A STOCHASTIC APPROACH FOR LOAD SCHEDULING OF COGENERATION PLANTS

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ABSTRACT

A STOCHASTIC APPROACH FOR LOAD SCHEDULING OF COGENERATION PLANTS

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In this thesis, load scheduling problem for cogeneration plants is interpreted in the context of stochastic programming. Cogeneration (CHP) is an important technology in energy supply of many countries. Cogeneration plants are designed and operated to cover the requested time varying demands in heat and power. Load scheduling of cogeneration plants represents a multidimensional optimization problem, where heat and electricity demands, operational parameters and associated costs exhibit uncertain behavior. Cogeneration plants are characterized by their 'heat to power ratio'. This ratio determines the operating conditions of the plant. However, this ratio may vary in order to adapt to the physical and economical changes in power and to the meteorological conditions. Employing reliable optimization models to enhance short term scheduling capabilities for cogeneration systems is an important research area.

The optimal load plan is targeted by achieving maximum revenue for cogeneration plants. Revenue is defined for the purpose of the study as the sales revenues minus total cost associated with the plant operation. The optimization problem, which aims to maximize the revenue, is modeled by thermodynamic analyses. In this context, the study introduces two objective functions: energy based optimization, exergy-costing based optimization. A new method of stochastic programming is developed. This method combines dynamic programming and genetic algorithm techniques in order to improve computational efficiency. Probability density function estimation method is introduced to determine probability density functions of heat demand and electricity price for each time interval in the planning horizon. A neural network model is developed for this purpose to obtain the probabilistic data for effective representation of the random variables. In this study, thermal design optimization for cogeneration plants is also investigated with particular focus on the heat storage volume.

Keywords: Stochastic analysis, load scheduling, cogeneration

ÖZ

KOJENERASYON SANTRALLERİNİN ÜRETİM PLANLAMASI İÇİN STOKASTİK BİR YAKLAŞIM

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Bu çalışmada kojenerasyon santrallerinin yük planlama problemi stokastik programlama çerçevesinde ele alındı. Birçok ülkede enerji arzında önemli bir teknoloji olan kojenerasyon santralleri tüketim davranışlarına göre zamana bağlı özellik gösteren ısı ve elektrik taleplerinin karşılanmasına yönelik olarak tasarlanır ve işletilirler. Kojenerasyon santrallerinin yük planlaması elektrik ve ısı taleplerinin, işletme parametrelerinin ve ilgili maliyetlerin belirsizlik taşıdığı çok boyutlu bir optimizasyon problemini teşkil etmektedir. Kojenerasyon santralleri ürettikleri ısının ürettikleri elektriğe oranı ile karakterize edilmektedirler. Bu oran santralin çalışma koşullarını belirler. Bununla birlikte bu oran enerji piyasalarındaki fiziksel ve ekonomik değişikliklere ve meteorolojik koşullara uyum sağlamak amacıyla değişebilir. Kojenerasyon sistemlerinin kısa vadeli işletim programını geliştirmek için güvenilir optimizasyon modellerinin detaylı olarak uygulanması önem arz etmektedir.

En iyi yük planı kojenerasyon santralleri için azami gelir üzerinden hedeflenmektedir. Bu çalışma kapsamında gelir tanımı satıştan kaynaklı gelirlerden santralin işletilmesine ilişkin maliyetlerin çıkarılması şeklinde yapılmıştır. Optimizasyon problemi termodinamik analizler ile modellenmiştir. Bu çalışmada enerji tabanlı optimizasyon ve ekserji-maliyeti tabanlı optimizasyon olarak iki amaç fonksiyonu tanımlanmıştır. Yeni bir stokastik programlama yöntemi geliştirilmiştir. Bu yöntem hesaplama verimliliğini iyileştirmek üzere dinamik programlama ve genetik algoritma tekniklerini birleştirmektedir. Her bir planlama aralığı için ısı talebi ve elektrik fiyatı olasılık dağılım fonkisyonlarını tahmin eden bir yöntem sunulmuştur. Modelde kullanılan tesadüfi değişkenlerin etkin olarak ifade edilmesi için kullanılacak olan probabilistik verinin elde edilmesi amacıyla bir yapay sinir ağları modeli geliştirilmiştir. Bu çalışmada, kojenerasyon santrallerinin ısıl tasarım optimizasyonu da ısı depolama hacmi odaklı olarak incelenmiştir.

Anahtar Kelimeler: Stokastik Analiz, yük planlaması, kojenerasyon

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LIST OF SYMBOLS

TES	Thermal Energy Storage
MYTM	Milli Yük Tevzi Merkezi
PMUM	Piyasa Mali Uzlaştırma Merkezi
MLP	Multilayer Perceptrons
R	Return Function
σ	Standard Deviation
μ	Mean Value
$\breve{D}$	Heat Demand
$\check{C}_P$	Electricity Market Price
$\widetilde{ss}$	System State
$c^{(ng)}$	Unit Cost of Natural Gas
$c^{(c)}$	Unit Cooling Cost of Excess Energy
$c^{(m)}$	Maintenance Cost

CHAPTER 1

INTRODUCTION

Load scheduling of cogeneration (combined heat and power, CHP) plants represents an optimization problem, where heat and electricity demands, operational parameters and associated costs are uncertain. In some cases, interaction of the plant with the electricity and heat markets poses additional optimization challenges.

1.1 The Load Scheduling for Cogeneration Plants

Cogeneration represents a series of proven, reliable and cost effective technologies. Cogeneration, as an important technology in energy supplies in many different countries, contributes in meeting global heat and electricity demands.

A typical cogeneration plant supplies heat to the district heating network and sells electricity to a power transmission company. It is designed and operated to cover the time varying heat and power demands. Cogeneration plants are basically characterized by their 'heat to power ratio' which determines the operating conditions of the plant. This ratio may vary in order to adapt to the physical and economical changes in power and to the meteorological conditions as well. Heat storage facilities are used to provide the 'heat to power ratio' variations.

Heat consumption of similar buildings under the same climatic conditions may show different values. Therefore, the heat demand estimated at the planning stage has a certain degree of uncertainty.

Electricity market prices also have uncertainties due to competitive market structure. In this thesis, load scheduling for cogeneration plants are considered for the case where heat demand and the revenue from selling electricity are uncertain.

It is vital to employ reliable optimization models and methods in detail in order to improve the operational performance of cogeneration systems. Previous work in load scheduling for cogeneration plants has largely focused on forecasts for the spot electricity prices and heat demands for planning horizon. In this thesis, load scheduling problem for a cogeneration plant is interpreted in the context of stochastic programming. Stochastic programming aims to determine an operational strategy that is feasible for all possible data instances and it maximizes the expectation of a function of the decision and the random variables.

A number of complications arise in stochastic programming approach in terms of complexity of the mathematical formulation as well as the computational time required. In this study, the method described by Gen [1997] is applied to load scheduling problem of a cogeneration plant. This method is based on genetic algorithms and Monte Carlo simulation of random variables. In this thesis, a new method of solution for the stochastic programming approach which combines dynamic programming and genetic algorithm methods in order to reduce the computational time is introduced.

In this study, the stochastic optimization is performed on the basis of exergy costing which appropriately combines thermodynamic evaluations based on exergy analysis with economic principles in addition to energy costing. This approach can also stand for a new theoretical basis for load scheduling problem of cogeneration plants.

Probability density estimation method to determine probability density functions of heat demand and electricity price for each time interval in the planning horizon is introduced. The approach presented is based on multilayer perceptrons concept, built on multilayer feed forward neural networks, to probability density function estimation from a set of samples.

1.2 Contributions of the Study

This thesis offers the following contributions:

- A stochastic optimization approach that takes the uncertainties in electricity price and heat demand into account is introduced to solve load scheduling problem for combined heat and power plants. This approach is further integrated with probability density estimation methods which are based on feed forward multilayer neural networks with sigmoid hidden units.
- Exergy costing is applied to stochastic optimization approach in addition to energy costing. This is a novel solution approach to load scheduling problem.
- Evolution algorithm is based entirely on the idea of genetic algorithms and is applied to solving the stochastic optimization problem. The generality of this solution technique allows for application to a wider variety of plant configurations. Traditional approaches perform local search by a convergent stepwise procedure. On the contrary, the solution technique proposed in this study is effective at performing global search. This represents another advantage of this solution technique over the traditional approaches.
- The solution method for the stochastic programming approach combines dynamic programming and genetic algorithm methods. This integrated approach reduces the computational time.
- General multilayer feed forward neural networks which have the probability density function approximation capabilities are applied to determine both the heat demand and electricity price probability density functions for each time interval in the planning horizon. Time series of electricity price data is used in

probability density function estimation for the electricity pool prices.

- Minimization of the negative log likelihood which is based on multilayer perceptrons is used for probability density function approximation. Training of multilayer perceptrons are performed by a genetic algorithm technique instead of traditional gradient descent methods, quasi Newton methods, and conjugate gradient methods. Since the dimension of problems is high, Monte Carlo method is employed to evaluate the network's integral.

1.3 Thesis Organization

In this thesis, load scheduling problem for a cogeneration plant is introduced. This includes the modeling of heat storage unit that allows the operator to deviate from characteristic heat to power ratio.

Relevant background information about stochastic programming, a framework for modeling optimization problems that involve uncertainty, is provided. Connections between load scheduling problem of a cogeneration plant and stochastic programming are structured.

Mathematical formulations for load scheduling problem based on energy and exergy costing are developed. The load scheduling problem is solved by applying stochastic programming techniques.

Probability density estimation approach is introduced to determine the probability density functions for both heat demand and electricity price.

The thesis is concluded by summarizing the findings and contributions. A number of new directions are also highlighted for future work.

CHAPTER 2

LOAD SCHEDULING OF COGENERATION PLANTS

In this chapter, background material about cogeneration is introduced. Load scheduling problem for cogeneration plants is defined and formulated as a new approach.

2.1 Overview of Cogeneration

Cogeneration (Combined Heat and Power - CHP) represents a series of proven, reliable and cost-effective technologies that are already making an important contribution to meeting global heat and electricity demand. Cogeneration plants contribute around 10 % of world electricity generation. Table 2.1 summarizes installed cogeneration capacities in the world (IEA [2008]). Cogeneration share in national power production of countries is demonstrated in Figure 2.1 (IEA [2009]). Cogeneration plants contributed to 4% of total electricity generation in Turkey in 2008.

Cogeneration is the simultaneous utilization of heat and power from a single fuel or energy source, at or close to the point of use. An optimal cogeneration system is designed to meet the heat demand of the energy user – whether at building, industry or city-wide levels – since it costs less to transport surplus electricity than surplus heat from a cogeneration plant. For this reason, cogeneration can be viewed primarily as a source of heat with electricity as a by-product.

Table 2.1 Installed CHP capacities (MWe)
(International Energy Agency [2009])

Australia	1864	Greece	240	Portugal	1080
Austria	3250	Hungary	2050	Romania	5250
Belgium	1890	India	10012	Russia	65100
Brazil	1316	Indonesia	1203	Singapore	1602
Bulgaria	1190	Ireland	110	Slovakia	5410
Canada	6765	Italy	5890	Spain	6045
China	28153	Japan	8723	Sweden	3490
Czech Republic	5200	Korea	4522	Taiwan	7378
Denmark	5690	Latvia	590	Turkey	790
Estonia	1600	Lithuania	1040	United Kingdom	5440
Finland	5830	Mexico	2838	United States	84707
France	6600	Netherlands	7160		
Germany	20840	Poland	8310		

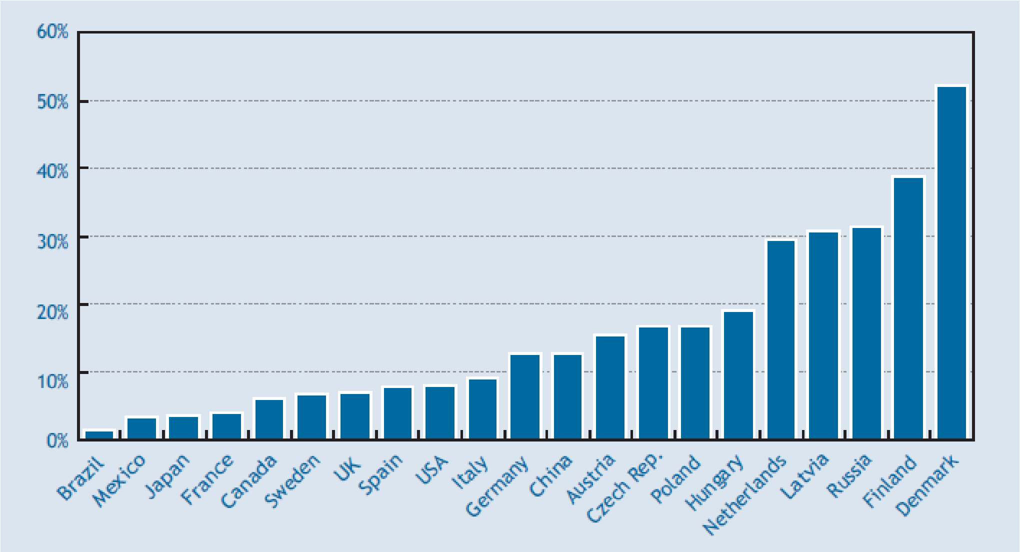


Figure 2.1 Share of cogeneration in total national electricity production
(International Energy Agency [2009])

Although cogeneration can take many forms and include a range of technologies, it is always based upon an efficient, integrated system that combines electricity production and a heat recovery system. By using the heat output from the electricity production for heating or industrial applications, cogeneration plants generally convert 75-80 % of the fuel source into useful energy, while the most of modern cogeneration plants reach efficiencies of 90% or more. Cogeneration plants also reduce network losses as they are located close to the end user (International Energy Agency [2008]).

