production and fuel scheduling were coordinated centrally.

This was true until relatively recently as the electricity industry was considered a natural monopoly. But, regulation did not protect consumers in the ways that populist rhetoric suggested. Under regulation in the 60s, certain economic "truths" governed the design and operation of electric generation facilities [1]. First, the cost of generating power decreased with plant size (i.e. it is cheaper to build a single 1000MW plant rather than four 250 MW plants). Second, the cost of producing steam from coal was cheaper than producing it from oil and natural gas. As a result of those two "truths," large coal-fired plants generated so-called base load power that was used all the time. Smaller (and older) coal, oil, and natural gas units were used to generate during the high demand (peak load) period when the demand exceeded base load levels. Some important factors changed that picture over the next 30 years:

- Interconnected grid
- High fossil-fuel prices during the "energy crisis" of the 1970s, and
- The development of gas-turbine technology.

The net effect of these factors was to place high cost obligations on the traditional utilities that were then vulnerable to competition from low-cost alternatives. In unregulated markets with a large number of suppliers, those events would have resulted in the bankruptcy of the high-cost alternatives. In the regulated electricity market, however, those events have produced prices for electricity so high that commercial and industrial consumers relocated, generated their own power, and agitated for relief from the rates of existing utilities [1].

As an aftermath of high-energy prices in 1970s oil embargoes, the political winds around the world wanted to remove the monopolistic price and put competition in electricity utilities. Hence, the concept of deregulation for competitive electricity emerged.

2.1.1 Deregulation Process

One of the first steps in the restructuring process of the power industry has been the separation of the transmission activities from the electricity generation activities. The subsequent focus has been to introduce competition in generation either through the creation of power pools, provision for financial transaction or bidding in the spot market. It is accepted by the analysts that the generation can become competitive but transmission and distribution, having significant economies of scale, still require regulation [1, 2]. Hence the transmission grid is operated as a neutral, natural monopoly subject to regulation by public authority. Mandatory open access, in which all generators have access to the transmission and distribution system at rates determined by regulation, is now a standard practice.

With the enforcement of the Electricity Act of 1989, the UK became one of the first nations to launch energy deregulation by introducing a national wholesale electricity market in March 1990 [2]. In Norway, market operation commenced in May 1992, two years after the passage of the Energy Act of June 1990. Sweden joined the Norwegian market in 1996 and the operating market was renamed to NordPool ASA. Finland joined the power exchange area in 1998, western Denmark in 1999 and eastern Denmark in 2000 [3]. Today, NordPool is one of the most successfully deregulated power market and

is also the first international power exchange in the world. Though Norway, Sweden, Finland and Denmark are the main participating countries in NordPool, Russia and Germany have also started participating in a limited way more recently. In the US, the Federal Energy Regulation Commission (FERC) mandated the establishment of the wholesale generation and bulk transmission to open access with its order 888 in April 1996 after which wholesale electricity market was established in various states such as California, New England, New York, PJM (Pennsylvania-NewJersey-Maryland) etc [4]. Similarly, New Zealand Electricity Market (NZEM) was established in 1996 [4]. Singapore's wholes electricity market, now called New Electricity Market (NEM) [5] and Australia's National Electricity Market were established in 1998 [4]. Other countries that have been undergoing energy deregulation include Argentina, Brazil, Germany, Spain, Taiwan, Malaysia etc.

With deregulation around the globe came various power market models, which can be classified into different groups based on the level of competition in the electricity market.

2.1.2 Power Market Models

2.1.2.1 PoolCo Model

In a PoolCo model, there is a central power pool commonly referred as Power Exchange (PX) for which the membership is mandatory for the generation companies (Gencos). The Gencos are required to bid for the supply and associated price to the PX. The market operator usually referred as Independent System Operator (ISO) carries out the unit commitment to obtain the optimal dispatch and settles the market and formulates generation schedules. To determine the Market Clearing Price (MCP), ISO stacks the bids from lowest to highest price until a sufficient amount of generation is identified to serve the load in each time period. The highest bid from the selected stack in each time period will be the MCP for that time period. Each Gencos whose generation has been selected in that period receives the MCP [4,6].

2.1.2.2 Bilateral Contracts Model

A bilateral contract allows sellers to directly negotiate with consumers in a market place for terms of delivery and price of electric energy and capacity. Bilateral contracts entail the use of contracts between sellers and consumers. The consumers could be wholesale or retail consumers, or aggregators representing a group of consumers. The sellers could be Gencos, marketers or brokers. To maintain reliability in real time, the sellers have to supply incremental and decremental energy bids to prevent transmission flow congestion [4,6,7].

2.1.2.3 Hybrid Model

The hybrid model is also referred as pool with bilateral contracts. This model envisions the use of both concepts and combines the best attributes and mitigates the alleged shortcomings of both. This structure provides the consumers with the flexibility to purchase from either the pool or directly from the supplier through bilateral contracts. [4,6].

2.1.3 Classification of a Market

2.1.3.1 Perfect Competition

Perfect Competition [8,9] is an idealized structure of an industry in which price competition is dominant. In this type of market, price is forced to the supply and demand equilibrium and at that price and the corresponding output, marginal benefit is equal to marginal cost, so the allocation of resources is efficient. For a market to have a perfectly competitive structure, it must have all four of these characteristics:

- Many buyers and sellers
- A homogenous product
- Sufficient knowledge
- Free entry

In the existing power markets around the world, the second and the third characteristics can be observed more often than the first and fourth. In most of the markets, sellers are still large compared to the size of the market and hence have the potential of controlling the price. Although, free entry is entertained, the uncertainty related with the market prices, the regular change in policies by the regulating bodies and the large initial investments required to setup a plant have deterred the new entrants. Observing the electricity market prices e.g. in Singapore, it can be seen that the concept of suppliers bidding at the marginal cost has not been realized, at least, not in the peak load periods.

2.1.3.2 Monopoly

By definition, a monopoly [8, 9] is the market structure having only one seller of a product for which there is no close substitute. It is an industry in which there is only one firm or conversely, a firm that has the whole industry to itself. For a monopoly to be stable, there must be some barrier to entry.

Traditional power markets were either a government owned and controlled monopoly or a government-regulated monopoly. Even after deregulation, all the regulations have not been eliminated, but their scope has been cut a great deal.

2.1.3.3 Imperfect Competition: Oligopoly

Imperfect competition [8-13] is defined by the ways in which they deviate from the four characteristics of perfectly competitive markets. The way that oligopoly differs both from perfect competition and monopoly is that there is more than one seller, but not very many. For the small number of sellers to be stable, there presumably must be some barriers to entry to the new competitors.

It is generally accepted that oligopoly price and profits will be somewhere between the monopoly and perfect competition. However, it should be noted that, in power industries before deregulation, the electricity price were regulated by the government and hence were never left to reach high levels. To find out the oligopolistic nature, the “four-firm

concentration ratio” (portion of the industry's sales revenue that is earned by the biggest four firms in the industry) has been in practice for long [8]. Herfindahl-Hirschman Index (HHI) of market power is the measure of concentration in the market [6]. The bigger the four-firm concentration ratio, the more concentrated and monopoly like the industry is. This shows the presence of market power.

It was sensed in early 20th century that traditional microeconomic theory just did not have an answer to the question of oligopoly pricing. In the 1930's, it seemed that the problem was that oligopoly-pricing decisions are strategic decisions, which meant that it is not a perfect competition. Monopoly pricing decisions were not strategic, as monopoly has, by definition, no rivals. But oligopolist's decisions are strategic in that they have to consider the reactions of their rivals. The difficulty of resolving the question of strategic price decisions within traditional microeconomic theory led to a new theory of strategic decisions that was developed by the great mathematician John von Neumann and was called Game Theory [8-10]. This theory has a lot of implications on the power markets around the world as these markets at its present state are considered more of an oligopolistic market rather than perfectly competitive [11,12].

Although, it has been more than a decade that the process of deregulation started in some countries, the electricity market is still viewed critically by the engineers and economists around the world. Though the reason behind choosing competitive markets has always been to increase efficiency, increase incentives and reduce the cost thereby increasing the consumer benefits, not everyone has benefited from deregulation. Hence, there are proponents [14] as well as opponents [1,15-17] of deregulation.

2.1.4 Continuous Changes in Market Structures and Rules

Looking at the global trend, however, it can be seen that after a decade of deregulated market around the globe, the countries that went ahead with deregulation have not reverted back to the previous monopolistic market structure. Moreover, despite the volatility in prices and hence the risk associated with deregulation and the feared events like the California blackouts which are regarded as the negative aspects of deregulation,

Chapter 2 Background Literature

more countries are opting for competitive markets. This indicates to some extent that there are benefits to be gained through competition. Hence, the electricity market at present is going through a phase of continuous improvement depending on the market structure, types of generation companies, load distribution, demand fluctuations and so on. Research is underway in all the sectors of the market – generation, transmission and distribution – to improve the system benefits and reliability as a whole. For instance, in England and Wales (restructured in 1990), three-generation companies owned substantial power until 2000, after which the generation sector was divided into 5 or 6 large companies as projected by Green and Newberry [2] and a large number of small companies. In March 2001, the mandatory gross electricity pool was converted to NETA (New Electricity Trading Arrangements), a net pool similar to NordPool, which only handles trades outside bilateral contracts [18].

Similarly, in Singapore, Singapore Electricity Pool (SEP) was implemented on April 01, 1998 to introduce competition in wholesale electricity market. In March 11, 2000, the key restructuring initiatives implemented were the separation of contestable and non-contestable parts of the electricity industry, the establishment of independent system operator (ISO) and the liberalization of the electricity retail market. In April 2001, the Energy Market Authority (EMA) [5] was formed to take the role of the industry regulator and system operator. At the same time, an Energy Market Company (EMC) was formed for the role of market operator. The ownership of Gencos was separated from the ownership of transmission and distribution companies to enhance competition. Consumers with maximum power demand of 2 MW and above became contestable since 1 July 2001. The structure of the market before 2003 is shown in Figure 2.1.

In January 01, 2003, New Electricity Market (NEM) commenced after further enhancements were made to facilitate competition (see Figure 2.2). With the opening of NEM, SEP ceased operation. The Singapore NEM became a self-commitment market i.e. unit commitment became the responsibility of each Genco as no startup and shutdown payments were made. This meant that Gencos were expected to factor these costs into their bidding strategies. From 1 June 2003, phases of retail market liberalization

commenced to allow consumers with monthly consumption of 20MWh and then above 10 MWh to become contestable so that they can buy electricity from retailers of their choice. EMA implemented vesting contracts from Jan 1, 2004 to control market power of the three largest Gencos that hold 90% of the total installed capacity in Singapore. Vesting contract has been imposed on 65% of total demand thereby capping the price of 65% of the demand. The price for the remaining 35% is determined by competition in the wholesale market. In this way, the non-contestable consumers (mainly residential load) are fully covered by the vesting contracts [5] and hence are protected from pool price volatility.

Figure 2.1 Electricity wholesale market before 2003 in Singapore

These changes in market structures with the establishment of a deregulated electricity market are accompanied by fundamental changes in the planning process for power producers.

Figure 2.2 Electricity wholesale market after 2003 in Singapore

2.2 Generation Planning in Competitive Electricity Markets

The power producers in the competitive environment need to coordinate their operational and financial decisions at different levels of planning process.

2.2.1 Long Term Planning

The long term planning is mainly concerned with inventory decisions with a planning horizon of usually more than 1 year. Cost and possible revenues have to be compared to predict on the kind of technologies that is most promising. Traditional calculations do not apply as the earnings of power producers depend on factors completely different from those in the past. The behaviors of consumers can also influence the future value of investments. Similarly, technological progress and changing prices of gas, oil and other fossil fuels can result in fundamental changes in the infrastructure in power generation. Apart from these, as the financial contracts can be signed up to several years in advance

depending on the markets, a decision made now can affect the decisions to be made in future.

2.2.2 Medium Term Planning

Medium term planning deals with scheduling of existing generating units with the planning horizon of usually up to 1 year. In competitive markets these decisions have to be coordinated with different trading activities. These can be agreements on physical deliveries like forward contracts as well as derivatives like futures and options. The acquisition and use of contracts is a major concern of most power providers because of the high price volatilities in competitive markets. Power producers use bilateral contracts to minimize their risks. The amount of bilateral contracts signed depends on the expected future spot prices and willingness of participants to take risk. Too much use of contracts means a net loss if the spot price turns out to be higher and net gain if it turns out to be lower. Again, if the amount signed exceeds the power producing capacity in the future due to limitations of the power plants (e.g. inadequate water in the reservoir for hydro plants), the power producer may have to buy power (at higher prices) from the market to meet the bilateral contract.

2.2.3 Short Term Planning

This has been the most commonly addressed issue in the existing market. Usually a period of less than a month is considered in this regard. Unit commitment problems and generation scheduling with a time horizon of up to 1 week with time intervals of ½ hour or 1 hour are addressed here. These scheduling targets can only be achieved through bids and hence bidding strategies of power producers based on the anticipation of the market conditions also form a part of short term decisions. Moreover, financial contracts are also available for use, usually in blocks for a year, quarter of a year, a month, a week or a day. The strike price for the contract depends on the market rules. For instance, in the Nordic market, the reference price for financial market is the system price [19].

2.2.4 Real Time Optimization

Real time optimization in power generation has a time horizon of hours or minutes and is done with respect to the actual requirements observed in the system or in accordance with the instructions from the system operator. Normally, minor modifications in the scheduling obtained from short term planning are necessary.

In summary, it can be said that the task of decision making for competitive Gencos with the objective of profit maximizing has increased manifold. This can be seen from the factors that affect the power producers' profits, which can be divided into the following categories.

- Types of power plants owned: hydro, thermal, nuclear etc.
- Model of market: PoolCo, bilateral or hybrid.
- Type of market: oligopoly, perfect competition.
- Willingness to take risk: risk averse, risk neutral and risk seeking.
- Financial tools available for risk mitigation: forward contracts, futures, options etc
- Price fluctuations: daily, weekly, monthly, yearly etc.
- Forecasts: price forecasts, load forecasts, inflow forecasts (hydro) etc.
- Demand Fluctuations: weather changes, festivals etc.
- Weather variations: temperatures, rainfall etc.
- Other participants response (Oligopoly): market power
- Others: congestion, interconnected grid, transmission right, reserve market etc

This indicates the need of generation planning models with the objective of profit maximization, which can coordinate the existing physical resources in concert with the available financial resources, in the face of the risks associated with fluctuating prices in the deregulated market.

2.3 Market Strategies in Competitive Markets

In competitive market, resource planning for Gencos has become more sophisticated due to uncertainty surrounding future customer demand, market prices and even the potential for new regulations. Although, the market has become far more complex, few Gencos seem to have resource planning activities that can deal with these complexities [17]. Since, resource planning with traditional planning tools does not address the opportunities and risks associated with the present stochastic markets, new tools must be adapted in the new market environment [17].

The planning decisions of Gencos that include their own production and a set of power contracts for delivery or purchase, depend on their objective of profit maximization. Hence, planning tools need to coordinate between contracts, such as forwards and options and the level of generation depending on the participant's willingness to take risk. This means that resource planning and risk management are interlinked and hence need to be considered simultaneously by competitive Gencos. In short it can be said that optimal generation planning strategies should be developed that will help producers in their trade-off between the goals of achieving as high profit as possible while taking into consideration their risk attitudes. Power producers' decision on the volume of generation and contracts for different time periods, in general, will involve the following (see Figure 2.3):

- Generation Scheduling /Unit Commitment
- Forecasts
- Risk Management
- Bidding Strategies

Figure 2.3 Electricity market models [13]

2.3.1 Generation Scheduling

2.3.1.1 Traditional Power Market

In the traditional power market where power generation, transmission and distribution are all owned and operated by a single entity, the basic planning and dispatch activities of the system operator consists of many basic aspects of economic operation of a power system.

A) Economic Load Dispatch (ELD)

The ELD activity is executed in the dispatch stage and it primarily involves allocating the total load among the available generating units in such a way that the total cost of operation or the system cost, J , is kept at the minimum [4, 20]. Cost minimization subject to accepted minimum reliability standards is the principal objective since the rates that the utility charges the customers is set by an independent government regulatory body. Thus, the maximizing profit could only be reached by minimizing cost. Hence, for a system of NT thermal generating units ($i \in 1, 2, \dots, NT$), each unit feeding power G_i , to a transmission system that serves a total load of PD , the objective function is obtained as

$$J = \min \sum_{i=1}^{NT} C_i(G_i) \quad (2.1)$$

where $C_i(G_i)$ is the unit cost characteristic of the generating units which is a function of G_i and is derived from the heat-rate characteristics, usually represented as a quadratic function as

$$C_i(G_i) = a_i + b_i G_i + c_i G_i^2 \quad (2.2)$$

where, a_i, b_i and c_i are constants.

The objective (2.1) is solved for the following constraints.

$$\sum_{i=1}^{NT} G_{i,t} - PD_t - P_{Loss,t} = 0 \quad (2.3)$$

$$G_i^{\min} \leq G_i \leq G_i^{\max} \quad (2.4)$$

where,

t is the time period ($t \in 1, 2, \dots, T$) and

$P_{Loss,t}$ is the transmission loss in period t

A more elaborate form of the above task is the dynamic economic dispatch (DED) where the generation scheduling problem is considered over a time range and the optimal dispatch evaluated for a time interval within this range considering load variation as well as unit ramping constraints. For such problems, the ramp up/down limits of the units [21,22] and time dependent spinning reserve requirement [21] are also taken into consideration as

$$RDN_i \leq G_i^{t+1} - G_i^t \leq RUP_i \quad (2.5)$$

where, RDN and RUP are unit down and up ramp rates and t denotes the time interval.

For the system spinning reserve (SR),

$$\sum \{ \min(G_i^{\max} - G_i^t, RU_i) + \min(G_i^{t+1} - G_i^t, 0) \} \geq SR(t) + \Delta PD^t \quad (2.6)$$

where, RU_i is the maximum allowable generation change for i^{th} unit .

B) Optimal Power Flow (OPF)

In ELD demand is considered to be an aggregate parameter for the entire system i.e., the assumption is that the power flow follows simple equality constraints. In practice power flows follow Kirchoff's laws as represented by load flow equations. With this change of

the decision variable the same objective of cost minimization is obtained with OPF, which is a constrained nonlinear problem.

The objective functions is:

$$J = \min \sum_{i=1}^{NG} C_i(G_i) \quad (2.7)$$

where, NG is the set of all generating units including generator on slack bus.

And the constraints are:

1. Network Equations:

$$G_i - PD_i = \sum_j |V_i| |V_j| Y_{i,j} \cos(\theta_{i,j} + \delta_j - \delta_i) \quad \forall i = 1, 2, \dots, NL, i \neq \text{slack} \quad (2.8)$$

$$Q_i - QD_i = \sum_j |V_i| |V_j| Y_{i,j} \sin(\theta_{i,j} + \delta_j - \delta_i) \quad \forall i = 1, 2, \dots, NL \quad (2.9)$$

where ,

V is the bus voltage

δ is the angle associated with V

$Y_{i,j}$ is the element of bus admittance matrix

θ is angle associated with admittance matrix

G & Q are real and reactive power generation

PD & QD are real and reactive power demand

NL is the number of P-Q buses.

2. Generation Limits

$$\begin{aligned} G_i^{Min} &\leq G_i \leq G_i^{Max} & \forall & i \in NG \\ Q_i^{Min} &\leq Q_i \leq Q_i^{Max} & \forall & i \in NG \end{aligned} \quad (2.10)$$

These are the upper and lower limits on real power generation and reactive power generation for a unit.

3. Bus Voltage Limits

$$\begin{aligned} |V_i| &= \text{constant} & \forall & i = 1, 2, \dots, NG \\ V_i^{Min} &\leq V_i \leq V_i^{Max} & \forall & i \in NL \end{aligned} \quad (2.11)$$

4. Limits on Power Flow

$$G_{i,j} \leq G_{i,j}^{\max} \quad \forall Y_{i,j} \neq 0 \quad (2.12)$$

where $G_{i,j}$ is the power flow from bus i to bus j

C) Unit Commitment (UC)

Scheduling covering a range of 24 hours to 1 week ahead is a unit commitment problem handled by the operator in the pre-dispatch stage. Again, the target is cost minimization while meeting the demand forecast to decide the unit up/down status for every hour. The objective function now includes the start up and shutdown decisions as follows.

$$J = \sum_{t=1}^T \sum_{i=1}^{NT} [C_{i,t}(G_{i,t})W_{i,t} + ST_{i,t}UST_{i,t} + SD_{i,t}USD_{i,t}] \quad (2.13)$$

where,

ST & SD represent the start up and shutdown cost

W represents the unit status (1= running, 0=off)

UST denotes unit startup state (1=startup, 0=no startup)

USD denotes unit shutdown state (1= shutdown, 0=no shutdown)

The constraints include demand supply balance and spinning reserves, maximum up down time constraints on thermal units, ramp rate constraints, generation limits, must run units etc.

This UC problem is a non-convex highly constrained nonlinear mixed integer optimization problem, which can only be fully solved by complete enumeration. Based on the different time intervals, forecasts (load, inflow, prices), system combinations and system constraints many methods have been used to solve the scheduling problems viz linear programming, non linear programming, dynamic programming and their combinations. Among these dynamic programming is among the most widely used as a solution method [23]. Dynamic Programming can directly handle the non-convex, non-linear and stochastic characteristics. However, direct application of the dynamic programming method is impractical due to the curse of dimensionality that leads to excessive computational time [24]. To reduce computational time, multi-pass dynamic programming is combined with successive approximation technique to solve the hydrothermal coordination problem [25]. A dual dynamic programming technique for staircase linear programs is proposed in [26]. Ref [27] combines the advantages of dynamic programming and evolutionary programming based on AI-techniques to solve the operational cost minimizing problem for hydrothermal systems.

A cost minimization problem for a short term is solved through mixed integer programming for hydropower in [28] by including the schedules with good efficiency only. In [29], by using Lagrangian multipliers to relax system-wide demand and reserve requirements, the operating cost minimization problem is decomposed in to hydro and thermal subproblems. First, the thermal subproblem is solved using dynamic programming. Then the commitment status of thermal units thus obtained is used to solve the hydrothermal scheduling. In [30] the relaxed cost minimized problem is solved through differential dynamic programming and mixed coordination.

However, in a deregulated power markets, electricity generation becomes an unbundled and liberalized activity in which both expansion and operation decisions no longer depend on administrative and centralized procedures based on cost minimization schemes. Instead, these decisions depend on the management team of the generation companies looking to maximize their own profits [31]. Hence, optimal scheduling of each company will not only depend on the companies production cost profiles but also on the market behavior resulting from the interaction of all market participants. In this line, hydrothermal scheduling with a profit-maximizing objective for a Genco in the Spanish power market is formulated in [31] and solved as a mixed complementary problem. In [32], hydrothermal coordination problem for a Cournot market model is solved for the profit-maximizing objective using dual dynamic programming.

2.3.1.2 Competitive Electricity Market

A) ISO and Genco

With the disintegration of Gencos, Transcos (Transmission Companies) and Discos (Distribution Companies), several players have emerged in the competitive market. Consequently, many activities of system operation have been taken over by different entities and hence each now have a role to play, independent of each other, while at the same time have to coordinate their activities in order to maintain the system security and reliability.

The ISO is generally responsible for carrying out market activities such as receiving demand and supply bids, unit commitment & dispatch simulations for Gencos, setting up market clearing price and at the same time ensuring system security and undertake congestion management for which it has to procure ancillary services etc. The generation scheduling practices in different electricity markets depend on the information received by the ISO through bids as shown in Table 2.1 [4,5]. Hence, the ISO must be equipped with powerful computational tools, involving market monitoring, ancillary services auctions, and congestion management, for example, in order to fulfill its responsibility.

Table 2.1 Generation scheduling practices in different electricity markets

Market	Information received through bids	Responsibility of Unit Commitment
Singapore	Energy price, ramp rate limits, reserve bids	Self commitment by individual genco
NY	Energy price, start up costs, minimum and maximum generation level	Self commitment by individual genco
PJM	Energy price, start up costs, minimum and maximum generation level	ISO
NZEM	Energy prices, ramp rate limits, reserve bids	Self commitment by individual gencos
NordPool	Energy price and quantity for both buying and selling. There is also a short-term market for trade close to real time.	Self commitment by individual gencos

Two types of market settlements have been proposed.

- Social Welfare Maximization [4,33]
- Consumer payment minimization (CPM) [4,34,35]

In deregulated markets, Gencos are usually entities owning generation resources and participating in the market with the sole objective of maximizing the profits without concern of the system unless there is an incentive for it. In this market, Gencos would no longer be controlled by entities that control the transmission system and could choose to acquire computational tools, such as price forecasting, unit commitment, bidding and risk management tools, to make sound decisions in this volatile market. Figure 2.3 depicts a general electricity market with the functions of ISO and Gencos [13].

B) Price Based Unit Commitment (PBUC)

Spot price volatility has exposed the Gencos to a considerable uncertainty. Decision makers have to consider the complex issues arising from these uncertainties in market price and technical constraints associated with unit operations while scheduling its generating units and optimizing its generation so as to meet the forward contracts (if any) and trade during the next day. The decision on the volume of contracts and the selection of the type of financial contracts varies with the current and the expected market conditions and hence calls for tools to forecast uncertainties.

In pool markets Gencos are required to bid for energy supply and associated price to the market operator. The type of information that a producer should supply to the system operator is market specific as shown in the Table 2.1. If the market is a centralized pool, the market operator, based on bidding curves and operational parameters of all the units provided by the Gencos, carries out unit commitment to obtain the optimal dispatch and settles the market and formulates the generation schedules. However in decentralized market, the Gencos carryout their own self-commitment and do not have to submit any other information apart from bid prices and quantities e.g. NEMS, Singapore.

In a bilateral contract market, Gencos enter direct buy / sell contracts with selling/ buying participants. These contracts are usually made on a long-term basis and the prices are decided in advance. In these markets as well, Gencos have the responsibility of unit commitment. In the hybrid market, in addition to the bilateral contracts, Gencos can also participate in the spot market to sell excess generation or to buy from the market to meet the bilateral contract.

If the Gencos have the responsibility for UC, then all the technical constraints such as the uptime/downtime limits, ramp rate limits, startup costs etc have to be internalized in the bid price. These technical constraints are critical for the Gencos having predominantly thermal generating plants as they reduce their flexibility of operation as against those with predominantly hydro capacity. Obviously, the benefits of the Gencos are directly related to their generation plans. Based on trading decisions and price forecasts,

Chapter 2 Background Literature

appropriate scheduling and dispatch schemes considering bidding strategies should be developed to maximize their benefits from the market. As the result of these changes, UC problems have gained renewed interest in the last decade.

According to [36,37], redefining the UC problem (2.13) for competitive environment involves changing the demand constraints (2.3) from equality to less than equal and the objective function from cost minimization to profit maximization. In [38], UC based on forecasted market price with a profit maximizing objective has been emphasized for the deregulated power market. Hence the new objective function is in general represented as:

$$\max \Pi = \sum_{t=1}^T \sum_{i=1}^{NT} (G_{i,t} \cdot FP_t) W_{i,t} - C_{i,t} (G_{i,t}) W_{i,t} + ST_{i,t} UST_{i,t} + SD_{i,t} USD_{i,t} \quad (2.14)$$

and demand constraint is changed to:

$$\sum_{i=1}^{NT} G_{i,t} \cdot W_{i,t} - P_{Loss,t} \leq PD'_t \quad (2.15)$$

where, FP_t is the forecasted price and PD'_t is the forecasted demand.

There may be a tendency to think that maximization of profit is essentially the same as minimizing the cost [37]. This is not the case because Gencos have no longer the obligation to serve. They may choose to generate less than demand, which allows more flexibility in UC schedules. Profit depends not only on cost but also on revenue and revenue is the function of price, which is very volatile in the competitive market. Moreover, what is generated is independent of the expense incurred because the pool determines the amount of generation to be dispatched based on the bids submitted. This means that the efficient production does not guarantee optimal revenue. Hence, in a competitive market, the winner is the one who can respond best to the market conditions.

According to [39], significant change is necessary to the traditional planning because the utility do not have to worry about the transmission constraints either because the

transmission is not the utility's responsibility or because there is sufficient capacity in the transmission grid. The necessary changes have been put in three categories.

- Firstly, objective of planning models is now profit maximization.
- Secondly, demand constraints in these models becomes superfluous since utilities no longer have an obligation to serve demand by using only their own generation resources as they can also use the spot market and contract markets (i.e. other companies resources) to meet customer obligation.
- Thirdly, as spinning reserves and other ancillary services have become the ISO's responsibility, reserve constraints as used in UC is also unimportant for the utility.

Although all the assertions in [39] hold in most markets, the third assertion is somewhat different. For instance, in markets like NEMS (Singapore), Gencos have to bid in the pool to get their reserves dispatched. But, ISO is still responsible for maintaining system reliability as Gencos can choose not to offer reserves. However, as reserves are considered the responsibility of Gencos, depending upon their energy contributions, 'reserve responsibility shares' are calculated and reserve charges are passed back to the Gencos [5] i.e. the reserve charges and payments is a zero-sum settlement among the Gencos. Hence, in order to avoid losses due to charges, Gencos bid in such a way that their 'reserve responsibility shares' are satisfied at all times. Moreover, reserve dispatch at a level higher than the 'reserve responsibility share' adds to Genco's profits.

C) Forecasts

The generation plans made in the competitive market depend to a great extent on the forecasts. Forecasting loads and prices in wholesale markets are mutually intertwined activities, and the fundamental approach to this is to look for the intersection of the demand and supply functions at each period in the market. Hourly load forecasts are still made as extensions of conventional time series methods using weather variables and specific market information but not the prices [40]. In the competitive market framework, power producers need accurate price forecasting tools as these forecasts embody crucial information when developing generation plans and dispatch using bidding strategies to maximize the benefits. In the medium term, decisions have to be made on how much

energy to sell through bilateral contracts and how much to sell to the pool. Accuracy in price forecasting is very critical since more accuracy in forecasting reduces the risk of under/over estimating the revenue for power producers and provides better risk management [41].

Although the focus has not been particularly given to build a forecasting technique in this research, a simple method using an Artificial Neural Network (ANN) is used in chapter 3 to present a realistic price scenario. However, different forecasting models can be found in the literature viz- dynamic regression and transfer function models based on time series analysis [42], ANN with back propagation [43], regime switching models [44]. Review of the main methodological issues and techniques is provided in [40].

2.3.2 Risk Management

Risk in economic theory is defined as an option where the profit is not known in advance with absolute certainty but for which an array of alternative outcomes and associated probabilities are known or can be derived. The purpose of the risk management is to adjust risk to the market situations at all times based on today's status and expectations regarding future outcomes and the probability distribution associated with this.

The general strategies of dealing with risk has been categorized in [45] as

- Investing for flexibility so that changes can be easily and inexpensively made
- Investing in projects that are robust i.e. perform well across variety of futures
- Ignoring risk.

2.3.2.1 Tools of Risk Mitigation

In the power market, uncertainties that create risk are mainly:

- Price Risk: The deregulated electricity markets show severe price volatility.

- Quantity Risk due to Inflow uncertainties: this is the case with hydropower plants where the inflows to the reservoirs are dependent on the weather conditions.
- Quantity risk due to demand uncertainty (in case of end use sales): demand fluctuations due to unexpected weather conditions etc comes under this category.
- Others: Risk associated with forced unit outages, congestion, loads forecasts etc.

For both generators and consumers, the greatest risk posed by electricity pools is the financial consequences of fluctuating pool prices. Pool prices will vary each half hour and will be determined by the balance of supply and demand. Whilst the level of demand can be estimated, the availability of generation capacity in the market is less predictable as Gencos themselves choose how much electricity to offer for dispatch. The Genco with the highest marginal bid that is operating at any point of time determines the pool price. These uncertainties consequently affect the stability of pool prices in the short, medium and long term. Therefore, for generators and consumers, to protect themselves from the risk, tools of risk mitigation exist in various forms.

A) Forward Contract

Forward Contracts are usually private (Over-the-Counter) agreements between two parties among which one assumes a long position and agrees to buy the commodity at a certain specified date for a certain price whereas the other party takes the short position and agrees to sell the commodity at the same date for the same price. These types of forward contracts are sometimes referred to as bilateral contracts. However, forward contracts can also be traded on an exchange. Exchange traded forward contracts are standardized contracts with power being traded in monthly on and off-peak blocks. The trader taking short position (seller of forward contract) is obligated to deliver power physically at a constant rate to a location specified in the contract. The contract does not specify the location at which the power is produced or consumed. However, the trader can avoid delivery by purchasing a long position, which exactly offsets the short position for the same delivery month [13,46-51].

B) Future Contract

Futures contract [13, 46-50, 52] is also an agreement to buy or sell a commodity for a certain price at a certain date in the future and are similar to the exchange traded forward contracts. But unlike the forward contracts, parties entering into futures contracts have no intention of physically producing or consuming the power but rather use it as a hedge against other positions in the market. These contracts are closed few days (3 or 4) before the start of delivery month.

C) Options

Options contract is an agreement between two participants where the holder of the contract has the right but not the obligation to buy (sell) a specified amount of power at a certain future time for a certain time horizon at a specified price (strike price). The holder of the contract has to pay the seller a certain payment called the premium. These options are of two types- Call Option and Put Option [49,52-55].

All of these contracts are most widely used for hedging. Hedging allows the participants in the market to offset the risk of fluctuating prices. Hedgers use the contracts to stabilize their income by taking an offsetting position in the physical market. Given the resources available, a producer's decision involves tradeoff between risk and expected return.

2.3.2.2 Decision Making

Decision-making under uncertainty and risk assuming various probabilistic methods has been widely used in the power market models. A method of ranking the policies with the reliability concept of Total Time on Test (TTT) Transform by identifying probabilistically the optimal policies has been shown in [56]. Thermal generation is represented as the probabilistic production costing to solve a hydrothermal reliability problem in [26].

Some of the techniques available to address these issues are

- Mean Variance and Efficient Frontier [39, 57-59]
- Capital Asset Pricing Model (CAPM)[11]
- Value at Risk (VaR) [11,38]
- Utility Theory [45, 60,61]

2.3.2.3 Hedging

For the purpose of hedging risk in the competitive market, the profit function for a producer, say producer 1, in general, is represented as

$$\Pi_1 = S_T Q_{sT}^1 + F_t Q_{ft}^1 - c_1 Q_1 \quad (2.16)$$

where,

S_T Expected spot price at delivery time T and is given by the inverse demand curve

F_t Forward price at time t for delivery at time T

Q_1 Quantity produced by producer 1

Q_{sT}^1 Spot quantity produced by producer 1 at time T

Q_{ft}^1 Quantity forward by producer 1 at time t for delivery in time T

c_1 is the cost coefficient (thermal units) of producer 1

However, the solution methodology varies in view of market models, presence of market power etc. Ref [54] uses a Cournot duopoly model of electricity pools to show that the generators have a purely strategic incentive to sign forward contracts so as to raise their share of the overall electricity market. The concept of “delivery to an index” is proposed in [50] that could be accomplished by making daily settlements to all accounts based on actual spot price realized during the delivery month. In [12], it is shown that the interaction between the strategy, risk hedging, and conjectural variation detects whether

an oligopolist take long or short position in the market. A scenario simulation and probabilistic simulations are used in [51] to show how the forward contract offer a way of sharing between supply and demand sides the risks associated with periods of supply constraints.

2.3.3 Strategic Bidding in Competitive Market

In a perfect electricity market, any power supplier is a price taker. Microeconomic theory holds the optimal bidding strategy for a power supplier is to simply bid marginal cost. When a generation bids other than the marginal cost, in an effort to exploit imperfections in the market to increase profits, this is called strategic bidding. This has many implications for power producers because the competition mainly exists at the generation side and the transmission system is still a monopoly. Hence, the bidding problem in electricity markets is concerned mainly with power suppliers although demand side bidding is also gaining importance.

Bidding strategies can be broadly categorized in four ways [62]:

- A) Relying on the estimation of the MCP in the next trading period
- B) Estimating the bidding behavior of the rival participants
- C) Game theory
- D) Simulation and experimental method

Some of the parameters affecting bidding strategies [37,63,64] are

- A) Non convexity of cost curves
- B) Inter-temporal constraints
- C) Bilateral Contracts
- D) Price Uncertainty
- E) Hydro availability for the next day in case of hydropower producers
- F) Load and weather forecast for the next day

However, due to the different trading rules in different markets, the bidding strategies also differ. Some of the trading rules that affects can be summarized as follows.

A) Simple and Multipart bids

In simple bids, participants submit a simple quantity and its price e.g. Singapore, Norway, California. But multi-part bids also reflect startup costs, shutdown costs, running cost etc in addition e.g. PJM.

B) Static and Dynamic Repetition Bids

Static bids allow one single bid daily whereas dynamic bids allow the modifications of the bids until the gate closure time. E.g. Singapore allows bids modifications up to 2 hours before real dispatch.

C) Single Side Bid and Double Side Bid

In Single side bids, only power producers submit bids but consumers do not. However, in double sided bids, demand side bidding is also allowed.

D) Single Energy and Energy-Reserve Market

In single energy market, energy is traded in spot market through power exchange whereas reserves are traded in ancillary market e.g. California. In energy-reserve market both energy and reserve are considered simultaneously e.g. Singapore.

E) Centralized and Decentralized Markets

In centralized markets, the system operator based on the multi-part bids obtained from the participants, conducts unit commitment e.g. PJM. In decentralized markets, self-scheduling is the responsibility of individual power producers e.g. Singapore, Norway.

Moreover, the market rules may allow certain kinds of bidding curves for the participants. For example Singapore NEM allows stepwise non-decreasing bid curves whereas California PX allows linear bids. As bidding plays a vital role in determining the revenue

of Gencos, attempts have been made to formulate strategies to obtain best bids. David and Wen [37] provide a literature survey on the works done in recent years.

Bidding problems have been, in general, addressed in view of the following [37, 63, 65-73]:

- Market structure (perfectly competitive, Oligopoly, bilateral, spot, hybrid)
- Units owned (thermal, hydro, hydrothermal)
- Bid functions (step function, linear, non-linear) etc.

In [65] the influence of a set of bidding strategies on the Market Clearing Price (MCP) is described and some good bids are isolated probabilistically. Then the unit commitment problem is solved for the set of good bids to come up with the best bid. An optimal solution methodology for risk management combining Lagrangian Relaxation and stochastic dynamic programming is applied in [66] for a producer owning hydro, thermal and pumped storage units. In [67], Huse et al suggests a bidding strategy with producers' bidding marginal cost (MC) if MC is more than the breakeven price or simply the breakeven price. In [68], a genetic algorithm is used to update bidding strategies as Gencos and Discos trade power in an environment in which Gencos and Discos buy power via double auctions implemented in a regional commodity exchange. A stochastic optimization formulation is presented in [69] assuming that in an oligopoly each supplier bids a linear supply function and chooses the coefficients in the supply function to maximize benefits subject to expectations about how rival suppliers will bid. In [70], an innovative model and an efficient Lagrangian relaxation-based method are presented to solve the bidding and self-scheduling problem. Revenue adequacy constraints and iterative bid adjustment process are considered while making a bidding strategy in [63]. Bidding behaviors under a simple auction market are modeled in [71]. Bidding strategy by adjusting the minimum output and price has been developed to optimize the suppliers' benefits in [72]. The bidding problem is formulated as optimal assignment problem in [73], where the necessary and sufficient conditions for Nash Equilibrium bidding strategies are derived for a bilateral market. Most of these methods [63, 69-73], however,

rely on the information on the load and other bidders cost distribution which is not easy to estimate and are often outdated even if available [71, 72].

2.4 Concluding Remarks

The process of deregulation in the electricity industry is explained first in this chapter along with the types and classification of market models. The fundamental changes in the planning process for power producers due to the changes in the market structures as a result of deregulation is then explained in view of long term planning, medium term planning, short term planning and real time optimization. Considering the fact that there is no common market structure and no common sets of trading rules, it is explained that power producers' objective of profit maximization is affected by various factors viz. model of market, types of power plants owned, type of market, risk preference of producers, financial contracts available, price uncertainty, forecasts etc. In view of the generation strategies of the power producers, the factors that influence the decision making is explained with regards to demand and price forecasts, generation scheduling, risk management, bidding strategies, etc. and compared to the traditional market, where applicable.

3. Medium Term Power Planning

3.1 Introduction

Long term generation planning will not be very easy or accurate in deregulated power markets because of the high price volatility in the market. However, medium term generation planning would be crucial for longer-term decisions such as bilateral contracts or futures. Once these decisions are made in the medium term, they have to be incorporated in everyday generation planning.

In case of thermal generators, medium term planning is focused on the acquisition and use of financial contracts. Some of the factors influencing the medium term planning decisions are forecasted future spot prices, cost characteristics of thermal units and risk preference of power producers. Hence, hedging against price uncertainty for thermal generators is relatively simple as it mainly involves decision on contracts.

However, medium term power planning in case of finite resource generation like hydropower presents a more challenging problem for power producers. Firstly, generation capacity in the medium term planning horizon is not certain as it depends on the water availability. Hence, the planning model should incorporate inflow uncertainty in addition to price uncertainty. Secondly, hydro generation is somewhat different from the other generations in that it can be stored to some extent. Utilities that control hydro resources can, subject to some constraints, move energy between periods by adjusting the rates of release from their reservoirs. Water in a reservoir can be used now, or it can be stored for use in the future. The choice of using water straightaway or storing for later use arises at any point in time. Hence, the water may be used to generate electricity for spot market sale in any future period. This presents a complex but an important medium term planning problem for power producers owning hydro resources.

According to Pereira and Pinto [74], the aim of reservoir management in a conventional power system is to minimize expected costs, while maintaining an adequate security of supply. In a purely hydroelectric system there is no fuel cost, and the security of supply is

Chapter 3 Medium Term Power Planning

the only concern, whereas in mixed hydrothermal systems, balancing short-term costs with long term economic and security considerations is a complex and important problem.

However, in deregulated markets, Gencos participate in the market with the primary objective of maximizing profits. Maintaining the security of supply is not the main concern of producers, but that of the system operator as Gencos can choose not to participate in the reserve market. A major concern for producers in restructured markets is, however, the profit uncertainty caused by e.g. uncertainty in spot prices and reservoir inflow. For hydro producers, large variability of water inflow means a large variability in profit. Thus, decision makers have to consider the uncertainty in market prices and inflows, as well as technical constraints associated with unit operations, while scheduling its generating units so as to meet the company's contractual obligations, e.g. in the form of forward contracts.

In [57], risk management using futures contract, jointly with power scheduling, is considered in a (static) mean-variance framework. Using a continuous-time framework, [75] considers long term hydro scheduling and joint risk management using electricity and weather derivatives. Also related is the work in [76], which presents a four-stage stochastic programming model with 256 scenarios for simultaneous risk management via contracts and hydropower generation planning on a 1.5 year horizon.

A new long-term hydro-thermal production scheduling method is proposed in [77] which maximizes the profit of hydro plants in the region based on the projection of the regions system load(s) and/or energy requirements(s) instead of the traditional thermal production cost minimization. But the study is focused on the South African system, which is yet to be deregulated, and no reference to the financial market has been made in the study. Ref [78] is an extension of Baleriaux¹ methodology where the production costing problem is decomposed into a chronological hydro reliability problem and analytically solved by a

¹ The Baleriaux scheme decomposes the production costing problem into generation reliability evaluation sub-problems. In turn, the reliability problems reduce to the comparison between the distribution of available capacity and system demand, which is carried out by discrete convolution [78].

Chapter 3 Medium Term Power Planning

sequence of convolutions of reservoir storage levels, demand, inflows and generation capacity. Ref [79] shows the existence of market power in a hydropower dominated Norwegian region where a monopolist finds it profitable to use water in the reservoir to generate more than the competitive amount in order to reduce storage for future and thus increase future prices. The consideration of a monopolist supplier, however, does not resemble the competitive suppliers in deregulated markets.

In this study, issues relating to the optimal management of hydropower resources owned by a power producer are addressed. For this purpose, Norway presents a perfect testing bed as over 99% of Norway's electricity supply is derived from the country's abundant hydropower. Hence, a hydropower producer in Norway, participating in the Nordic power market, the NordPool, is considered for analysis. In the Nordic market, contracts are mostly traded bilaterally (65% or more) but are also offered by some power exchanges. However, to keep the model simple, bilateral contracts are only considered as means to hedge risk in the medium term.

The decision is to be made on a medium term for both the generation scheduling and forward (bilateral) contracts. Spot prices are modeled as given exogenously, consistent with an assumption of a relatively small producer, or a power market with little market power, i.e. without large producers having opportunities for influencing prices in order to raise profit significantly. Such an assumption is supported by e.g. [80]. Stochastic linear and non-linear programming has been used as a framework for modeling and solution. Results are expositied for a Norwegian power producer participating in NordPool, the Nordic power exchange.

The consideration of bilateral contracts with the medium term scheduling makes the proposed formulations more realistic in terms of decision-making as contracts will help to reduce the risk exposure of a producer. Moreover, bilateral contract is common in Nordic system where hydro is prevalent. The proposed method of using corrective measures based on both inflow and price uncertainty using a scenario tree is expected to further help power producers make better scheduling and hedging decisions.

This chapter is organized as follows. The spot and the financial market that exist in NordPool are outlined before the actual problem is formulated. Then the medium term planning issues are discussed with respect to the NordPool. This is followed by case study, results and conclusions.

3.2 NordPool

NordPool, one of the most successfully deregulated power market, is also the first international power exchange in the world. Norway, Sweden, Finland and Denmark are the main participating countries in the NordPool with Russia and Germany participating in a limited way more recently. Various types of power plants are in operation in the region (Figure 3.1) and the pool has been able to take advantage of the combinations of plants. The presence of hydro plants have been attributed to the very low electricity prices when compared to other countries in the region, in particular, when the inflows to the reservoirs are very high. In addition, the pool being a hybrid market structure, both bilateral and pool market participation are entertained. The financial tools are available in various forms for the participants' to use. Contracts may be bought or sold (up to three years in advance) for a period of a day, a week, a month, a quarter and/or a year [3].

This indicates that an investigation of this market should resemble, to some extent, most of the markets around the world. Moreover, the success of this market as compared to other deregulated markets adds to the interest in this market. As Norway was the startup for this pool, the focus given to the producers in the Norwegian region is expected to provide insights into the medium term planning problem. To begin with, the features of NordPool are discussed.

The Nordic electricity market is non-mandatory and a significant share of the physical power and financial contracts are traded bilaterally. The main reason for power trade and exchange between countries is that this allows them to take advantage of the characteristics of power supply sectors that are based on different production methods. Norway has only hydro power plants. Sweden has hydro, nuclear and small share of

conventional thermal. Finnish is similar to Swedish but smaller share of hydro and thermal whereas Denmark is mostly coal-fired thermal plants. Because the cost structure of hydropower technology and various forms of thermal power technology is different, there are profits to be made from a combination of these technologies in trade between Norway and other countries [3, 19, 81, and 82].

Figure 3.1 NordPool generations

3.2.1 Financial Market in Nordpool

In the zonal pricing framework in Nordpool, low electricity prices and lack of market power in Norway have been attributed to the fact that the country relies almost entirely on hydro resources [83]. Due to the large variability of water inflow in the region, hydropower dependency means very volatile prices and also high variability in producer profit. Hence, to minimize this risk due to price uncertainty, financial contracts are available in various forms.

Hedging allows the participants in the market to offset the risk of fluctuating prices when they buy or sell electricity. It should be remembered that power producers use these contracts to help stabilize their revenues because they have an offsetting position in the physical market. Today the relatively stable price of electricity in the Nordic region has been attributed to a bilateral market for the over-the-counter (OTC) contracts [84], which

makes up 70% of the total power consumption [11]. This is true for other markets as well, for instance, forward contracts leading to lower price has been shown with respect to the New Zealand Electricity Market (NZEM) in [85].

Increasingly popular are the option contracts (European call-options and Asian call-options) in the Nordic market [11]. European call-options provide the buyer the right but not the obligation to receive the difference between the price of the underlying contract and the option strike price. An Asian call-option gives the buyer the payoff equal to the difference, if positive, between average spot price during a specified delivery period and the strike price. In the current study, however, the options and futures are not considered. The emphasis has been given to hydro scheduling and bilateral contracts while considering the uncertainty in price and inflow.

3.3 Problem Formulation

The variable cost of hydro generation is the opportunity cost of water and hence depends on the producers' subjective expectations regarding future spot prices and inflow conditions. In a perfectly competitive market each plant should simply bid a price for electricity that reflects its water value and the efficiency of the turbine. If the producer submits a bid lower than the water value, it risks getting dispatched at a price that is lower than marginal cost, invoking a loss. If it submits a bid that is higher than the water value, it risks not getting dispatched at prices above costs, invoking an opportunity loss, and ending up with more storage at the end of the period. The higher storage tends to lower the water value at the plant thus bringing it in line with the rest of the market [83].

The value of water at the end of horizon is a function of the reservoir level. This function must be specified to avoid the model recommending emptying the reservoir near the end of the planning period. If a long term scheduling model is available then such a reservoir function may be extracted from the results of the long-term model. However, in the model under consideration, the end of horizon is considered the beginning of snow melting, which means that the value of extra water stored is low as this water has a high

risk of being spilt. Hence, the water value at the end of horizon is considered negligible, implying that the producer will have an incentive to use all the water in the reservoir by the end of horizon.

Let us consider a producer seeking to make decisions regarding generation scheduling and bilateral contracts with the objective of maximizing the expected revenue in a medium term. The time under consideration can be divided into several periods (not necessarily equal) as shown in Figure 3.2.

Figure 3.2 Time periods

3.3.1 Expected Value Analysis

If the expected value of the price and inflow for each time period, t , is considered to determine the optimal generation schedule and the volume of bilateral contracts to be signed for each time period for a power producer with the objective of gaining maximum revenue, the revenue in each period, R_t , is given by

$$R_t = P_{st}G_t + (P_{ft} - P_{st})Q_{bt} \quad (3.1)$$

where,

P_{st} is the expected average spot price in period t (\$/MWh)

G_t is the generation in period t (MWh)

Q_{bt} is the bilateral contract signed for period t (MWh)

P_{ft} is the forward price for the bilateral contract in period t (NOK/ MWh)

Summing up the revenues for n number of periods, the objective function is obtained as

$$\max \sum_{t=1}^n R_t = \sum_{t=1}^n P_{st} G_t + (P_{ft} - P_{st}) Q_{bt} \quad (3.2)$$

Constraints:

Water Reservoir Balance

Water reservoir level at the end of a period depends on the water reservoir level at the beginning of the period, inflow during the period, discharge for generation in the period and the spillage in the period. In terms of energy equivalent² (MWh), water reservoir balance can be written as,

$$\begin{aligned} W_t &= W_{t-1} + I_t - G_t - SP_t \\ W_t - W_{t-1} + G_t + SP_t &= I_t \end{aligned} \quad (3.3)$$

where

W_t is the water reservoir level in period t (MWh)

SP_t is the spillage in period t (MWh)

I_t is the expected inflow in period t (MWh)

Generation Upper and Lower Limit

$$G_{\min} \leq G_t \leq G_{\max} \quad (3.4)$$

Contract Upper and Lower Limit

$$0 \leq Q_{bt} \leq G_t \quad (3.5)$$

Reservoir Upper and Lower Limit

$$W_{\min} \leq W_t \leq W_{\max} \quad (3.6)$$

² Water reservoir level (in Mm^3) is converted into energy equivalent (MWh) using 'Average Energy Equivalent' given in Table A.1 in the Appendix.

Spillage

$$SP_t \geq 0 \quad (3.7)$$

To analyze the price structure and inflow variations in the region, the forecasting issues and the price scenario in the Norwegian region are discussed next.

3.3.2 Forecasting

In the absence of market power, the hydropower producer is considered a price taker. As the hydro generators are the sub-marginal power plants, it can, therefore, be said that they can always successfully bid in the NordPool and dispatch the power when required. Hence, in the absence of transmission constraints, the participants in the Nordpool can take the expected system price as reference price while making dispatch decisions.

3.3.2.1 Nordic Price Scenario

Electricity prices depend on supply and demand in the Nordic market (Figure 3.3), which provides a simplified explanation of how prices are determined. The rising curve shows the supply curve for power capacity in the Nordic region as short-term production costs rise. The falling curve shows the demand for power in the Nordic region. Production costs are lowest for hydropower and nuclear power (Figure 3.1). For hydropower, precipitation and inflow to the reservoir are important factors in determining how much electricity can be generated, and thus in determining the price of electricity. Production costs are higher for thermal power plants such as coal-fired and gas fired plants. At the current level of demand in the region, it is often Danish gas-based power that "balances" the market, and therefore determines the price. In a year when hydropower production is close to the average level, electricity prices will therefore largely be determined by the costs of producing electricity from coal. In Figure 3.3, the intersection between demand supply curves indicate the coal-fired plants' costs. In periods when the demand is higher, power plants with higher production costs, such as oil condensate plants or gas turbine plants, become the marginal units and determine the prices. These are peak-load power plants, and are only used to produce electricity for short periods at a time. In Figure 3.3, they would lie on the steeply rising part of the supply curve. Temperature and general economic activity are two factors that are important in determining demand [3].

Chapter 3 Medium Term Power Planning

Figure 3.4 shows the variation of the reservoir level and the average monthly price over a period of ten years. It can be observed from the graph that there is a pattern that is generally followed by both the curves. The pattern is more obvious in case of the reservoir level. A closer look suggests that the price is related to the reservoir level in many ways:

Figure 3.3 Sketch in principle: Short-term variable costs in NordPool [3]

Figure 3.4 Variation in reservoir level and spot price over several years

- When the reservoir level is high the price in general is low (year 1993, 1998,1999...)
- The higher price in 1995 and 1996 was the result of the lower reservoir level in average due to the very low inflow in those years in the region
- The rise and fall of the reservoir and the price level tend to follow a pattern and is more visible in the years 1998, 1999 and 2000.

Artificial Neural Network is used as a tool for forecasting for our purpose.

3.3.2.2 Artificial Neural Network

Artificial Neural Networks (ANN) is based on a non-linear regression method, which has been used for decades for forecasting. The basic idea in this method is to use historical data's and other relevant information to fit and extrapolate the future scenarios. Conventional nonlinear regression techniques involve either a prior specification of the form of the regression equation with subsequent statistical determination of some undetermined constants or statistical determination of the constants in a general regression equation, usually in polynomial form. The first technique is constrained to yield a best fit for the specified form of equation whereas the classical polynomial regression is usually limited to polynomials in one independent variable or low order. Unlike the conventional methods, an ANN makes no prior assumption concerning the data distribution and allows high order curves if they are necessary to fit the data. Moreover, its advantage lies in their resilience against distortions in the input data and their capability of learning.

For our purpose, the forecasting for the price and inflow is done using Generalized Regression Neural Network (GRNN), a variant of Radial basis network.

The GRNN was originally proposed and developed by Specht [86]. This class of network paradigm has the distinctive features of learning swiftly, working with simple and straightforward training algorithm, and being discriminative against infrequent outliers

Chapter 3 Medium Term Power Planning

and erroneous observations. As its name implies, GRNN is capable of approximating any arbitrary function from historical data. The algorithmic form can be used for any regression problem in which the assumption of linearity is not justified [87]. The foundation of GRNN operation is the theory of nonlinear (kernel) regression estimation of the expected value of output given a set of inputs. It is capable of solving any problem that can also be solved by a statistical regression model, but does not require a specific model type (e.g. multiple linear or logistic) be specified in advance.

Historical data of the last ten years was used to train the neural network to forecast inflow and price in the region.

3.3.2.3 Inflow Forecast

In the study a time span starting from week 42 for the year 2001 to week 19 of year 2002 is considered. Each period is considered as shown in Table 3.1.

Table 3.1 Periods under consideration

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
Weeks	42-46	47-51	52-04	05-09	10-14	15-19
Year	2001	2001	2001/02	2002	2002	2002

The expected aggregate inflow in each period was estimated as shown in Table 3.2.

Table 3.2 Forecasted inflow

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
Inflow (Mm ³)	40.45	17.94	20.31	22.82	23.62	32.96

3.3.2.4 Price Forecast

The expected average system price for each period is shown in Table 3.3

Table 3.3 Forecasted price

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
Price (NOK/MWh)	156.71	165.62	166.81	162.05	146.62	110.28

Chapter 3 Medium Term Power Planning

The simple application of GRNN used for forecasting can be further improved to obtain more accurate estimates that can be used in the expected value analysis (described in Section 3.1.1) to obtain the optimal generation scheduling. However, relying on expected values means that the performance of the optimal solution obtained from the objective function (Equation 3.2) is seriously compromised if the actual state of nature turns out to be different from the expected values. Hence, analysis based merely on the expected value must be modified in order to deal with the uncertainty associated with some of the parameters- in this case water inflows and spot price.

It is important to note that the decision made now will be based solely on the information available at the point of decision. Hence, in particular, the decision cannot be based on the actual outcome of the random event, since the information presently available about the future event can be conveyed only through a probability distribution. In other words, we say that the decision should be non-anticipative. Obviously this means that problem described above, the constraint (3.3) do not seem appropriate when the decision must be made before the outcome of the uncertain event I_t (inflow) is known. Thus, a new model is needed to represent a well-defined problem, producing a non-anticipative solution that is in some sense optimal.

The notion of optimality though, is still not obvious since the choice of an objective for maximization as well as the formulation of the constraints depend to some extent on the preferences of the decision-maker, and in particular on the attitude of the decision-maker toward risk. In this study, a risk neutral and a risk averse participant are considered.

It should also be noted that if an expected value (objective function (3.2)) is used and it should turn out that the forecasted values of price and inflow are accurate enough, the decisions made by the producer based on expected values are optimal. But in practice, it is impossible to always accurately forecast the prices and inflow in the market, as there are always uncertainties in a real market. Therefore, it is expected that the stochastic approach incorporating the forecast variations may be more appropriate way to represent the forecasted results of the power prices. For this purpose a scenario tree as shown in Figure 3.5 is considered.

Figure 3.5 Scenario tree

3.3.3 Scenario Tree

It is customary in stochastic programming to assume that the probability distribution of random parameters is known [88]. For a decision-maker choosing to incorporate the uncertainty into some stochastic programming model, the uncertain parameters must be specified, and hence the approach really comes down to specifying a probability distribution where all mass is put into a single point. Therefore, a more accurate and appropriate model is obtained if some effort is put into the estimation of the probability distribution of random parameters.

In this study, the price and inflow in each period under consideration is discretized based on the forecasted values of the expected price and inflow given in Section 3.3.2.3 and Section 3.3.2.4. The standard deviations associated with price and inflow are simply obtained from the historical data as shown in Table A.2 and Table A.3 in the Appendix where the maximum/ minimum indicates the highest/lowest price or inflow recorded in the past.

For scenario tree construction, [89] presents a method based on non-linear programming that can be used to generate a limited number of discrete outcomes that satisfy specified statistical properties. This technique has been applied in [76] for the Nordic electricity market. Here, the decision maker specifies the market expectations using statistical properties that are considered relevant for the problem and constructs a tree with these statistical properties. Some statistical properties are state dependent while others are independent. If the price have been high in the previous period, then it is likely that prices in the following period are also high. However, at the moment, we will stick to a similar but a simpler representation, ignoring the state dependencies, which are explained hereafter.

The process for which information about the uncertain prices and inflow is resolved is a scenario tree, as shown in Figure 3.5. The model requires decisions to be made at discrete points in time based on discrete probability distributions for the uncertain variables (see Tables A.2 and A.3 in the Appendix). Due to the strong negative correlation between the inflow and price in the Norwegian region [90] and because 99 percent of the power generation in Norway is through hydropower, a simple situation is considered to represent inflow and price uncertainty at each node in the scenario tree. Three possible cases are represented as

- High price and low inflow with probability 0.3
- Mean price and mean inflow with probability 0.4
- Low price and high inflow with probability 0.3

Precise statistical characterization of the spot price and the inflow is not the main emphasis of this research. It is assumed that the price and inflow are normally distributed in the medium term. In other words the forecasted price and the standard deviation obtained from GRNN are used to form scenarios with the above desired values of probabilities, assuming the distribution to be normal. When available, more accurate information or data on the distribution of the variables and their actual values can easily be used in this analysis.

Here, six periods of 5 weeks each with 243 scenarios are considered. The topmost node represents the decisions today and hence is considered deterministic in a sense that the uncertainty is revealed for period 1. The nodes further down represent conditional decisions at later stages considering the probability as shown in the arcs. The arcs linking the nodes represent realization of uncertain variables. In this way a scenario tree captures the dynamics of decision making as the decisions are adjusted to the realizations of uncertainties.

In Figure 3.5, scenario 122 represents the mean price and inflow scenario, i.e. the most likely scenario. Scenario 1 represents a high price and low inflow scenario throughout the periods whereas scenario 243 represents a low price and high inflow throughout. The other scenarios are the combinations of high and low price/inflow periods. The probability of each scenario is the product of the arc probabilities making up that scenario.

3.3.4 Stochastic Program with Recourse

Stochastic programs with recourse are problems in which the decisions can be divided in two groups – a group of first-stage decisions that must be made without full knowledge about some (random) parameters of the model, and a group of second-stage decisions that can be made after uncertainty has been revealed. Consider the problem described by objective (3.2) and assume that a temporary violation of the group of constraints is allowed. Feasibility must be restored, however, through some corrective or recourse

Chapter 3 Medium Term Power Planning

actions that can be taken after the actual outcome of the random variables has been observed.

If S is the set of all the scenarios as depicted in Figure 3.5 and s represent the index of each scenario, then $Prob^s$ represent the probability associated with the scenario s . For a decision-maker seeking to maximize the expected revenue while taking into consideration the expected recourse, the problem may now be given the following formulation,

$$\max \sum_{t=1}^n R_t = \sum_{t=1}^n P_{st} G_t + (P_{ft} - P_{st}) Q_{bt} + \sum_{s \in S} Prob^s \sum_{t=1}^n P_{st}^s G_t^s \quad (3.8)$$

where,

P_{st}^s is the spot price associated with scenario s

G_t^s represent the corrective recourse action taken for generation in each period for scenario s after the price and inflow (the uncertainties) are observed.