Theoretically all types of fuels are suitable for cogeneration plants. Natural gas is the main fuel source at present. Other common fuel sources include fossil-fuel based commercial fuels, municipal solid waste and biomass. It is possible to gain considerable increase in the performance of a cogeneration unit by the use of gasified biofuel in the unit's fuel mix (Wu [2006]).

In electrical output terms, cogeneration plant size range from 1 kWe to over 500 MWe. The proportions of heat and power outputs vary according to the site specific characteristics as well major objectives of the operator.

The great majority of cogeneration applications can be grouped into three categories: industrial, commercial, and district heating and cooling. Cogeneration has a long history within the industrial sector, with concurrent heat and power demands, and in the district heating sector in countries with long heating seasons. However, advancements in technology development have led to the availability of smaller cogeneration systems, with reduced costs, reduced emissions and greater customization. As a result, cogeneration systems are increasingly used for smaller applications in the commercial and institutional sectors, and are being incorporated more often in district heating systems. For larger plants, the equipment is generally site specific while smaller-scale applications can use pre-packaged units.

Since cogeneration plants are usually sized to meet heat demand, any excess electricity can be sold back to the grid or supplied directly to another customer via a distribution system. Supplemental heat is typically provided by boilers.

2.2 Load Scheduling

Finding the optimal production schedule for the near future is generally known as the 'short-term planning' problem, the 'unit commitment and economic dispatch' problem or simply the 'unit commitment' problem. The short-term planning problem is often formulated as an optimization problem, where the objective is to minimize the operational costs over a planning horizon and under well defined constraints.

Lin [1998] developed an operation model composed of two objectives which are, meeting the customer's space heating requirements and maximizing the CHP plant profit. In the study it is presented that a CHP plant is used as a peak load regulating plant, to have a correlation between the CHP plant heat output and the space temperatures.

Larsen [1998] extended the Baleriaux–Booth method which is used traditionally for power only systems and permits the evaluation of loss of load probability and unexpected energy predicted as the indicators of total system adequacy. In traditional systems such as power only systems, the dimensioning problem of the system is analyzed by probabilistic production simulation. In the study probability distribution for power demand and capacity of power plant with forced outage rate are represented. As in the classical method of probabilistic production simulation, a multidimensional probability distribution represents the combined heat and power demand.

Tkahashi [1998] studied on the influence of demand prediction error on the efficiency of cogeneration plants in order to evaluate relative importance of various demand components such as annual energy demands, annual heat-to-electricity ratio and daily load factor. In the analysis the energy merit or the financial merit is used as the indication of efficiency of a cogeneration system. Efficiency of a cogeneration system which also depends on capacity or efficiency of the generator, software factor such as load variations or the control system, defined by an evaluation function whose variable is building energy demand vector. Energy demand factor is in terms of ith month and jth hour electricity demand and cooling, heating and hot water demands. The new building energy vector is defined by using a transformation function which permits to evaluate relative importance of energy demand components quantitatively. Transformation function is in terms of annual energy demand, annual heat-to-electricity ratio(ratio of annual heat demand to annual electricity demand), annual cooling and heating-to-hot water ratio (ratio of annual cooling and heating demand to hot-water demand), yearly load factor (ratio of monthly average demand to monthly peak-demand) and daily load factor (ratio of hourly average demand to hourly peak-demand). Demand prediction errors are implemented to the model and described by probability-density function. It is concluded that the analysis depends on many factors and that it is necessary to collect energy demand data at minimum cost and maximum efficiency.

Dotzauer [2001] showed that the problem statements related to the short-term scheduling of power can be formulated as interdependent unit commitment and economic dispatch problems. Deterministic and stochastic models applied to these problems were discussed in that study.

Nielsen [2001] aimed to generate a load schedule for a decentralized cogeneration plant. In case of expectations change such as cost of fuel varying by time, expected heat demand changes due to large changes in weather forecast, operator needs to make a decision to estimate the uncertainties. In that study however it is indicated that the stochastic nature or heat load and supply temperature predictions can be used and scheduling can be considered to be a stochastic problem which covers the correlation structure of the errors predicted. A set of time varying constraints and reference values are used as inputs to the distribution network in order to generate a plan for scheduling.

Gamou [2002] suggested a method for determining the unit size of cogeneration systems by using the energy demands as continuous random variables. Method proposed in the study includes equipment capacities and maximum contract utility demands embedded in the operational strategies of the systems for the purpose of minimizing the expected annual total cost while having satisfied energy demands. Decision variables and objective functions are considered to be piece-wise linear functions of energy demands in order to specify expected value, by applying a sensitivity analysis in linear programming and a enumeration method in mixed-integer programming. Formulated optimization problem is solved with the method of hierarchical optimization algorithm.

CHP plant design simplicity is directly depends on the variation of sales prices. Lund [2005] defined the methodology of determining optimal operations strategies and computer tool used for identifying optimal CHP plant designs. The methodology improved, uses different sales prices and it is resulted with different optimal solutions. It is also shown in the study that the optimal design depends not only on sales prices but also on fuel prices, taxes and financial costs. The study shows that input data must be identified according to actual conditions.

Handschin [2006] predicted that a powerful optimization technique is required in order to increase the economic efficiency of dispersed generation (DG). The study covers a mathematical model which includes different kinds of DG units and optimization techniques used to the solve problem with the existing uncertainties. The uncertainties such as power demand, power prices and in feed from renewable resources are enclosed in the presented model and provided the base for the development of optimization tool. The mathematical model mentioned in the study is based on stochastic programming extensions to mixed-integer linear programs.

Streckiene [2009] analyzed the optimal size of a CHP-plant with thermal store under German spot market conditions. It is explained that in Germany there are variations between the prices of electricity peak and off-peak hours by the European Energy Exchange (EEX). It is needed to shift production from off-peak to peak hours in order to improve the profit from CHP plant and installation of a big thermal store at a CHP-plant can provide the balance between production of electricity and heat to hours. The study covers many calculations to find the optimal ratio between CHP-unit and the thermal store and emphasizes the importance of having a thermal store which brings the flexibility of planning the schedule.

2.3 Heat Storage

Cogeneration plants are characterized by their 'heat to power ratio'. This ratio determines the operating conditions of the plant. However, this ratio may vary in order to adapt to the physical and economical changes in power and to the meteorological conditions. Cogeneration plants utilize heat storage facilities for providing flexibility in deviating from the fixed heat to power ratio.

Hasnain [1998] describes the development of thermal energy storage technologies and discusses the advantages and disadvantages of various thermal storage mediums. In the study thermal storage techniques are firstly grouped into two which are sensible heat storage and latent heat storage. Sensible heat storage is the technique that the storage medium temperature changes with the amount of energy stored. In the latent heat storage technique the stored energy can be used by phase change of the substance. Sensible heat storage is classified on the basis of heat storage media such as liquid media storage and solid media storage. Sensible heat storage is also grouped according to heat capacity, long term stability under thermal cycling, compatibility with its containment and the main classification factor is its cost. Latent heat storage is shown as an attractive technique which provides high energy storage density and has the advantage of smaller mass and volume requirements for the storage media.

Domanski [1998] analyzed a complete system of charging-discharging cycle of sensible heat for a thermal energy storage system and aimed to find the performance of the storage systems at the minimum total cost of owning, maintaining and operating the described system. The study was performed for different monetary values which are important to find the optimum number of heat transfer units, charging time, and second-law efficiency. Comparisons were done for the results based on exergy analysis. Thermo economic analysis was done and the influence of the rate for cost of irreversibility due to pressure drop to rate of cost due to temperature difference, ratio of cost rate of owning and maintaining the storage system to cost of irreversibility due to temperature difference, charging temperature, mass flow rate on the performance of storage unit at the minimum total price are determined.

Rosen [2001] investigated the importance of stratification in improving and optimizing thermal energy storage systems. The use of exergy analysis for rationally assessing of thermal energy storage systems is emphasized. Exergy content of a thermal energy storage increases with stratification, even if energy remains fixed.

Zubair [2002] studied on the thermo economical analysis of a sensible heat-storage system with Joulean heating in which the storage element is cooled by flowing steam of gases. The aim of the study is to minimize the total cost of owning and maintenance, in order to optimize the total cost. Systems with different charging and removal times and with different pressure ratios of the removal gas are examined in the study. In the analysis, irreversible loses caused by the finite-temperature difference heat transfer and pressure drop during the heat removal process are taken into consideration and unit cost values are kept as constraints.

Rolfsman [2004] studied the municipalities with district heating supplied via boilers and combined-heat-and-power (CHP) plants. It is shown that heat storage can be used to maximise the amount of electricity produced in the CHP plants during peak-price periods and for minimising the usage of plants with higher operational costs. Mixed integer linear-programming model is used in order to analyse the heat storage, both a hot-water accumulator at the CHP plant and storage in the building stock. The study showed that the storage potential both in the building stock and in the hot water accumulator are neccessary for the calculation which is made on a deterministic basis. It is also concluded that for more realistic situations, spot prices for electricity are evaluated by regression analysis model, a lower accumulated investment potential for storage is obtained through the limited ability to estimate the spot prices for electricity.

Khan [2004] evaluated and presented the economical and technical feasibility of cogeneration with double-effect absorption chiller. In that study first of all, the electrical and cooling load demands are studied in a detailed manner for an institutional building. The analysis of cash-flow including, internal rate of return (IRR), net present value (NPV) and the net profit is performed. Cogeneration coupling with thermal energy store is compared with the sole cogeneration systems and the advantages of thermal energy storage such as technical and economical feasibilities are discussed. In order to compare the advantages and the disadvantages of cogeneration systems and cogeneration systems with thermal energy store (TES), revenues from two sources, one from power generation and the other from the produced cooling effect are taken into account and economic evaluation of cogeneration systems is performed by computation of investment, operation and maintenance costs. After comparing the advantages of the two systems, it is recommended to combine the cogeneration systems with thermal energy store (TES).

Kostowski [2005] studied on the improvement of energy performance and economic feasibility of a CHP plant with a hot water storage tank. Energy balance for the system composed of a peak boiler and the heat storage unit is done in order to define the storage efficiency. A numerical model is developed for the heat transfer model in the storage tank and its effects on energy balance are discussed. It is claimed that using water storage tanks as heat accumulators in the CHP plants result in reduction of the energy consumption in the systems. It is suggested that three parameters, namely the CHP electric output, the power of the peak boiler and the volume of the storage tank, shall be considered while optimizing the system, where the main constraint refers to the cost of investment.

Barelli[2006] analysed the benefits for the realization of the district heating, combined to a cogeneration unit fed by natural gas in terms of energetic and enviromental savings. It is aimed to create a model which permits to determine hourly trend of the thermal load of all of the users, for each day of the heating season. By knowing only few parameters such as power installed in the thermal plant, the seasonal operation hours, the timetable of the heating service distribution and the external temperature trend, a simulation model for daily trend of the thermal load is proposed. The model allows to evaluate the size of the plant which satisfies the thermal load demand.

Bogdan [2006] used the ACOM (Advanced Cogeneration Optimization Model) for the purpose of determining the influence of the district heat accumulator on the Elektrana-Toplana (EL-TO) Zagreb cogeneration plant economic performance. In the study, it is shown that charging accumulator when the electricity price is high and releasing heat during night hours when the electricity prices are relatively low brings economic benefits. The calculations for investigation of heat accumulator impact on the mentioned plant are done with ACOM. The mathematical model built as the combination of mathematical models of its components and each model for each component is solved with its own boundary conditions and other input data.