In the above formulation (3.8), the first part is the first stage decision based on the expected price as in equation (3.2). However, a corrective measure is taken through the second term, which represents the second stage corrective recourse action, based on the uncertainty revealed by each scenario $s \in S$ with respective probabilities. This means that the first term in the expression gives priority to the expected scenario, in the sense that it is the most probable outcome in the future. At the same time the probable fluctuations regarding both price and inflow are represented by the second term, i.e. an unfavorable decision (negative G_t^s) will be penalized, and favorable decisions will be rewarded. Hence the optimal solution needs to balance the favorable and unfavorable decisions with reference to each probable scenario so that the decision in favor of higher expected revenue is made.

For the new objective function, the constraints need to be redefined.

Constraints:**Water Reservoir Balance**

$$\begin{aligned}
W_t^s - W_{t-1}^s + (G_t + G_t^s) + SP_t^s &= I_t^s \\
G_t + G_t^s + SP_t^s + W_t^s - W_{t-1}^s &= I_t^s
\end{aligned} \tag{3.9}$$

where,

SP_t^s represent the recourse action taken for spillage in each period for scenario s , after the price and inflow are observed.

Generation Upper and Lower Limit

$$G_{\min} \leq G_t \leq G_{\max} \tag{3.10}$$

Reservoir Upper and Lower Limit

$$W_{\min} \leq W_t^s \leq W_{\max} \tag{3.11}$$

Contract Upper and Lower Limit

$$0 \leq Q_{bt} \leq G_t^{mean} \tag{3.12}$$

It is assumed that amount of power a producer will sell in the forward market is limited to the generation associated with the scenario corresponding to the mean price, i.e. the most probable scenario.

Recourse Variables Upper and Lower Limit

$$0 \leq SP_t^s \leq W_{\max} \tag{3.13}$$

Stochastic Generation Balance

$$G_{\min} \leq G_t + G_t^s \leq G_{\max} \tag{3.14}$$

Spillage Balance

$$SP_t^s \geq 0 \tag{3.15}$$

Non-Anticipativity Constraints

The non-anticipativity principle has been stated in [91] as follows:

“If two different scenarios s and s' are identical up to stage t on the basis of the information available about them at stage t , then the values for the decision variables must be identical up to stage t .”

This can be represented as

$$G_t^s = G_t^{s'} \quad (3.16)$$

$$SP_t^s = SP_t^{s'} \quad (3.17)$$

3.3.5 Risk Averse Decision Maker

It can be seen from equation (3.8) that the decisions made are solely based on the expected revenue without the concern of probable variation in income. Hence, the objective suits a risk neutral producer who would accept the maximum of the expected value of revenue as an optimum regardless of its variance under uncertainty. But a risk averse producer would be willing to accept a solution that had a lower expected value but also a lower variance. Hence, a producer seeking to reduce the risk in the revenue can consider changing the position in the contracts after the realization of the generation scheduling decision for all the scenarios under consideration. This means that a decision maker looking for more stable revenue closer to the expected revenue can consider reducing this fluctuation by minimizing the difference in revenue in each scenario from the expected revenue as

$$R_{dev} = \min \sum_{s \in S} \text{Prob}^s \sum_{t=1}^n \left[P_{st}^s (G_t + G_t^s) + (P_{ft} - P_{st}) Q_{bt} - E(\text{Rev}) \right]^2 \quad (3.18)$$

where,

$E(\text{Rev})$ is the expected revenue based on the expected price and inflow.

Here the decision on the generation level G_t and G_t^s is obtained from (3.8) and hence the generation in (3.18) is known in advance. The aim is to calculate the bilateral contracts Q_{bt} that will minimize the objective function.

3.4 Medium Term Scheduling

The number of future time periods that needs to be considered is limited by the storage bounds of the reservoir. If it is known that the reservoir will be full in some future period then there is no value in committing any extra water to storage for use beyond that time as it could not be carried over and consequently be spilt. Further, the reservoir cannot have negative amount of storage, which means that one cannot use more water than there is in storage. These constraints imply that marginal value of water held in storage is only affected by the value that water would have up until the next time the reservoir hits one of its storage bounds.

In the model, the period starting from the beginning of week 42 to the end of week 19 of the next year is considered. This period covers the time span when the production is more than the rate of reservoir filling (Figure 3.6). The intersection of the useful inflow and the production curve also indicate the time of the end of wet season (~week 43) and the end of dry season (~week 17). In Norway, water is collected from snow melting mainly in June, July and August and from rainfall throughout the year, most intensive in September and October. The load is highest in winter, November to March. Consequently, storage of water and the disposal of the water resources over time become important decision variables for the power producers, especially when the inflow is low, such as in the period under consideration.

Figure 3.6 Power production and useful inflow over a typical year [19]

To keep the model simple, a single aggregate reservoir is assumed. Time is divided into six periods each of 5 weeks (periods can however be changed depending on the expected inflow and price behavior). The producer is considered to be a price taker.

As the period under consideration is the dry season, generation capacity in that period is greater than the inflow rate. Large generators having a significant share of electricity market may be able to exert market power by spilling water without generating in order to reduce the storage and thereby increasing future prices [83]. However, for price taking companies, the spillage of water results in a direct loss in revenue. Hence, the model will try to avoid spillage as long as it is possible.

Again, the end of the dry season or the beginning of the wet season means that the increase in inflow which eventually reach a level where the inflow is more than the upper generation bound. Hence, the target is to use all the water before the start of the wet season. In other words:

$$W_6^s = 0 \quad (3.19)$$

3.4.1 Case Study

Consider a power plant participating in the Nordic market for a period starting from week 42, 2001 to week 20, 2002 with the specifications as shown in Table A.1 in the Appendix. The specifications provided are of a real producer, hereafter referred to as power plant X, participating in the Nordic power pool from Norway.

3.4.2 Results

The objective functions (3.2) and (3.8) were solved using the large-scale linear programming algorithm in MATLAB optimization toolbox ('linprog' function) for both the expected value (12 variables) and stochastic problem (for 4143 variables) [92].

Similarly, the contract position problem minimizing (3.18) was solved under the constraint (3.12) using a medium-scale nonlinear programming algorithm in MATLAB optimization toolbox ('fmincon' function) [92]. Some of the results are summarized below.

Two different forward prices are considered for analysis. In line with [93], the forward price is the risk adjusted expected spot price. This makes the first choice of expected value a reasonable choice for bilateral contracts. Table 3.4 shows a case when the forward strike prices are equal to the expected spot price in each of the periods under consideration. But as the contracts are bilateral, the price is usually the price two interested parties- buyers and sellers agree upon, which in practice can be anything as long as the two parties agree. Hence, the second choice is considered to investigate how the decision would differ if bilateral contracts were possible at a price higher or lower than the expected mean. This would provide an insight to the problem in hand as the region is mostly hydro dependent and the effect of strong negative correlation between the inflow and price and its effect on the decisions being made could be observed. Hence, the choice of average price was a simple option that would make contract price higher in

Chapter 3 Medium Term Power Planning

some periods and lower in the others. In Table 3.5, the forward prices are assumed to be equal to the average of all expected prices, i.e. 151.35 NOK/MWh.

Table 3.4 Comparison for the case when price forward is equal to the expected mean

	Expected Value	Stochastic	
		Risk Neutral	Risk Averse
Q2 (MWh)	0	4116	0
Q3 (MWh)	0	3038	0
Q4 (MWh)	0	3143	0
Q5 (MWh)	0	2390	2500
Q6 (MWh)	0	3059	3491
Expected Revenue (NOK)	7430798	7615619	7615618
Standard Deviation (NOK)	494374	584646	473570

Table 3.5 Comparison for the case when price forward is average of expected prices

	Expected Value	Stochastic	
		Risk Neutral	Risk Averse
Q2 (MWh)	0	0	0
Q3 (MWh)	0	0	0
Q4 (MWh)	0	0	0
Q5 (MWh)	4449	10537	2952
Q6 (MWh)	8168	11760	7358
Expected Revenue (NOK)	7430798	8128158	7931783
Standard Deviation (NOK)	401813	665038	486106

Chapter 3 Medium Term Power Planning

The difference between the expected value method (objective (3.2)) and the stochastic cases are compared here. Objective (3.8) represents a risk neutral producer, whereas objective (3.18) represents a risk averse producer. Q represents the optimal contract decisions for various periods for all the cases.

As can be expected, the total expected revenue is highest for risk neutral participant but so is the variance. Similarly, the variance in income considering all probable scenarios is lower for slightly less expected revenue in case of the risk averse producer. For the expected value case, expected revenue is low, as can be seen in Table 3.4 and Table 3.5.

The variance in the income can be seen more clearly in Figure 3.7 and Figure 3.8, which represent the cases depicted in Table 3.5. It can be seen that variation for the decisions suggested by stochastic case results in higher total expected revenue. The fluctuation is very low for the risk averse producer as compared to risk neutral (see Figure 3.8). For the expected value case also, the variance is low, but so is the expected revenue, and hence the fluctuation is on the lower revenue range (see Figure 3.7).

Figure 3.7 Revenue comparisons for risk neutral and expected value cases

Figure 3.8 Revenue comparisons for risk neutral and risk averse producers

An interesting observation made in this study is that, in the case of risk averse behavior, less amount of bilateral contracts are required as compared to the amount required in case of risk neutral behavior (see Table 3.4 and Table 3.5). This can be explained as follows. As has been discussed in Section 3.4, in the Nordic region, water is collected from snow melting mainly in June, July and August and from rainfalls throughout the year, most intensive in September and October. The load is highest in the winter, November to April. Consequently, storage of water and the disposal of the water resources over time become seriously important decision variables for the power producers. In case of thermal power producers, large volume of bilateral contract at a price (slightly) higher than the system cost (which is quite well defined and is dependent on the fuel price which can be forecasted) would mean a steady income for risk averse power producers. But for hydropower producers, due to the negative correlation between price and inflow and higher degree of uncertainty associated with it, large amount of bilateral contract may mean that the producers have to buy from the market at a very high price to meet the contract obligations if the inflow in the reservoirs turns out to be very low. This brings

more problems for the risk averse decision makers. Hence, it is even seen that slightly less bilateral contracts meant more stability in the case presented. However, in the wet season, when the inflow is very high and hence the prices are very low, going for bilateral contract would mean a more stable income. This is mainly because excess water would mean that the value of water is very low and any spillage is always a loss of money. When bidding in the spot market, one cannot guarantee that the bids are accepted as all producers may be bidding low prices (all hydro), producers may try to secure contracts to guarantee production. This may also be the reason why the participation in the bilateral market has decreased in the years after deregulation.

3.5 Concluding Remarks

A medium term power-planning problem with the objective of optimizing the expected revenue for a hydropower producer has been presented. It utilizes scenario tree analysis with corrective recourse actions for probable scenarios. Adjustment of contract positions has been used as the means to minimize the variation of revenues from the expected values for risk averse producers.

Using the proposed formulation, a medium term planning problem of a Nordic hydropower producer is studied, emphasizing hydro scheduling and bilateral contracts. It can be said that the amount of bilateral contract signed and the decision on generation scheduling, needs to be decided in advance but affects the revenue as the uncertainty unfolds in real time. The maximum revenue path determined incorporates the current market structure in the Nordic region. Compared to the expected value problem, a stochastic program performs better, as several probable future events are considered in order to represent uncertainty.

Bilateral contracts are important in generation scheduling with a profit-maximizing objective. But, it was also seen that higher volume (larger short position) of bilateral contract does not necessarily mean more stable or higher income, as interaction of various uncertainties comes into the picture.

Chapter 3 Medium Term Power Planning

Medium term decisions on bilateral contracts, for both hydro and thermal power producers, add dimension to the short term power planning because producers, depending upon the short run price forecasts and cost of generation, have to decide whether to use their own generation or buy from the spot market to meet their contractual obligations. Additionally, for hydro generators, the release of water recommended by medium term planning provides the target generation for the short-term planning horizon so that the benefits to be gained from variable prices (seasonal) in different planning periods are duly realized. These medium term decisions will have to be incorporated in the short term generation planning problem to obtain overall optimal generation schedules.

4. Production Scheduling in Competitive Markets

4.1 Introduction

In the short term, usually up to a month, generation scheduling problem needs to be coupled with the decision-making problem of the power producers to attain a trade-off between the goals of achieving as high profit as possible at acceptable or the lowest possible risk. In view of these objectives, the decision-making of power producers in the short term, in general, would involve the following.

- Generation Scheduling / Unit Commitment
- Bidding Strategies
- Risk Management

In competitive markets, price based generation scheduling with time horizon of up to 1 week, provide the scheduling targets for the power producers depending upon the expected future prices. However, these targets can only be achieved through bids and hence bidding strategies of power producers based on the anticipation of the market conditions form a part of short term decisions. Moreover, financial contracts are also available for use, usually in blocks for a year, quarter of a year, a month, a week or a day. The short-term contracts are tools to manage risk and need to be coordinated with scheduling decisions.

Unlike the medium term planning problem, the inflow uncertainty for hydropower plants is not very critical in the short-term planning horizon. Moreover, the cost of production is negligible for hydro generation. However, in case of thermal power plants, the cost of generation is an important factor that dictates the decisions being made. It was discussed in the previous chapter that a medium term planning decision for thermal generation is simplistic in a sense that contracts are the only decision variable. In contrast, short term planning of thermal generation presents a more challenging problem for thermal power generators. In this chapter, production scheduling for thermal power generators are investigated. The aspects of generation planning related to uncertainty management and bidding in short term planning horizon are investigated in subsequent chapters.

4.2 Unit Commitment in Competitive Markets

Unit commitment (UC) problems have been addressed in the literature mainly with respect to a traditional power market structure and to some extent with respect to competitive power markets. Generally, optimal scheduling for a time horizon of up to 1 week with time intervals 1 (or $\frac{1}{2}$) hour is addressed.

Optimal scheduling is a non-convex highly constrained nonlinear mixed integer optimization problem, which can only be fully solved by complete enumeration. Moreover, the solution must be obtained within a time that makes it useful for the intended purpose. Hence, UC has been a consistent research interest of the electric power system and in the competitive electricity supply industry, there has been renewed interests in methods that can provide more profits from the spot market. Some of the reported methods for solving UC problem include priority list, expert systems, linear programming, non-linear programming, dynamic programming, evolutionary techniques, simulated annealing and their combinations [67,94-96].

Keeping in view the requirement for competitiveness and hence to provide the savings in the operation costs, many algorithms have been proposed in recent years for solving the UC problem. Orero and Irving [94] uses hybrid genetic algorithm to solve large-scale unit commitment as a cost minimization problem. With a similar objective, a simulation technique has been proposed in [67] focused on competitive market and the procedures of bidding and market clearing is described. Zhai et al [95] have proposed a new method that combines the concepts of augmented Lagrangian relaxation and surrogate sub-gradient to solve the UC problem with identical units. Senjyu et al [96] proposed a fast-extended priority list method for the UC problem where a technique for getting a better initial solution rapidly has been developed.

All the above proposed methods are, however, based on cost minimization objective, similar to the one used for the traditional markets. But, in deregulated markets, Gencos need not have concern of the system unless there is an incentive for it. Their main objective is to maximize their benefits. Hence, if generation planning for a period of, say

Chapter 4 Production Scheduling in Competitive Markets

24 hours in advance is considered, Gencos should carryout UC on the basis of price forecast, generation unit characteristics, unit availability etc to determine the bidding strategy for each bidding period next day. In real time, they would have to meet generation as ordered by the ISO.

The traditional planning objective of cost minimization has been differentiated from the competitive objectives in [39]. Richter et al [36] have proposed a genetic algorithm for the UC problem, which considers softer demand constraints and allocates fixed and transitional costs to scheduled hours. Arroyo and Conejo [97] proposes a 0/1 mixed integer linear programming to maximize the unit profit from selling both energy and spinning reserve in spot market.

While addressing the UC problem in the competitive market, the following factors should be considered.

- The UC perspective of Gencos varies depending upon the market structures, bidding rules, size of Gencos, presence of market power, etc.
- Time taken for solving UC problems may not be very critical in Gencos perspective as it is mainly used for finding better bidding strategies which later on determines their real time commitments based on system demand and supply equilibrium determined by the system operator. These bidding strategies are made hours in advance before the real time dispatch is made.
- The maximization of profit is different than the minimization of cost because Gencos no longer have the obligation to serve which allows more flexibility in demand to be met and hence more flexibility in the UC schedules.

In addition to the above changes, it is worth noting that continuous improvement in technology has meant sharp decrement in the computational time. Hence, the prospects of using methods associated with the ‘curse of dimensionality’ and hence higher computational time like dynamic programming [24], enumeration and other heuristic

Chapter 4 Production Scheduling in Competitive Markets

techniques need to be reconsidered in the solution methodology. In this chapter, in view of the above changes in the last decade, two different UC methods for competitive Gencos to meet the profit-maximizing objective are developed using dynamic programming, enumeration and quadratic programming in the solution process. The methods differ from one another with respect to the perspectives of the Gencos in different contexts of competitive markets. Moreover, the methods are extended to solve self-scheduling problems and are compared with the traditional cost minimization objective with hard demand constraints to evaluate the performance.

The UC problem is addressed in the following sequence. The objective of the traditional power system is briefly stated before modifying it to address the UC objective in two different perspectives. The UC problems are further extended to solve self-commitment problem for the Gencos.

4.2.1 Traditional Power Markets

In the traditional power market, the total cost over the entire scheduling periods is the sum of the running cost, start up cost, and shut down cost for all of the units. Accordingly, overall objective function of the UC problem is obtained as the minimization of the total cost, J [4, 20].

Objective Function:

$$\min J = \sum_{t=1}^T \sum_{i=1}^{NT} [C_{i,t}(G_{i,t}).W_{i,t} + ST_{i,t}.UST_{i,t} + SD_{i,t}.USD_{i,t})] \quad (4.1)$$

where,

t is the time period ($t \in 1, 2, \dots, N$)

i is the index of thermal units ($i \in 1, 2, \dots, NT$),

NT is the total number of thermal generating units

Chapter 4 Production Scheduling in Competitive Markets

T is the total number of periods

$G_{i,t}$ is the generation in period t by unit i (MWhr)

$C_i(G_i)$ is the cost of producing G_i units of power

W is the unit status ($1 = \text{running}$, $0 = \text{off}$)

UST is the startup state ($1 = \text{startup}$, $0 = \text{no startup}$)

USD is the unit shutdown state ($1 = \text{shutdown}$, $0 = \text{no shutdown}$)

$ST_{i,t}$ is the startup cost

$SD_{i,t}$ is the shutdown cost

Running Cost:

Here, $C_i(G_i)$, the unit cost characteristic of the generating units, is a function of G_i and is derived from the heat-rate characteristics as

$$C_i(G_i) = a_i + b_i G_i + c_i G_i^2 \quad (4.2)$$

where a_i, b_i & c_i are the cost coefficient of unit i

Startup Cost:

Either an exponential function as in [67,94] or a two-step function as in [96] is used to represent the startup cost of the generator.

Exponential Startup Function:

$$ST_i = \sigma_i + \delta_i [1 - \exp(-T_{t,i}^{off} / \tau_i)] \quad (4.3)$$

Two Step Startup Function:

$$ST_i = \begin{cases} \delta_i & \text{if } T_{t,i}^{off} \geq \tau_i \\ \sigma_i & \text{otherwise} \end{cases} \quad (4.4)$$

Chapter 4 Production Scheduling in Competitive Markets

where

σ_i is the hot startup cost

δ_i is the cold startup cost

τ_i is the time (hrs) it takes for the boiler to cool down (unit cooling time constant)

$T_{i,t}^{off}$ is the time unit i is in off state at time t

Shutdown Cost:

Shutdown Cost is usually given a constant value for each unit.

Constraints:

The objective function is then solved with the following constraints

Demand Balance:

$$\sum_{i=1}^{NT} G_{i,t} = PD_t \quad (4.5)$$

Spinning Reserve Requirement:

$$\sum_{i=1}^{NT} G_i^{\max} W_{i,t} \geq PD_t + R_t \quad (4.6)$$

Rated Maximum and Minimum Capacities:

$$G_i^{\min} W_{i,t} \leq G_{i,t} \leq G_i^{\max} W_{i,t} \quad (4.7)$$

Minimum Up/Down Time:

$$(T_{i,t-1}^{on} - MUT_i)(W_{i,t-1} - W_{i,t}) \geq 0 \quad (4.8)$$

$$(T_{i,t-1}^{off} - MDT_i)(W_{i,t} - W_{i,t-1}) \geq 0 \quad (4.9)$$

Chapter 4 Production Scheduling in Competitive Markets

where

PD_t is the power demand at time t

R_t is the reserve requirement in each period

$G_i^{\max}$ is the generation upper limit of unit i

$G_i^{\min}$ is the generation lower limit of unit i

MUT_i is the minimum up time of unit i

MDT_i is the minimum down time of unit i

$T_{i,t}^{on}$ is the time unit i is in on state at time t

$T_{i,t}^{off}$ Time unit i is in OFF state at time t

These traditional formulations are still very important because the electricity industries in most of the countries in the world are still state/government-regulated vertically integrated monopolies. Even in the electrical industries that have opted competitive markets, deregulation has not meant complete removal of all regulations. Hence, UC problems for Gencos are, in many markets, dependent to a greater extent on the market rules and regulations. This means that the existing traditional UC formulations with slight modifications can still be applied in some competitive markets depending upon company policies, market rules and market obligations. However, in some other markets with significant change in market rules, the UC problems need to be formulated in a different perspective. For example, in NEMS (Singapore), UC for Gencos require them to consider the vesting contract requirement imposed by the market regulators (on average 65% of system demand is covered by vesting contract). Hence, demand constraint exists but is more flexible compared to traditional market. Whereas this not the case for Gencos in Nordpool as they can choose not to participate in the financial market. Thus, Gencos in competitive markets require UC methods, which are consistent with the policies adopted by the regulating bodies.

Chapter 4 Production Scheduling in Competitive Markets

In this chapter, UC problem is addressed which suit two different scenarios that may exist for Gencos in evolving competitive markets. The first UC problem considers a case where Gencos can estimate or fix their demand with reasonable accuracy within a certain tolerance and the objective function is optimized for this flexible demand constraint. The second UC formulation considers individual unit scheduling of generating units and is relevant to Gencos who are either required to bid for individual units separately or have insignificant market power.

4.2.2 Price Based Unit Commitment (PBUC)

The decision to commit a generating unit in a competitive market is price based and bidding strategies need to be made accordingly. However, commitment levels despite being flexible in the competitive markets, in general, can be governed by many other factors like the following.

- It can sometimes be in Gencos advantage to maintain their generation level above a certain minimum due to the market rules imposed on them. For instance in Singapore, the vesting contract requirements at 65% imposed on the Gencos means that it is profitable for Gencos to maintain the generation at or above that level because the vesting contract prices are attractive when compared to the market clearing prices.
- Bilateral contract obligations from the long or the medium term planning decisions can also govern their short term decisions on the generation level as the Gencos can choose to use their own production or buy from the market at spot prices to fulfill their contractual obligations.
- Gencos, in accordance with their own internal company policy or management decisions prefer their generation level to be maintained approximately at a certain level so as to maintain the market share above certain percent or within a certain range.

In addition, it can be said that Gencos participating in a market, from the experience and knowledge of the market behavior can estimate their probable market demand within a

Chapter 4 Production Scheduling in Competitive Markets

certain tolerance. Hence, either based on the scheduling decisions conducted in the past or based on possibilities like stated above, it could be assumed that Gencos can successfully establish their demand targets within a certain range of tolerance. And, within the tolerance, UC problem can be solved to realize the competitive objective.

4.2.2.1 Problem Formulation

Redefining the UC problem for competitive Gencos in competitive market environment involves modifying the objective function from cost minimization to profit maximization [36] which can be represented as,

Objective Function:

$$\max \Pi = \sum_{t=1}^T \sum_{i=1}^{NT} \{G_{i,t} PS_t - C_{i,t}(G_{i,t}) W_{i,t} - ST_{i,t} UST_{i,t} - SD_{i,t} USD_{i,t}\} \quad (4.10)$$

or,

$$\max \Pi = \sum_{t=1}^T \sum_{i=1}^{NT} G_{i,t} PS_t - J \quad (4.11)$$

where,

PS_t is the expected average spot price forecast in period t (\$/MWh)

Demand Constraints:

$$\sum_{i=1}^{NT} G_{i,t} \leq PD_{sys,t} \quad (4.12)$$

The demand, $PD_{sys,t}$, is the system demand. It should be noted that in markets with many participants, this constraint might never be binding and hence have no effect of the optimal solution. The demand constraint as above can exist for Gencos in markets where installed capacity of large Gencos can approach system demand especially in off-peak periods.

Chapter 4 Production Scheduling in Competitive Markets

In accordance with the discussions in the beginning of Section 4.2.2, the maximum demand constraint in [36] does not fully represent the Gencos obligations in the competitive markets and hence the demand constraint needs to be redefined within a certain tolerance as,

$$PD_t^{\min} \leq \sum_{i=1}^{NT} G_{i,t} \leq PD_t^{\max} \quad (4.13)$$

The minimum and maximum demand limit shown above reflects company policies or the market rule limits or the expectations based on past experience or their combinations. This constraint indicates the flexibility in demand constraint as the result of competitive objective that makes the demand constraint a soft constraint unlike the hard constraint associated with the traditional power market. And with the maximum demand constraint (4.13), Equation (4.12) will almost always be redundant.

4.2.2.2 Solution Technique

In the traditional economic dispatch, all marginal units have the same incremental energy cost (system lambda) at the solution but in the PBUC, ideally the marginal units incremental cost should be equal to that of the marginal price. As it is profitable to produce as long as the cost of producing is lower than the revenue obtained by selling that quantity produced, the average cost is utilized as the basis of enumerating the best possible combination for the operation of the generating units. The solution is obtained using dynamic programming (Figure 4.1) in coordination with selective enumeration method and quadratic programming.

4.2.2.2.1 Selective Enumeration Method

Dynamic programming technique (described later in Section 4.2.2.2.2) involves selecting among the possible UC schedules for making best commitment decisions while moving from stage 1 to stage N (see Figure 4.1). The UC decision at each stage is made on the basis of the aggregate profit until that stage which depends on the expected price and cost characteristics of the units available. A selective enumeration method is developed here to generate the best possible UC schedules while satisfying the constraints in each time

Chapter 4 Production Scheduling in Competitive Markets

period (or stage) so that the UC decisions can be made in each time period through dynamic programming until the final period is reached. The steps involved in the process of generating the best possible UC schedules are explained next.

Figure 4.1 Stages in dynamic programming for PBUC

A) Average Cost at Maximum Output

The orders in which the units can be turned on/off are first stacked on the basis of increasing/decreasing average cost. The minimum average cost is calculated considering both the average cost and startup cost for each unit within the limits of rated maximum and minimum capacities as follows:

$$\min AC = \frac{C_i(G_i)}{G_i} + \frac{ST_i}{MUT_i} \quad (4.14)$$

The importance of MUT_i above is to reduce the effect of startup cost based on the minimum number of hours it should operate if the unit is turned on. The treatment of cost

in this way ensures that a unit with low running cost but high starting cost will not be left out from the selective enumeration process.

B) Selective Enumeration

Selective enumeration is adopted following an increase or decrease in demand in each period. Figure 4.2 shows an example where the demand has increased from period $t-1$ to t . The arrow pointing to unit C suggests that on the basis of unit minimum average costs at least 3 units i.e. A, B and C should be turned on to meet the increased demand.

Consider the case where more units are selected, say D and E. This allows for the difference in the startup costs and marginal cost characteristics of the different units, which may affect the overall costs. The number of extra units considered are usually problem dependent and can be chosen on the basis of cost characteristics and the maximum generation capacity of the units under consideration. The units are then enumerated in different combinations using the ‘Algorithm 452’ developed by Liu and Tang [98].

Figure 4.2 Selective enumeration process

Chapter 4 Production Scheduling in Competitive Markets

Even fewer than the minimum required number of units (e.g., two units in this case) can be considered, particularly if the next unit being considered is a very large unit. On the other hand, all five units (A, B, C, D, E) may be considered. Moreover, to allow for the expensive units which could not be turned off in the previous periods due to the MUT constraints, a combination of a few units to be turned off is also taken into account. For example, let us assume that unit I was triggered on in period 't-3' due to high demand (higher than t) and the MUT of unit I is 3. This means that despite less demand in period t-1, the unit cannot be turned off due to MUT constraint. Now in period t, unit I is not required and it can be turned off but as demand increased from t-1 to t, considering only the units that can be turned on (i.e. 'units can on' in Figure 4.2) will prevent the possibility of turning off unit I. In cases like this, the criterion of considering the online units that can be turned off (i.e. unit I and J in figure 4.2), allows for the possibility of unit I to be turned off. In this way the possibility of obtaining good results is increased, in particular, when the MUT of some units are high.

C) Filtering Process

From all the enumerated combinations, the ones not satisfying the demand constraint (4.13) are first discarded. For the remaining, the minimum average cost is calculated and sorted out in ascending order of cost. As the minimum average costs considered represent a very close approximation of the actual costs, the best few combinations are chosen for the remaining calculations. In the comparative examples in Section 4.2.5, results for the 10 unit systems were obtained by considering only the best five combinations whereas for 40 and 110 unit system best 20 combinations were considered. The method described above is detailed in the bold rectangular box in Figure 4.3.

4.2.2.2.2 Dynamic Programming

The stages of the dynamic programming are the nodes and the line joining the nodes represent time periods (see Figure 4.1). The state variables associated with the individual stages are $T_{i,t}^{on}$, $T_{i,t}^{off}$ and $W_{i,t}$. The decision variable, $G_{i,t}$ is obtained by treating the

Chapter 4 Production Scheduling in Competitive Markets

Figure 4.3 Flow chart showing the solution procedure for 'PBUC'

Chapter 4 Production Scheduling in Competitive Markets

input state, $W_{i,t-1}$, as a parameter. The profit at each stage is obtained by solving the subproblem (4.15) for the constraints (4.5) and (4.7):

$$\max \Pi_t = \sum_{i=1}^{NT} [G_{i,t} \cdot PS_t - C_{i,t}(G_{i,t}) \cdot W_{i,t} + ST_{i,t} \cdot UST_{i,t} + SD_{i,t} \cdot USD_{i,t}] \quad (4.15)$$

where, $t \in 1, 2, \dots, N$

As a set of UC schedules satisfying the constraints are obtained from the selective enumeration process described in Section 4.2.2.2.1, the state variable $W_{i,t}$ is known and hence $ST_{i,t}$ and $SD_{i,t}$ can be calculated separately and can be treated as constants in equation (4.16) thereby reducing the problem to:

$$\max \Pi_t = \sum_{i=1}^{NT} G_{i,t} \cdot PS_t - C_{i,t}(G_{i,t}) \cdot W_{i,t} \quad (4.16)$$

This is a simple quadratic problem, which can be solved by quadratic/nonlinear programming methods in each stage t .

The decision functions for each stages $1, 2, \dots, N$ can be represented by the forward recursion procedure:

$$f_1(G_{i,1}) = \max \Pi_1 \quad (4.17)$$

$$f_t(G_{i,t}) = \max(\Pi_t + F_{t-1}(G_{i,t-1})) \text{ for } t = 2, 3, \dots, N \quad (4.18)$$

where, $F_{t-1} = f_{t-1}^{\max}$

However, at each stage, two maximum profit schedule obtained from decision functions corresponding to each node are chosen. For example for node G in stage 2, as shown in

Chapter 4 Production Scheduling in Competitive Markets

Figure 4.1, both the schedules representing the paths A-B-G and A-E-G are stored. This is required to account for $T_{i,t}^{on}$, $T_{i,t}^{off}$, MUT_i and MDT_i of units i , which will have effect on the profit function at future stages. Finally, to decrease the dimensionality of the problem, not all but best few maximum profit nodes are selected at the end of each stage. The overall flowchart representing the complete solution process is shown in Figure 4.3.