Streckiene [2009] analyzed the relation between cogeneration size and thermal storage capacity under spot market conditions. They concluded that cogeneration plants with thermal storage gain flexibility and can achieve improved economic results.

2.4 Electricity Market Structure and Architecture

Market structure defines market players and their competition positions, while market architecture defines how market players interact with each other. The reform of the electric power industry breaks the vertically integrated utilities into horizontally independent entities. The independent entities are the buyers, sellers, and coordinators of electricity market. Gül [2007] reviewed the reform of Turkey's electricity market structure. Until 1993, generation, transmission and distribution of electricity were provided by Turkish Electric Authority (TEK). In September 1993, TEK was divided into two public companies: TEAŞ (generation and transmission) and TEDAŞ (distribution). The share of TEAŞ generation in total fell to less than 80% in 1999 from more than 90% in 1995. Transmission and wholesale trade of electricity remained under TEAŞ control. TEAŞ was further divided into generation (EÜAŞ), transmission (TEİAŞ), and wholesale trade (TETAŞ) companies in 2001 by the enactment of the Electricity Market Law (EML). EML aims to create a competitive, transparent and commercially viable electricity market providing sufficient, reliable and affordable electricity to consumers (Energy Market Regulatory Authority [2009]).

Turkish electricity market is based on bilateral contracts in principle, which is complemented by a balancing mechanism (Güray [2006]). National Load Dispatch Center ("Milli Yük Tevzi Merkezi" - MYTM) is the system operator and the Balancing and Settlement Center ("Piyasa Mali Uzlaştırma Merkezi" - PMUM) is the market operator in Turkish electricity market architecture. Both MYTM and PMUM are organized under the Transmission Company (TEİAŞ). PMUM conducts day-ahead physical balancing and financial settlement of the bilateral contracts whereas real time balancing is taken over by the MYTM.

In general, for a competitive market, market operation includes operation of a day-ahead market and settlement of transactions. These provide scheduling and balancing services, but operating these markets is itself an entirely separate service. PMUM operates both of these markets in Turkey.

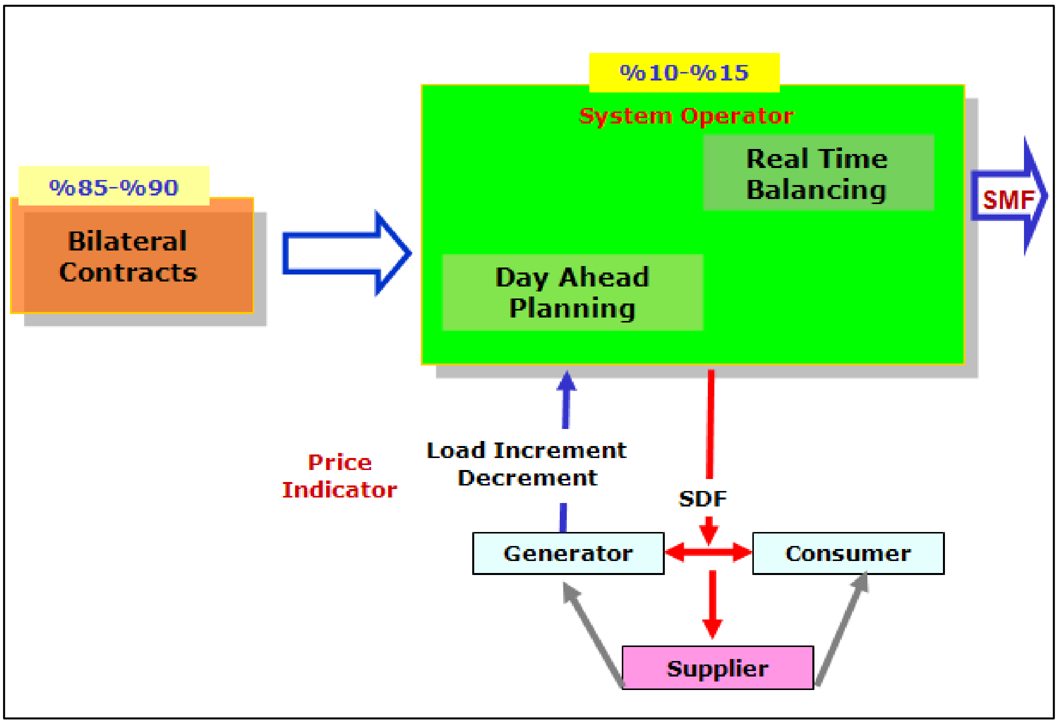


Figure 2.2 Market architecture of electricity markets in Turkey

A market's architecture is a map of its component submarkets. This map includes the type of each market and the linkages between them. The submarkets of a power market include the wholesale spot market, wholesale forward markets, and markets for ancillary services. Figure 2.2 illustrates the market architecture of electricity markets in Turkey.

Trading for the power delivered in any particular minute begins years in advance and continues until real time. Forward trading stops about one day prior to real time. At this point, system operator holds its day-ahead market. This is followed by a real time market also conducted by the system operator. All of these markets except the real time market are classified as forward markets. A forward contract is traded at least 1 day prior to the operating day, which includes 24h markets. Real time markets are used to reschedule and reduce the forecast errors. Figure 2.3 illustrates the market architecture applied in Turkey from time perspective.

The day-ahead market can utilize one of three basic architectures or a combination. Bilateral markets, exchanges and pools can each provide hedging and unit commitment (Stoft [2002]). Market balancing activities are illustrated in Figures 2.3-2.8. These activities are

- Finding demand to be met by dispatching units.
- Determining the hourly load increment or decrement requirement of the system.
- Finding the system marginal price by accepting the load increment or decrement bids.

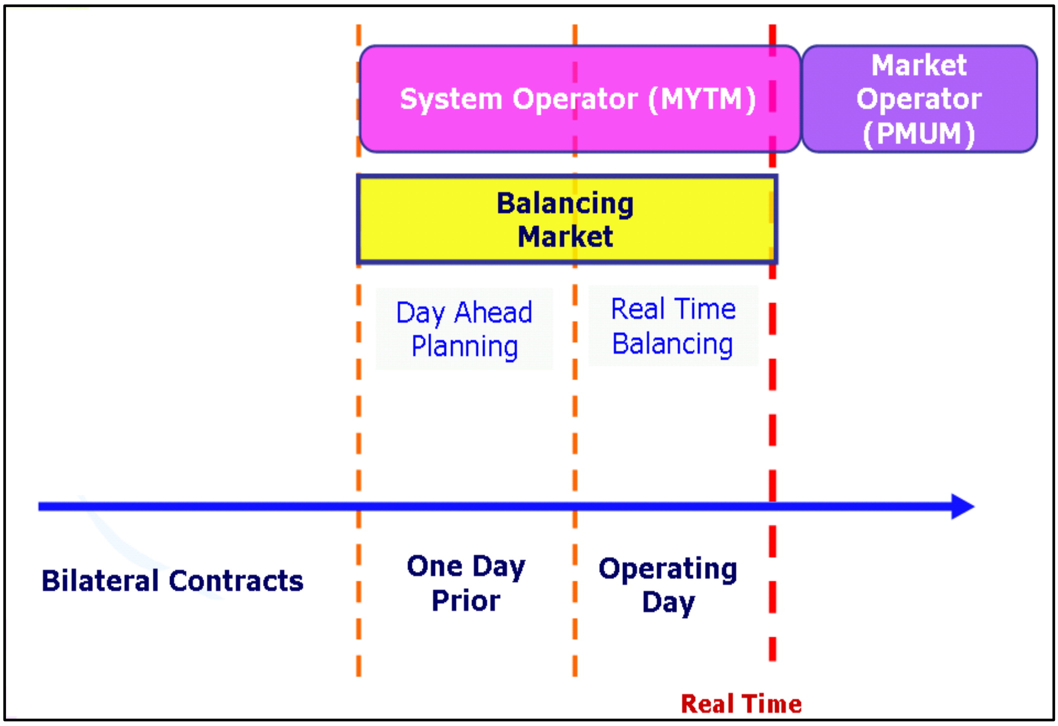


Figure 2.3 Market architecture from time perspective

Demands and bids are submitted to PMUM by the participants on a day ahead basis. Demands and bids are determined by the participants according to their consumption or generation projections. The mechanism is explained in the "Electricity Market Balancing and Settlement Regulation" published by the Energy Market Regulatory Authority (Energy Market Regulatory Authority [2009]).

First rule of the exchange approach is to make no side payments. To prevent oversupply, some of dispatching units need to reduce power. This might be done by accepting a decremental bid.

The principle of the mechanism is explained below which is based on an example concerning the demands, bids, balancing rules and other details.

Electricity generation companies participating in the electricity market are named as dispatching units. These units submit bids to PMUM for both load increment (sale) and load decrement (purchase) of hourly contracts including production projections for the following day. PMUM collects all projections for demand and generation and balances them on hourly basis. Figure 2.4 illustrates total electricity production and demand data on hourly basis for a day selected to demonstrate the balancing mechanism. As can be seen from the figure, demand and supply do not match on hourly basis. Two different hours of the day is chosen to illustrate the working of the balancing mechanism.

Figures 2.5 and 2.6 present balancing process for the hour 11:00-12:00 in which the electricity demand is 2000 MW higher than electricity production. Therefore, the system operator accepts load increment bids to cover the gap between the demand and supply. The load increment bids are accepted in ascending order until the electricity requirement is satisfied. As a result of this process, the system market price of electricity, which is 160.58 TL/MWh for this sample case, is determined. The participants whose bids are accepted are paid by the system operator at system market price.

Figures 2.7 and 2.8 present balancing process for the hour 05:00-06:00 where the electricity production is 1000 MW higher than electricity demand. Therefore, the system operator accepts load decrement bids to remove the electricity oversupply. The load decrement bids are accepted in descending order until the necessary electricity energy decrease for ensuring supply and demand balance is satisfied. As a result of this process, the system market price of electricity, which is 39.21 TL/MWh for this sample, is determined. In this example case; it would be an offer by dispatching unit to pay system operator 39.21 TL/MWh to allow the dispatching unit to reduce its output while still being paid according to all prior contracts as if it were producing its entire contracted output. If the bilateral contract price were 42.00 TL/MWh and the system operator bought the electricity at 39.21 TL/MWh, the dispatching unit would be paid 42.00 TL/MWh and would in turn pay the system operator at 39.21 TL/MWh.

The Figures 2.4-2.8 are modified illustrations built upon the graphs used by Terzi [2005].