4.2.3 Scheduling of Individual Units

In the present context of deregulation, many power markets require the Gencos to submit the bid for individual generating units and clear the power for each generator separately. In such a situation, it may be more sensible to decide the individual UC separately and then combine these individual schedules to optimize the scheduling of the whole group of generators, where permissible. Another situation where individual scheduling makes sense is that of insignificant market power of the Genco. If a Genco is relatively small compared to the rest of the market, it makes sense to schedule each individual and independent generator separately, since a price taker assumption can be made and the operation of one generator is independent of the others.

In the absence of binding demand constraints, a Genco may consider UC of individual generating unit to maximize profit. To address this, a UC approach which considers the commitment of individual generators based on forecasted market price to optimize its profit over a period of time using a modified dynamic programming technique is proposed. The decision to commit a generation is price based and the bidding strategy need to be made accordingly. However, in some markets, a few or even only one round of bidding is allowed and after these rounds the Gencos are assigned generation schedules for the near future viz.- next 12-36 hours. In these cases the demand constraints may become relevant again; and there may be scope to optimize the schedule of all the units of a Genco as a group.

It is clear that in competitive markets, it is not the UC decisions of Gencos that give the actual dispatch but the bids submitted to the pool that determines dispatch. Hence, any

Chapter 4 Production Scheduling in Competitive Markets

UC formulations in relation to Gencos commitment decision can be best used in conjunction with other market decision parameters like contracts to develop effective bidding strategies. Hence, one of the objectives of scheduling of individual units in this section is to use the simplicity of the scheduling models to develop better decisions techniques for uncertainty management and bidding strategy (Chapter 5 and 6).

4.2.3.1 Problem Formulation

Optimal scheduling in this study is formulated in the context of an electricity market similar to that in Singapore where Gencos are required to bid for each unit separately and supply in accordance with what has been cleared by the ISO. Optimal scheduling of individual units is also valid for Gencos with insignificant market power. For profit maximizing Gencos, the objective function can be expressed as:

$$\max \Pi_i = \sum_{t=1}^T \{G_{i,t} \cdot PS_t - C_{i,t}(G_{i,t}) \cdot W_{i,t} - ST_{i,t} \cdot UST_{i,t} - SD_{i,t} \cdot USD_{i,t}\} \quad (4.19)$$

where, $i \in 1, 2, \dots, NT$

The objective (4.19) is solved sequentially for all the units i for the constraints (4.7), (4.8) and (4.9). The usefulness of equation (4.19) will be for Gencos in markets where individual bids for each unit have to be submitted to the pool for dispatch e.g. NEMS, Singapore. A method of using this technique to derive effective bids is proposed in Chapter 6.

4.2.3.2 Solution Technique

Since, each unit of a Genco is considered individually, the dimension of the UC problem is considerably reduced. Hence, optimal solutions for small number of periods (say 12 or less) can be guaranteed by enumeration as the possible number of UC decisions are limited to 4069 (i.e. 2^{12}) but for longer periods, say 24 hours, the UC possibilities increases to 16777216 (i.e. 2^{24}) and complete enumeration is not feasible.

Chapter 4 Production Scheduling in Competitive Markets

Instead, dynamic programming can be used for solving this problem but there are modeling limitations associated with dynamic programming as well. Consider the dynamic programming model shown in Figure 4.4. The stages of the dynamic programming are the nodes and the line joining the nodes represent time periods. The state variables associated with the individual stages are $T_{i,t}^{on}$, $T_{i,t}^{off}$ and $W_{i,t}$. Assume that at time $t = 0$, the unit status is 0 (initial condition). Now at time $t = 2$, the dynamic programming can give the best path for reaching $t = 2$ as 011 (instead of 001) and hence store 011 as the optimal path to reach state 1 in period 2. But if we consider period $t = 4$, the best UC decision can be 00110 (which is not obtained due to decision at $t = 2$) instead of 01100 due to startup cost and minimum uptime constraint. This limitation can be overcome by enumerating for a certain number of periods at one time. In this way, to overcome the limitations of enumeration and dynamic programming, dynamic programming in coordination with enumeration is proposed.

Figure 4.4 Stages in dynamic programming for Scheduling of Individual Units

Chapter 4 Production Scheduling in Competitive Markets

A few periods, say PN , are considered at each stage (e.g. $PN = 3$ in Figure 4.4) and possible UC on/off status $W_{i,t}$ for those periods are enumerated. Hence, for 3 periods considered in each stage, only 2^3 possible combinations exists which can be handled with ease. Hence, the stages in the dynamic program are now reduced from 24 to 8 (i.e. $24/3$).

The decision variable, G_n in each stage n is obtained by treating the input state, W_{n-1} , as a parameter. Hence, the profit at each stage is obtained by solving the subproblem (4.20) for the constraints.

$$\max \Pi_n = \sum_{t \in PN_n} [G_{i,t} \cdot PS_t - C_{i,t}(G_{i,t}) \cdot W_{i,t} + ST_{i,t} \cdot UST_{i,t} + SD_{i,t} \cdot USD_{i,t}] \quad (4.20)$$

where, $i \in 1, 2, \dots, NT$

The decision functions for each stage $1, 2, \dots, N$ can be represented by the forward recursion formula

$$f_1(G_{i,1}) = \max \Pi_1 \quad (4.21)$$

$$f_t(G_{i,n}) = \max (\Pi_n + F_{n-1}(G_{i,n-1})) \text{ for } n = 2, 3, \dots, \frac{N}{PN} \quad (4.22)$$

where, $F_{n-1} = f_{n-1}^{\max}$

In this way individual scheduling described above gives the target production for each unit so that bidding strategies can be made to achieve the target.

4.2.3.3 Sample Implementation

Solving the problem with this objective will provide optimal power scheduling decision corresponding to each decision period for the forecast price as shown in Figure 4.5. The area within the dotted lines in Figure 4.5 corresponds to the range of marginal cost of the

Chapter 4 Production Scheduling in Competitive Markets

unit between its capacity limits. It can be seen that price being equal to marginal cost (period 7-14) does not necessarily mean that turning the units on in those periods are profitable because the other factors like startup/shutdown costs and the uptime/downtime constraints also have effect on the decisions being made. The UC decisions obtained for each unit in this way is the optimal solution obtained for the unit in view of the forecasted spot price. The power schedule as shown in Figure 4.5 can be considered the target schedule for the unit of the Genco and hence provides information for the Genco to make bidding strategy accordingly to obtain the targets.

Figure 4.5 Power dispatch for single unit for forecasted price

4.2.4 Price Based Self Commitment

In markets such as New Zealand Energy Market, UC is the sole responsibility of individual Gencos. In these markets the Gencos use their bidding strategies and submit single part bids to the ISO. For this type of market as well, UC described in Section 4.2.2 and Section 4.2.3 respectively gives optimal dispatch for the forecast price if it can be

Chapter 4 Production Scheduling in Competitive Markets

achieved through bidding. Hence, the information on optimal production obtained is still valuable when making bidding strategies. These bidding strategies may, however, include (i) uncertainty in price, (ii) the behavior of other participants, (iii) risk averseness of the Gencos, etc. Moreover, a cumulative bid for the entire units owned by a Genco may be submitted to the pool. But only after the market is cleared, each Gencos would know their individual demand in the spot market. Based on these demands, Gencos can again carryout self-commitment to obtain optimal decisions for all the units. Now, the demand constraints become relevant for competitive Gencos. This makes the UC at this stage similar to that in the traditional power systems where the objective is to minimize system cost to meet the system demand.

4.2.4.1 Extension of ‘Price Based Unit Commitment’

The extension of ‘PBUC’ for self-commitment simply involves changing the demand constraint. Flexibility in demand for competitive Gencos that may exist due to various reasons described in Section 4.2.2 is represented by equation (4.13). Once the individual demand of Gencos is known, the demand constraint is no longer flexible. Hence, PBUC can be solved with $PD_t^{\min} = PD_t^{\max} = PD_t$ in equation (4.13), which makes it equivalent to demand constraint (4.5) for the traditional system. With demand as a hard constraint, the profit maximization objective (4.10) becomes equivalent to the cost minimization objective (4.1) because fixed demand makes the term $\sum_{t=1}^T \sum_{i=1}^{NT} G_{i,t} \cdot PS_t$ in the profit-maximizing objective (4.10) a constant.

4.2.4.2 Extension of ‘Scheduling of Individual Units’

4.2.4.2.1 Self Commitment for Individual Units

The ‘Scheduling of Individual Units’ described in Section 4.2.3 gives the best commitment decision for a particular price for individual units. If the scheduling is done with the same set of prices for all the units owned by a Genco and the optimal quantities for each unit are aggregated, the optimal total quantity for the Genco at that price is obtained. This means that for that cumulative quantity, the UC schedules obtained is

Chapter 4 Production Scheduling in Competitive Markets

optimal. In other words, if that cumulative quantity was the actual demand to be delivered by the Genco, then the UC decision obtained through individual scheduling is optimal. But the demand of Gencos is determined by the pool and can be quite different from the target depending upon their bidding strategies and various other reasons like system security, reserve requirements etc. to be met by the ISO. In this case, scheduling solution considering individual generating units would not be optimal and hence will require some adjustment to meet the actual demand. Here, an attempt has been made to resolve the problem by adjusting (increasing or decreasing) the price fictitiously in each period until the demand condition is satisfied. This result of using this adjustment in price on the optimal dispatch is seen in Figure 4.6. This is the same example as in Figure 4.5 but for increased price (shown in bold) for period 9. The effect on dispatch can be seen in the changes in period 9,10 and 11.

Figure 4.6 Power dispatch for change in price

Chapter 4 Production Scheduling in Competitive Markets

4.2.4.2.2 Self Commitment for Groups of Units

The same technique can be applied for committing a group of units to meet the demand target. An iterative method is proposed where price in different period is subsequently increased or decreased, so that the units committed also increase or decrease respectively until the demand constraint is satisfied. This method, which uses price as a guideline for solving self-commitment problem with demand constraint is explained with the help of following steps.

BEGIN

Step 1: Initialize the price for $t \in 1, \dots, N$ to expected average spot price forecast PS_t

Step2: Begin Iteration

Step3: For the price PS_t solve ‘Scheduling of Individual Units’ described in Section 4.2.3 to obtain $W_{i,t}$ and $G_{i,t}$.

Step 4: For all t , $t \in 1, \dots, N$

$$\text{If } \sum_{i=1}^{NT} G_{i,t} < PD_t \text{ then } PS_t = PS_t + \Delta PS$$

$$\text{Else if } \sum_{i=1}^{NT} G_{i,t}^{\max} > PD_t \text{ then } PS_t = PS_t - \Delta PS$$

$$\text{Else } PS_t = PS_t$$

Here, the change in price for the given conditions prevents over scheduling and under scheduling which increases the cost of production and violates the demand constraint respectively.

Step5: For the $W_{i,t}$ obtained, solve objective function (4.19), which is now a simple quadratic equation and can be solved using ‘quadprog’ function from MATLAB optimization toolbox [92] for the demand constraint (4.5).

Step6: Store the optimal solution obtained so far.

Step 7: After every 2 iterations,

$$\text{Set } PS_t = \max(PS_{t-1}, PS_{t-2}) \text{ and } \Delta PS = \Delta PS / 2$$

Chapter 4 Production Scheduling in Competitive Markets

PS_t is set in this way so that the UC decision obtained using this price guarantees the fulfillment of demand constraints after every iteration. In addition, reducing the amount by which the price is changed (ΔPS) helps in fine-tuning the scheduling decisions in subsequent iterations to reach the optimal solution.

Step 8: Repeat steps 3 to 7 until maximum number of iteration is reached.

END

The proposed procedure was implemented in different systems reported in the literature and Figure 4.7 shows the effect of this self-commitment method on the target dispatch obtained through individual scheduling. The solid lines in Figure 4.7 indicate the target commitment plan for the forecasted price obtained from scheduling for a Genco owning a 10-unit system given in [94] (see Table B.1 in the Appendix) for a 12-hour period. Let us assume that the total power cleared by ISO for the Genco is shown by the dotted lines in the topmost graph in Figure 4.7. Now, self-commitment of the units as described above suggests an optimal power dispatch schedule for the 10 units as shown by dotted lines in the figure.

For a Genco, price PS_t , that gives the economic dispatch, can provide vital information about the performance of the bidding strategy. The final prices that gives the optimal schedule for the Gencos load, reveals the marginal cost of the dispatched units. For this load, if the fictitious price, PS_t , is higher than the actual spot price, it indicates that some of the dispatched units are not economical. On the contrary, if the fictitious price is lower, it indicates the possibility of higher dispatched. Information like these can be very useful for market analysts in any Genco to improve the bidding strategy.

4.2.5 Comparative Examples

The proposed techniques of unit commitment were applied to four different systems given in [94] and [96], and the results obtained are compared with those reported by different authors in literature. The plant characteristics and forecast prices of the systems are tabulated in the Appendix B.

Figure 4.7 Effect of self-commitment on target dispatch of 'PBUC'

For comparing traditional and competitive markets on a common ground, some assumptions are required. In [94] and [96], 10, 40 and 110 units systems are used for

Chapter 4 Production Scheduling in Competitive Markets

numerical examples in view of traditional market and hence the UC is solved for the whole system with the objective of cost minimization. While solving the PBUC in competitive markets, a single Genco owing 10, 40 and 110 units is assumed. With this assumption, the solutions reported in the literature can now be treated as a Genco participating in the competitive markets with 10, 40 or 110 units but following the traditional method of cost-minimization as the objective. In this manner, a common ground for comparing the proposed methods with the ones reported in the literature is established.

Table 4.1 shows the optimal solutions obtained from the methods developed in this chapter and the best solutions for the UC problem reported in the literature. The profits shown are cumulative profit for all the units in the system. The effect of the hard demand constraint is visible from the difference in the profit with the traditional UC objective and PBUC. For all the cases, the profit obtained from the proposed method is higher than that of the traditional UC. This shows that flexibility in demand prevents the units from dispatch if the prices are not favorable (i.e. if the prices are lower than the cost of generation) and allows dispatch of additional units if the prices are favorable (i.e. if the prices are higher than the cost of generation).

Additionally, the expected profits in Table 4.1 indicate that the ‘Scheduling of Individual Units’ performs as good as, if not, better than ‘PBUC’. This is expected mainly because the search space for optimal solution is limited in case of ‘PBUC’ as all the units are considered simultaneously while moving from one stage to the next in the dynamic programming. However, in case of ‘Scheduling of Individual Units’ each unit is taken individually and hence the search space for the optimal solutions is very large.

To observe the performance of the self-commitment problem with hard demand constraint (which is similar to the traditional UC problem), self commitment methods described in Section 4.2.4 were implemented. Table 4.2 and Table 4.3 show the minimum cost obtained from optimal UC schedules for different unit systems with the demand constraint (4.5) and the spinning reserve constraint (4.6). In line with formulations in [94]

Chapter 4 Production Scheduling in Competitive Markets

and [96], exponential startup cost function (Equation (4.3)) for systems in [94] (Table B.1 and B.2 in the Appendix) and two step start up cost function (Equation (4.4)) for systems in [96] (Table B.3 and Table B.4 in the Appendix) were used.

A cursory look at the results in Table 4.2 and Table 4.3 indicate that both UC methods proposed in this chapter perform better when compared to the other techniques reported in the literature. Comparison of the methods developed in this chapter show that ‘Scheduling of Individual Units’ gives better dispatch schedules for larger systems where as ‘PBUC’ gives better dispatch schedules for smaller systems. The reason for this can be explained as follows.

Table 4.1 Profit comparison for four systems

Solution Method	Total Cost (\$)	Revenue (\$)	Profit (\$)
10 Unit System [94] (Table A.1)			
PBUC	49416	51293	1876
Scheduling of Individual Units	41010	42910	<u>1899</u>
Traditional UC	47121	48790	1669
110 Unit System [94] (Table A.2)			
PBUC	3831212	5162900	<u>1331688</u>
Scheduling of Individual Units	3752662	5084350	<u>1331688</u>
Traditional UC	3819044	5129551	1310506
10 Unit System [96] (Table A.3)			
PBUC	534210	568573	34363
Scheduling of Individual Units	402718	437517	<u>34799</u>
Traditional UC	550835	568573	17738
40 Unit System [96] (Table A.4)			
PBUC	2149249	2323798	174548
Scheduling of Individual Units	1590447	1764995	174548
Traditional UC	2209847	2323800	113953

Chapter 4 Production Scheduling in Competitive Markets

Table 4.2 Cost comparisons for 10 and 110 unit system [94] (Appendix B)

Solution Method	Total Cost (10 Unit System)	Total Cost (110 unit System)
PBUC	<u>47262</u>	3819044
Scheduling of Individual Units	47383	<u>3810705</u>
Simulated Competition [67]	47289	3812139
Lagrangian Relaxation	47511	-
Hybrid Genetic Algorithm	47511	3826775
Normal Genetic Algorithm	47576	3834467
Unit Decommitment	47704	3819282
Artificial Neural Network	48293	-

Table 4.3 Cost comparisons for 10 and 40 unit system [96]

Solution Method	Total Cost (10 unit system)	Total Cost (40 unit system)
PBUC	<u>563937</u>	2246500
Scheduling of Individual Units	564761	<u>2245716</u>
Extended Priority List [96]	563977	2246508
Genetic Algorithm	565825	2251919
Evolutionary Programming	565352	2252612

In ‘Scheduling of Individual Units’, dispatch based on increment or decrement in price means that the least cost units are always given higher priority for dispatch. This can be explained with an illustration. Let us say there are 3 units to be dispatched – unit A, unit B and unit C (see Figure 4.8). Unit A and B are cheaper but smaller units whereas unit C is larger but slightly more expensive. Now, if the demand to be met (shown by arrow in Figure 4.8) is such that unit C must be dispatched, this method will dispatch all the units A, B and C because A and B are cheaper than C. But, in this example, the best dispatch could have been dispatching A and C only. The effect of this while searching for optimal solutions is the decrease in solution space that results in suboptimal solutions. This makes ‘Scheduling of Individual Units’ not very suitable for smaller systems. However, search

Chapter 4 Production Scheduling in Competitive Markets

methods like 'PBUC' can do thorough search when system size is small. In this case, smaller systems allows the method to search for almost the entire solution space in the process of selective enumeration while enumerating the possible UC schedules in each stage thereby resulting in better solutions.

Figure 4.8 Possible combinations of 3 units

But, when the system is large, solution space also increases exponentially. Hence, in case of 'PBUC', a compromise should be made between search space and the solution time. Faster solution means less search space and hence possibility of sub-optimal solutions. In case of 'Scheduling of Individual Units', however, the solution space is still large without much increment in the solution time. The reduction in solution space because of dispatch based on least cost units as discussed above is very less when compared to the size of the solution space for larger systems. Hence, this PBUC method can solve larger systems very fast with higher possibility of finding better solutions. Moreover, the larger number of units provides more flexibility in a sense that there are more units available to choose from.

The optimal schedule obtained for the profit of \$1899 as shown in Table 4.1 for 10-unit system (Table B.1 in the Appendix) from 'Scheduling of Individual Units' is given in Table C.1 in the Appendix. Similarly, the optimal unit status obtained from self-commitment for 110-unit and 40-unit system (Table B.2 and Table B.4 in the Appendix) using 'Scheduling of Individual Units' is given in Table C.4 and Table C.5 in the Appendix. The self-commitment schedules obtained from 'PBUC' for 10 unit systems

Chapter 4 Production Scheduling in Competitive Markets

(Table B.1 and Table B.3 in the Appendix)] are shown in Table C.2 and Table C.3 in the Appendix. The underlined units indicate the differences in UC schedule from those of the simulated competition method [67].

For ‘PBUC’, solution time for self-commitment problem is 2 minutes and 30 minutes for 10 unit and 110 unit systems respectively. For ‘Scheduling of Individual Units’, the solution time for the self-commitment problem for the 110-unit system is 15 minutes and for individual unit commitment is 35 seconds. Both methods were implemented using MATLAB in an Intel PIV, 2.4 GHz, and 256MB RAM platform.

The price based commitment methods thus developed gives the scheduling targets for Gencos in accordance with the expected future prices. These production-scheduling methods can, in one hand, be coordinated with short term contracts to manage risk and on the other hand can be used to obtain the scheduling targets for making bidding strategies. In the next section, UC [36,42,67,97,99,100], bidding [66,67,69,101] and hedging [50,51,56,57,102] are coupled for making strategies to manage price uncertainty in short term planning horizon.

4.3 Concluding Remarks

In this chapter, two different price based unit commitment techniques were developed. The first method, ‘PBUC’, involved the inclusion of flexible demand within a tolerance range to meet the profit-maximizing objective. The commitment of all the units as a group was optimized while moving from one time period to the next. The second method, ‘Scheduling of Individual Units’, is developed from the prospective of a single generating unit to optimize its operations in power markets. It allows individual units to develop optimal power schedules for making bidding strategies. Comparisons with previous work show improvement in the optimal solutions.

The techniques were extended to self-commitment problem to meet the load schedule set by ISO for a Genco with a group of generators. Comparative examples with previous

Chapter 4 Production Scheduling in Competitive Markets

works indicated that ‘PBUC’ performed better for smaller systems whereas ‘Scheduling of Individual Units’ performed better for larger systems. It is noteworthy that the proposed techniques, despite using computation intensive methods like enumeration and dynamic programming that are associated with the ‘curse of dimensionality’, need significantly reduced computational time.

In addition, the proposed scheduling approaches highlighted the need of addressing various aspects of scheduling problem in different ways depending upon market rules, market structures, company policies etc.

5. Uncertainty Management in Generation Planning

5.1 Introduction

Deregulation of the electricity industry has brought along with it new uncertainties and risks in the operation of Gencos. The main concern for power producers has become the risk of financial nature as a result of price volatility that has marked the competitive power industry. The uncertainty in price is especially serious in high load situations when the system demand approaches the installed generation capacity. With this uncertainty in price, risk management has become vital for Gencos. Depending upon the tolerance for risk, strategies have to be made to maximize their expected profits under market volatility.

The purpose of risk management is to adjust risk to the market situations at all times based on today's status and expectations regarding future outcomes. To manage risk resulting from fluctuating electricity prices in competitive electricity markets, Gencos can use hedging strategies. When a Genco takes an offsetting financial position to protect itself against risk due to market uncertainties such as the fluctuations in electricity spot price, it is called a hedge. In case of electricity generation resources, approaches for hedging to manage risk associated with price uncertainty mainly involve decisions on generation quantity and contracts. For example, Gencos can sell forward contracts entitling them to sell a specified amount of electricity at an agreed-on price on a particular date thereby reducing the risk of a low price at a future date. These contracts are available in different types or blocks to the market participants with varying quantity and different time periods of delivery such as peak load hours' contracts, off peak hours' contracts, day contracts, weekly contracts, etc.

Different methods with different objectives have been proposed in the past for choosing proper contract volume to mitigate risk associated with the electricity market. Kaye et al [51] describe how the forward contracts offers an opportunity to reduce risk exposure without removing the incentive to respond to spot price fluctuation. Focus has been given on the consumer point of view for a market with a monopolistic supplier. The 'efficient

Chapter 5 Uncertainty Management in Generation Planning

frontier' is used as a tool to identify preferred portfolios of contracts in [57]. Dahlgren et al [102] provides a literature survey of the tools from financial engineering (e.g. value at Risk etc.) that has been applied in the power markets for portfolio analysis.

Andrews [45], focuses on the environmental uncertainties that can be managed with the help of technical investigation and discusses the robustness and flexibility of the different strategies. The use of callable and puttable forward contracts to mitigate risk has been discussed in [53]. In [103], the basis cost of carry and reverse cost of carry approaches to arbitrage has been used to compare the electricity future pricing behavior with Eurodollar futures, Coppers and Gold. Hobbs et al [104], presents the importance of including Demand Side Management (DSM) in the Integrated Resource Planning (IRP) models. In [58] closing out the future position by buying back the same amount of future contract sold earlier is the strategy used to find the optimal hedging ratio.

However, most of these works concentrate on the issues related with longer time spans (i.e. months and years). They do not deal with choosing among the different blocks of contracts available in the time period being considered in this chapter.

Gencos strategies to manage risk also depend on their risk attitude, which is generally characterized as risk averse, risk neutral and risk seeking. Depending upon the risk attitudes, Gencos can alter their generation quantity and opt for forward contracts to hedge against price uncertainty.

An analysis of risk mitigation using forward contracts is presented Section 5.2. The 'maxmin' criterion of decision-making with the objective of maximizing the minimum expected income of a producer for an acceptable level of risk aims at minimizing the effect on profit earned if the spot price turns out to be unfavorable. A simple two-stage model effectively illustrates the influence of generation strategy on uncertainty management.

5.2 Risk Mitigation Using Forward Contracts

The use of forward contracts to deal with market risks is investigated by evaluating the effects of hedging power generation by suitable contracts. For Gencos, suitable analytical tools for financial markets are very important for reducing the risk exposure of the company.

5.2.1 Expected Income Analysis

Expected income analysis for a power producer is carried out for hedged and unhedged cases. For the analysis, a two-stage model as shown in Figure 5.1 is considered. Time 't' is the time when the decision is to be made on how much to go forward so that the contract can be made for delivery of electricity in time T (maturity/delivery date). It is assumed that the forward contract will not be closed out but will definitely lead to delivery at the delivery date T.

Figure 5.1 Stages in the market

where,

S_T Spot Price at time t for delivery at Time T (\$/MWh)

F_t Forward Price at time t for delivery at time T (\$/MWh)

Q_1 Quantity Produced by Producer 1 (MWh)

Q_{sT}^1 Spot Quantity produced by producer 1 at time T (MWh)

Q_{ft}^1 Quantity Forward by Producer 1 at time t for delivery in Time T

Chapter 5 Uncertainty Management in Generation Planning

To simplify the initial analysis, the cost function (C) is considered to be a linear function of the quantity produced. It is given by,

$$C = c_I Q_I$$

where,

c_I is the Cost Coefficient of producer 1

The spot price at time T is given by the inverse demand function.

$$S_T = A_{iv} - B_{iv} Q_T$$

where,

A_{iv} and B_{iv} are constants of inverse demand function where A_{iv} is greater than c_I at all times.

Q_T is the total quantity produced by all producers (MWh)

To investigate the effect of hedging on the stability of the expected income, two different cases are considered.

- 1) Profit without hedging
- 2) Profit with hedging

5.2.1.1 Profit Without Hedging

Without hedging, the profit function Π_I for any producer (producer 1) at spot market at T (maturity) will be

$$\Pi_I = S_T Q_I - c_I Q_I = (A_{iv} - B_{iv} Q_T) Q_I - c_I Q_I \quad (5.1)$$

The minimum profit (income) due to fluctuation in the spot price will thus be,

Chapter 5 Uncertainty Management in Generation Planning

$$\begin{aligned}\Pi_I &= (A_{iv} - B_{iv}Q_T)Q_I - c_I Q_I - r_I \sigma_s Q_I \\ &= [A_{iv} - B_{iv}(Q_I + Q_{T-I})]Q_I - c_I Q_I - r_I \sigma_s Q_I\end{aligned}\quad (5.2)$$

where,

r is the risk preference.

σ_s is the standard deviation of the spot price.

Q_{T-I} is the total quantity produced in the market minus the quantity produced by Producer1

Risk preference, r , indicates the willingness of a participant to take risk. The higher the value of r more risk averse is the participant. Risk preference of zero indicates a risk neutral participant. More discussion on the choice of r is provided in Section 5.2.1.2.1 and Section 5.2.1.2.2.

Here, $(r_I \sigma_s Q_I)$ is the probable deviation from the mean income due to the reduction in price from the expected spot mean. The objective here is to maximize this minimum expected profit. From equation (5.2),

$$\frac{\partial \Pi_I}{\partial Q_I} = A_{iv} - B_{iv}(Q_I + Q_{T-I}) + Q_I(-B_{iv}) - c_I - r_I \sigma_s \quad (5.3)$$

Therefore, the optimal quantity is given by,

$$Q_I^* = \frac{A_{iv} - B_{iv}Q_{T-I} - c_I - r_I \sigma_s}{2B_{iv}} \quad (5.4)$$

$$\text{or, } Q_I^* = \frac{A_{iv} - B_{iv}Q_T - c_I - r_I \sigma_s}{B_{iv}} \quad (5.5)$$

The maximized minimum income is thus,

Chapter 5 Uncertainty Management in Generation Planning

$$\Pi_I^* = \frac{(A_{iv} - B_{iv}Q_T - c_I - r_I\sigma_s)^2}{B_{iv}} \quad (5.6)$$

5.2.1.2 Profit With Hedging

The profit function with a forward contract, which leads to delivery, can be written as

$$\Pi_I = S_T Q_{sT}^I + F_t Q_{ft}^I - c_I Q_I \quad (5.7)$$

$$\Pi_I = (A_{iv} - B_{iv}Q_T)(1 - h_f)Q_I + F_t h_f Q_I - c_I Q_I \quad (5.8)$$

where,

h_f is the hedging ratio (ratio of the quantity forward to the total quantity produced)

$$Q_{ft}^I = h_f Q_I \quad (5.9)$$

$$Q_{sT}^I = Q_I - Q_{ft}^I = (1 - h_f)Q_I \quad (5.10)$$

Minimization of the variance of profit, which is a function of spot and future prices, is used to find the optimal hedging ratio in [47, 49, 58]. In this study, however, variance of profit (marginal) is a function of only the variance in spot price at maturity. Hence, the variance minimization criteria as used in case of futures cannot be applied here for forwards. However, the hedging ratio can be determined from probabilistic considerations.

The reason for going forward for a producer is to offset the risk due to prices going down because the prices going up is an advantage to an unhedged producer. Hence, to stabilize the income a producer can use a probability distribution curve of the spot price and the risk preference to decide on how much to go forward and how much to stay spot. In this analysis, without loss of generality, the spot price is assumed to be normally distributed (This is only an assumption, which can be changed to other distributions as it may turn out to be. But the procedure will remain unaltered). As the objective is to maximize the

Chapter 5 Uncertainty Management in Generation Planning

minimum income of a producer, the minimum income scenario is considered, which occurs when the spot price turns out to be a minimum.

The minimum profit function can be written as

$$\Pi_I = (E(S_T) - r_I \sigma_s) Q_{sT}^I + F_t Q_{ft}^I - c_I Q_I \quad (5.11)$$

where,

$E(S_T)$ is the expected value of the spot price.

From the probabilistic considerations, it can be said with 99.7% confidence level that the price will stay within 3 times the standard deviation from the mean. This means that if the mean price is \$30/MWh and the standard deviation is \$2.5/MWh then the price will remain within the range of \$22.5/MWh and \$37.5/MWh with 99.7 % certainty.

5.2.1.2.1 Risk Preference

A risk neutral investor will accept the maximum of the expected value of profit function as an optimum regardless of its variance under uncertainty whereas a risk averse investor would be willing to accept a solution that had a lower expected value but also a lower variance [45].