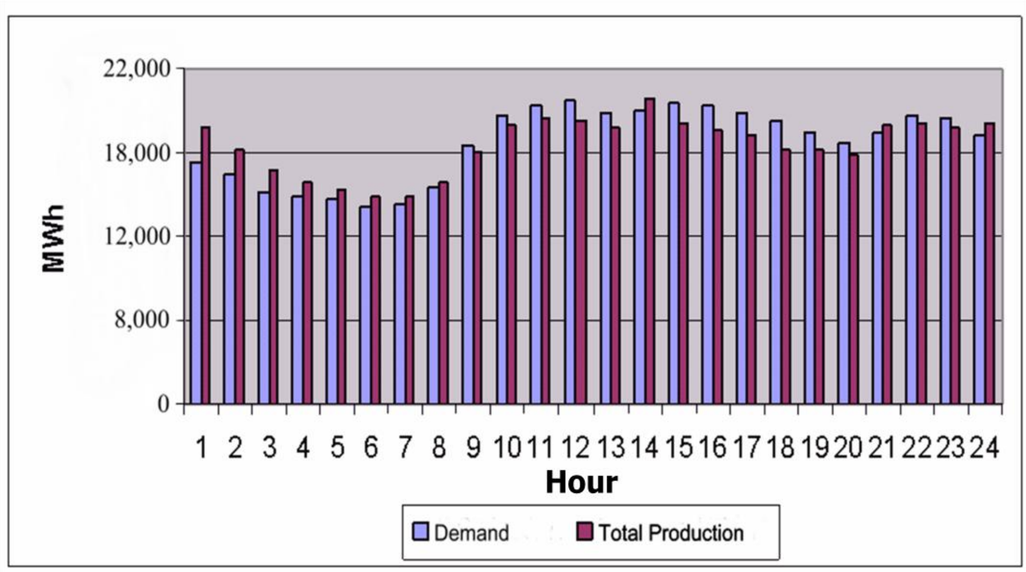


Figure 2.4 Load requirement of system

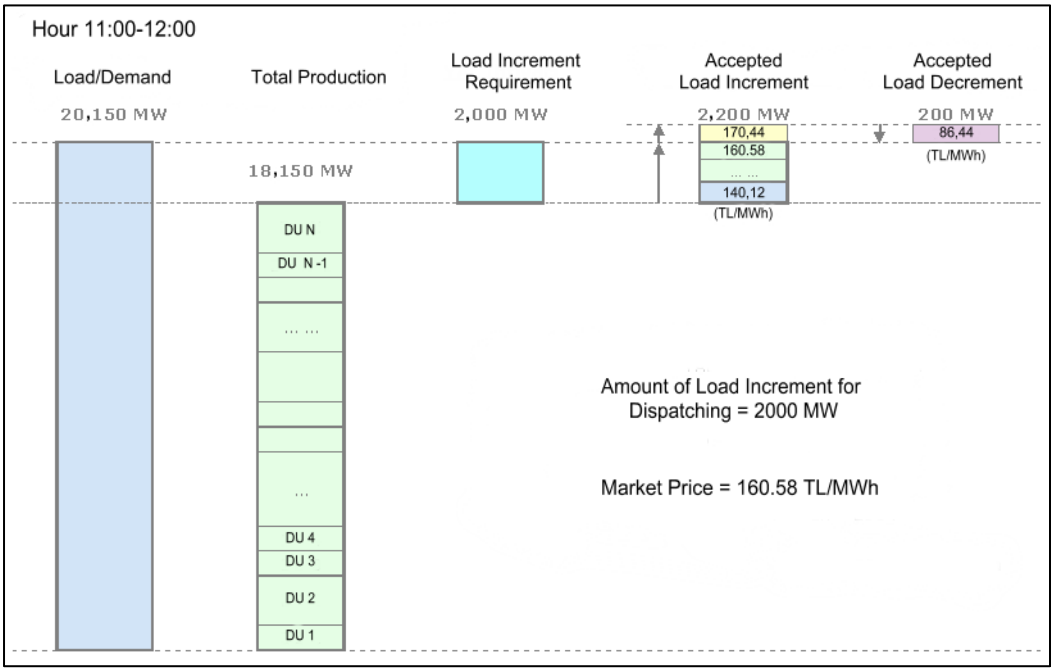


Figure 2.5 System marginal price calculation for load increment case

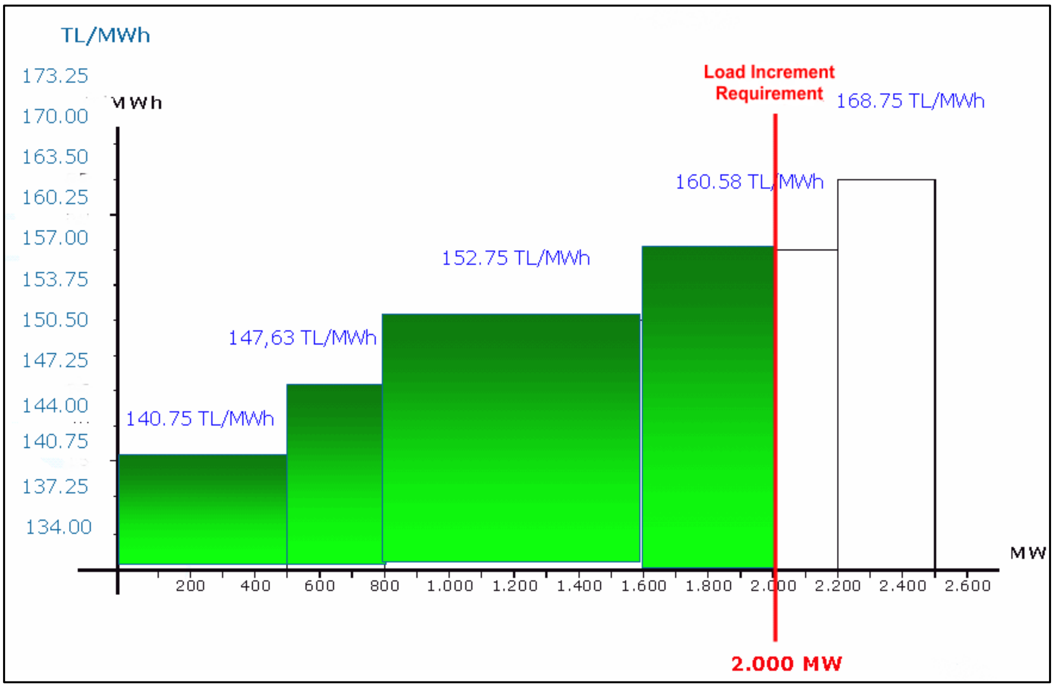


Figure 2.6 Accepting load increment bids by system operator

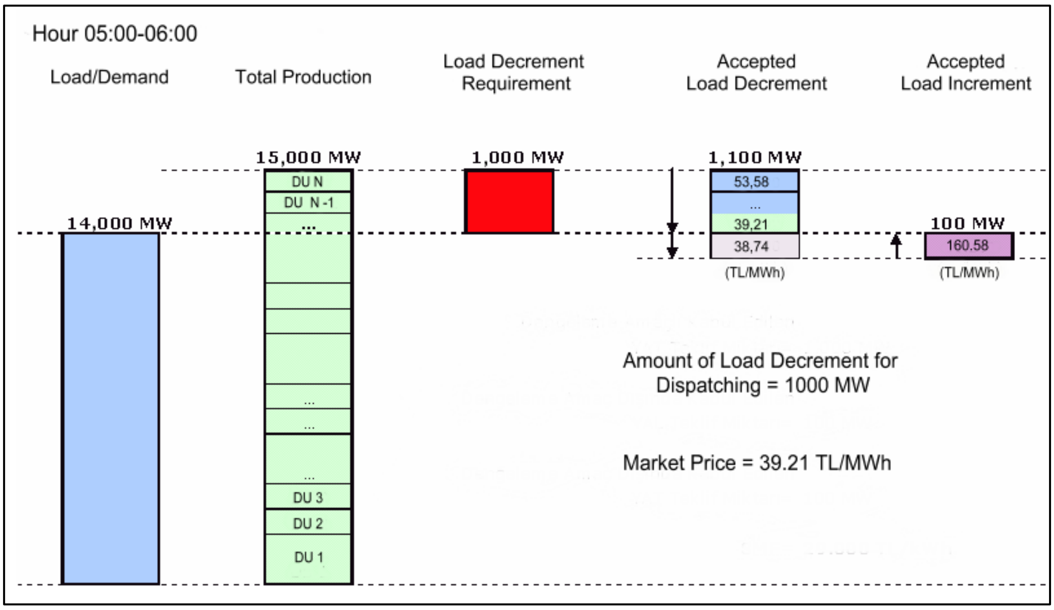


Figure 2.7 System marginal price calculation for load decrement case

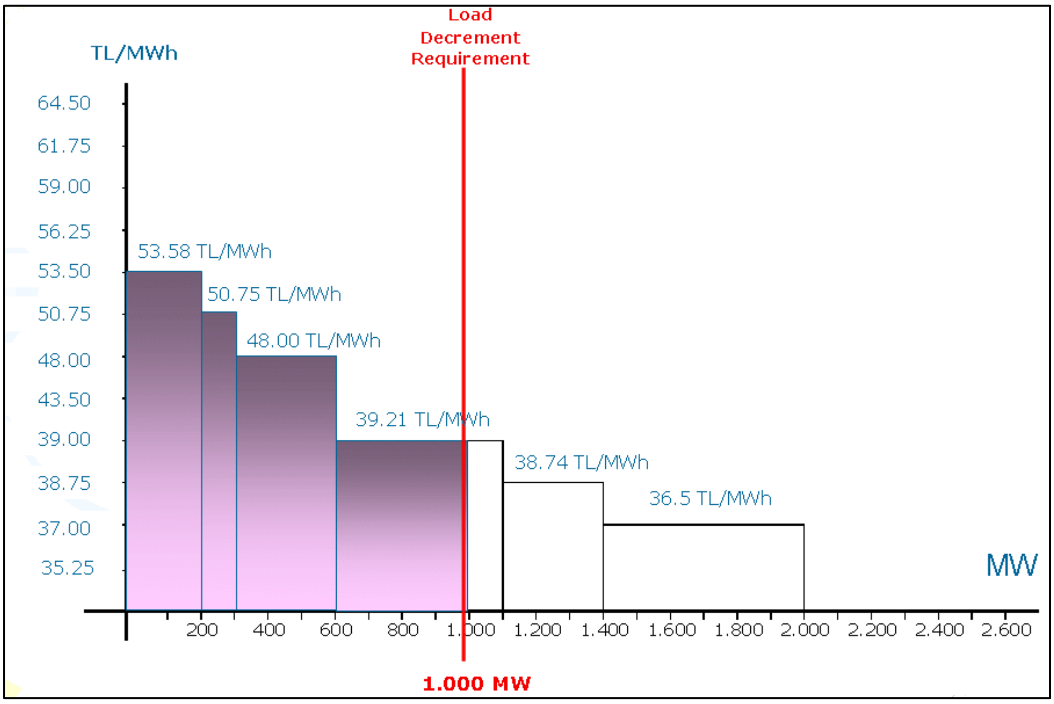


Figure 2.8 Accepting load decrement bids by system operator

CHAPTER 3

STOCHASTIC OPTIMIZATION

Heat demand and the revenue from selling electricity are parameters of load scheduling problem for a cogeneration plant; their true values may not become known at planning. Stochastic optimization is an approach for treating this type of problems involving uncertainty. In this chapter, stochastic optimization as a mathematical application tool to formulate uncertainty is introduced. Basic concepts in probability and random variables are described as they are necessary for understanding the techniques of stochastic optimization. An overview of Monte Carlo methods is also given. "Evaluation program" for stochastic optimization problems which is proposed by Gen [1997] is described and a new method which combines principles of genetic algorithms and stochastic dynamic programming is introduced.

3.1 Stochastic Programming

Stochastic optimization deals with optimization problems which contain random parameters; that is, true values of these parameters are affected by random events. Deterministic approaches to this type of problems are very misleading (Kall [1994]). Stochastic programming is an approach for mathematical programming under uncertainty. The definition of stochastic programming problem is given by Gen [1997] as follows:

$$\max E\left[f\left(\vec{x},\vec{\xi}\right)\right] \tag{3.1}$$

$$st. E\left[g_i\left(\vec{x},\vec{\xi}\right)\right] \leq 0 \qquad i = 1,2,..,m_1 \tag{3.2}$$

$$E\left[h_i\left(\vec{x},\vec{\xi}\right)\right] = 0 \qquad i = m_1 + 1,..,m(= m_1 + m_2) \tag{3.3}$$

where E denotes the expected operators, $\vec{x} = [x_1, x_2, \ldots, x_n]$ is an n-dimensional real vector, $\vec{\xi} = [\xi_1, \xi_2, \ldots, \xi_n]$ is an l-dimensional stochastic vector, and f, g_i, h_i are real-valued functions. The function f is the objective function. The functions g_i, h_i denote inequality and equality constraint functions respectively. Expected value of functions f, g_i, h_i can be expressed in terms of the distribution and density functions of stochastic vector $\vec{\xi}$, which are $\Phi(\vec{\xi})$ and $\phi(\vec{\xi})$ respectively (Gen [1997]).

$$E\left[f\left(\vec{x},\vec{\xi}\right)\right] = \int_{R^m} f\left(\vec{x},\vec{\xi}\right) d\Phi\left(\vec{\xi}\right) = \int_{R^m} f\left(\vec{x},\vec{\xi}\right) \phi\left(\vec{\xi}\right) d\vec{\xi} \tag{3.4}$$

$$E\left[g_i\left(\vec{x},\vec{\xi}\right)\right] = \int_{R^m} g_i\left(\vec{x},\vec{\xi}\right) d\Phi\left(\vec{\xi}\right) = \int_{R^m} g_i\left(\vec{x},\vec{\xi}\right) \phi\left(\vec{\xi}\right) d\vec{\xi} \quad i = 1,2,..,m_1 \tag{3.5}$$

$$E\left[h_i\left(\vec{x},\vec{\xi}\right)\right] = \int_{R^m} h_i\left(\vec{x},\vec{\xi}\right) d\Phi\left(\vec{\xi}\right) = \int_{R^m} h_i\left(\vec{x},\vec{\xi}\right) \phi\left(\vec{\xi}\right) d\vec{\xi} \quad i = m_{1+1},..,m \tag{3.6}$$

For the remainder of this thesis, stochastic programming constitutes the basis for the solution approach to load scheduling problem of cogeneration plants. A review of the basic concepts of probability theory and Monte Carlo simulation that is used to evaluate the multivariate integrations in Equation (3.4), Equation (3.5), and Equation (3.6) will be described in Section 3.2 and Section 3.3 respectively.

3.2 Probability and Random Variables

The main goal of this section is to review some basic concepts of probability theory and random variables, to define the notation and terminology that will be used.