5.2.1.2.2 Numerical Example

Let us assume that the expected mean of the spot price is \$30/MWh and the standard deviation is \$2.5/MWh. This means that within 99.7% confidence level, the minimum spot price can be \$22.5/MWh. A very risk averse participants will consider this worst case (i.e. $r=3$) while going forward where as a less risk averse will choose a value of r between 1 and 3 depending on their preference while making decisions. A risk neutral

Chapter 5 Uncertainty Management in Generation Planning

participant who is indifferent to the uncertainty will make decisions considering that the spot price at maturity will be the expected mean price (i.e. $r=0$).

Let us consider each type of risk preference and their corresponding hedging ratio.

A) *Very Risk Averse: $r=3$*

For a forward price of \$27.5/MWh at time t ,

$$P_1 = \text{Prob}(S_T < F_t(=27.5)) = 0.158655$$

$$P_2 = \text{Prob}(S_T < F_t(\mu - r_1\sigma_s = 22.5)) = 0.00135$$

Hence the amount of hedge forward,

$$h_f = P_1 - P_2 = 0.157305$$

B) *Less Risk Averse: $r=1$*

For a forward price of \$27.5/MWh at time t ,

$$P_1 = \text{Prob}(S_T < F_t(=27.5)) = 0.158655$$

$$P_2 = \text{Prob}(S_T < F_t(\mu - r_1\sigma_s = 27.5)) = 0.158655$$

Hence the amount of hedge forward,

$$h_f = P_1 - P_2 = 0$$

C) *Risk Neutral: $r=0$*

For a forward price of \$27.5/MWh at time t ,

$$P_1 = \text{Prob}(S_T < F_t(=27.5)) = 0.158655$$

$$P_2 = \text{Prob}(S_T < F_t(\mu - r_1\sigma_s = 30)) = 0.5$$

Hence the amount of hedge forward,

$$h_f = P_1 - P_2 = -0.34134$$

For a forward price of \$27.5/MWh at time t , a very risk averse participant who is making a decision based on the minimum income considers the worst case scenario (the price

Chapter 5 Uncertainty Management in Generation Planning

going down to \$22.5/MWh) and will take short position by selling some quantity forward at a price of \$27.5/MWh. In case of participant with risk preference as 1, the decision is based on the spot price going down by one standard deviation (i.e. price reaching \$27.5/MWh in the worst case). So, for a forward price of \$27.5/MWh (i.e. the minimum expected by the producer), he does not take any position. Where as a risk neutral participant who is unworried about the variation in price bases the decision on the mean price. So for a price less than the mean, he takes a long position.

5.2.1.2.3 Optimal Quantity and Profits

From equation (5.8) it can also be seen that, at time t , for a given forward price, the variation in the profit solely depends on the variance in the spot price. The variation in the profit is thus given by

$$\begin{aligned}\sigma_{\Pi I}^2 &= \sigma_s^2 (1-h)^2 Q_I^2 \\ \sigma_{\Pi I} &= \sigma_s (1-h) Q_I\end{aligned}\tag{5.12}$$

So, the objective function of minimum profit in hedged case can be written as,

$$\begin{aligned}\Pi_I &= (A_{iv} - B_{iv} Q_T)(1-h)Q_I + F_t h Q_I - c_I Q_I - r_I \sigma_s (1-h) Q_I \\ &= [A_{iv} - B_{iv}(Q_I + Q_{T-I})](1-h)Q_I + F_t h Q_I - c_I Q_I - r_I \sigma_s (1-h) Q_I\end{aligned}\tag{5.13}$$

$$\frac{\partial \Pi_I}{\partial Q_I} = (1-h)[A_{iv} - B_{iv}(Q_I + Q_{T-I})] - B_{iv}(1-h)Q_I + F_t h - c_I - r_I \sigma_s (1-h)\tag{5.14}$$

Therefore, the optimal quantity with hedge is given by,

$$\begin{aligned}Q_I^* &= \frac{A_{iv} - r_I \sigma_s}{2B_{iv}} + \frac{F_t h - c_I}{2B_{iv}(1-h)} - \frac{Q_{T-I}}{2} \\ \text{or, } Q_I^* &= \frac{A_{iv} - r_I \sigma_s}{2B_{iv}} + \frac{F_t h - c_I}{B_{iv}(1-h)} - Q_T\end{aligned}\tag{5.15}$$

Chapter 5 Uncertainty Management in Generation Planning

The maximum income can thus be obtained by substituting equation (5.15) in (5.14).

5.2.2 Significant Observations

The observations made are based on a hypothetical normal distribution curve of spot price with mean value of \$30/MWh and standard deviation of \$2.5/MWh (as used in the numerical example). The variations in the price are assumed to within the confidence interval of three standard deviations from the mean (i.e. 99.7% confidence level).

5.2.2.1 Maximum and Minimum Profits

For a fixed quantity produced in the spot market, Figure 5.2 shows the maximum and minimum expected profit if a participant makes a decision based on different risk preferences (0,1 and 3). From the graph it can be seen that when a forward position is taken, the minimum income for various forward prices is greater in case of a very risk averse decision (Rmin3) and lesser in case of risk neutral decision (Rmin0). However, if the spot price at maturity turns favorable for the producers, the risk neutral decision (Rmax0) makes a greater profit.

Figure 5.2 Maximum/minimum profit for different risk preference & forward prices

Chapter 5 Uncertainty Management in Generation Planning

5.2.2.2 Effect of Variance on Quantity Forward

Figure 5.3 shows how the quantity forward changes for risk preference, $r=2$, for different standard deviations (or variances) of the spot price. If the forward price is less than the expected mean, then for less variance of the spot price, the participant go forward less and vice versa. This is logical because for a distribution (mean \$30/MWh) with less variance (say \$1/MWh), the probability of forward price going below (say \$28/MWh) is less compared the distribution (mean \$30/MWh) with more variance (say \$2.5/MWh). The negative value of forward quantity indicates the participant taking a long position (buyer of forward contract).

5.2.2.3 Hedged and Unhedged Profits

Figure 5.4 shows the comparison between hedged and unhedged (WH) condition for risk preference, $r=3$, and standard deviation, $\sigma = \$2.5/\text{MWh}$. With hedging, the minimum income is greater than or equal to the unhedged case for all possible values of forward price. However, the maximum possible profit is less for hedged condition. From the graph it can also be seen that hedging decreases the variance of profit and hence increases the income stability.

Figure 5.3 Effect of spot price variance on quantity forward

Chapter 5 Uncertainty Management in Generation Planning

Figure 5.4 Comparison of hedged and unhedged situation

5.2.2.4 Hedging Ratio

Figure 5.5 shows how the hedging ratio of decision makers changes with the forward price for a particular risk preference ($r=1$) and standard deviation (\$2.5/MWh).

Figure 5.5 Hedging ratio and forward price

Chapter 5 Uncertainty Management in Generation Planning

5.2.2.5 Profit and Optimal Quantity

Figure 5.6 shows that for risk preference, $r=3$ and forward price of \$28/MWh, the optimal total quantity (~463MWh) that gives maximized value of minimum profit. A greater quantity than the optimal would have a slight (though nominal) effect in pushing the price down and hence less profit. A lesser quantity will increase the price nominally but the decrease in profit due to decreased quantity is not offset by the increase in price and decrease in cost.

5.2.2.6 Optimal Minimum Profit Comparison

Figure 5.7 shows a difference between maximized minimum profit and optimal quantities for different forward prices in hedged and unhedged situation ($r=3$). In an unhedged case, the quantity and hence the maximized minimum profit is a constant as no forward position is taken. However, in hedged situation, the quantity spot that gives the maximized minimal income increases with the increase in forward price. But, it should also be realized that there is always a limit on what a producer can produce. Let us assume that the limit is at 400MWh. Then, even though the optimal solution occurs at a quantity more than 400MW for forward prices above \$28.5/MWh, the producer can only go forward based on the maximum quantity limit.

Figure 5.6 Optimal minimum profit

Figure 5.7 Comparison of optimal minimum income

Although the ‘maxmin’ criterion of decision-making show a possible method of risk mitigation using forward contracts, the two-stage model considered can be very simplistic for short term planning decisions as generation planning involves, for instance, 24 hourly decisions (24 stages) for Gencos participating in a day ahead market. Hence, a technique of hedging in coordination with generation scheduling that provides better representation of the actual markets is proposed in the next section.

5.3 Managing Price Uncertainty in Generation Scheduling

As generation scheduling provide vital information for making bidding strategies, Gencos should plan in advance on how to use their available capacity to meet the awarded bids in future. Hence, Gencos need proper models to coordinate their risk management strategies with generation scheduling schemes in order to make decisions in the short term. The short term planning problem becomes more complex if Gencos have signed bilateral contracts as they may even have to decide on whether to buy from the market at market

Chapter 5 Uncertainty Management in Generation Planning

clearing prices (MCPs) to serve its market obligations or use their own capacity. These bilateral contracts or in case of some markets, the imposed vesting contract as required by market rules, combines the “self scheduling requirements” of Gencos with offering strategies. To address this complex problem, the selection and representation of modeling parameters should be given proper consideration or else the developed models may not be able to properly represent the problem in hand.

A price taker bidding strategy under price uncertainty has been studied in [101] considering next day price as log-normally distributed [42]. Keeping in view the excessive number of scenarios (3^{24}) even when considering only 3 price values per hour for 24 hours, the authors have resolved to using the expected mean value (price forecast) to determine the unit scheduling decisions. However, using the expected price and 2-step bid functions may give good results but not the optimal, in particular, when risk attitudes of participants are considered. This will be discussed further in subsequent sections.

In [67], Huse et al suggests a bidding strategy with a bidder bidding either marginal cost (MC) if MC is more than the breakeven price or simply the breakeven price. But, as the bid clearance is dependent on the balance of demand and supply, clearance for a unit may result in a unit schedule violating the minimum uptime/downtime (MUT/MDT) constraints.

With all of the complexities associated with short term planning, decision-making under uncertainty and risk is vital for power producers. Although, there is no universally accepted decision making method to resolve the risk verses gain tradeoff, some popular approaches have been efficient frontier [39, 57-59], capital asset pricing model (CAPM)[11], value at risk (VaR) [11,38] and utility theory [45, 60,61].

Uncertainty in short term generation planning is investigated in this section by combining the hedging problem with UC to arrive to an optimal contract and generation decisions under price uncertainty while considering the risk attitudes of the participant. The model which gives each hour decision for 24 hours uses utility theory as the decision making

Chapter 5 Uncertainty Management in Generation Planning

tool and shows how uncertainty management can be accomplished by varying the level of generation and/or short-term contracts.

5.3.1 Modeling Parameters

Proper modeling of market parameters will be critical in developing generation schedules. But competitive markets are undergoing constant changes in market structures and trading rules. Hence, the parameters can vary significantly from one market to another or even within the same market with evolving structural and regulatory changes. On the basis of reported literature, the following models are adopted in this investigation.

5.3.1.1 Price Distribution

The proper representation of the spot price distribution is very important for Gencos because it has a direct impact on the performance of the optimal solution provided by the planning models. It should be noted that the distribution of price cannot be the same in all markets but can be different in different markets. Whatever the distribution of price, its implications on decision-making needs due investigation. In this research, the focus is not on the exact formulation of the stochastic spot price process but is on the impact of price processes in decision-making. The uncertainty in prices has been represented in many ways in different contexts [e.g. 42, 66, 69]. In this chapter, the next day electricity prices are considered to follow a lognormal distribution as derived in [42]. The reason behind the choice can be explained as follows.

A probability density function of a lognormal distribution, which represents the uncertainty in price, is shown in Figure 5.8. Two assumptions on the price behavior must be made while considering this lognormal distribution.

- The minimum price in the market is always greater than or equal to zero. Hence, the prices, which seldom are seen to go negative, will never be realized.

Chapter 5 Uncertainty Management in Generation Planning

- The maximum value of price has theoretically no upper limit as suggested by the open end of the curve. However, it should be noted that the probability of price getting high decreases with the increase in price.

In the competitive electricity market, price spikes as a result of unexpected events (e.g. failure effects, system constraint etc) can be quite frequent. Not only the energy but the reserve constraints can also result in high energy prices in markets where energy and reserve markets are dispatched simultaneously using co-optimization techniques e.g. NEMS, Singapore. The possibility of price rising to a very high level is, to some extent, represented through the open end of the lognormal distribution (Figure 5.8). Hence, the selection of the lognormal distribution to represent prices is expected to present a ‘closer to reality’ price scenarios thereby making the numerical examples presented in the thesis more realistic.

For a decision maker, a possibility of higher price P_{high} , would mean a strategy that would result in more quantity dispatch. But, a decision to dispatch more comes at a risk of losing profit if price turns out to be low. Similarly, a decision based on P_{low} would favor a strategy to dispatch less generation quantity. But, this will prevent high profits if price turns out to be high. Only considering the mean is also not optimal due to the unsymmetrical nature of the expected price (positively skewed) and generation characteristics (MUT/MDT) of the units. Hence, making decisions under uncertainty becomes more difficult. Moreover, when the risk attitudes of Gencos are considered, optimal solutions can be quite different. This can be explained with an illustrative example.

Chapter 5 Uncertainty Management in Generation Planning

Figure 5.8 Lognormal distribution

Let us consider unit 1 from Table D.1 in the Appendix for the forecast prices given in Table D.2 in the Appendix [67]. For the given forecasts, it is seen that unit commitment (UC) decision is optimal if unit 1 is turned ON throughout 24 hours. Now, the price for period $T=4$ (i.e. 4th hour) is lowered while keeping prices intact for rest of the periods. The optimal UC schedule is shown in Table 5.1. It is seen that a price of 11.5 and above in hour 4 favors the first decision whereas price of 11.4 and below favors the second decisions. The optimal solution shows that the effect of a price change in period 4 affects the UC decision not only in period 4 but also in periods 3,5 and 6 because of the MUT/MDT constraints that has to be satisfied.

For the moment, let us assume that the expected price at the time of decision making for period 4 was 11.4 with prices in other periods unchanged. This means that a decision based on expected price would support turning off the units in periods 3-6. However, considering uncertainty in price and the positively skewed lognormally distributed price, the decision may result in huge loss in profit in those periods if price turns out to be higher. Moreover, the strategies of Gencos can be quite different based upon their willingness to take risk e.g. a risk seeker will prefer a decision which gives the possibility of higher profits despite increase in risks involved and vice versa.

Chapter 5 Uncertainty Management in Generation Planning

Table 5.1 Unit 1 optimal schedules variations

Units	Price at $T=4$ (\$/MWh)	Unit Schedule (1-24 Hours)
Unit 1	≥ 11.5	11111111111111111111111111111111
Unit 1	≤ 11.4	11000011111111111111111111111111

This means that Gencos must consider how to allocate their limited generation capacity to maximize profits considering price uncertainty and willingness of the participants to take risk rather than simply using the expected mean. In this paper, Gencos decisions are analyzed on the basis of their risk attitudes and the next day electricity prices, which are considered to follow lognormal distribution. However, whatever the outcomes are for target generation levels, getting to produce in the real market depend upon the bids submitted to the pool. Hence, bidding strategies has an important role in order to attain the production targets.

5.3.1.2 Bidding Strategies

Let us consider that Gencos have a simple bidding strategy as described in [101] where the producer carry out PBUC based on the price forecasts and

- Bids very low for the capacity he wants to produce.
- Bids very high for the capacity he does not want to produce.

These 2-step bids can obtain the desired generation targets but submitting such bids can never take advantage of the probable high price scenarios. Hence, this method of bidding for a fixed generation target needs to be reconsidered and will be discussed more in Section 5.3.3

5.3.1.3 Hedging

The hedging method under consideration is based on Daniel Bernoulli's (1738) expected utility hypothesis, which was axiomatized in 1944 by John von Neumann and Oskar Morgenstern in [105]. The solution involves two ideas which include 1) Peoples utility to

Chapter 5 Uncertainty Management in Generation Planning

wealth $u(\Pi)$ is not linearly related to wealth Π but rather increases at a decreasing rate (diminishing marginal utility) i.e. $U'(\Pi) > 0$ and $U''(\Pi) < 0$ and 2) A person's valuation of a risky venture is not the expected return of that venture but rather the expected utility from that venture. This brings us to the concept of univariate risk aversion, which, intuitively, implies that when facing choices with comparable returns, individuals tend to choose the less-risky alternative. More discussion on the Utility theory is given in Appendix E.

Therefore, in view of managing price uncertainty, the strategies of Gencos to decide on generation and contracts are considered in this study, in view of the following factors.

- Price forecast and associated uncertainty
- Utility function without forward contracts
- Utility function with forward contracts

5.3.2 Problem Formulation

5.3.2.1 Price Uncertainty

The random variable PS_t^{rand} representing the next day price can be represented as lognormal distribution [42].

$$PS_t^{rand} = \text{Lognormal}(PS_t, \sigma_t) \quad (5.16)$$

where, PS_t is the price forecast and σ_t is the estimate of the standard deviation of the random variable PS_t^{rand} .

Here, using PS_t and σ_t as the parameters, prices are randomly generated using Monte Carlo simulation. Price and variance in each hour can be obtained from any of the several

Chapter 5 Uncertainty Management in Generation Planning

forecasting techniques in use (e.g. [42]). Full treatment of the forecasting technique is not the focus of this work and hence for the analysis it is assumed that the forecasts and the variance associated with it are available and are given in Table D.2 in the Appendix.

Using Monte Carlo simulation, a large set of market clearing prices is randomly generated based on a lognormal price distribution for the given forecast and variance.

5.3.2.2 Objective Function

In view of the competitive electricity market, ‘scheduling of independent units’ has been discussed in more detail in Chapter 4 for an expected market price. In this study, the same method is considered but for multiple price scenarios. Depending upon the strategies and decision variables, the objective function of Gencos can be defined in various ways.

5.3.2.2.1 Profit in Spot Market

The profit of a Genco depends on the revenue and the cost of the energy dispatched in the spot market. The optimal dispatch for forecasted prices can be obtained using the individual scheduling method developed in Section 4.2.3.1 (Equation (4.19)). However, to incorporate the uncertainty in price (using a large number of price scenarios), Equation (4.19) is extended as follows.

$$\begin{aligned} \max \Pi_{i,spot} = & \sum_{s=1}^S prob_{s,t} \sum_{t=1}^T \{G_{i,t}.PS_{s,t} - C_{i,t}(G_{i,t}).W_{i,t}\} \\ & - \sum_{t=1}^T ST_{i,t}.UST_{i,t} + SD_{i,t}.USD_{i,t} \end{aligned} \quad (5.17)$$

where

S	Total Number of Price Scenarios
s	Index of a Scenario ($s = 1, 2, \dots, S$)
$prob_{t,s}$	Probability associated with scenario s

Chapter 5 Uncertainty Management in Generation Planning

For a large Monte Carlo sample (Section 5.3.2.1), S , the probability associated with each price scenarios are equal and hence, the equation (5.17) can be rewritten as follows.

$$\begin{aligned} \max \Pi_{i,spot} = & \frac{1}{S} \sum_{s=1}^S \sum_{t=1}^T \{G_{i,t} \cdot PS_{s,t} - C_{i,t}(G_{i,t}) \cdot W_{i,t}\} \\ & - \sum_{t=1}^T ST_{i,t} \cdot UST_{i,t} + SD_{i,t} \cdot USD_{i,t} \end{aligned} \quad (5.18)$$

5.3.2.2.2 Utility Function

Equation (5.18) gives a risk neutral decision for a Genco on the optimal quantity to generate in the spot market. To include the risk attitude, each scenario in equation (5.18) is first segregated as,

$$\Pi_{i,s,spot} = \sum_{t=1}^T \{G_{i,t} \cdot PS_{s,t} - C_{i,t}(G_{i,t}) \cdot W_{i,t} - ST_{i,t} \cdot UST_{i,t} - SD_{i,t} \cdot USD_{i,t}\} \quad (5.19)$$

For risk management by controlling the generation level, the objective can be written as maximization of the expected utility, U for each scenario as,

$$\begin{aligned} \max E(U \mid prob_s) &= \sum_{s=1}^S prob_s U(\Pi_{i,s,spot}) \\ \text{Or, } \max E(U \mid prob_s) &= \frac{1}{S} \sum_{s=1}^S U(\Pi_{i,s,spot}) \end{aligned} \quad (5.20)$$

Chapter 5 Uncertainty Management in Generation Planning

5.3.2.2.3 Including Contracts in the Objective

For Gencos further interested in managing risk, forward contracts are available. Hedging with contract changes the profit in each price scenario s by $\Delta\Pi_{i,s}$.

$$\Delta\Pi_{i,s} = \sum_{t=1}^T QF_{i,t} (PF_t - PS_{s,t}) \quad (5.21)$$

and

$$QF_{i,t} = h_{i,t} G_i^{\max} \quad (5.22)$$

Where,

QF_t is the quantity forward in time t

h_t is the hedging ratio in period t such that $0 \leq h_t \leq 1$

Now, let us consider Figure 5.9 that shows a possible way in which the contracts may be available in blocks of hours. Block 1, for instance, represents a 24-hour (day) contract block with forward price $PF_{t,B(24),1}$. To represent these blocks equation (5.21) is modified to:

$$\Delta\Pi_{i,s} = \sum_{t=1}^T \sum_{all\ B} QF_{i,t,B(HL),BI} (PF_{t,B(HL),BI} - PS_{s,t}) \quad (5.23)$$

Explaining further, $QF_{t,B(8),3}$ in Figure 5.9 represents quantity forward in time t for 8 hours block contracts ($HL = 8$) between time period 17 to 24 ($BI = 3$). It should be noted that the time span of the blocks are market specific and Figure 5.9 is just an illustration of a possibility.

Chapter 5 Uncertainty Management in Generation Planning

Figure 5.9 Blocks of contracts

A set of constraints is required to limit the volume of contracts. Firstly, the volume of contract with same block hour length HL and same block index BI must be equal in the time frame represented by the block index. Hence,

$$QF_{t,B(HL),BI} = QF_{t+1,B(HL),BI} \quad (5.24)$$

In terms of hedging ratio,

$$h_{t,B(HL),BI} = h_{t+1,B(HL),BI} \quad (5.25)$$

Secondly, the sum of all block contracts in each time period should be less than the maximum capacity of the unit. Hence,

$$\sum_{all \ B} QF_{i,t,B(HL)} \leq G_i^{\max} \quad (5.26)$$

In terms of hedging ratio

$$\sum_{all \ B} h_{i,t,B(HL)} \leq 1 \quad (5.27)$$

Chapter 5 Uncertainty Management in Generation Planning

Now, the attitude towards risk for price uncertainty can be expressed in terms of the expected utility function as

$$E(U \mid prob_s, \Delta\Pi_{i,s}) = \frac{1}{S} \sum_{s=1}^S U(\Pi_{i,s,spot} + \Delta\Pi_{i,s}) \quad (5.28)$$

The determination of the utility function is subjective as it depends on the attitude of an individual towards accepting risk. Von Neumann-Morgenstern concept based on identifying the most favorable and least favorable outcome can be applied to find the individual utility function. These limiting outcomes are taken as the reference for identifying the other possible outcomes. In this study, the exponential expected utility (Equation E.4 in the Appendix) function is considered in the following ways.

For risk averse Gencos,

$$U_s = \lambda(1 - e^{-\alpha(\Pi_{i,spot} + \Delta\Pi_{i,s}) - \beta}) \quad (5.29)$$

For risk seeking Gencos,

$$U_s = \lambda(e^{\alpha(\Pi_{i,spot} + \Delta\Pi_{i,s}) + \beta} - 1) \quad (5.30)$$

where, α , β and λ are constants which represent the attitude of an individual towards risk.

The objectives (5.17), (5.20) and (5.28) are solved using MATLAB ‘fmincon’ function [92].

5.3.3 Bidding Analogy

Simple two-step bids, though shown to give good results for price takers in [101], may be sub-optimal, as those bids cannot take advantage of the possibility of high prices. Even price takers cannot neglect the prospect of price reaching very high level, although their individual decisions may not have any impact on the market price. To illustrate this, some assumptions are made on generation decisions:

Assumptions:

1. It is assumed that Gencos decisions to turn on or off a unit (UC) are fixed i.e. similar two-step bid function considered as in [101] is considered.
2. An ideal situation is envisioned where Gencos can vary production from $G_i^{\min}$ to $G_i^{\max}$ to get the optimal generation level, whatever the price scenario.

The UC schedules obtained with these assumptions for the profit maximizing objective should be able to indicate the difference in the expected profits between the case which considers expected price and an ideal case which considers price uncertainty. The difference in the profits shall indicate the need of proper representation of price uncertainty in the bid curves. To obtain the best UC decisions in accordance to the above assumptions a method based on Genetic algorithms is considered.

5.3.3.1 Genetic Algorithms for Bidding Analysis

Genetic Algorithms (GAs) are adaptive search techniques based on the principles and mechanisms of natural selection and the “survival of the fittest” from natural evolution [99]. GAs belong to the class of probabilistic algorithms as they combine elements of directed search and stochastic search and hence is more robust than existing directed search methods. GAs has been used by various researchers to solve UC problems with the objective of minimization of total system cost [94,100]. In this study, GA has been used to solve the profit-maximizing objective under uncertainty for each unit independently.

Chapter 5 Uncertainty Management in Generation Planning

The advantage of this method is that a group of good UC schedules for the objective function can be obtained.

In GAs terminology, the maximized profit (Equation 5.18) is the fitness function. To deal with the MUT/ MDT constraints, a penalty function, Pen , is introduced to penalize for any violations in those constraints. This function helps to produce feasible solutions by making sure that non-feasible solutions are assigned lower fitness than that of the feasible solutions and is derived in the following way:

$$\begin{aligned}
 &\text{if } UST_t = 1 \text{ and } T_t^{off} < MDT \\
 &\quad Pen_t = (MDT - T_t^{off}) W_{pen} \\
 &\text{elseif } USD_t = 1 \text{ and } T_t^{on} < MUT \\
 &\quad Pen_t = (MUT - T_t^{on}) W_{pen} \\
 &\text{else} \\
 &\quad Pen_t = 0 \\
 &\text{End}
 \end{aligned}$$

In the above function, the violations of constraints, which are far from the feasibility boundary, are awarded higher penalties. Moreover, weight of the penalty function, W_{pen} , is set to a low value in the initial generations and increased steadily with the number of generations. This ensures that the large search space is covered in the initial generations to reach the optimal region and the higher penalty function in later generations helps in fine-tuning the optimal solution while satisfying all the constraints. Now the objective function for GAs can be written as,

$$\begin{aligned}
 \max \Pi_i = & \frac{1}{S} \sum_{s=1}^S \sum_{t=1}^T \{G_{i,t} \cdot PS_{s,t} - C_{i,t}(G_{i,t}) \cdot W_{i,t}\} \\
 & - \sum_{t=1}^T ST_{i,t} \cdot UST_{i,t} + SD_{i,t} \cdot USD_{i,t} + Pen_t
 \end{aligned} \tag{5.31}$$

The stages of GAs are considered in the following way:

Chapter 5 Uncertainty Management in Generation Planning

A) Initialization

The sequences of stored UC decisions (best 10) are obtained from ‘scheduling of individual units’ described in Chapter 4 for the forecasted price. As these are the sequences fulfilling all the constraints associated with the unit, it can be said that these form highly fit schemas. These building blocks for the GA problem will perform computations by recombining amongst each other to form better strings in each generation.

B) Reproduction, Crossover and Mutation

Stochastic Universal Sampling (SUS), two point crossover and non-dynamic mutation is used for reproduction, crossover and mutation respectively. Probability of crossover and mutation is set at 0.7 and 0.1 respectively. Moreover, to prevent premature convergence, linear fitness scaling with scaling parameter of 2 is used.

C) Replacement

Elitist strategy was used as the replacement method in each generation.

D) Objective Function

Here each chromosome in the population represents a candidate solution i.e. a possible generation schedule. This means that W, UST, USD in equation (5.31) are known for each time period for each candidate solution and hence ST, SD and Pen can be treated as constants. Therefore, the last three terms in equation (5.31) can be calculated separately for all the chromosomes in the population and the objective function can be solved using the following procedure, written in pseudo code.

Chapter 5 Uncertainty Management in Generation Planning

BEGIN

For all population

For all scenarios

Calculate profit for each scenario:

$$\Pi_{p,s} = \sum_{t=1}^T \{G_{p,i,t} \cdot PS_{s,t} - C_{i,t}(G_{p,i,t}) \cdot W_{p,i,t}\} \quad (5.32)$$

where, p is the chromosome index

End

Calculate fitness function:

$$Fitness_p = \frac{1}{S} \sum_{s=1}^S \Pi_{p,s} + ST_p + SD_p + Pen_p \quad (5.33)$$

End

Store Fitness for the population size

END

Here, the fitness function stored is the maximum profit represented by equation (5.19) for all the chromosomes in the population, which is calculated using MATLAB ‘quadprog’ function [92].

GA solution obtained in this way gives the best few UC schedules and corresponding profits that should indicate the need of multiple bid steps that can represent price uncertainty in a better way.

5.3.4 Numerical Examples

The examples are based on units provided in [94], the characteristics of which are given in Table D.1 in the Appendix. The forecasted price [67] and standard deviation considered for analysis are given in Table D.2 in the Appendix. To consider the effect of increase in uncertainty of price on the profit objective, 2 sets of standard deviations in price are taken for the same expected mean price. Based on lognormal price distribution,

Chapter 5 Uncertainty Management in Generation Planning

Monte Carlo simulation is performed and 10000 sets of market clearing prices are randomly generated to investigate the effect of price uncertainty on the expected profit.

Table 5.2 shows the best 3 unit commitment status obtained from GA that gives the highest fitness values (not in order of fitness) for unit 2 in Table D.1 (see Appendix D). Each of the UC status is referred to as UC1, UC2 and UC3 hereafter. The mean value in Table 5.2 is the expected profit obtained for the unit status considering price forecast and 2-step bid function in a similar way as in [101]. In accordance with the method in [101], UC1 is the optimal solution obtained from UC whose target generation level is given in Table 5.3 for Risk Neutral Genco.

However, with the assumptions considered in Section 5.3.3, fitness values obtained from GA for the unit status in Table 5.1 for high and low level of uncertainty in next day electricity price is shown in Table 5.4.

From Table 5.4, it can be said that:

- The flexibility in scheduling provided by assumptions 2 described in Section 5.3.3, shows quite an improvement in expected profits (i.e. \$4054.3 as compared to \$3650.6 for UC1). This indicates that multiple bid curves should be able to represent price uncertainty better and hence can be expected to improve the expected profits.