The probability is a way of expressing likelihood of an event. An event represents the outcome of a single experiment which denotes the act of performing something the outcome of which is subject to uncertainty and is not known exactly (Rao [1996]). If E denotes an event, the probability of occurrence of the event E is given by Rao [1996] as follows:

$$P(E) = \lim_{n\to\infty} \frac{m}{n} \tag{3.7}$$

where m is the number of successful occurrences of the event E and n is the total number of trials. Axioms of probability for the sample space S of all possible events are given by Soong [2004] as follows:

- Axiom 1: $P(E) \geq 0$ (nonnegative).
- Axiom 2: $P(S) = 1$ (normed).
- Axiom 3: for a countable collection of events E_1, E_2…in S.

$$P(E_1 \cup E_2 \cup \dots) = P\left(\sum_j E_j\right) = \sum_j P(E_j) \tag{3.8}$$

If the occurrence or nonoccurrence of an event E_1 in no way affects the probability of occurrence or nonoccurrence of another event E_2, the events E_1 and E_2 are said to be statistically independent. In this case the probability of simultaneous occurrence of both the events is given by

$$P(E_1E_2) = P(E_1)P(E_2) \tag{3.9}$$

"The point function $X(s)$ is called a **random variable** if (a) it is a finite real-valued function defined on the sample S of a random experiment for which the probability is defined, and (b) for every real number x, the set $\{s: X(s) \leq x\}$ is an event. The relation $X = X(s)$ takes ever element s in S of the probability space onto a point X on the real line $R^1 = (-\infty, \infty)$ Soong [2004]." The second condition in this definition is 'measurability condition'. The random variable is called discrete random variable, if the random variable is allowed to take only discrete values. However, if the sample space has an unaccountably infinite number of sample points, the associated random variable is called a continuous random variable Soong [2004].

The behavior of a random variable is characterized by its probability distribution. A probability distribution function or a probability mass function is required to specify a discrete random variable. The corresponding functions for a continuous random variable are the probability distribution function and the probability density function.

The probability that the value of the random variable X is less than or equal to some number x is defined as the **probability distribution function**, or cumulative distribution function.

$$F_X(x) = P(X \leq x) \tag{3.10}$$

The **probability mass function** for discrete random variables, denoted as $p_X(x)$, or simply as $p(x)$, gives the probability of realizing the random variable $X = x_i$. Therefore,

$$p(x_i) = p_X(x_i) = P(X = x_i) \tag{3.11}$$

The probability distribution function and the probability mass function are related by:

$$p_X(x_i) = F_X(x_i) - F_X(x_{i-1}) \tag{3.12}$$

$$F_X(x) = \sum_{i=1}^{i:x_i \leq x} p_x(x_i) \tag{3.13}$$

These relations denote that each function can be obtained from the other. The probability density function of a continuous random variable is as follows:

$$f_x(x)\, dx = P(x \leq X \leq x + dx) \tag{3.14}$$

Equation (3.14) defines the probability of occurrence in the infinitesimal interval $(x,\ x + dx)$. By combining Equation (3.10) and Equation (3.11), the probability distribution function for continuous random variable can be obtained.

$$F_X(x) = \int_{-\infty}^{x} f_X(z)\,dz \tag{3.15}$$

A typical probability density function and the corresponding distribution functions are illustrated in Figure 3.1. The probability density function does not exist for a discrete random variable, since its associated probability distribution function is not differentiable at discrete jumps.

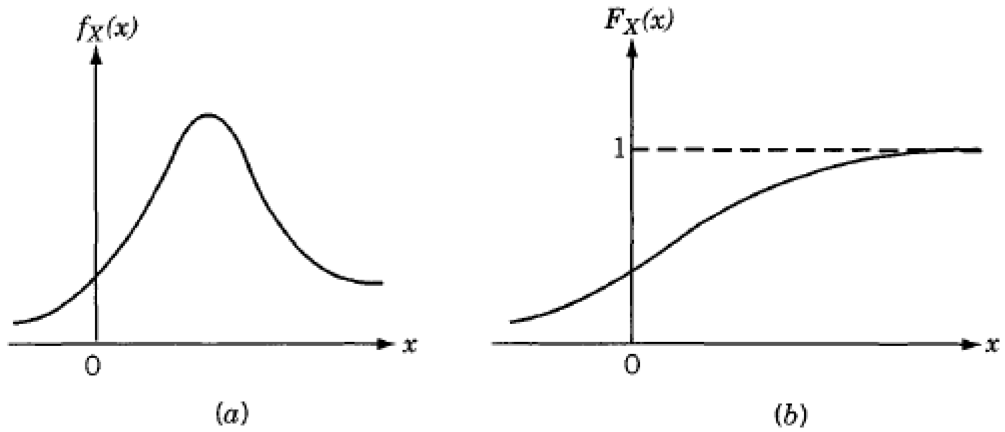


Figure 3.1 Probability density and distribution functions of a continuous variable X: (a) density function; (b) distribution function

Expected value is used to describe the central tendency of a random variable. Equation (3.16) and Equation (3.17) give mean values of discrete and continuous random variables respectively.

$$\bar{X} = E(X) = \sum_{k=1} x_k f_k\,(x_k) \tag{3.16}$$

$$\bar{X} = \mu_k = E(X) = \int_{-\infty}^{\infty} x\, f_X(x)\,dx \tag{3.17}$$

Standard deviation is a measure of the variability of a random variable. The mean square deviation or variance of a random variable *X* is defined as

$$\sigma_X{}^2 = Var(X) = E[(X-\mu_X)^2]$$
$$= E[X^2 - 2X\mu_X + \mu_X{}^2]$$
$$= E(X^2) - 2\mu_X E(X) + E(\mu_X{}^2)$$
$$= E(X^2) - \mu_X{}^2 \tag{3.18}$$

Therefore the standard deviation is as follows:

$$\sigma_X = \sqrt{Var(X)} = \sqrt{E(X^2) - \mu_X{}^2} \tag{3.19}$$

If X is a random variable, any other random variable Y defined as a function of X will also be a random variable. If $f_X(x)$ and $F_X(x)$ denote, respectively, the probability density and distribution function of X, the problem is to find the density function $f_Y(y)$ and the distribution function $F_Y(y)$ of the random variable Y. Let the functional relation be

$$Y = g(X) \tag{3.20}$$

By definition, the distribution function of Y is the probability of realizing Y less than or equal to y:

$$F_Y(y) = P(Y \le y) = P(g \le y)$$
$$= \int_{g(x)\le y} f_X(x)\,dx \tag{3.21}$$

The probability density function of Y is given by

$$f_Y(y) = \frac{\partial}{\partial y}[F_Y(y)] \tag{3.22}$$

If $Y = g(X)$, the mean and variance of Y are defined, respectively, by

$$E(Y) = \int_{-\infty}^{\infty} g(x) f_X(x)\,dx$$

$$Var[Y] = \int_{-\infty}^{\infty} [g(x) - E(Y)]^2 \, f_X(x) \, dx \qquad (3.23)$$

Joint probability functions determine joint behavior of two or more random variables which are being considered simultaneously. If a distribution involves more than one random variable, it is called a multivariate distribution. Joint density function of *n* continuous random variables is as follows:

$$f_{X_1 \dots X_n}(x_1, \dots x_n) \, dx_1 \dots dx_n = P \begin{pmatrix} x_1 \le X_1 \le x_1 + dx_1, \\ x_2 \le X_2 \le x_2 + dx_2, \\ \dots, \\ x_n \le X_n \le x_n + dx_n \end{pmatrix} \qquad (3.24)$$

If the random variables are independent, the joint density function is given by the product of individual or marginal density functions as

$$f_{X_1 \dots X_n}(x_1, \dots x_n) \, dx_1 \dots dx_n = f_{X_1}(x_1) \dots f_{X_n}(x_n) \qquad (3.25)$$

The joint distribution function is given by

$$\begin{aligned} F_{X_1 \dots X_n}(x_1, \dots x_n) \, dx_1 \dots dx_n \\ &= P[X_1 \le x_1, \dots, X_n \le x_n] \\ &= \int_{-\infty}^{x_1} \dots \int_{-\infty}^{x_n} f_{X_1 \dots X_n}(x_1', \dots x_n') \, dx_1' \dots dx_n' \qquad (3.26) \end{aligned}$$

If $X_1, X_2, \dots, X_n$ are independent random variables, the joint distribution function is as follows:

$$F_{X_1 \dots X_n}(x_1, \dots x_n) \, dx_1 \dots dx_n = F_{X_1}(x_1) \dots F_{X_n}(x_n) \qquad (3.27)$$

It can be seen that the joint density function can be obtained by

differentiating the joint distribution function as

$$f_{X_1 \dots X_n}(x_1, \dots x_n) \, dx_1 \dots dx_n = \frac{\partial^n}{\partial x_1 \partial x_2 \cdots \partial x_n} F_{X_1}(x_1) \dots F_{X_n}(x_n) \qquad (3.28)$$

If Y is a function of several random variables $X_1, X_2, \ldots, X_n$, the distribution and density functions of Y can be found in terms of the joint density function of $X_1, X_2, \ldots, X_n$ as follows:

Let

$$Y = g(X_1, X_2, \cdots X_2) \tag{3.29}$$

Then the joint distribution function $F_Y(y)$, by definition is given by

$$F_Y(y) = P(Y \leq y)$$

$$= \int_{x_1} \int_{x_2} \cdots \int_{x_n} f_{X_1 \ldots X_n}(x_1, \ldots x_n)\, dx_1 \ldots dx_n \tag{3.30}$$

where the integration is to be done over the domain of the *n*-dimensional $(X_1, X_2, \ldots, X_n)$ space in which the inequality $g(x_1, x_{2,} \cdots x_n) \leq y$ is satisfied.

There are several types of probability distributions for describing various types of discrete and continuous random variables. Some of the common discrete probability distributions are discrete uniform distribution, binomial, geometric, multinomial, Poisson, hypergeometric, negative binomial and some of the common continuous probability distributions are uniform distribution, normal (Gaussian), gamma, exponential, beta, Rayleigh, Weibull. In any physical problem, one chooses a particular type of probability distribution depending on the nature of the problem, the underlying assumptions associated with the distributions, the shape of the graph between $f(x)$ or $F(x)$ and x obtained after plotting the available data, and the convenience and simplicity afforded by the distribution.

The central limit theorem describes a very general class of random phenomena for which distributions can be approximated by the normal distribution. In words, when the randomness in a physical phenomenon is the cumulation of many small additive random effects, it tends to a normal distribution irrespective of the distributions of individual effects. The central limit theorem can be stated as follows:

Let $X_1, X_2, \dots, X_n$ are *n* mutually independent random variables with finite mean and variance, the sum

$$S_n = \sum_{i=1}^{n} X_i \tag{3.31}$$

tends to a normal variable if no single variable contributes significantly to the sum as *n* tends to infinity.

Normal (Gaussian) distribution is the best known and most widely used probability distribution which has a probability density function given by

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma_X} e^{-1/2[(x-\mu x)/\sigma x]^2}, \qquad -\infty < x < \infty \tag{3.32}$$

where μ_X and σ_X are the mean and standard deviation of *X* respectively. About 68.3%, 95.5%, and 99.7% of the values are located, respectively, in the ranges $\mu_X \pm \sigma_X$, $\mu_X \pm 2\sigma_X$, $\mu_X \pm 3\sigma_X$. This is called as the 3-sigma rule. A normal distribution with parameters $\mu_X = 0$ and $\sigma_X = 1$ is called the standard normal distribution. The joint normal density function for n-independent random variables $X_1, X_2, \dots, X_n$ is given by

$$f_{X_1 \dots X_n}(x_1, \dots x_n) = \frac{1}{\sqrt{(2\pi)^n}\sigma_1\sigma_2 \dots \sigma_n} exp\left[-\frac{1}{2}\sum_{k=1}^{n}\left(\frac{x_k - \bar{X}_k}{\sigma_k}\right)^2\right]$$

$$= f_{X_1}(x_1) f_{X_2}(x_2) \cdots f_{X_n}(x_n) \tag{3.33}$$

where $\sigma_i = \sigma_{X_i}$. If the correlation between the random variables X_k and X_j is not zero, the joint density function is given by

$$f_{X_1 \dots X_n}(x_1, \dots x_n) = \frac{1}{\sqrt{(2\pi)^n |\boldsymbol{K}|}} exp\left[-\frac{1}{2}\sum_{j=1}^{n}\sum_{k=1}^{n}\{\boldsymbol{K}^{-1}\}_{jk}\left(x_j - \bar{X}_j\right)(x_k - \bar{X}_k)\right] \tag{3.34}$$

where ***K*** is the correlation matrix which is defined as follows:

$$\boldsymbol{K} = \begin{bmatrix} K_{11} & \cdots & K_{1n} \\ \vdots & \ddots & \vdots \\ K_{n1} & \cdots & K_{nn} \end{bmatrix} \tag{3.35}$$

and $\{\boldsymbol{K}^{-1}\}_{jk}$ is *jk*th element of $\boldsymbol{K}^{-1}$. If there is no correlation between X_j and X_k, $K_{jk} = 0$ for $j \neq k$ and $K_{jk} = \sigma_{X_j}^2$ for $j = k$. In this case Equation (3.35) reduces to Equation (3.33).