Table 5.2 Comparison in fitness value for unit 2

SN	Unit Status (1-24 Hours)	Mean (\$) [101]
UC 1	11100001111111111111111111111111	3650.6
UC 2	11100011111111111111111111111111	3650.1
UC 3	11111111111111111111111111111111	3577.7

Chapter 5 Uncertainty Management in Generation Planning

Table 5.3 24-hours schedules from utility functions for various risk attitudes for UC1,
UC2

UC1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Risk Neutral	140	140	30	0	0	0	0	100	104	124	122	105	74	55	140	140	84	136	140	140	140	140	140	114
Risk Averse	140	140	30	0	0	0	0	98	100	120	118	99	71	53	140	140	77	125	140	140	140	140	140	108
Risk Seeker	140	140	30	0	0	0	0	107	111	131	127	111	80	60	140	140	88	140	140	140	140	140	140	122
UC2																								
Risk Neutral	140	140	30	0	0	0	78	100	104	124	122	105	74	55	140	140	84	136	140	140	140	140	140	114
Risk Averse	140	140	30	0	0	0	76	98	101	120	118	100	71	53	140	140	77	125	140	140	140	140	140	108
Risk Seeker	140	140	30	0	0	0	83	107	111	131	127	111	80	60	140	140	88	140	140	140	140	140	140	122
UC3																								
Risk Neutral	140	140	30	30	30	30	78	100	104	124	122	105	74	55	140	140	84	136	140	140	140	140	140	114
Risk Averse	140	140	30	30	30	30	76	98	100	120	118	100	71	53	140	140	77	126	140	140	140	140	140	108
Risk Seeker	140	140	30	30	30	30	81	104	107	127	125	108	77	57	140	140	86	140	140	140	140	140	140	118

Table 5.4 Comparison in fitness value for unit 2

Price Variance	UC Cases	Mean (\$)	Maximum (\$)	Minimum (\$)	Standard Deviation
Low	UC 1	4054.3	6264.0	2195.1	625.29
	UC 2	4081.4	6424.6	2154.9	632.18
	UC 3	4032.5	6582.9	2123.9	638.00
High	UC 1	4271.9	7315.6	1485.7	805.63
	UC 2	4317.3	7421.5	1501.2	813.96
	UC 3	4301.4	7611.8	1511.7	828.43

- Considering that higher prices would make higher profits if more generation is scheduled, it is seen that UC2 gives higher expected profits than UC1 as the unit is turned on for period 7.
- Higher uncertainty in price means even higher profits if prices reach higher level. Hence, for higher price variance both UC2 and UC3 give higher expected profits as compared to UC1.

This shows that a simple 2-step bid function limits the possibility of higher profits as it fixes the quantity produced at either zero or a fixed value in each time period. Hence, even for price takers, a multiple bid function should be considered which could take

Chapter 5 Uncertainty Management in Generation Planning

advantage of the possibility of higher prices by bidding at multiple quantity levels for different prices. It can be said that proper representation of uncertainty can be the key to improving profits. However, further discussions and method of obtaining proper bid curves under price uncertainty is considered in chapter 6. Here, the focus is given to other aspects of managing price uncertainty. Hence, for analysis and comparisons, the bid function is still considered a 2-step function [101] as has been described in Section 5.3.1.2.

In accordance with the discussions in Section 5.3.1 and Section 5.3.2, the effects of generation level and contracts on strategies to manage uncertainty are considered next. To express the risk attitude, utility function as discussed in Section 5.3.2.2 is considered with constants $\alpha = 0.0003$, $\beta = 0.001$ and $\lambda = 1$ for risk averse Gencos and $\alpha = 0.0003$, $\beta = 0.0001$ and $\lambda = 1/8.5$ for risk seeking Gencos. For contract decisions, four cases are considered with two types of block contracts available for hedging as shown in Table 5.5. Forward price for each block is considered to be the mean of the expected prices in the time periods that represent the blocks. For instance, the forward price of the 24-hour contract is assumed as the average of the expected prices of the 24 hour time periods the contract covers.

Table 5.3 shows the effect of hedging by controlling the generation level for Gencos differing in their willingness to take risk. In addition to the generation level, Table 5.6 shows the effect of using contracts for the four cases of Table 5.5 considering risk attitudes of Gencos.

Table 5.5 Four cases under study

	Period Length (Hours)	24-hour Block Contract (Nos)	12-Hour Block Contract (Nos)
Case 1	24	1	0
Case 2	24	0	2
Case 3	24	1	2
Case 4	24	0	0

Chapter 5 Uncertainty Management in Generation Planning

Table 5.6 Profits and contract comparisons for UC1, UC2 and UC3

UC1	Case	Utility	Expected Mean	Maximum	Minimum	Standard Deviation	Contract Blocks		
							h t,B(24)1	h t,B(12)1	h t,B(12),2
Risk Averse	case 1	0.6636	3649.6	5005.2	2226.7	379.4	0.682	0.000	0.000
	case 2	0.6645	3654.1	4928.5	2348.7	338.8	0.000	0.437	0.878
	case 3	0.6645	3654.5	4957.9	2350.5	342.2	0.127	0.290	0.756
	case 4	0.6556	3658.0	6550.1	355.2	853.1	0.000	0.000	0.000
Risk Seeking	All	0.2476	3657.9	6750.6	233.4	884.7	0.000	0.000	0.000
Risk Neutral	All	0.6554 / 0.2473	3659.8	6652.6	296.91	867.88	0.000	0.000	0.000
UC2									
Risk Averse	case 1	0.6639	3650.2	4925.7	2197.3	353.9	0.702	0.000	0.000
	case 2	0.6647	3654.7	4887.2	2398.7	322.9	0.000	0.461	0.885
	case 3	0.6647	3654.8	4894.7	2382.9	325.4	0.120	0.339	0.768
	case 4	0.6555	3658.8	6625.0	367.5	859.8	0.000	0.000	0.000
Risk Seeking	All	0.2480	3658.7	6750.2	247.8	892.5	0.000	0.000	0.000
Risk Neutral	All	0.6553 / 0.2477	3660.7	6681	311.06	874.86	0.000	0.000	0.000
UC3									
Risk Averse	case 1	0.6570	3577.1	4662.5	2384.8	301.7	0.725	0.000	0.000
	case 2	0.6576	3581.1	4621.2	2505.1	281.9	0.000	0.512	0.886
	case 3	0.6576	3580.8	4623.3	2514.4	280.2	0.017	0.486	0.868
	case 4	0.6478	3586.0	6614.2	290.3	863.3	0.000	0.000	0.000
Risk Seeking	All	0.2402	3587.5	6738.4	201.8	887.9	0.000	0.000	0.000
Risk Neutral	All	0.6476 / 0.2399	3587.9	6696.8	233.02	878.45	0.000	0.000	0.000

Changes in generation level in Table 5.3 can be explained with the help of Figure 5.10. It can be seen from Figure 5.10 that risk averse Gencos opt for lower generations to maximize their utility values whereas risk seeking Gencos decide on producing more to maximize their utility. Considering that Gencos use 2-step bids, it can be seen from Table 5.6 that risk neutral Gencos looking for maximum expected profit, schedule as per UC1 status, which gives expected profit of \$3659.8. Similarly, risk averse Gencos choose UC1 schedule as it gives highest utility of 0.6556 (i.e. case 4 in Table 5.6). However, risk-seeking Gencos will bid as per unit status UC2 that gives the maximum utility of 0.248. Hence, the large shift in generation from 0 MWhr to 83 MWhr is observed in Figure 5.10 in period 7 for risk seeking Gencos.

Chapter 5 Uncertainty Management in Generation Planning

Figure 5.10 Optimal generations for different risk attitudes

The effect of hedging considering contract decisions, given in Table 5.6 are compared in Figure 5.11 and Figure 5.12 for a risk averse and risk seeking Gencos respectively. In both figures, it can be seen that the expected mean of risk neutral Genco is slightly higher than other two cases for Gencos with and without contracts. This is expected because risk neutral participants decisions are based on highest expected profits without regards to uncertainty. However, the utility that risk seeker and risk averse participant receive from the decisions of risk neutral participant is lower despite having higher mean, as can be seen from Table 5.6. In case of risk averse Genco, changing the generation level helps in reducing the deviation of the income. Hence, the reduction in the gap between maximum and minimum income and the reduced standard deviation means a more stable income. Similarly, the availability of contracts shows a significant improvement in the stability of the income. In this way, it is seen that decisions on generation as well as contracts help in hedging price uncertainty for risk averse Gencos.

Now, looking at risk seeking participants, forward contract considered in this study plays no role in improving their objective because contracts will prevent them from reaping the

Chapter 5 Uncertainty Management in Generation Planning

benefits if price turns out to be high. However, changing the level of generation helps them in achieving slight improvement in their utility. This can be seen from slight increase in the maximum profit, which comes at the cost of increased standard deviation of profit in Figure 5.12.

Table 5.7 shows the comparison of optimal contract size for a risk averse Genco in view of the level of uncertainty. The results provide an insight into the need of proper representation of price uncertainty while making strategies to manage it. In general, it is expected that a risk averse Genco would hedge more in the market for higher uncertainty in price. But, cases 1 and 2 indicate that the optimal hedging ratio is higher for less uncertainty as compared to higher uncertainty. This may again be accounted to the lognormal price distribution where the probability of price reaching very high is there when uncertainty is more. Hence, the utility derived by reducing the hedging ratio slightly gives better output when price uncertainty is high.

Table 5.7 Contract size and uncertainty

	Uncertainty	Contract Blocks	Hedging Ratio		
			UC1	UC2	UC3
Case 1	More	h t,B(24)1	0.682	0.702	0.725
	Less	h t,B(24)1	0.739	0.757	0.777
Case 2	More	h t,B(12)1	0.437	0.461	0.512
		h t,B(12),2	0.878	0.885	0.886
	Less	h t,B(12)1	0.578	0.616	0.665
		h t,B(12),2	0.861	0.863	0.861

With regards to the choice of contract blocks, comparing case 1 and case 2 in Table 5.6 shows that both utility and expected mean is higher for case 2. Hence, it can be said that for the hedging objective, 12-hour blocks are better choice as compared to 24-hour blocks for the forward price considered. Also, case 3, comprising both 12 hour and 24-hour blocks, provide the same utility as case 2. This means that the choice in contract block selection does not have an added advantage with respect to utility derived in the example under consideration. However, as it can be seen from Figure 5.13, the availability of

Chapter 5 Uncertainty Management in Generation Planning

multiple contract combinations resulting in the same optimal utility provides flexibility in the selection of the types of contracts.

Figure 5.11 Comparisons for risk averse Genco

Figure 5.12 Comparisons for risk seeking Genco

Figure 5.13 Sets of optimal contract solutions for case 3

5.4 Concluding Remarks

This chapter presented two approaches to manage uncertainty for power producers in the competitive electricity market. In the first method, the amount of hedging with forward contracts is determined on the basis of the probability distribution of the expected spot price, the forward price for delivery at maturity. The decrease in variance of the income indicates that the income of the producers is more stabilized. It is seen that, hedging with forward contracts by maximizing the minimum income can prove to be an important tool for risk mitigation for producers to prevent the disastrous situation that may arise due to prices moving down. Not only for risk averse decision makers but also for risk takers, this method can be useful in keeping open the chances of high income and limiting the possible damage due to price fluctuations. Hence, the method sheds light on how the willingness of power producer to take risk can be incorporated in the model.

In the second approach, issues related with the management of price uncertainty were investigated with properly characterizing price distribution curves, PBUC, bidding strategies and hedging possibilities. In addition, GA based technique was developed to

Chapter 5 Uncertainty Management in Generation Planning

highlight the need of proper representation of price uncertainty rather than relying on simple bid curves while making bidding strategy.

A method for making decisions on generation level and short run contracts using utility function was proposed to hedge against price uncertainty while considering risk attitudes of market participants. Digital simulation studies were conducted to show the effectiveness of the proposed method. From the simulation results, it was seen that both generation level and contracts do affect on income stability. Hence, for short term planning, the proposed method can be appropriate for Gencos in making strategies to manage price uncertainty in accordance with their risk preferences.

6. Price Based Bidding Strategy

6.1 Introduction

In a competitive market, Gencos sell surplus power and buy deficit power from the pool. This is achieved through an auction system, in which the pool collects bids for buying and selling from all market participants. A bid contains information on how much power, at which prices, in which area, at what time, a market participant is willing to buy or sell. Bidding in competitive markets, is the main means of attaining profit targets, which may require market strategies by individual participants. As the bids submitted to the pool determine the revenue of Gencos, attempts have been made to formulate strategies to obtain best bids. In chapter 5, simple two-step bids were assumed to meet the scheduling targets derived from price based generation scheduling and was subsequently used for uncertainty management in generation planning. However, such bids may be less than optimal and hence need further improvements. A method of developing multi-step bidding curves is proposed in this chapter.

Bidding problems have, in general, been addressed according to the market structure (perfectly competitive, Oligopoly etc.), units owned (thermal, hydro, hydrothermal etc.), bid functions (step function, linear, non-linear) etc. [63, 65-72, 101]. David and Wen [37] provide a literature survey on the works reported in recent years.

In [101], UC is carried out first to obtain the generation schedules using the price forecast for the next 24 hours. Based on this schedule, a simple price-taker bidding strategy is developed by bidding at either very low or very high prices so that the bids will either be accepted or rejected respectively when the market is cleared. However, the use of 2-step bid function compared to the higher number of steps prevents it from representing the unit characteristics optimally to improve on the objective of maximizing the expected profit. Moreover, use of expected value of price may give suboptimal solution because a slight disturbance in the price in real time may mean profit lost.

Chapter 6 Price Based Bidding Strategy

In this chapter, a method of developing bidding strategies using price based generation scheduling is proposed, with the objective of maximizing profit under price uncertainty. The decision to commit a generation is price based and the bidding strategies are made and updated accordingly. Generation planning for a period of 24 hours in advance is considered. Gencos with various generation unit characteristics, unit availability etc carry out generation scheduling for a range of price scenarios and then determine the bidding strategies for each bidding period for the next day.

6.2 Bidding Framework

For power producers with low generation cost units, constructing bid curves is not difficult as they just have to make sure that the units are dispatched each hour. In such cases, a simple 2-step bid function as suggested in [101] (i.e. to bid very low for the capacity they want to dispatch and bid very high for the capacity they don't want to dispatch) may give optimal bids. Similarly, the same bidding method can be applied for units with very high cost and producers prefer not to dispatch them. However, for marginal or near marginal units, producers must choose from the options of shutting down the unit completely, keeping it in banking mode or making sure it is dispatched. To make decisions on bid curves that maximize the profits, two factors must be considered: (i) the uncertainty in price, whose effect on profit has been discussed in more detail in Chapter 5, and (ii) generation scheduling, as it takes into consideration the time dependent unit constraints such as MUT/MDT etc while maximizing the profit.

6.2.1 Price Uncertainty

As detailed in Chapter 5, the random variable PS_t^{rand} representing the next day prices is represented by lognormal distribution [42] by

$$PS_t^{rand} = \text{Lognormal}(PS_t, \sigma_t) \quad (6.1)$$

where,

PS_t is the price forecast and σ_t is the estimate of the standard deviation of the random variable PS_t^{rand} .

6.2.2 Price Based Generation Scheduling

As have been discussed in previous chapters, in competitive markets, it is profitable to operate a unit as long as the cost of producing is lower than the revenue obtained by selling the quantity produced. Many power markets, for instance New Electricity Market (NEMS) in Singapore, require the Gencos to submit bids for individual generating units. In such situation, it may be more sensible to decide the individual unit commitment separately and then use the optimal schedule to build bidding curves, as has been proposed in this chapter.

Initially, using PS_t and σ_t as the parameters, 2500 prices scenarios are randomly generated from a lognormal distribution and using Monte Carlo simulation as in Chapter 5. Subsequently, for all price scenarios, the objective of profit maximization is calculated through ‘scheduling of individual units’ for the objective function (6.2). The optimal generation schedule and corresponding profits obtained for each unit from generation scheduling is the optimal solution for the unit in view of the price scenario. These optimal solutions for each scenario are then used as the building blocks for solving the bidding problem.

6.2.3 Problem Formulation

The PBUC problem and the bidding problem are described for the objective of profit maximization with constraints in the following subsections.

6.2.3.1 PBUC Problem

The objective for ‘scheduling of individual units’ described in chapter 4 is rewritten as follows.

$$\max \Pi_i = \sum_{t=1}^T \{G_{i,t} \cdot PS_t - C_{i,t}(G_{i,t}) \cdot W_{i,t} - ST_{i,t} \cdot UST_{i,t} - SD_{i,t} \cdot USD_{i,t}\} \quad (6.2)$$

where,

$i \in 1, 2, \dots, NT$ and the constraints to be satisfied are the unit capacity limits and MUT/MDT constraints.

6.2.3.2 Bidding Problem

A typical 3-step bidding curve is shown in Figure 6.1. The non-decreasing nature of the curve can be mathematically written as,

$$PB_{B-1,t} \leq PB_{B,t} \quad \forall B = 2, \dots, NB \quad (6.3)$$

$$QB_{B-1,t} \leq QB_{B,t} \quad \forall B = 2, \dots, NB \quad (6.4)$$

where,

B is the bidding block ($B \in 1, 2, \dots, NB$)

$PB_{B,t}$ is the bid price for block B

$QB_{B,t}$ is the bid quantity for block B

Based on all the demand and supply bids submitted, the market-clearing price is derived and each bid are either accepted or rejected. Hence, the bid status, UB for each price scenario (probable market clearing price) is given by

$$UB_{B,s,t} = 0 \quad \text{if} \begin{cases} PR_{s,t} < PB_{B,t} \\ or \\ UB_{B+1,s,t} = 1 \end{cases} \quad (6.5)$$

Chapter 6 Price Based Bidding Strategy

$$UB_{B,s,t} = 1 \quad \text{if } PR_{s,t} \geq PB_{B,t} \quad (6.6)$$

where,

$PR_{s,t}$ is the price corresponding to scenario s

$PB_{B,t}$ is the bid price for block b

S is the total number of scenarios

s is the index of a scenario ($s = 1, 2, \dots, S$)

Figure 6.1 Bidding curve

The bid quantity corresponding to $UB_{B,s,t} = 1$ in Equation (6.6) is $QB_{B,s,t}$.

And for each bid submitted,

$$\sum_{B=1}^{NB} UB_{B,s,t} \in (0,1) \quad (6.7)$$

The expected revenue under price uncertainty for S price scenarios can be calculated as,

$$R_i = \frac{1}{S} \sum_{s=1}^S \sum_{t=1}^T \sum_{B=1}^{NB} PR_{s,t} QB_{s,t,B} UB_{s,t,B} \quad (6.8)$$

Only when the bids are cleared in the market will the Gencos know their commitment status and based on this market clearance the Gencos need to decide whether to run the generator, shut it down, buy power from the market or keep it in banking mode. This decision will depend on the generation costs, which consists of three components.

A) Running Cost:

The running cost, C_i^r , is incurred when the bids are accepted and the generator is running

$$\text{i.e. } \sum_{B=1}^{NB} UB_{s,t,B} = 1 \text{ and } W_{s,t} = 1.$$

This is given by,

$$C_i^r = \sum_{s=1}^S \sum_{t=1}^T \sum_{B=1}^{NB} C_i(QB_{s,t,B}) \quad (6.9)$$

B) No Load Cost/Banking Cost:

The banking cost, C_i^b , is incurred when the bids are not accepted but the generator is kept running at no load due to various reasons (e.g. MUT/MDT constraints etc.) i.e.

$$\sum_{B=1}^{NB} UB_{s,t,B} = 0 \text{ and } W_{s,t} = 1.$$

This cost is calculated as,

$$C_i^b = \sum_{s=1}^S \sum_{t=1}^T a_i \quad (6.10)$$

Chapter 6 Price Based Bidding Strategy

The cost of banking may differ depending on the unit characteristics and can be changed if and when required. However, due to the unavailability of data, it is calculated simply as shown in equation (6.10).

C) *Decremental Cost:*

The decremental cost, C_i^d , is incurred when the bids are accepted and the generator is not running due to reasons like MUT/MDT constraints i.e. $\sum_{B=1}^{NB} UB_{s,t,B} = 1$ and $W_{s,t} = 0$. This

can be considered as the cost of buying from the market and can be calculated as,

$$C_i^d = \sum_{s=1}^S \sum_{t=1}^T \sum_{B=1}^{NB} PB_{s,t,B} QB_{s,t,B} \quad (6.11)$$

The expected total cost can be written as

$$C_i^{total} = \frac{1}{S} (C_i^r + C_i^b + C_i^d) \quad (6.12)$$

Hence, the expected profit is,

$$\Pi_i = R_i - C_i^{total} \quad (6.13)$$

The objective of the bidding problem is to maximize this expected profit under price uncertainty.

6.3 Bidding Strategy

Some reasonable assumptions are made in the development of bidding strategies.

1. While making price quantity bid, the gencos choice of quantity are fixed in blocks i.e. if Genco bid in 5MWhr blocks of quantity, then the quantity bids can be, for example 50, 55, 60... 85 etc in intervals of 5 MWhr.

2. Similarly, price bids are also limited to the intervals of 0.25 e.g. 10.25, 10.50, 10.75...etc.

6.3.1 Price Quantity Relationship

In the method for ‘scheduling of individual units’ described in Chapter 4, the scheduling problem with profit maximizing objective (Equation 6.2) is solved for each scenario to obtain the optimal schedules with corresponding profits. The price, quantity and profit for each of the 2500 scenarios obtained from the scheduling, is sorted out in the ascending order of optimal quantity dispatch as required for a stepwise non-decreasing bid curve (see Figure 6.1). Figure 6.2, Figure 6.3 and Table 6.1 are outcomes from a sample implementation carried out to observe the price quantity relation for a marginal generation unit. The following observations could be made.

Figure 6.2 Price distributions for discrete quantities

- The solution of generation quantity from ‘scheduling of individual units’ results in number discrete quantities. For example, in the sample considered, 10 discrete quantities are obtained for all price scenarios as can be seen from Figure 6.2 and Table 6.1.
- With the increase in quantity dispatched it can be seen that the price range for which the quantity is dispatched has, in general, an upward slope i.e. more quantities are dispatched for higher prices.

Table 6.1 Price distributions

Quantity (MWh)	Price (\$/MWh)	
	From	To
0	8.50	14.50
55	8.50	12.25
60	12.50	12.50
80	12.75	12.75
100	13.00	13.00
120	13.25	13.25
135	13.50	13.50
155	13.75	13.75
175	14.00	14.00
185	14.25	18.00

Figure 6.3 Cumulative profit distributions for discrete quantities

Figure 6.2 is a typical graph for a period, which shows the relation between price and quantity. The quantities shown in the x-axis are the discrete values of quantities obtained for a period while solving the generation scheduling problem for 2500 price scenarios. The figure shows the range of price at which those quantities give optimal solutions. For instance, generation scheduling gives the optimal profit with quantity as 0 MWhr in several scenarios when the price in the period is between \$8.5 and \$14.5. In the same manner, for

Chapter 6 Price Based Bidding Strategy

quantity as 55 MWhr, optimal profit is obtained when the price in the period is between \$8.5 and \$12.25. From the characteristics of the unit and optimal solution from price based generation scheduling indicated in Figure 6.1, some generation observations can be made.

1. Above a certain maximum price (14.25 in this case), its in the Gencos interest to bid maximum capacity i.e. 185 MWhr.
2. The main difficulty here is, however, to choose the price below which to turn the units OFF, i.e. the decision between 0 MWhr and 55 MWhr. This is very important because this is where the inter-temporal constraints (MUT/MDT) become binding and the decision in one period is interlinked with the decision in other periods.
3. Once the above decisions are made the other price quantity relations are mostly straight forward as they follow the cost characteristics of the unit.

Figure 6.3 shows cumulative profit corresponding to various quantities. To obtain the cumulative profit, the ratio of profit (obtained from ‘scheduling of individual units’) in one scenario to the maximum profit from the entire price scenarios is first calculated. These profit ratios are aggregated for each set of discrete quantities to obtain cumulative profit. Figure 6.3 shows cumulative profit corresponding to those quantities. For example the cumulative profit obtained for the optimal quantity as zero for price between \$8.5 and \$14.5 is 333.42. This may seem to suggest that the decision to bid zero is a favorable decision for the price less than \$14.5 but is not so as will be explained next.

6.3.2 Formation of Bid Curve

The objective here is to make a bidding curve which is a stepwise non-decreasing price quantity curve (constraint (6.3) and (6.4)). From Figure 6.2 it can be seen that, when the price scenarios are treated individually to solve the generation scheduling problem, similar prices at different scenarios tend to give different optimal quantity. Hence, in order to obtain the bid curve, profit information corresponding to each price and quantity, similar to Figure 6.3 is used. Table 6.1 shows the price distribution based on 2500 price scenarios. These price

Chapter 6 Price Based Bidding Strategy

intervals are first categorized in an ascending order of intervals (e.g. <8.50,8.50 to less than 10.50, 12.25 to less than 12.50, 12.5 to less than 12.75 etc) so that the best quantity corresponding to each of those price intervals can be obtained as demanded by the bidding curve constraints (6.3) and (6.4).

But before making decisions on all bid quantities, the price at which to start the unit or in other words, the price below which to put the unit ‘OFF’ should be established. The process adopted in this chapter for this is shown in Figure 6.4. The optimal power corresponding to each scenario is considered to be either ON (≥ 55 MWh i.e. greater than generation lower limit $G_i^{\min}$) or OFF (=0 MWh). Initially, small price intervals between maximum and minimum price is considered and the status ‘ON’ or ‘OFF’ which gives maximum cumulative profit for each interval is calculated. As the bid curves are required to be a stepwise non-decreasing price quantity curve, it can be seen that iteration 1 in Figure 6.4 for a small price interval does not fulfill this condition i.e. condition $QB_{B-1} \leq QB_B$ is not satisfied for all bidding blocks B and $B-1$ ($\forall B \in 1,2,\dots,NB$). Hence, price intervals are increased (at the rate in accordance with the second assumption at the beginning of Section 6.3 i.e. \$0.25) iteratively until the condition is satisfied. In the sample considered, it can be seen that the condition is satisfied in the 3rd iteration and hence for the price range shown by the arrow in iteration 3, the unit is turned OFF. In this way, PB_1 is derived.

To derive $QB_{B,t}$ corresponding to each price interval, a profit weight, $\Pi_{s,B}^{wt}$, for each price scenario is calculated as the ratio of the profit corresponding to a scenario in the price range to the sum of profits corresponding to all the scenarios in the range. i.e.

$$\Pi_{s,B}^{wt} = \frac{\Pi_{s,B}}{\sum_{s,B} \Pi_{s,B}} \quad (6.14)$$

The profit weight $\Pi_{s,B}^{wt}$ thus obtained for each scenario corresponds to the effect of each scheduling decisions obtained from ‘scheduling of individual units’ towards the aggregate

Chapter 6 Price Based Bidding Strategy

profit for all scenarios. Hence, the product of the profit weight and the corresponding scheduled quantity contributes to the bidding quantity, $QB_{B,t}$, which is calculated as

$$QB_{B,t} = \sum_{s,B} \Pi_{s,B}^{wt} \cdot QB_{s,t} \quad (6.15)$$

where,

S is the total number of scenarios

s is the index of a scenario ($s = 1, 2, \dots, S$)

Figure 6.4 Determining ON/OFF price

The quantity chosen for bidding in this way by considering profit weights as the basis of making decisions on bid quantity is the bid quantity that is expected to increase the overall profit under uncertainty.

Figure 6.5 shows the cumulative profit when the price range is divided into different price intervals. It can be seen that, the decision to turn the units OFF (0 MWh) has more cumulative profit for price less than \$10.5/MWh. Similarly, from \$10.50/MWh to less than

Chapter 6 Price Based Bidding Strategy

\$12.50/MWh, quantity of 55 MWh has the higher cumulative profit and so on. In this example, if the market allows 10-step bid function, then 10 price bids corresponding to 10 discrete quantities as shown in Figure 6.5 is expected to give the optimal bid. These price intervals correspond to $PB_{B,t}$ and can be interpreted as $PB_{1,t} = \$10.25$ for 0 MWh, $PB_{2,t} = \$12.25$ for 55 MWh and so on.

Figure 6.5 Cumulative profit distributions for small price intervals

However, if the market allows less bid steps, then the decisions on the minimum price to start i.e. \$10.5 for 55 MWh and the price above which maximum quantity is dispatched i.e. \$14.25 and above for 185 MWh is first made. From the remaining price range, for instance, 10.50 to 14.25 in the example, the quantities having higher cumulative profit are chosen.

In this way, bid curve as shown in Figure 6.6, which is a stepwise non-decreasing curve can be obtained which considers the multiple price scenarios based on the cumulative profit corresponding to each scenario.

Figure 6.6 Price and quantity bid based on profit weight

6.3.3 Bidding Analysis

Bidding analysis is conducted for a time period of 24 hours using the above procedure. Once the bidding curves are obtained for 24 hours, a different set of 2500 price scenarios is generated to investigate the effectiveness of the bids constructed. With bid curves available, the actual clearance in the market for each scenario can be calculated. A slight modification in the cost calculations according to the conditions of the cost functions (6.9), (6.10) and (6.11) in the stages of dynamic programming shown in Figure 4.4 (Chapter 4) makes the inclusion of running, banking and decremental cost possible. Thus the expected profit for the bidding problem according to equation (6.13) is obtained. For the same set of price scenarios, expected profit for a two-step bidding curve [101] is also calculated for comparisons.

6.4 Numerical Example

These examples are based on units provided in [94]. The characteristics of these units are given in Table D.1 in Appendix D. The forecasted price [67] and standard deviation used to

Chapter 6 Price Based Bidding Strategy

generate Monte Carlo samples for next day electricity prices are given in Table D.2 in Appendix D. Unit 1 and unit 2, are considered independently to develop individual bid curve for each unit for 24 hours. Using the method proposed, bids are first generated for the entire time period. Figure 6.7 show a 5-step bid curve for unit 1 for each of the 24-hour period using the method proposed. The expected profit for the bid curve obtained is then calculated as described in Section 6.3.3 for a different set of 2500 price scenarios. The results obtained from two-step bids [101] and the proposed method in this chapter are shown in Table 6.2 and Table 6.3,

In Table 6.2, comparisons are made on the expected profits under price uncertainty calculated using the proposed method in this chapter and the method reported in [101]. Using the comparison mode explained in Section 6.3.3, the expected profits are tabulated in Table 6.2 for 3, 5 and 10 step bids. It is clearly seen from the table that the expected profit under uncertainty is higher for the proposed method as compared to the one reported in [101]. The standard deviations associated with the expected profit are similar in all the cases. It is also evident that the increase in the number of steps of bid function increases the expected profit because more bid steps can represent the cost behavior of the unit in a better way. However, the number of bid steps allowed for bidding is market dependent and should be selected as required.

As the method proposed in [101] considers the forecasted price to form the bids, comparisons are made considering only the forecasted price. The forecasted price is the most likely price based on the prevailing market conditions and hence it is desirable that the expected profit for the price is as high as possible. Table 6.3 provides the comparison of the profits for different bid functions while considering only the forecasted price. The results indicate that for both unit 1 and unit 2, profits obtained from the proposed method for 5 and 10 step bids are very similar to that of the method reported in [101]. As Ref [101] only considers forecasted price for developing bids, the profit for the forecast, as expected, is higher (Table 6.3). However, if the market clears at a different price, it is evident from Table 6.2 that the Genco following the proposed method is more likely to benefit.

Chapter 6 Price Based Bidding Strategy

Figure 6.7 5-Step bid curves for 24 periods for unit 1

Chapter 6 Price Based Bidding Strategy

Table 6.2 Comparison of expected profits with price uncertainty

Unit	Bid Function	Expected Profit (\$)	Maximum Profit (\$)	Minimum Profit (\$)	Standard Deviation (\$)
1	Ref [101]	9751	13658	6331	1041
	3-Step	9757	13694	6439	1044
	5-Step	9860	13700	6440	1032
	10-step	9885	13700	6440	1029
2	Ref [101]	3865	6192	2073	602
	3-Step	4086	6502	2119	623
	5-Step	4155	6614	2190	626
	10-step	4173	6614	2219	626

Table 6.3 Comparison of profits for expected mean price

Method	Profit (\$)	
	Unit 1	Unit 2
Ref [101]	9666.3	3650.6
3-step bid	9570.5	3493.1
5-step bid	9619.6	3602.4
10-step bid	9640.5	3638.1

6.5 Concluding Remarks

A method of building bidding curves under price uncertainty using price based generation scheduling is presented in this chapter. The profits obtained using ‘scheduling of individual units’ for each of the price scenarios is used as the basis for making bidding decisions.

The method is demonstrated with a numerical example to evaluate the effect of the bidding strategy on the expected profit. Comparisons made show that the proposed method results in higher expected profits under price uncertainty. As expected, increase in the number of bid steps is found to improve the optimal expected profit because the higher number of steps can better represent the plant characteristics and price uncertainty.

7. Conclusions and Recommendations

7.1 Conclusions

Several aspects of generation planning for the electricity industry that is increasingly exposed to competition have been studied in this thesis. Generation planning issues and strategies has been investigated in the medium term as well as short term planning horizon. New approaches for Gencos to adapt to the evolving market environment have been proposed. These planning processes involve optimization and coordination between various tasks such as generation scheduling, contract evaluation, risk management, uncertainty representation and development of bidding strategies.

7.1.1 Medium Term Planning of Hydro Generators

A complex risk management problem for hydropower producers was investigated in Chapter 3. Decisions on generation scheduling and bilateral contracts have been made considering negatively correlated price and inflow uncertainty. As simple deterministic models based on the expected future prices is found to be incapable of capturing the stochastic nature of price and inflow, a new approach has been developed through the application of stochastic programming with corrective recourse. The proposed model integrates the operational and financial decisions of an electricity provider who can trade in spot market as well as forward market using bilateral contracts for the present and all subsequent periods in a medium term. The stochastic nature of the negatively correlated price and inflow was represented through a scenario tree of probabilities. The model was further extended for risk averse producers seeking a more stable income and hence willing to accept a solution that provide suboptimal profits but with a lower variance in income. Illustrative numerical example addressed a planning problem from the end of a wet season to the beginning of the subsequent snow-melting season for a small hydropower producer in the Nordic region, which provided a number of interesting results. It was observed that the representation of the stochastic nature of the price and the inflow better resembles reality and can provide an improvement in the revenue of power producers. As expected, bilateral contract decision was found to have an effect on the

Chapter 7 Conclusions and Recommendations

scheduling decisions. It was found that risk averse behavior results in less amount of bilateral contracts (short position) as compared to risk neutral behavior. This happens with hydropower producers due to the negative correlation between price and inflow and higher degree of uncertainty associated with it. Large amount of bilateral contract may mean that the producers may have to buy from the spot market at a very high price to meet the contract obligations if the inflow in the reservoirs turns out to be very low. Hence, it was seen that slightly less bilateral contracts meant more stability (for higher load and lower inflow winter period), which further indicates the problems faced by risk averse decision makers in competitive markets. However, it was noted that in the wet season, when the inflow is very high and hence the prices are very low, opting for larger bilateral contract would mean higher expected income.

7.1.2 Production Scheduling in Competitive Markets

The effect of market rules, market structures and possible company policies has been investigated with respect to production scheduling in the competitive electricity market and three different production scheduling approaches has been proposed in chapter 4 for thermal power producers.

➤ Price Based Unit Commitment

The PBUC approach was developed for Gencos whose demand are dictated by market rules, company policies, contract obligations, etc. and hence are able to approximate their output within a certain range. The proposed technique to maximize the redefined objective of Gencos with flexible demand constraint made use of enumeration algorithm to obtain optimal commitment schedules in the stages of dynamic programming.

➤ Generation Scheduling of Individual Unit

Generation scheduling of individual generating units presented a new perspective in view of Gencos participating in competitive markets. It was observed that as an effect of certain market rules or characteristics of Gencos, scheduling of individual units separately and producing at a level where price equals to the marginal cost gives optimal solution. The reduction in the dimension of the scheduling problem suggested that Gencos in these circumstances could develop their own scheduling models instead of

Chapter 7 Conclusions and Recommendations

relying on expensive commercial software or complicated models. In this aspect, a simple approach using enumeration techniques and dynamic programming was developed which was seen to effectively give optimal solutions almost instantly.

➤ **Self-Commitment: An extension**

For markets that allowed self-scheduling after the bids are cleared, the already developed scheduling approaches were extended to address the self-commitment problems. The extension of PBUC approach primarily involved modifying the demand constraint. The extension of generation scheduling for individual units involved fictitiously increasing or decreasing the price and successively solving the scheduling problem until the demand constraint is met. Solving self commitment problem served as a perfect example to show that the existing solution techniques can be very important and slight modifications of those techniques can help Gencos adapt to the consistently changing market rules and structures.

The comparisons of the proposed techniques with the previously reported methods in literature showed improvements in the competitive objective. In addition, the techniques highlighted the importance of addressing various aspects of scheduling problem in different ways depending on market rules, market structures etc. In a different note, the reduced computational time due to technological advancement in the recent years, show that techniques associated with higher computational time viz. - dynamic programming and enumeration that was used for modeling and solution took relatively short time and hence presents renewed scope in real time applications.

7.1.3 Uncertainty Management

Two approaches for uncertainty management in generation planning were proposed in Chapter 5. A simple analysis was carried out using ‘maxmin’ criterion of decision-making where the objective of risk mitigation is obtained by maximizing the minimum income of the power producers owning only thermal plants. The effect of forward price on the hedging decision and income stability was studied for varied risk preference of the

Chapter 7 Conclusions and Recommendations

participants. The proposed approach has shown the importance of uncertainty management technique on income stability of the Gencos. The study presented a possible risk mitigation tool for power producers in competitive markets.

In the second approach, the need of proper representation of bid curves and stochastic nature of price was shown using a technique based on genetic algorithms. Next day prices scenarios were randomly generated using Monte Carlo simulation. A method based on utility theory was developed to capture the nature of risk preference of the power producers. Short-term forward contracts, which have rarely been addressed in reported literatures, were included in the model developed as an extension to the generation scheduling technique for individual units. Both short-term contracts and level of generation were found to be effective tools to manage uncertainty while considering risk attitudes of market participants.

7.1.4 Bidding Strategy

For securing the target generation in the market, a bidding strategy was formulated in Chapter 6, considering multiple price scenarios. Generation scheduling of individual units was first solved for each scenario and the scheduling solutions thus obtained were rigorously analyzed to develop bidding curves that is able to respond best under price uncertainty. The numerical examples demonstrated the improvement in the profit-maximizing objective under price uncertainty for price taking Gencos.

7.1.5 Summary

Power producers' decisions in competitive markets are influenced by many factors viz.- market structures, trading rules, market power, uncertainties and so on. Various aspects of generation planning for short term and medium term planning horizons were developed in this thesis to suit some market structures and trading rules that are predominant in the deregulated power industry. The uncertainties in the markets were particularly emphasized and its representation and impact on the profit-maximizing

Chapter 7 Conclusions and Recommendations

objective were clearly highlighted. To accommodate the risk preference of the participants, different hedging approaches were implemented in coordination with generation scheduling models to determine the optimal level of generation and optimal contract position.

However, a particular market model or a specific technique cannot represent all power producers in different market. Each producer will have his own specific characteristics. For example, seasonal variations may almost be non-existent in tropical regions where temperature and rainfall are more or less consistent with very little variation throughout the year. So, the models for hydro producers discussed in Chapter 3 may need refinements for hydro producers in tropical region. In the same note, while forecasting uncertainties, seasonal segregation of forecasting models have little meaning in tropical countries and hence the selection of the modeling variables can be substantially different in different regions. Similarly, bidding rules, self scheduling requirements, price caps, number of market players, existence of demand side bidding, types of contracts available, vesting contracts requirements, transmission rights, transmission congestions etc each may influence the decision of power producers as these factors are governed by the market rules which vary in different markets. Equally important are power producers' own risk preferences, company policies/targets and generation capacity and characteristics that dictate the modeling parameters. Therefore it is imperative that standard rigid or predetermined planning tools will not suffice to address the requirement of Gencos in competitive markets. However, many general approaches may be suitably modified and adopted to suit the needs of each Genco. This has been amply demonstrated by the variety of issues addressed and the whole range of solution techniques developed in this thesis to deal with these issues.

7.2 Recommendations

The study on the aspects of generation planning and application of the proposed methods introduced several new ideas. There are ample scopes for extension of the research work, which are recommended for investigation.

Financial Tools

Options contracts are becoming increasingly popular in certain markets, e.g. Nordic market [9]. Hence, it might be worthwhile to extend this research to include option trading and future contracts so that hedging possibilities of a power producer can be fully exploited. This will potentially help risk averse power producer cope better with the prevalent market uncertainties.

Refinement of Uncertainty Tools

It has been stated repeatedly that the competitive electricity markets have been marked by price uncertainty. Hence, more adequate representation of price processes, which have been identified as key influences in the profit-maximizing objective, is essential. Comprehensive forecasting models for developing scenario trees of probabilities would be able to provide even more realistic nature of the markets under study. Although the proper representation of spot price distribution is essential, the assumption that the spot price is normally or lognormally distributed may not always be true for all markets. Hence, further research can give more light into this aspect of spot price behavior.

Extension to the Medium Term Planning Problem

In the medium term planning, the inclusion of different blocks of bilateral contracts having different maturity dates and its effect on the bilateral contract decisions will be interesting to investigate. The possibility of changing the bilateral contract positions stochastically to the optimum can be an extension to the current work. Moreover, the objective of maximizing expected utility rather than expected revenue could provide better insight into the nature of risk averseness of power producers.

Chapter 7 Conclusions and Recommendations

Price Discovery as an Extension to Self-commitment Problem

The self-commitment approach developed as an extension to the ‘scheduling of individual units’ presents a technique based on fictitiously increasing or decreasing price until the demand is met. This presents a possibility of further extending the approach for price discovery in markets like PJM, where ISO commit generating units and calculates market-clearing prices using multipart bids submitted by Gencos.

Co-optimizing in different levels of planning process

More rigorous representation of variables, when available, will make the application of medium term decisions as boundary conditions for short-term decisions more accurate and feasible. This will make possible, the investigation into the influence of medium term decisions on short-term decisions. This may open the possibility of co-optimizing these decisions for different planning periods and hence will be an interesting extension of this research.

A Comprehensive Generation Planning Procedure

A comprehensive generation planning procedure incorporating all aspects presented in this thesis would be a very good tool for Gencos in the competitive electricity market. Despite the existing and the ongoing research in various aspects of generation planning, it has been pointed out that different factors influence the decision making process in different ways and requires at times significantly different approach to handle the problems in hand. Even if a comprehensive procedure is developed, it is likely to be market specific or even Genco specific. Developing a comprehensive procedure for a Genco in a particular market is in itself a huge but important task that requires coordinating and correlating among different aspects of generation planning and in different levels of planning process.

Author's Publications

Portions of different sections of this research work have been reported in various publications.

Journal Papers:

1. Shrestha, G.B., Pokharel, B.K., Lie, T.T. and Fleten, S-E, "Medium Term Power Planning with Bilateral Contracts", IEEE Trans. Power Systems, Vol.20, No.2, p.627-633, May 2005.
2. Shrestha, G.B., Pokharel, B.K., Lie, T.T. and Fleten, S-E, "Managing Flexibility In Short-Term Generation Planning Under Price Uncertainty (submitted to IEEE Trans. Power Systems).
3. Shrestha, G.B., Pokharel, B.K., Lie, T.T. and Fleten, S-E, "Price Based Bidding in Competitive Electricity Markets" (submitted to IEEE Trans. Power Systems).

Conference Papers:

4. Pokharel, B.K., Shrestha, G.B., Lie, T.T. and Fleten, S-E, "Price Based Unit Commitment for Gencos in Deregulated Markets", IEEE PES General Meeting, San Francisco, USA, June 2005.
5. Pokharel, B.K., Shrestha, G.B., Lie, T.T. and Fleten, S-E, "Profit Based Unit Commitment in Competitive Markets", International Conference on Power System Technology (IEEE POWERCON), Singapore, November 2004.
6. Shrestha, G.B., Lie, T.T., Pokharel, B.K. and Fleten, S-E, "Risk Mitigation using Forward Contract in Power Market", Sixth international power engineering conference, p. 1022-1027, November 2003.

References

- [1] Borenstein, S. and Bushnell, J., "Electricity Restructuring: Deregulation or Reregulation?", Regulation, Vol. 23 No.2, 2000. Available Online: <http://www.cato.org/pubs/regulation/regv23n2/boren.pdf>
- [2] Green, R. J. and Newberry, D. M., "Competition in the British Electricity Spot Market", The Journal of Political Economy, Vol. 100, Issue 5, p. 929-953, October 1992.
- [3] Available Online: <http://www.nordpool.no/>, NordPool ASA
- [4] Bhattacharya, K., Bolllen, M. H. J. and Daalder, J. E., "Operation of Restructured Power Systems", Kluwer Academic Publishers, 2001.
- [5] Available Online: <http://www.ema.gov.sg/>, Energy Market Authority, Singapore
- [6] Shahidehpour, M. and Alomoush, M., "Restructured Electrical Power Systems", Marcel Dekker, Inc.
- [7] Ilic, M., Galiana, F. and Fink, L., "Power System Restructuring: Engineering and Economics", Kluwer Academic Publishers, 1998.
- [8] McCain, R. A., "Essential Principles of Economics: A Hypermedia Text", Available Online: <http://william-king.www.drexel.edu/top/prin/txt/EcoToC.html>
- [9] Rasmusen, E., "Games and information: an introduction to game theory", Oxford, OX, UK.
- [10] Gibbons, R., "An Introduction to Applicable Game Theory", Journal of Economic Perspectives, Vol. 11, No.1, p 127-149, Winter 1997
- [11] Fleten, S-E, "Portfolio Management Emphasizing Electricity Market Applications", Dr. Eng. thesis prepared at NTNU, Norway, January 2000.
- [12] Allaz, B., "Oligopoly, Uncertainty and Strategic Forward Transactions", International Journal of Industrial Organization, 10, p. 297-308, 1992.
- [13] Shahidehpour, M., Yamin, H. and Li, Z., "Market Operations in Electric Power Systems: Forecasting, Scheduling and Risk Management", John Wiley & Sons, Inc., 2002.
- [14] Higley, C., "Disastrous Deregulation", Public Citizen's Critical Mass Energy & Environment Program December 2002. Available Online: www.citizen.org/cmep.

References

- [15] Hunt, S., "The State of U.S. Electricity Restructuring", The Electricity Journal, June 2002.
- [16] Coyle, E. P., "Economists Stories and Culpability in Deregulation, " The electricity Journal, October 2002.
- [17] Lesser, J. A., "Welcome to the New Era of Resource Planning: Why Restructuring May Lead to More Complex Regulation, Not Less", The electricity Journal, 2002.
- [18] Shuttleworth, G., "Hot Topics in European Electricity: What is Relevant and What Isn't?", The Electricity Journal, p. 25-39, October 2002
- [19] Available Online: <http://odin.dep.no/>, Norway Fact Sheet 2000.
- [20] Wood A.J and Wollenberg B.F., "Power Generation Operation and Control", John Wiley and Sons Inc, Second Edition, 1996.
- [21] Somuah, C.B. and Khunaizi, M., "Application of Linear Programming Redispatch Technique to Dynamic Generation Allocation", IEEE Trans. Power Systems, Vol.5, No.1, p. 20-26, February 1990.
- [22] Demartini, G., Granelli, G.P., Marannino, P., Montagna, M. and Ricci, M., "Co-ordinated Economic Dispatch and Advance Dispatch Procedures", IEEE Trans. Power Systems, Vol.1, No.4, p. 1785-1791, November 1996.
- [23] Yang, J.S. and Chen, N., "Short Term Hydrothermal Coordination Using Multi-Pass Dynamic Programming", IEEE Trans. Power Systems, Vol. 4, No.3, p. 1050-1056, August 1989.
- [24] Ferrero, R.W., Rivera, J.F. and Shahidehpour, S.M., "A Dynamic Programming Two-Stage Algorithm for Long-term Hydrothermal Scheduling of Multireservoir Systems", IEEE Trans. Power Systems, Vol.13, No.4, p.1534-1540, November 1998.
- [25] Erkmen and B. Karatus "Short Term Hydrothermal Coordination ByUsing Multi-Pass Dynamic Programming with Successive Approximation", Electrotechnical Conference, IEEE Proceedings, p. 925-928, 12-14 April 1994.
- [26] Rotting, T.A. and Gjelsvik, A., "Application of a dual dynamic programming algorithm to staircase linear programs arising in scheduling of hydro power plants", CompEuro '92, 'Computer Systems and Software Engineering', Proceedings, IEEE Proceedings, p. 53 -58, 4-8 May 1992.

References

- [27] Cau, T. D. H. and Kaye, R. J., “Evolutionary Optimisation Method for Multistorage Hydrothermal Scheduling”, *Generation, Transmission and Distribution, IEE Proceedings*, Vol. 149, No.2, p. 152-156, March 2002.
- [28] Nilsson, O. and Sjelvgren, D., “Mixed-Integer Programming Applied to Short-Term Planning of a Hydrothermal System”, *IEEE Trans. Power Systems*, Vol. 11, No.1, p. 281-286, February 1996.
- [29] Salam, M. S., Nor, K.M. and Hamdan, A. R., “Hydrothermal Scheduling Based Lagrangian Relaxation Approach to Hydrothermal Coordination”, *IEEE Trans. Power Systems*, Vol. 13, No.1, p. 226-235, February 1998.
- [30] Tang, J. and Luh, P.B., “Hydrothermal Scheduling via Extended Differential Dynamic Programming and Mixed Coordination”, *IEEE Trans. Power Systems*, Vol. 10, No.4, p. 2021-2028, November 1995.
- [31] Ventosa, M., Rivier, M., Ramos, A. and Garcia-Alcalde, A., “An MCP Approach for Hydrothermal Coordination in Deregulated Power markets”, *Power Engineering Society Summer Meeting, IEEE*, Vol. 4, p.2272 –2277, 16-20 July 2000.
- [32] Scott, T. J. and Read, E.G., “Modeling Hydro Reservoir Operation in a Deregulated Electricity Market”, *International Transactions in Operational Research*, Vol. 3, p.243-253, 1996.
- [33] Alvey, T., Goodwin, D., Ma, X., Streiffert, D. and Sun, D., “A Security Constrained Bid- Clearing System for New Zealand Wholesale Electricity Market”, *IEEE Trans. Power Systems*, Vol.13, No.2, p. 340-346, May 1998.
- [34] Hao, S., Angelidis, G.A., Singh, H. and Papalexopoulos, A. D., “A consumer payment minimization in Power Pool Auctions”, *IEEE Trans. Power Systems*, Vol.13, No.3, p. 986-991, August 1998.
- [35] Alonso, J., Trias, A., Gaitan, V. and Alba, J.J., “Thermal Plant Bids and Market Clearing in an Electricity Pool: Minimization of Cost Vs Minimization of Consumer Payments”, *IEEE Trans. Power Systems*, Vol.14, No.4, p. 1327-1334, November 1999.
- [36] Richter, C.W. and Sheble, G.B., “A Profit-Based Unit Commitment GA for the Competitive Environment”, *IEEE Trans. Power Systems*, Vol.15, No.2, p. 715-721, May 2000.

References

- [37] David, A.K. and Wen, F., “Strategic Bidding in Competitive Electricity Market: a Literature Survey”, IEEE Power Engineering Society Summer Meeting, Vol. 4, p. 2168 – 2173, 16-20 July 2000
- [38] Shahidehpour, M., “Tools for Generation Risk Management”, Power Engineering Society Summer Meeting, IEEE, Vol. 1 , 15-19 July 2001.
- [39] Bjorkvoll, T., Fleten, S.E., Nowak, M.P., Tomasgard, A. and Wallace, S.W., “Power Generation Planning and Risk Management in a Liberalised Market”, IEEE Porto Power Tech Conference, 10-13 September 2001.
- [40] Bunn, D.W., “Forecasting Loads and Prices in Competitive Power Markets”, Proceedings of the IEEE, vol. 88, No.2, p. 163–169, Feb 2000.
- [41] Bastian, J., Zhu, J., Banunarayanan, V. and Mukerji, R., “ Electricity Energy Prices in a Competitive Market”, IEEE Computer Application in Power, vol. 12, Issue.3, p. 40–45, July. 1999.
- [42] Nogales, F.J., Contreras, J., Conejo, A.J. and Espinola, R., “Forecasting Next-Day Electricity Prices by Time Series Models”, IEEE Trans. Power Systems, Vol. 17, No. 2, p. 342-348, May 2002.
- [43] Szkuta, B.R., Sanabria, L.A. and Dillon, T.S., “Electricity Price Short-Term Forecasting Using Artificial Neural Networks”, IEEE Trans. Power Systems, vol. 14, No.3, p. 851–857, Aug. 1999.
- [44] Huisman, R. and Mahieu, R., “Regime Jumps in Electricity Prices”, Energy Economics, vol. 25, p. 425–434, 2003.
- [45] Andrews, C.J., ”Evaluating Risk Management Strategies in Resource Planning”, IEEE Trans. Power Systems, Vol. 10, No.1, p. 46-52, February 1995.
- [46] Skantze, P. L. and Ilic, M. D., “Valuation, Hedging and Speculation in Competitive Electricity Markets”, Kluwer Academic Publishers, 2001.
- [47] Hull, J. C., “Introduction to Futures and Options Market”, Prentice Hall, Inc., Third Edition. 1998.
- [48] Available Online: www.NYMEX.com
- [49] Stoll, H. R. and Whaley, R. E., “Futures and Options Theory and Applications”. South-Western Publication Co., 1993.

References

- [50] Collins, R. A., "Economics of Electricity Hedging and a proposed modification for future contract for Electricity", IEEE Trans. Power Systems, Vol. 17, No.1, p. 100-107, February 2002.
- [51] Kaye, R.J., Outhred, H.R. and Bannister, C.H., "Forward Contract for the Operation of an Electricity Industry under Spot Pricing", IEEE Trans. Power Systems, Vol. 5, No.1, p. 46-52, Feb 1990.
- [52] Cheng, J.W.M., Galiana, F.D. and McGillis, D.T., "Studies of Bilateral Contract with Respect to Steady State Security in a Deregulated Environment", IEEE Trans. Power Systems, Vol. 13, No.3, p. 1020-1025, August 1998.
- [53] Gedra, T. W., "Optional Forward Contracts for electric power markets", IEEE Trans. Power Systems, Vol. 9, No.4, p. 1766-1773, Nov 1994.
- [54] Gans, J. S., Price, D. and Woods, K., "Contracts and Electricity Pool Prices", Australian Journal of Management, Vol. 23, No.1, p. 83-96, June 1998
- [55] Lane, D.W., Richter, C.W. and Sheble, G.B., "Modeling And Evaluating Electricity Options Markets With Intelligent Agents", Electric Utility Deregulation and Restructuring and Power Technologies, IEEE Proceedings, p.203 –208, 4-7 April 2000.
- [56] Campo, R. A., "Probabilistic Optimality in Long-Term Energy Sales", IEEE Trans. Power Systems, Vol. 17, No.2, p. 237-242, May 2002.
- [57] Bjorgan, R., Liu, C. C. and Lawarree, J., "Financial Risk Management in a Competitive Electricity Market", IEEE Trans. Power Systems, Vol. 14, No.4, p. 1285-1291, November 1999.
- [58] Tanlapco, E., Lawarree, J. and Liu, C. C., "Hedging with Future Contracts in a Deregulated Electricity Industry", IEEE Trans. Power Systems, Vol. 17, No.3, p. 577-582, August 2002.
- [59] Domingues, E.G., Arango, H., Policarpo, J., Campinho, C.B. and Paulillo, G., "Applying Modern Portfolio Theory to Investment Projects in Electric Energy Markets", IEEE Porto Power Tech Conference, 10-13 September 2001.
- [60] Siddiqi, S.N., "Project Valuation and Power Portfolio Management in a Competitive Market", IEEE Trans. Power Systems, Vol. 15, No.1, p. 116-121, February 2000.

References

- [61] Smith, J.E. and Nau, R.F., “Valuing Risky Projects: Option Pricing Theory and Decision Analysis”, *Management Science*, Vol. 41, No.5, p. 795-816, May 1995.
- [62] Song, K., “Aspects of Strategic Bidding in Deregulated Power Markets”, PhD thesis, Nanyang Technological University, Singapore, p.129, 2003
- [63] Li, C. A., Svoboda, A. J. Guan, X. H. and Singh, H., “Revenue adequate bidding strategies in competitive electricity markets,” *IEEE Trans. Power Systems*, vol. 14, pp. 492–497, May 1999.
- [64] Rajaraman, R. and Alvarado, F., “Optimal Bidding Strategy in Electricity Markets Under Uncertain Energy and Reserve Prices”, *Power System Engineering Research Center (PSERC) Publication 03-05*, Apr 2003. Available Online: <http://www.pserc.org/>
- [65] Guan, X., Ho, Y. and Lai, F. “An Ordinal Optimization Based Bidding Strategy for Electric Power Suppliers in the Daily Energy Market”, *IEEE Trans. Power Systems*, Vol.16, No.4, p. 788-797, November 2001.
- [66] Ni, E., Luh, P. B. and Rourke, S., “Optimal Integrated Generation Bidding and Scheduling With Risk Management Under a Deregulated Power Market.”, *IEEE Trans. on Power Systems*, Vol. 19, No. 1, p. 600-609, Feb 2004.
- [67] Huse, E. S., Wangenstein, I. and Faanes, H.H., “Thermal Power Generation Scheduling by simulated competition”, *IEEE Trans. Power Systems*, Vol. 14, No. 2, p. 472-477, May 1999.
- [68] Richter Jr., C. W. and Sheblé, G. B., “Genetic algorithm evolution of utility bidding strategies for the competitive marketplace,” *IEEE Trans. Power Systems*, vol. 13, pp. 256–261, Feb. 1998.
- [69] Wen, F. and David, A. K., “Optimal Bidding Strategies and Modeling of Imperfect Information Among Competitive Generators.”, *IEEE Trans. on Power Systems*, Vol. 16, No. 1, p. 15-21, Feb 2001.
- [70] Zhang, D., Wang, Y. and Luh, P. B., “Optimization based bidding strategies in the deregulated market,” *IEEE Trans. Power Systems*, vol. 15, pp. 981–986, Aug. 2000.
- [71] Hao, S., “A study of basic bidding strategy in clearing pricing auctions,” *IEEE Trans. Power Systems*, vol. 15, pp. 975–980, Aug. 2000.

References

- [72] Shrestha, G.B., Song, K., and Goel, L., “Strategic bidding for minimum power output in the competitive power market,” *IEEE Trans. Power Systems*, vol. 16, pp. 813–818, Nov. 2001.
- [73] Song, H., Liu, C. C. and Lawarrée, J., “Nash equilibrium bidding strategies in a bilateral electricity market,” *IEEE Trans. Power Systems*, vol. 17, pp. 73–79, Feb. 2002.
- [74] Pereira, M.V.F and Pinto, L.M.V.G., “Stochastic optimization of a multireservoir hydroelectric system: A decomposition approach”, *Water Resource Research*, Vol. 21 No.6, p. 779-792, 1985.
- [75] Keppo, J., “Optimality with Hydropower System”, *IEEE Trans. Power Systems*, Vol. 17, No. 3, p. 583-589, August 2002.
- [76] Fleten, S-E, Wallace, S.W. and Ziemba, W.T., “Hedging electricity portfolios via stochastic programming”, in C. Greengard and A. Ruszczynski (eds), *Decision Making Under Uncertainty: Energy and Power*, Vol. 128 of IMA Volumes on Mathematics and Its Applications, Springer-Verlag, New York, p. 71-93, 2002.
- [77] Yu, Z., Sparrow, F.T. and Bowen, B.H., “A New Long-Term Hydro Production Scheduling Method for Maximizing the Profit of Hydroelectric Systems”, *IEEE Trans. Power Systems*, Vol.13, No.1, p. 66-71, February 1998.
- [78] Maceira, M.E.P. and Pereira, M.V.F., “Analytical Modeling of Chronological Reservoir Operation in Probabilistic Production Costing”, *IEEE Trans. Power Systems*, Vol.11, No.1, p. 171-180, February 1996.
- [79] Johnsen, T.A., “Hydropower Generation and Storage, Transmission Constraints and Market Power”, *Utility Policy*, Vol.10, p. 63-73, 2001
- [80] Hjalmarsson, E., “NordPool: A Power Market Without Market Power “, Working paper. Available Online: <http://swopec.hhs.se/gunwpe/abs/gunwpe0028.htm>.
- [81] Available Online: <http://www.ssb.no/english/>, Statistics Norway.
- [82] Available Online: <http://www.statnett.no/>, Statnett Norway
- [83] Johnsen, T.A., Verma, S.K. and Wolfram, C.D., “Zonal Pricing and Demand Side Bidding in the Norwegian Electricity Market”, University of California Energy Institute, Power Working Paper-063, 1999.

References

- [84] Herguera, I., “Bilateral Contracts and the Spot Market for Electricity: Some Observations on the British and the NordPool Experiences”, *Utility Policy*, Vol 9, p 73-80, 2000.
- [85] Scott, T. J., “Hydro Reservoir Management for an Electricity Market with Long Term Contracts”, PhD Thesis, University of Canterbury, 1998.
- [86] Specht, D. F., “A General Regression Neural Network”, *IEEE Trans on Neural Network*, Vol. 2, No. 6, Nov 1991.
- [87] Spetcht, D.F. and Ronsdahl, H., “Experience With Adaptive Probabilistic Neural Networks and Adaptive General Regression Neural Networks”, *IEEE Conference*, 1994
- [88] Riis, M., “Classical and Non-Classical Stochastic Recourse Programs with Applications in Telecommunications”, PhD thesis, University of Aarhus, Denmark, June 2003
- [89] Hoyland, K. and Wallace, S.W., “Generating Scenario Trees for Multistage Decision Problems”, *Management Science*, Vol. 47, No. 2, p 295-307, February 2001
- [90] Dupacova, J., Consigli, G. and Wallace, S.W., “Scenarios for Multistage Stochastic Programs” *Annals of Operations Research* 100, p25–53, 2000
- [91] Rockafellar, R.T. and Wets, R.J-B, “Scenarios and policy aggregation in optimization under uncertainty”, *Mathematics of Operations Research*, Vol 16, No. 1, pp. 119-147, 1991.
- [92] Coleman, T., Branch, M. A. and Grace, A., “Optimization Toolbox for use with matlab, User Guide”, The Math Works Inc. Available Online: http://www-ccs.ucsd.edu/matlab/pdf_doc/optim/optim_tb.pdf.
- [93] Hull, J. C., “Options, Futures, and Other Derivatives”, Prentice Hall, 5th Edition, 2003.
- [94] Orero, S. O. and Irving, M. R., “Large scale unit commitment using Hybrid Genetic Algorithm”, *Electrical Power and Energy Systems*, Vol. 19 No.1, p.45-55., 1997.
- [95] Zhai, Q., Guan, X. and Cui, J., “Unit Commitment With Identical Units: Successive Subproblem Solving Method Based on Lagrangian Relaxation”, *IEEE Trans. Power Systems*, Vol. 17, No. 4, p. 1250-1257, Nov 2002.