3.3 Monte Carlo Integration

Most of the effort required to solve the stochastic programming problem which is defined by Equation (3.4), Equation (3.5), and Equation (3.6) is spent in the multivariate integration. Standard numerical analysis techniques are not effective to evaluate this type of integrals. Alternatively, Monte Carlo is a statistical integration technique based on employing random numbers to evaluate the value of an integral. This section gives a brief introduction to Monte Carlo integration.

Veach [1997] explains inadequacy of standard numerical techniques in evaluating integrals on high dimensional domains. According to Bakhvalov's theorem, for any *s*-dimensional quadrature rule with *N*-point has not an error bound better than $O\left(N^{-1/s}\right)$ (Veach [1997]). Therefore, the efficiency of quadrature rules decreases with dimension. Qudrature rules includes Newton-Cotes rules such as the midpoint rule, the trapezoid rule, Simpson's rule, and Gauss-Legendre rules.

Let

$$I = \int_{\Omega} f(x)\, d\mu(x) \tag{3.36}$$

be the integral to be evaluated where $f(x)$ is a real valued function that is not analytically integrable. To solve this problem by Monte Carlo integration, let *Y* be the random variable $f(X)/p(X)$, where *X* is a continuous random variable distributed on Ω. Then the expected value of *Y* is

$$E[Y] = E[f(X)/p(X)]$$

$$= \int_{\Omega} \frac{f(x)}{p(x)} p(x)\, d\mu(x) = \int_{\Omega} f(x)\, d\mu(x) = I \qquad (3.37)$$

Thus the problem of evaluation of the integral is then reduced to estimating $E[Y]$ provided that $f(X)/p(X)$ is finite whenever $f(x) \neq 0$. In particular $E[Y]$ can be estimated by the sample mean

$$\bar{Y}(n) = \frac{1}{n}\sum_{j=1}^{n} f(X_j) \qquad (3.38)$$

where $X_1, X_{2,\cdots,} X_n$ are independent and uniformly distributed random variables. The standard deviation of $\bar{Y}(n)$ is

$$\sigma[\bar{Y}(n)] = \frac{1}{\sqrt{n}}\sigma_Y \qquad (3.39)$$

which shows that it converges at a rate of $O(N^{-1/2})$ (Veach [1997]). It is also noted that $\bar{Y}(n)$ will be close to I for large values of *n* and the number of sampling points required to obtain a given degree of accuracy is independent of dimensions.

To evaluate stochastic integrals in Equation (3.4), Equation (3.5), and Equation (3.6) in the form of

$$E[f(\vec{x},\vec{\xi})] = \int_{D} f(\vec{x},\vec{\xi})\, \phi(\vec{\xi})\, d\vec{\xi} \qquad (3.40)$$

random sampling can be used as follows:

$$\bar{Y}(n) = \frac{|D|}{n}\sum_{j=1}^{n} f(X_j, \Xi_j)\, \phi(\Xi_j) \qquad (3.41)$$

where *Y* is the random variable $|D|\, f(X_j, \Xi_j)\phi(\Xi_j)$ and Ξ_j is a random vector uniformly distributed over the bounded domain *D*. *D* is the volume of bounded domain. $\Xi_1, \Xi_2, \cdots, \Xi_n$ are independent random vectors uniformly distributed over the bounded domain. Figure 3.2 illustrates the psedo-code for evaluation of $\bar{Y}(n)$ (Gen [1997]).

```
begin
objective ← 0;
for j ← 1 to number_simulation do
   Ξ_j ← random_vector();
   objective ← objective + f(x, Ξ_j)φ(Ξ_j)
end
objective ← objective × |D|/number_simulation
end
```

Figure 3.2 Psedo-code for Monte Carlo integration

The advantages of Monte Carlo integration can be summarized as follows (Veach [1997]).

- It converges at a rate of $O(N^{-1/2})$ in any dimension, regardless of the smoothness of the integrand.
- Sampling and function evaluation are sufficient operations for Monte Carlo integration. Therefore, it allows flexible software design.
- Monte Carlo is a general method. It can be applied to integrands with singularities.

Although the error estimate of Monte Carlo integration is independent of the dimension of the integral, the integral converges relatively slow to the true value at the rate of $1/\sqrt{N}$. Several techniques which are simply called **variance reducing** methods can be used to improve the performance of Monte Carlo integration. Classical variance reducing techniques such as stratified sampling, importance sampling, Russian roulette and the adaptive VEGAS-algorithm are discussed.

Stratified sampling technique is based on the idea of dividing the full integration space into subspaces, performing a Monte Carlo integration in each space, and adding up the partial results in the end. If the subspaces and the number of points in each subspace are chosen carefully, this can lead to a dramatic reduction in the variance compared with crude Monte Carlo. However, it can also lead to a larger variance if the choice is not appropriate (Weinzierl [2000]). It is mainly effective for low dimensional integration problems, but for high dimensional problems it will not help significantly (Veach [1997]).

Another important technique for improving the efficiency of Monte Carlo integration is **importance sampling** which corresponds to a change of integration variables. To change the integration variable a distribution $p(x)$ is chosen so that it generates samples where integrand's value is relatively large. However, it is dangerous to choose a distribution which approaches zero somewhere where integrand is not zero which may cause unreasonable results (Weinzierl [2000], Veach [1997]).

Russian roulette method increases the performance of Monte Carlo integration by decreasing the computational expense of evaluating terms which have small contributions to overall. In this method, with a certain probability, value of integrand is not evaluated and instead replaced with a constant term (Pharr [2005]).

Adaptive sampling techniques are preferred when knowledge of the behavior of the function to be integrated is not available. Adaptive sampling attempts to place more samples where the variance is large and learns about the function as it proceeds. **VEGAS-algorithm** is widely used adaptive Monte Carlo method in high energy physics. Vegas-algorithm combines stratified and importance sampling into an iterative algorithm, which decides automatically the regions where the integrand is evaluated (Weinzierl [2000]). However, it is not very effective for high dimensional problems (Veach [1997]).

3.4 Genetic Algorithms

Genetic algorithms are stochastic search techniques used to find solutions to optimization problems which are quite hard to solve by conventional methods. Genetic algorithms are a particular class of evolutionary algorithms which are based on the simulation of natural evolutionary process of human beings. The books by Weise [2009] and Michalewicz [1996] are good references on the origins of Genetic algorithms.

How a simple genetic algorithm works is illustrated in Figure 3.3. The genetic algorithm starts with an initial set of random solutions called **population**. Each individual in the population is called a **chromosome**, referring to a candidate solution to a problem. A chromosome is a sequence of **genes**. In general, a chromosome is encoded as a bit string. Genetic algorithms process populations of chromosomes. Each iteration of this process is called a **generation**. Generation number for a typical genetic algorithm is in the range 50-500, but more generations can be required. Chromosomes are evaluated using a fitness function that assigns a fitness value to each chromosome in the current population. The next generation is created from current generation by means of selection, crossover and mutation operators. **Selection** operator selects chromosomes according to the fitness values in the current population for reproduction. Fitter chromosomes have higher probabilities to be selected to reproduce. Some of the chromosomes are rejected to keep the population size constant. **Crossover** operator merges two chromosomes from current generation to create two offspring. **Mutation** operator modifies a chromosome in current generation. At the end of the entire set of generations, the algorithm converges to the best chromosome, which represents the optimum or suboptimal solution to the problem.

The way in which a chromosome is encoded is a factor in the success of a genetic algorithm. Although most genetic algorithm applications use bit strings, there have been many successful applications with other kind of encodings. But there is no certain approach for predicting which encoding will work best (Melanie [1999]).

Selection method is another decision to be made in using a genetic algorithm. "Roulette wheel" selection, "Stochastic universal" sampling, sigma scaling, elitism, "Boltzmann selection", rank selection, tournament selection and steady state selection are some of most common selection methods. Similar to the case for encodings, which method should be used depends on the problem. The purpose of selection is to transfer chromosomes that their offspring will probably have higher fitness to the next generation. However, at the same time "exploitation/exploration balance" should be satisfied; that is small proportion of less fit solutions are selected to explore all solution space.

"Roulette wheel" selection and tournament selection methods are well-studied selection methods. "Roulette wheel" selection method assigns a probability of selection to each chromosome in the current generation according to their fitness values. Then a random selection is made similar to how the roulette wheel is rotated. Tournament selection involves running several "tournaments" among a few chromosomes chosen at random from the population. Tournament selection is computationally efficient and allows the selection pressure to be easily adjusted (Melanie [1999]). An analysis of this method was presented by Miller [1995].

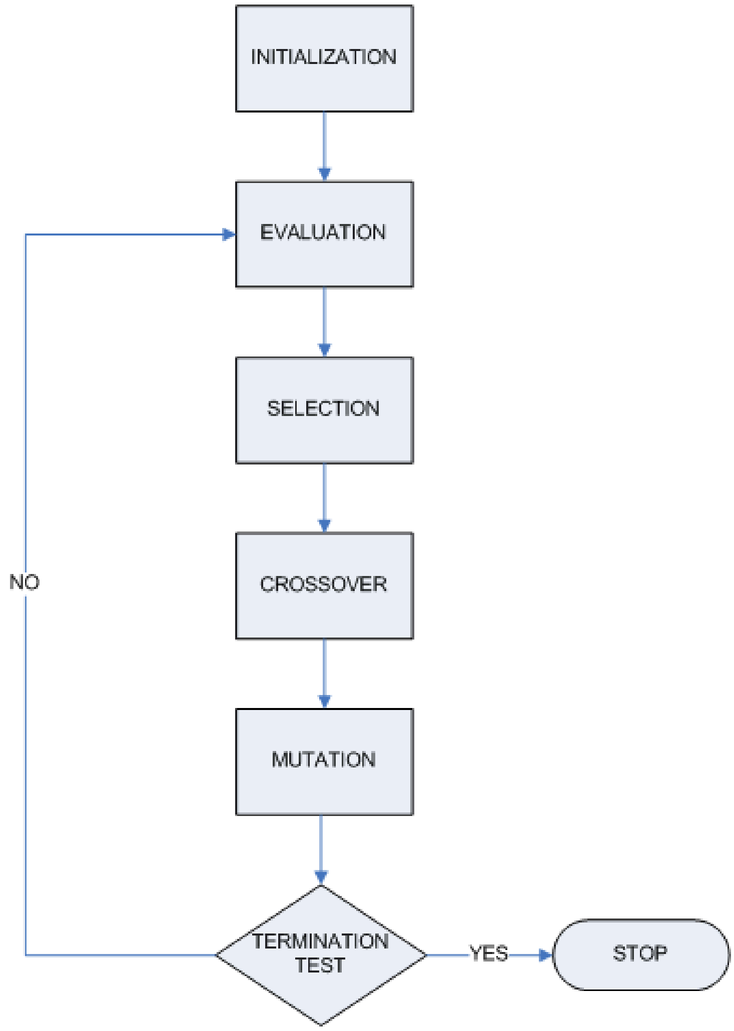
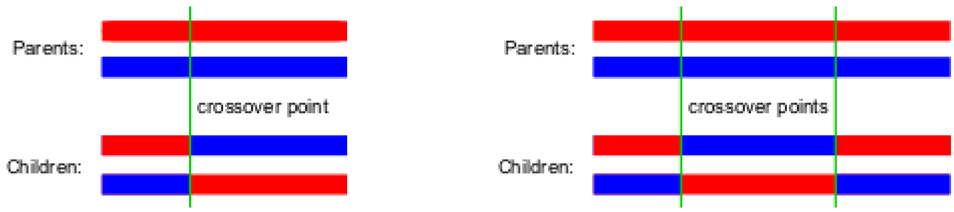


Figure 3.3 General structures of genetic algorithms

Crossover is the main genetic operator which operates on two chromosomes and generates offspring by combining both chromosomes' features. Single-point crossover and two-point crossover are the most widely used crossover techniques. Single-point crossover is performed by choosing a random cut point and exchanging the parts of two parents after the cut point to form two offspring (see Figure 3.4 (A)). Melanie discussed positional bias and "endpoint" effects that are disadvantages of single-point crossover. Two-point crossover, in which two positions are chosen at random and segments between them are exchanged, is used to reduce those effects by many genetic algorithms practitioners. Figure 3.4 (B) illustrates two-point crossover operation. Single-point crossover and two-point crossover methods work well with the bit string representation. Other types of encodings may require specially defined crossover operation. However, the success of crossover depends on many factors such as the fitness function, encoding, and other details of the genetic algorithm. The **crossover rate** is another parameter that controls the expected number of chromosomes to undergo the crossover operation. Increasing crossover rate yields exploration of more of solution space. On the other hand, high crossover rate results in increase of the computation time due to exploring unpromising regions of the solution space.