References

- [96] Senjyu, T., Shimabukuro, K., Uezato, K. and Funabashi, T., “A Fast Technique for Unit Commitment by Extended Priority List ”, IEEE Trans. Power Systems, Vol. 18, No. 2, p. 882-888, May 2003.
- [97] Arroyo, J. M. and Conejo, A. J., “Optimal Response of a Thermal Unit to an Electricity Spot Market”, IEEE Trans. on Power Systems, Vol.15, No.3, p.1008-1104, Aug 2000.
- [98] Liu C.N., Tang D.T., ‘Algorithm 452: Enumeration Combinations of m out of n objects [G6], Communication of the ACM, Volume 16, Issue 8, p485, August 1973.
- [99] Goldberg, D.E., “Genetic Algorithms in Search Optimization and Machine Learning, Reading”, MA: Addison-Wesley, 1989.
- [100] Swarup, K.S. and Yamashiro, S., “Unit Commitment Solution Methodology Using Genetic Algorithms”, IEEE Trans. on Power Systems, Vol. 17, No. 1, p. 87-91, Feb 2002.
- [101] Conejo, A.J., Nogales, F.J. and Arroyo, J. M., “Price-Taker Bidding Strategy Under Price Uncertainty”, IEEE Trans. Power Systems, Vol. 17, No. 4, p. 1081-1088, November 2002.
- [102] Dahlgren, R., Liu, C.C. and Lawarree, J., “ Risk Assessment in Energy Trading”, IEEE Trans. Power Systems, Vol. 18, No.2, p. 503-511. May 2003.
- [103] Brooks, R. and El-Keib, A.A., “A life cycle view of Electricity Futures Contracts. Journal of Energy Finance and Development”, Vol. 3, No.2, p. 171-183, 1998.
- [104] Hobbs, B. F., Rouse, H. B. and Hoog, D. T., “Measuring the Economic Value of Demand-side and Supply Resources in Integrated Resource Planning Models”, IEEE Trans. Power Systems, Vol.8, No.3, p. 979-987, August 1993.
- [105] Neumann, J.V. and Morgenstern, O., “Theory of Games and Economic behavior”, Princeton University Press, 3rd Edition, 1990.
- [106] Available Online: <http://cepa.newschool.edu/het/essays/uncert/aversion.htm>.

APPENDICES

APPENDIX A: Data for Hydro Plant for Medium Term Planning in Chapter 3

Table A.1 Specifications of hydro power plant

Specification	Values	Unit	Comments
$G_{\min}$	3.5	MW	
$G_{\max}$	14	MW	
Average Energy Equivalent	0.223	KWh/m ³	
Maximum Reservoir Level (Wmax)	76.5	Mm ³	Million cubic meter
Minimum Reservoir Level (Wmin)	0	Mm ³	
Initial Reservoir Level (W0)	70.4	Mm ³	Beginning of week 42, 2001

Table A.2 Price details (Chapter 3)

Period	Maximum (NOK/MWh)	Minimum (NOK/MWh)	Standard Deviation (NOK/MWh)
2	266.46	95.88	37.35
3	387.78	96.86	37.43
4	633.36	77.74	68.66
5	310.76	64.79	58.37
6	282.39	19.87	58.74

Table A.3 Inflow details (Chapter 3)

Period	Maximum (Mm ³)	Minimum (Mm ³)	Standard Deviation (Mm ³)
2	53.3	3.4	13.3
3	66.2	4.4	14.29
4	72.2	3.1	17.17
5	45	9.6	10.91
6	72.2	12.7	14.2

APPENDIX B: Unit & Forecast Data for Production Scheduling in Chapter 4

Table B.1 Characteristics of 10 unit system [94]

Unit	G _{max}	G _{min}	MDT	MUT	IC	IP	a	b	c	s	d	t	SD	Status
1	500	140	5	8	5	500	210.000	12.00	0.0014	500	800	4	0	1
2	100	25	3	2	-2	0	220.000	12.50	0.0039	10	60	2	0	0
3	250	75	4	4	-1	0	140.000	12.40	0.0012	50	20	3	0	0
4	360	110	4	5	-2	0	120.000	10.30	0.0038	200	35	4	0	0
5	180	40	3	4	-5	0	40.000	12.70	0.0056	50	80	3	0	0
6	40	10	1	1	-1	0	80.000	13.40	0.0011	10	20	1	0	0
7	120	45	3	4	-3	0	218.895	19.00	0.0072	80	80	4	0	0
8	200	50	4	4	1	200	250.000	13.20	0.0036	50	400	3	0	1
9	80	20	2	2	-4	0	210.000	14.20	0.0088	50	40	2	0	0
10	150	40	3	5	-7	0	75.000	25.60	0.0340	18	113	5	29	0

Table B.2 Characteristics of 110 unit system [94]

Unit	G _{max}	G _{min}	MDT	MUT	IC	IP	a	b	c	s	d	t	SD	Status
1	12	2.4	0	0	-1	0	24.389	25.55	0.0253	0	0	1	0	0
2	12	2.4	0	0	-1	0	24.411	25.68	0.0265	0	0	1	0	0
3	12	2.4	0	0	-1	0	24.638	25.80	0.0280	0	0	1	0	0
4	12	2.4	0	0	-1	0	24.760	25.93	0.0284	0	0	1	0	0
5	12	2.4	0	0	-1	0	24.888	26.06	0.0286	0	0	1	0	0
6	20	4	0	0	-1	0	117.755	37.55	0.0120	20	20	2	0	0
7	20	4	0	0	-1	0	118.108	37.66	0.0126	20	20	2	0	0
8	20	4	0	0	-1	0	118.458	37.78	0.0136	20	20	2	0	0
9	20	4	0	0	-1	0	118.821	37.89	0.0143	20	20	2	0	0
10	76	15.2	2	3	3	76	81.136	13.33	0.0088	50	50	3	0	1
11	76	15.2	2	3	3	76	81.298	13.35	0.0089	50	50	3	0	1
12	76	15.2	2	3	3	76	81.464	13.80	0.0091	50	50	3	0	1
13	76	15.2	2	3	3	76	81.626	13.41	0.0093	50	50	3	0	1
14	100	25	2	4	-3	0	217.895	18.00	0.0062	70	70	4	0	0
15	100	25	2	4	-3	0	218.335	18.10	0.0061	70	70	4	0	0
16	100	25	2	4	-3	0	218.775	18.20	0.0060	70	70	4	0	0
17	155	54.3	3	5	5	155	142.735	10.69	0.0046	150	150	6	0	1
18	155	54.3	3	5	5	155	143.029	10.72	0.0047	150	150	6	0	1
19	155	54.3	3	5	5	155	143.318	10.74	0.0048	150	150	6	0	1
20	155	54.3	3	5	5	155	143.597	10.76	0.0049	150	150	6	0	1
21	197	68.9	4	5	-4	0	259.131	23.00	0.0026	200	200	8	0	0
22	197	68.9	4	5	-4	0	259.649	23.10	0.0026	200	200	8	0	0
23	197	68.9	4	5	-4	0	260.176	23.20	0.0026	200	200	8	0	0

Appendices

24	350	140	5	8	10	350	177.057	10.86	0.0015	300	200	8	0	1
25	400	100	5	8	10	400	210.002	7.49	0.0019	500	500	10	0	1
26	400	100	5	8	10	400	211.910	7.50	0.0019	500	500	10	0	1
27	500	140	5	8	5	500	210.000	12.00	0.0014	500	800	4	0	1
28	500	140	7	8	-2	0	180.000	12.10	0.0013	250	800	4	0	0
29	200	50	4	4	1	200	240.000	12.20	0.0026	40	300	3	0	1
30	100	25	3	2	-2	0	220.000	12.50	0.0039	10	60	2	0	0
31	50	10	2	1	-3	0	60.000	23.00	0.0051	25	10	1	0	0
32	20	5	1	1	-2	0	50.000	13.50	0.0050	10	15	1	0	0
33	80	20	2	3	-4	0	200.000	13.20	0.0078	40	30	2	0	0
34	250	75	4	4	-1	0	140.000	12.40	0.0012	50	20	3	0	0
35	360	110	4	5	-2	0	120.000	10.30	0.0038	200	35	4	0	0
36	400	130	8	8	3	400	90.000	9.90	0.0043	400	30	5	0	1
37	40	10	1	1	-1	0	80.000	13.40	0.0011	10	20	1	0	0
38	70	20	1	1	-2	0	70.000	13.30	0.0023	50	300	1	0	0
39	100	25	2	2	-1	0	115.000	12.90	0.0034	10	150	2	0	0
40	120	20	2	4	-3	0	150.000	12.80	0.0067	15	120	3	0	0
41	180	40	3	4	-5	0	40.000	12.70	0.0056	50	80	3	0	0
42	220	50	4	5	-1	0	300.000	12.60	0.0023	150	50	3	0	0
43	440	120	8	7	2	440	250.000	7.40	0.0012	450	30	4	0	1
44	560	160	8	8	-6	0	100.000	6.60	0.0045	300	45	5	0	0
45	660	150	9	9	4	660	160.000	6.50	0.0022	400	50	6	0	1
46	700	200	12	12	4	700	130.000	6.20	0.0067	650	70	8	0	1
47	32	5.4	0	0	-1	0	34.389	26.55	0.0353	0	0	1	0	0
48	32	5.4	0	0	-1	0	34.411	26.68	0.0365	0	0	1	0	0
49	52	8.4	1	1	-1	0	34.638	26.80	0.0380	0	0	1	0	0
50	52	8.4	1	1	-1	0	34.761	26.93	0.0384	0	0	1	0	0
51	52	8.4	1	1	-1	0	34.888	17.06	0.0386	0	0	1	0	0
52	60	12	1	2	-1	0	127.755	38.55	0.0320	30	30	2	0	0
53	60	12	1	2	-1	0	128.108	36.66	0.0326	30	30	2	0	0
54	60	12	1	2	-1	0	128.458	38.78	0.0236	30	30	2	0	0
55	60	12	1	2	-1	0	128.821	38.89	0.0243	30	30	2	0	0
56	96	25.2	2	3	3	96	82.136	14.33	0.0098	60	60	3	0	1
57	96	25.2	2	3	3	96	82.298	14.35	0.0099	60	60	3	0	1
58	100	35	3	3	3	100	82.464	14.38	0.0092	60	60	3	0	1
59	100	35	3	3	3	100	82.626	14.41	0.0094	60	60	3	0	1
60	120	45	3	4	-3	0	218.895	19.00	0.0072	80	80	4	0	0
61	120	45	3	4	-3	0	219.335	19.10	0.0071	80	80	4	0	0
62	120	45	3	4	-3	0	219.775	19.20	0.0070	80	80	4	0	0
63	185	54.3	4	5	5	185	143.735	11.69	0.0066	160	160	6	0	1
64	185	54.3	4	5	5	185	144.029	11.72	0.0057	160	160	6	0	1
65	185	54.3	4	5	5	185	144.318	11.74	0.0058	160	160	6	0	1
66	185	54.3	4	5	5	185	144.597	11.76	0.0059	160	160	6	0	1
67	197	70	4	5	-4	0	269.131	24.00	0.0036	210	210	8	0	0
68	197	70	4	5	-4	0	269.649	24.10	0.0036	210	210	8	0	0
69	197	70	4	5	-4	0	270.176	24.20	0.0036	210	210	8	0	0
70	360	150	5	8	10	360	187.057	11.86	0.0025	210	210	8	0	1
71	400	160	6	8	9	400	320.002	8.49	0.0029	510	510	10	0	1

Appendices

72	400	160	6	8	9	400	321.910	8.50	0.0030	510	510	10	0	1
73	300	60	4	4	-1	0	52.136	13.33	0.0054	40	60	3	0	0
74	250	50	3	3	-1	0	42.298	12.35	0.0055	65	70	2	0	0
75	90	30	2	2	-1	0	32.464	11.38	0.0099	60	90	2	0	0
76	50	12	1	1	-1	0	23.626	9.41	0.0031	68	30	2	0	0
77	450	160	5	6	5	450	22.000	14.00	0.0024	600	900	4	0	1
78	600	150	7	8	-2	0	190.000	13.10	0.0023	350	900	4	0	0
79	200	50	4	4	1	200	250.000	13.20	0.0036	50	400	3	0	1
80	120	20	3	3	-2	0	230.000	13.50	0.0049	20	70	2	0	0
81	55	10	1	1	-3	0	70.000	24.00	0.0061	35	20	1	0	0
82	40	12	1	1	-2	0	60.000	14.50	0.0070	40	25	1	0	0
83	80	20	2	2	-4	0	210.000	14.20	0.0088	50	40	2	0	0
84	200	50	4	4	1	200	150.000	13.40	0.0022	60	30	3	0	1
85	325	80	4	4	-2	0	130.000	11.30	0.0048	300	45	4	0	0
86	440	120	5	6	3	440	80.000	8.90	0.0053	500	40	5	0	1
87	35	10	0	0	-1	0	90.000	14.40	0.0021	20	30	1	0	0
88	55	20	1	1	-2	0	80.000	14.30	0.0033	60	400	1	0	0
89	100	20	3	2	-1	0	125.000	13.90	0.0034	20	160	2	0	0
90	220	40	2	3	-3	0	160.000	13.80	0.0037	25	130	3	0	0
91	140	30	3	3	-4	0	50.000	13.70	0.0066	60	90	3	0	0
92	100	40	3	2	-1	0	400.000	13.60	0.0043	160	40	3	0	0
93	440	100	6	6	2	440	260.000	8.40	0.0022	460	40	4	0	1
94	500	100	8	8	-6	0	110.000	7.60	0.0055	310	55	5	0	0
95	600	100	9	8	4	600	170.000	7.50	0.0032	410	60	6	0	1
96	700	200	12	12	4	700	140.000	7.20	0.0077	660	80	8	0	1
97	15	3.6	0	0	-1	0	26.389	26.55	0.0353	0	0	1	0	0
98	15	3.6	0	0	-1	0	25.411	26.68	0.0365	0	0	1	0	0
99	22	4.4	0	0	-1	0	25.638	26.80	0.0380	0	0	1	0	0
100	22	4.4	0	0	-1	0	25.760	26.93	0.0384	0	0	1	0	0
101	60	10	1	3	-1	0	65.000	15.30	0.0210	20	85	5	15	0
102	80	10	1	3	-1	0	82.000	16.00	0.0230	20	101	5	25	0
103	100	20	2	4	1	100	86.000	20.20	0.0240	22	114	5	40	1
104	120	20	2	4	5	120	84.000	20.20	0.0350	10	84	5	32	1
105	150	40	3	5	-7	0	75.000	25.60	0.0340	18	113	5	29	0
106	280	40	2	5	3	280	56.000	30.50	0.0370	27	176	6	42	1
107	520	50	7	7	-5	0	67.000	32.50	0.0390	34	267	11	75	0
108	150	30	2	4	3	150	68.000	26.00	0.0350	45	282	11	49	1
109	320	40	5	5	-6	0	69.000	25.80	0.0280	38	187	7	70	0
110	200	20	5	5	-3	0	72.000	27.00	0.0260	26	227	9	62	0

Table B.3 Characteristics of 10 unit system [96]

Unit	$G_{\max}$	$G_{\min}$	MDT	MUT	IC	IP	a	b	c	s	d	t	SD	Status
1	455	150	8	8	8	0	1000.000	16.19	0.0005	4500	9000	5	0	1
2	455	150	8	8	8	0	970.000	17.26	0.0003	5000	10000	5	0	1
3	130	20	5	5	-5	0	700.000	16.60	0.0020	550	1100	4	0	0
4	130	20	5	5	-5	0	680.000	16.50	0.0021	560	1120	4	0	0

5	162	25	6	6	-6	0	450.000	19.70	0.0040	900	1800	4	0	0
6	80	20	3	3	-3	0	370.000	22.26	0.0071	170	340	2	0	0
7	85	25	3	3	-3	0	480.000	27.74	0.0008	260	520	2	0	0
8	55	10	1	1	-1	0	660.000	25.92	0.0041	30	60	0	0	0
9	55	10	1	1	-1	0	665.000	27.27	0.0022	30	60	0	0	0
10	55	10	1	1	-1	0	670.000	27.79	0.0017	30	60	0	0	0

Table B.4 Characteristics of 40 unit system [96]

Unit	$G_{\max}$	$G_{\min}$	MDT	MUT	IC	IP	a	b	c	s	d	t	SD	Status
1	455	150	8	8	8	0	1000.000	16.19	0.0005	4500	9000	5	0	1
2	455	150	8	8	8	0	970.000	17.26	0.0003	5000	10000	5	0	1
3	130	20	5	5	-5	0	700.000	16.60	0.0020	550	1100	4	0	0
4	130	20	5	5	-5	0	680.000	16.50	0.0021	560	1120	4	0	0
5	162	25	6	6	-6	0	450.000	19.70	0.0040	900	1800	4	0	0
6	80	20	3	3	-3	0	370.000	22.26	0.0071	170	340	2	0	0
7	85	25	3	3	-3	0	480.000	27.74	0.0008	260	520	2	0	0
8	55	10	1	1	-1	0	660.000	25.92	0.0041	30	60	0	0	0
9	55	10	1	1	-1	0	665.000	27.27	0.0022	30	60	0	0	0
10	55	10	1	1	-1	0	670.000	27.79	0.0017	30	60	0	0	0
11	455	150	8	8	8	0	1000.000	16.19	0.0005	4500	9000	5	0	1
12	455	150	8	8	8	0	970.000	17.26	0.0003	5000	10000	5	0	1
13	130	20	5	5	-5	0	700.000	16.60	0.0020	550	1100	4	0	0
14	130	20	5	5	-5	0	680.000	16.50	0.0021	560	1120	4	0	0
15	162	25	6	6	-6	0	450.000	19.70	0.0040	900	1800	4	0	0
16	80	20	3	3	-3	0	370.000	22.26	0.0071	170	340	2	0	0
17	85	25	3	3	-3	0	480.000	27.74	0.0008	260	520	2	0	0
18	55	10	1	1	-1	0	660.000	25.92	0.0041	30	60	0	0	0
19	55	10	1	1	-1	0	665.000	27.27	0.0022	30	60	0	0	0
20	55	10	1	1	-1	0	670.000	27.79	0.0017	30	60	0	0	0
21	455	150	8	8	8	0	1000.000	16.19	0.0005	4500	9000	5	0	1
22	455	150	8	8	8	0	970.000	17.26	0.0003	5000	10000	5	0	1
23	130	20	5	5	-5	0	700.000	16.60	0.0020	550	1100	4	0	0
24	130	20	5	5	-5	0	680.000	16.50	0.0021	560	1120	4	0	0
25	162	25	6	6	-6	0	450.000	19.70	0.0040	900	1800	4	0	0
26	80	20	3	3	-3	0	370.000	22.26	0.0071	170	340	2	0	0
27	85	25	3	3	-3	0	480.000	27.74	0.0008	260	520	2	0	0
28	55	10	1	1	-1	0	660.000	25.92	0.0041	30	60	0	0	0
29	55	10	1	1	-1	0	665.000	27.27	0.0022	30	60	0	0	0
30	55	10	1	1	-1	0	670.000	27.79	0.0017	30	60	0	0	0
31	455	150	8	8	8	0	1000.000	16.19	0.0005	4500	9000	5	0	1
32	455	150	8	8	8	0	970.000	17.26	0.0003	5000	10000	5	0	1
33	130	20	5	5	-5	0	700.000	16.60	0.0020	550	1100	4	0	0
34	130	20	5	5	-5	0	680.000	16.50	0.0021	560	1120	4	0	0
35	162	25	6	6	-6	0	450.000	19.70	0.0040	900	1800	4	0	0
36	80	20	3	3	-3	0	370.000	22.26	0.0071	170	340	2	0	0

Appendices

37	85	25	3	3	-3	0	480.000	27.74	0.0008	260	520	2	0	0
38	55	10	1	1	-1	0	660.000	25.92	0.0041	30	60	0	0	0
39	55	10	1	1	-1	0	665.000	27.27	0.0022	30	60	0	0	0
40	55	10	1	1	-1	0	670.000	27.79	0.0017	30	60	0	0	0

Table B.5 Price forecast for 24 hours

Periods	Price (\$/MWh) for 10 Unit System (Table B.1) [67]												
1-12	2.201	2.121	2.163	2.151	2.139	2.178	2.246	2.178	2.139	2.116	2.162	2.149	
13-24	2.124	2.110	2.099	2.073	2.048	2.008	1.950	1.925	1.899	1.990	2.060	2.498	
Periods	Price (\$/MWh) for 110 Unit System (Table B.2) [67]												
1-12	21.831	16.043	12.983	12.969	13.600	13.818	14.729	15.021	15.073	15.334	15.313	15.091	
13-24	14.673	14.431	16.107	16.534	14.808	15.491	16.101	20.215	22.949	16.055	15.857	15.201	
Periods	Price (\$/MWh) for 10 Unit System (Table B.3)												
1-12	17.412	17.443	17.505	20.018	17.502	20.178	20.576	20.974	20.735	23.228	26.234	27.417	
13-18	23.228	20.735	20.974	17.533	17.502	20.178	20.974	23.228	20.576	23.114	17.455	17.393	
Periods	Price (\$/MWh) for 40 Unit System (Table B.4)												
1-12	17.412	17.443	17.505	20.018	17.542	20.695	20.834	19.939	20.735	23.228	27.860	27.867	
13-18	27.799	20.685	19.939	17.452	17.421	17.483	19.939	27.828	22.869	22.563	17.536	17.474	

Table B.6 Load for 24 hours

Periods	Load (MWh) for 10 Unit System (Table B.1)											
1-12	1167	1097	1039	1028	1017	1051	1098	1051	1017	993	958	946
13-24	923	910	900	876	853	829	794	782	770	818	864	1167
Periods	Load (MWh) for 110 Unit System (Table B.2)											
1-12	11600	10900	9500	9300	10500	11200	12500	12900	13500	14500	14600	14000
13-24	13200	13000	14500	14600	14000	14700	15600	16200	16500	15000	14300	13500
Periods	Load (MWh) for 10 Unit System (Table B.3)]											
1-12	700	750	850	950	1000	1100	1150	1200	1300	1400	1450	1500
13-18	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800
Periods	Load (MWh) for 40 Unit System (Table B.4)											
1-12	2800	3000	3400	3800	4000	4400	4600	4800	5200	5600	5800	6000
13-18	5600	5200	4800	4200	4000	4400	4800	5600	5200	4400	3600	3200

Table B.7 Spinning reserve for 24 hours

Periods	Reserve (MWh) for 10 Unit System (Table B.1)											
1-12	350	329	329	300	300	300	300	300	300	300	280	280
13-24	280	270	270	260	260	260	240	240	240	240	260	350
Periods	Reserve (MWh) for 110 Unit System (Table B.2)											
1-12	700	700	700	700	700	700	700	700	700	700	700	700
13-24	700	700	700	700	700	700	700	700	700	700	700	700
Periods	Reserve (MWh) for 10 Unit System (Table B.3)											
1-12	70	75	85	95	100	110	115	120	130	140	145	150
13-18	140	130	120	105	100	110	120	140	130	110	90	80
Periods	Reserve (MWh) for 40 Unit System (Table B.4)											
1-12	280	300	340	380	400	440	460	480	520	560	580	600
13-18	560	520	480	420	400	440	480	560	520	440	360	320

APPENDIX C: Scheduling Results from Chapter 4

Table C.1 UC plan for 10 unit system [94] ('Scheduling of Individual Units')

PBUC-2	Time Periods (1-24 Hours)
Unit 1	1 1
Unit 2	1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0
Unit 3	1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0
Unit 4	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0
Unit 5	1 1
Unit 6	0 0
Unit 7	1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0
Unit 8	0 0
Unit 9	1 1
Unit 10	1 1

Table C.2 Self commitment schedule for 10 unit system [94] ('PBUC')

PBUC-1	Time Periods (1-24 Hours)
Unit 1	1 1
Unit 2	1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0
Unit 3	1 1 0
Unit 4	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0
Unit 5	1 1
Unit 6	0 1
Unit 7	1 1
Unit 8	0 0
Unit 9	1 1
Unit 10	1 1

Table C.3 Self commitment schedule for 10 unit system [96] ('PBUC')

PBUC-1	Time Periods (1-24 Hours)
Unit 1	1 1
Unit 2	1 1
Unit 3	0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0
Unit 4	0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0
Unit 5	0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0
Unit 6	0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0 0 0 0 1 1 1 1 0
Unit 7	0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0 0 0 0 1 1 1 0 0
Unit 8	0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 1 0 0 0 0
Unit 9	0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0
Unit 10	0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0

Table C.4 Self commitment for 110 unit system [94] ('Individual Units')

[illegible]

Table C.5 Self-commitment for 40 unit system [96] ('Individual Units')

PBUC-2	Time Periods (1-24 Hours)	PBUC-2	Time Periods (1-24 Hours)
Unit 1	1 1	Unit 21	1 1
Unit 2	1 1	Unit 22	1 1
Unit 3	0 0 0 1 0 0 0 0	Unit 23	0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0
Unit 4	0 0 1 0 0 0	Unit 24	0 0 0 1 0 0
Unit 5	0 0 0 0 1 0 0 0 0	Unit 25	0 0 0 0 1 0 0 0
Unit 6	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 0 0 0 0 0 1 1 1 0 0 0 0 0	Unit 26	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 0 0 0 0 0 0 1 1 1 0 0 0 0
Unit 7	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 0 0 0 0 0 0 1 1 1 0 0 0 0	Unit 27	0 0 0 0 0 0 0 0 0 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Unit 8	0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0	Unit 28	0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
Unit 9	0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0	Unit 29	0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
Unit 10	0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0	Unit 30	0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Unit 11	1 1	Unit 31	1 1
Unit 12	1 1	Unit 32	1 1
Unit 13	0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0	Unit 33	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0
Unit 14	0 0 0 1 0 0 0	Unit 34	0 0 0 1 0 0 0
Unit 15	0 0 0 0 1 0 0 0 0	Unit 35	0 0 0 0 1 0 0 0 0
Unit 16	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 0 0 0 0 0 0 1 1 1 0 0 0 0 0 0	Unit 36	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 0 0 0 0 0 0 1 1 1 0 0 0 0 0 0
Unit 17	0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	Unit 37	0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Unit 18	0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0	Unit 38	0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
Unit 19	0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0	Unit 39	0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Unit 20	0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	Unit 40	0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

APPENDIX D: Plant Data and Forecast for Chapter 5 and 6

Table D.1 Characteristics of two units [94]

Unit	Gmax	Gmin	MDT	MUT	IC	IP	a	b	c	s	d	t	SD	Status
1	185	54.3	4	5	5	185	143.735	11.694	0.007	160	160	6	0	1
2	140	30.0	3	3	-4	0	50.000	13.700	0.007	60	90	3	0	0

Table D.2 Price forecast [67] and standard deviations for 24 hours

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Forecast	21.831	16.043	12.983	12.969	13.600	13.818	14.729	15.021	15.073	15.334	15.313	15.091
Standard Dev 1	1.50	1.50	1.05	1.05	1.05	1.05	1.05	1.25	1.25	1.25	1.25	1.50
Standard Dev 2	2.50	2.50	2.00	2.00	2.00	2.00	2.00	2.50	2.50	2.50	2.50	2.50
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Forecast	14.673	14.431	16.107	16.534	14.808	15.491	16.101	20.215	22.949	16.055	15.857	15.201
Standard Dev 1	1.50	1.50	1.50	1.50	1.50	1.80	1.80	1.80	1.80	1.80	1.50	1.50
Standard Dev 2	2.50	2.50	2.50	2.50	2.50	3.00	3.00	3.00	3.00	3.00	2.50	2.50

APPENDIX E: Introduction to Utility Theory

The method is based on Daniel Bernoulli's (1738) expected utility hypothesis, which was axiomatized by John von Neumann and Oskar Morgenstern in their book "Theory of Games and Economic behavior" in 1944. The hypothesis challenged the old idea that people value random ventures according to its expected return in the following ways.

- Peoples utility to wealth $u(w)$ is not linearly related to wealth (w) but rather increases at a decreasing rate (diminishing marginal utility) i.e. $u'(w) > 0$ and $u''(w) < 0$.
- A person's valuation of a risky venture is not the expected return of that venture but rather the expected utility from that venture.

Risk Aversion:

The concept of risk aversion, which implies that when facing choices with comparable returns, individuals tend chose the less-risky alternative, can be explained with the help of Figure E.1 [106].

Let z be a random variable which can take on two values, $\{z_1, z_2\}$, and let p be the probability that z_1 happens and $(1-p)$ the probability that z_2 happens. The expected outcome, $E(z) = pz_1 + (1-p)z_2$, is depicted by a concave utility function and the expected utility $E(u) = pu(z_1) + (1-p)u(z_2)$ is shown by point E on the chord joining A and B in Figure E.1.

The comparisons between points D and E implies that the utility of expected income $u[E(z)]$ is greater than expected utility $E(u)$. This means that if one is to choose between a certain income z and a risky income with an expected value z , a risk averse person will choose the certain income because of the higher utility obtained. In the figure, $C(z)$ represents a "certainty-equivalent" allocation i.e. the utility of this allocation is equal to the expected utility of the random prospect or $u(C(z)) = E(u)$. Despite income $C(z)$ being less than the expected income, $E(z)$, an individual would be indifferent between receiving $C(z)$ with certainty and $E(z)$ with uncertainty. This difference, which

is denoted by $\Pi(z) = E(z) - C(z)$ is known as the risk-premium and can be defined as the maximum amount of income that an individual is willing to forego in order to obtain an allocation without risk.

Figure E.1 Risk aversion and certainty equivalence [106]

Let $C^u(z)$ denote the certainty-equivalent allocation. If the risk premium is represented as $\Pi^u(z) = E(z) - C^u(z)$, then, for a set of all random variables M , risk-aversion can be defined as [106]:

Risk-Aversion: An individual is "risk-averse" if $C^u(z) \leq E(z)$ or $\Pi^u(z) \geq 0$ for all $z \in M$.

But if an individual does not care about risk, receiving $E\{z\}$ with certainty or uncertainty should not matter. For such an individual, $u[E\{z\}] = E(u)$ and the utility function $u(z)$ becomes a straight line so that points D and E coincide.

Risk-Neutral: An individual is "risk-neutral" if $C''(z) = E(z)$ or $\Pi''(z) = 0$ for all $z \in M$.

This means that a risk neutral person only cares about the expected income. However, a risk-loving person would prefer receiving $E(z)$ with uncertainty rather than receiving it with certainty and hence $u(E(z)) < E(u)$. In such cases the utility function is convex with point E lying above point D. Thus,

Risk-Proclivity: an individual has "risk-proclivity" (or is "risk-loving" or "risk-seeking") if $C''(z) > E(z)$ or $\Pi''(z) < 0$ for all $z \in M$.

The determination of the utility function is subjective as it depends on the attitude of an individual towards accepting risk. Von Neumann-Morgenstern concept to find the individual utility function is based on identifying the most favorable and least favorable outcome. These limiting outcomes are taken as the reference for identifying the other possible outcomes. The utility function thus obtained is used to calculate the Risk Premium (RP) that shows the individual's attitude towards risk.

Some of the frequently used utility functions for income, W , are:

$$\triangleright u = W^\alpha \quad \forall \quad 0 < \alpha < 1 \quad (E.1)$$

$$\triangleright u = \ln W \quad (E.2)$$

$$\triangleright u = a + bW + cW^2 \quad \forall \quad W < -b/2c \quad (E.3)$$

$$\triangleright u = 1 - e^{-(\alpha W + \beta)} \quad (E.4)$$