(A) (B)

Figure 3.4 (A) Single-point crossover (B) Two-point crossover

Mutation is a genetic operator used to produce spontaneous random changes in various chromosomes. A simple way to perform mutation is to modify one or more genes of a chromosome probabilistically. Mutation operator maintains genetic diversity from one generation to the next. The **mutation rate** controls the rate at which new genes are introduced into the population. Low crossover rate results in omitting the genes that may be useful. However, high crossover rate brings about the lack of resemblance between offspring and their parents. There are no practical upper and lower bounds that can help guide selection.

Randomness plays a large role in genetic algorithms. Two runs of algorithm with different random number seeds may result in different detailed behavior. There is no guarantee to converge on a solution within a fixed time. On the other hand, due to their nature, each chromosome can be evaluated in parallel without affecting other that of other chromosomes. (See Sivanandam [2008] for more detailed discussion of these ideas.)

Major advantages of applying genetic algorithms to optimization problems are discussed by Gen (Gen [1997]).

- Genetic algorithms can handle any kind of objective functions and constraints. They use only fitness function, not derivatives or other auxiliary knowledge.
- Genetic algorithms are very effective at performing global search. They can rapidly find good solutions, even for difficult search spaces. However, for specific problem instances other optimization algorithms may find better solutions. In this case, a local optimizer can be added to genetic algorithm which is called a memetic algorithm.
- Genetic algorithms have a great flexibility. Therefore they can be combined with domain dependent heuristics.
- Genetic algorithms are inherently parallel; that is the individual solutions can be evaluated independently.

3.5 Dynamic Programming

Dynamic programming is a method of solving complex problems by dividing them into simpler steps (Rao [1996]). The problems in which the decisions are to be made at a number of sequential stages are called multistage decision problems. Dynamic programming is a mathematical technique well suited for the optimization of multistage decision problems. The term "dynamic" was used to identify the approach as being useful for problems in which times plays a significant role, and in which the order of operations may be crucial (Michalewicz [2002]). The word "programming" came from the term "mathematical programming"- a synonym for optimization. Dynamic programming was developed by Richard Bellman (Bellman [1957]). Afterwards, IEEE recognized the field as a system analysis and engineering topic. Dynamic programming can deal with discrete variables, nonconvex, noncontinuous and nondifferentiable functions. In general, it can also take the stochastic variability into account by a simple modification of the deterministic procedure.

The dynamic programming technique decomposes a multistage decision problem into a sequence of single-stage decision problems. The decomposition to subproblems is done such a manner that the optimal solution of the original problem can be obtained from the optimal solutions of the subproblems. In most cases, these subproblems are easier to solve than the original problem. It is important to note that any optimization technique can be used for the optimization of the single variable problems.

A multistage decision process is one in which a number of single-stage processes are connected in series so that output of one stage is the input of the succeeding stage. A single-stage decision process can be represented as a rectangular block (Figure 3.5). A decision process can be characterized by certain input parameters, **S**, certain decision variables (**X**), and certain output parameters (**T**) representing the outcome obtained as a result of making the decision. The input parameters are called input state variables, and the output parameters are called output state variables. Finally, there is a return function or objective function R, which measures the effectiveness of the decision made and the output that results from these decisions. For a single-stage decision process, the output is related to the input through a stage transformation function denoted by

$$\boldsymbol{T} = t(\boldsymbol{X}, \boldsymbol{S}) \tag{3.42}$$

Since the input state of the system influences the decision, the return function can be represented as

$$\boldsymbol{R} = r(\boldsymbol{X}, \boldsymbol{S}) \tag{3.43}$$

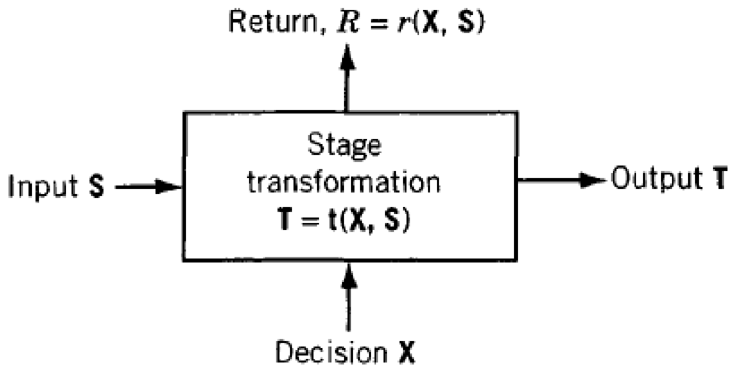


Figure 3.5 Single-stage decision problem (Rao [1996])

A serial multistage decision process can be represented schematically as shown in Figure 3.6. The stages are labeled in decreasing order.

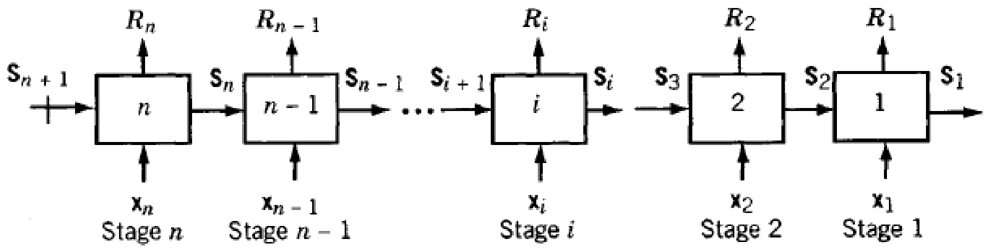


Figure 3.6 Multistage decision problem (Rao [1996])

For the *i*th stage, the input state vector is denoted by $\boldsymbol{s}_{i+1}$ and the output state vector as $\boldsymbol{s}_i$. Since the system is a serial one, the output from stage $i+1$ must be equal to the input to i. Hence the state transformation and return functions can be represented as

$$\boldsymbol{s}_i = \boldsymbol{t}_i(\boldsymbol{s}_{i+1}, \boldsymbol{x}_i) \tag{3.44}$$

$$\boldsymbol{R}_i = \boldsymbol{r}_i(\boldsymbol{s}_{i+1}, \boldsymbol{x}_i) \tag{3.45}$$

where $\boldsymbol{x}_i$ denotes the vector of decision variable at stage i. The objective of a multistage decision problem is to find $\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_n$ so as to optimize some function of the individual stage return, say, $f(R_1, R_2, \cdots, R_n)$ and satisfy Equation (3.44) and Equation (3.45). Since the method works as a decomposition technique, it requires the separability and monotonicity of the objective function. To have separability of the objective function, the objective function must be expressed as the composition of the individual stage returns. Additive and multiplicative objective functions satisfy this requirement. Additive objective functions:

$$f = \sum_{i=1}^{n} R_i = \sum_{i=1}^{n} R_i(\boldsymbol{x}_i, \boldsymbol{s}_{i+1}) \tag{3.46}$$

where $\boldsymbol{x}_i$ are real and nonnegative. The objective function is said to be monotonic if for all values of ***a*** and ***b*** that make

$$R_i(\boldsymbol{x}_i = \boldsymbol{a}, \boldsymbol{s}_{i+1}) \geq R_i(\boldsymbol{x}_i = \boldsymbol{b}, \boldsymbol{s}_{i+1}) \tag{3.47}$$

the following inequality is satisfied:

$$\begin{aligned} &f(\boldsymbol{x}_n, \boldsymbol{x}_{n-1}, \cdots, \boldsymbol{x}_{i+1}, \boldsymbol{x}_i = \boldsymbol{a}, \boldsymbol{x}_{i-1}, \cdots, \boldsymbol{x}_1, \boldsymbol{s}_{n+1}) \\ &\qquad \geq f(\boldsymbol{x}_n, \boldsymbol{x}_{n-1}, \cdots, \boldsymbol{x}_{i+1}, \boldsymbol{x}_i = \boldsymbol{b}, \boldsymbol{x}_{i-1}, \cdots, \boldsymbol{x}_1, \boldsymbol{s}_{n+1}), \\ &\qquad i = 1,2, \cdots, n \end{aligned} \tag{3.48}$$

The serial multistage decision problems can be classified into three categories: Initial value problem, final value problem, and boundary value problem. If the initial state variable s_{n+1}, is prescribed, the problem called an initial value problem. If the value of the final state variable s_1 is prescribed, the problem is called a final value problem. If the values of both the input and output variables are specified, the problem is called a boundary value problem. Final state problem can be transformed into an initial value problem.The dynamic programming makes use of the concept of suboptimization and the principle of optimality in solving the problem. The process of suboptimization was state by Bellman[1957] as the principle of optimality. An optimal policy (or a set of decisions) has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision. Suppose that the desired objective is to minimize the n-stage objective function f which is given by the sum of the individual stage returns:

$$Minimize\ f = R_n(x_n, s_{n+1}) + R_{n-1}(x_{n-1}, s_n) + \cdots + R_1(x_1, s_2) \tag{3.49}$$

where the state and decision variables are related as

$$s_i = t_i(s_{i+1}, x_i,), \qquad i = 1,2,\cdots,n \tag{3.50}$$

Consider the first stage subproblem of by starting at the final stage, $i = 1$. If the input to this stage s_2 is specified, then according to the principle of optimality, x_1 must be selected to optimize R_1.

$$f_1^*(s_2) = \underset{x_1}{\text{opt}}[R_1(x_1, s_2)] \tag{3.51}$$

where f_1^* is the optimum. This is called a one-stage policy since once the input state s_2 is specified, the optimal values of R_1, x_1, and s_1 are completely defined. Next, consider the second subproblem by grouping the last two stages together.

$$f_2^*(s_3) = \underset{x_1, x_2}{\text{opt}}[R_1(x_2, s_3) + R_1(x_1, s_2)] \tag{3.52}$$

where f_2^* denotes the optimum objective value of the second subproblem for a specified value of the input s_3. The principle of optimality requires x_1 be selected so as to optimize R_1 for a given s_2. Since s_2 can be obtained once x_2 and s_3 are specified. Then

$$f_2^*(s_3) = \underset{x_2}{\text{opt}}[R_1(x_2, s_3) + f_1^*(s_2)] \tag{3.53}$$

It can be seen that the principle of optimality reduced the dimensionality of the problem. The idea can be generalized and the *i*th subproblem defined by

$$f_i^* = \operatorname*{opt}_{x_i, x_{i-1}, \cdots, x_1} [R_i(x_i, s_{i+1}) + R_{i-1}(x_{i-1}, s_i) + \cdots + R_1(x_1, s_2)] \tag{3.54}$$

can be written as

$$f_i^*(s_{i+1}) = \operatorname*{opt}_{x_i} [R_i(x_i, s_{i+1}) + f_{i-1}^*(s_i)] \tag{3.55}$$

where f_{i-1}^* denotes the optimal value of the objective function corresponding to the last $i-1$ stages, and s_i is the input to the stage $i-1$.

3.6 Two Approaches to Solving a Stochastic Programming Problem

Two approaches to solving the stochastic programming problem which is defined by Equations (3.1), (3.2), and (3.3) are introduced. The first approach is an evolution program which was proposed by Gen (Gen [1997]). The second approach is stochastic dynamic programming which is based on dynamic programming (See section 3.5). In the Chapter 4, these techniques are applied to the load scheduling problem of a cogeneration plant with uncertain electricity price and head demand.

3.6.1 Evolution Program for Stochastic Programming Problem

The evolution problem is based entirely on the idea of genetic algorithms. (See Section 3.4 for more detailed discussion of genetic algorithms.) Michalewicz[1996] introduced the concept of evolution program first and applied it to the linear transportation problem. Thereafter, Gen[1997] proposed an evolution program for a version of the stochastic optimization problem which is formulated by Equations (3.1), (3.2), and (3.3). The difference is that constraint functions depend only on real variables.

$$\max E\left[f(\vec{x},\vec{\xi})\right]$$

$$st.\ g_i(\vec{x}) \leq 0 \quad i = 1,2,\cdots m \tag{3.56}$$

They suggested floating point representation; that is, each chromosome is encoded as a vector of floating numbers, with the same length as the vector of decision variables. They also defined genetic operators which are suitable for this representation. Figure 3.7 illustrates algorithm for the evolution program which was proposed by Gen [1997]. The function $random(\ \ )$ generates a real number in $(0,1)$ and $random(num)$ returns a real number in $(0, num)$. Initialization procedure generates initial population by obtaining feasible solutions from a predetermined interior point in the constraint set. Starting with an interior point and using decreasing value of M along with iterations guarantee to find a feasible solution in finite iterations. Gen et al suggested an exponential-fitness scaling scheme to overcome premature convergence which is a general problem of a fitness-proportional reproduction scheme. In this method, first the objective function for each chromosome is evaluated with Monte Carlo simulation. (See Section 3.4 for more detailed discussion of Monte Carlo integration.) Then the chromosomes are sorted with ascending order of their objective function values. After that, three critical chromosomes with ranking u_1, u_0, and u_2 are determined according to preferences parameters p_1, p_0, and $p_2 (0 < p_1 < p_0 < p_2 < 1)$ such that $u_1 = \lfloor p_1 . pop\_size \rfloor$, $u_0 = \lfloor p_0 . pop\_size \rfloor$, and $u_2 = \lfloor p_2 . pop\_size \rfloor$. To calculate the exponential fitness of a chromosome $\boldsymbol{v}$ with ranking u, the following relation is used:

$$eval(\boldsymbol{v}) = \begin{cases} exp\left[-\dfrac{u-u_0}{u_1-u_0}\right], & u < u_0 \\ 2 - exp\left[-\dfrac{u-u_0}{u_2-u_0}\right], & u \geq u_o \end{cases} \tag{3.57}$$

Selection operator employs those fitness values to make roulette which is used to generate new population.

```
Step 0. Parameter setting
  number of generations: max _gen
  population size: pop_size
  probability of crossover: p_c
  preference parameters: p_1, p_0, p_2
  probability of mutation: p_m
  a large positive number: M_0
  current generation: gen → 0

Step 1. Initialization process
  give an interior point v_0;
  for k ← 1 to pop_size do
    M ← M_0;
    produce a random dirction d;
    v_k ← v_0 + M.d;
    while(v_k is not feasible) do
      M ← random(M);
      v_k ← v_0 + M.d;
    end
  end

Step 2. Evaluation
  for k ← 1 to pop_size do
    compute the objectives f_k for v_k by Monte Carlo simulation;
  end
  rank chromosomes according to the objectives;
  for k ← 1 to pop_size do
    compute the exponential-fitness eval(v_k) based on the ranking;
  end

Step 3. Selection Operation
  for k ← 1 to pop_size do
    compute the selective probabilities p_k = eval(v_k) / Σ_{j=1}^{pop_size} eval(v_j) ;
  end
  for k ← 1 to pop_size do
    compute the cumulative probabilities q_k = Σ_{j=1}^{k} p_j;
  end
  for k ← 1 to pop_size do
    if q_{k-1} < random( ) ≤ q_k then
      select v_k;
    end
  end
```

Figure 3.7 Psedo-code for evolution program

Step 4. Crossover Operation

for $k \leftarrow 1$ **to** $pop_{size}/2$ **do**
  if $random(\ \ ) \leq p_c$ **then**
    $j \leftarrow random(pop\_size)$;
    $l \leftarrow random(pop\_size)$;
    $\alpha \leftarrow random(\ \ )$;
    $\boldsymbol{v}' \leftarrow \alpha \boldsymbol{v}_j + (1-\alpha)\boldsymbol{v}_l$;
    $\boldsymbol{v}'' \leftarrow \alpha \boldsymbol{v}_l + (1-\alpha)\boldsymbol{v}_j$;
  end
end

Step 5. Mutation Operation

for $k \leftarrow 1$ **to** pop_size **do**
  if $random(\ \ ) \leq p_m$ **then**
    $M \leftarrow M_0$;
    produce a random dirction $\boldsymbol{d}$;
    $\boldsymbol{v}_k{}' \leftarrow v_k + M.\boldsymbol{d}$;
    while($\boldsymbol{v}_k$ is not feasible) **do**
      $M \leftarrow random(M)$;
      $\boldsymbol{v}_k{}' \leftarrow v_k + M.\boldsymbol{d}$;
    end
  end
end

Step 6. Termination Test

$gen \leftarrow gen + 1$;
if $gen < \max\_gen$ **then**
  goto step 2;
else
  stop;
end

Figure 3.7 (continued) Psedo-code for evolution program

3.6.2 Stochastic Dynamic Programming for Stochastic Programming Problem

Stochastic dynamic programming is one of the techniques most commonly used in the solution of stochastic programming problem. It is based on dynamic programming in which some of the parameters in the return and state transformation functions are random instead of deterministic. Dreyfus [1965] introduced the concepts of stochastic optimization problems and showed applicability of dynamic programming to this area. Rao [1996] derived expressions for stochastic dynamic programming by introducing a random variable y_i to single-stage decision problem. Then stochastic return function is

$$R_i = R_i(s_{i+1}, x_i, y_i) \tag{3.58}$$

where s_{i+1} is the input state variable to stage i, and x_i the decision variable. If y_i is a continuous random variable with a probability density function of $\phi(y_i)$, the expected value of the return which is the criterion for stochastic dynamic programming as follows

$$\bar{R}_i(s_{i+1}, x_i) = \int R_i(s_{i+1}, x_i, y_i)\, \phi(y_i)\, dy_i \tag{3.59}$$

Figure 3.7 illustrates a multistage optimization problem with random variables. The objective function which is the sum of n individual returns as follows

$$F(x_1, x_2, \cdots, x_n) = \sum_{i=1}^{n} R_i(s_{i+1}, x_i, y_i) \tag{3.60}$$

where

$$s_i = t_i(s_{i+1}, x_i, y_i), \qquad i = 1,2,\cdots,n \tag{3.61}$$

The input state variables in a stochastic system depend on upstream decision variables, the initial input state s_{n+1}, and previously observed random variables. Therefore, the input to stage i $(i \neq n)$ will not be known before specific values of variables $y_{i+1}, y_{i+2}, \cdots y_n$ affecting the upstream stages have been realized.

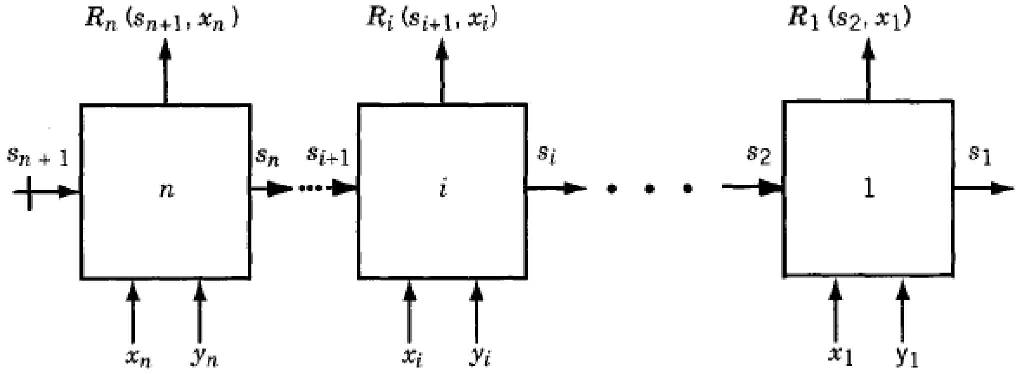


Figure 3.8 Multistage optimization with random variables (Rao [1996])

If the random variables $y_{i+1}, y_{i+2}, \cdots y_n$ are independent with probability density functions $\phi_1(y_1) \cdots \phi_n(y_n)$, respectively, the expected value of the total system return is

$$\bar{F} = \int_{y_1} \int_{y_2} \cdots \int_{y_n} [F(s_{n+1}, y_1, y_2, \cdots y_n)\phi_1(y_1) \cdots \phi_n(y_n)]\, dy_1 \cdots dy_n \qquad (3.62)$$

Rao[1996] derived the fundamental stochastic recurrence relations for discrete random variables. The fundamental stochastic recurrence relations for continuous random variables can be formulated as follows.

$$F_i^*(s_{i+1}) = \max_{x_i} \int_{y_i} \phi_i(y_i) Q_i(s_{i+1}, x_i, y_i)\, dy_i \qquad 1 \le i \le n$$

$$Q_i(s_{i+1}, x_i, y_i) = R_i(s_{i+1}, x_i, y_i) + F_{i-1}^*(t_i\{s_{i+1}, x_i, y_i\}) \qquad 2 \le i \le n$$

$$Q_1(s_2, x_1, y_1) = R_1(s_2, x_1, y_1) \qquad (3.63)$$

The introduction of random variables causes no increase in the state variables. Since each decision involves only one random parameter, difficulties in optimizing the functions of several random variables reduces. A computational procedure for the use of recurrence relationship (Equation 3.63) is composed from the following parts:

1. Optimize last stage (Stage 1) for a range of possible values of s_2 that is

$$F_1^*(s_2) = \max_{x_1} \int_{y_1} \phi_1(y_1) R_1(s_2, x_1, y_1)\, dy_1$$

2. Store the results of Step 1 in the form of a table which contains values of s_2, x_1^*, F_1^*, and s_1.
3. Optimize last two stages for a range of possible values of s_3 that is

$$F_2^*(s_3) = \max_{x_2} \int_{y_2} \phi_2(y_2)[R_2(s_3, x_2, y_2) + F_1^*(s_2)]\, dy_1$$

   where $F_1^*(s_2)$ is known from Step 2.

4. Store the results of Step 3 in the form of a table which contains values of s_3, x_2^*, F_2^*, and s_2.
5. Continue suboptimization until stage n is reached. At stage n only one value of s_{n+1} is considered.
6. Retrace the steps through the tables generated and gather complete set of x_i^*.

CHAPTER 4

STOCHASTIC LOAD SCHEDULING ANALYSIS

In this chapter, the load scheduling problem for a cogeneration plant is formulated as a stochastic optimization problem due to uncertainties in heat demand and the revenue from selling electricity in scheduling horizon. The evolution programming and stochastic dynamic programming techniques are used to solve stochastic load scheduling problem which aims to maximize the revenue for a cogeneration system selected as a case study. **Revenue is defined for the purposes of the study as the sales revenues minus total cost associated with the plant operation**. Exergy costing is applied to stochastic optimization approach in addition to energy costing; that is, a new solution approach to load scheduling problem. Then, to verify the analysis, scenarios with various distribution functions of heat demand and electricity price are simulated. Finally, a new approach is proposed to determine optimal storage content capacity to maximize the revenue by taking the uncertainties in plant operation into account.

4.1 Stochastic Load Scheduling

Cogeneration systems allow the simultaneous utilization of heat and power from an energy source. They are generally designed to meet the heat demand of the end customer. This general approach is attributed to the fact that it costs less to transport the surplus electricity than the surplus heat from a cogeneration plant. Therefore, cogeneration can be viewed primarily as a source of heat with electricity as a by-product.

In this study, the load scheduling for natural gas fired decentralized cogeneration plants which supply heat to the district heating network is considered. Electricity can be sold to its costumers based on bilateral contracts and to PMUM. The study incorporates a natural gas fired peak load boiler placed at the cogeneration plant which meets peak demand requirements.

Natural gas used in the plant is purchased from a distribution company. The gas price is assumed constant over the scheduling horizon.

Cogeneration plants are considered to sell electricity to a power transmission company which operates by day-ahead electricity market principles, in which the system price is determined by matching offers from generators to bids from consumers on an hourly interval. Bilateral contracts which are long term trades between counterparties are also allowed. Therefore, revenue from the electricity produced is uncertain.

Heat consumption of similar buildings under the same climatic conditions shows different values. Therefore, heat demand estimated at the planning stage has also a certain degree of uncertainty.

The aim of this study is to demonstrate how stochastic optimization can be applied to find optimal solutions for uncertain electricity price and heat demand in scheduling horizon. The purpose of the scheduling is to derive an operational plan that maximizes the revenue throughout the scheduling horizon. Scheduling is day-ahead based, i.e. the operator has to determine an operational plan for each hour of the following day.

4.2 Description of the Plant

- The case study plant consists of a gas turbine cycle and a bottoming steam cycle (Figure 4.1). Gas turbine cycle is based on the cogeneration system presented by Bejan [1996]. Table 4.1 and Table 4.2 give the data for the case study cogeneration system.

- The major components of the gas turbine cycle are a gas turbine, an air preheater, a compressor, and a combustion chamber.
- The steam cycle is composed of a steam turbine, a heat exchanger, a mixing chamber, a steam condenser with its cooling system, and a pump.
- Energy transfer between the two cycles is realized by means of a heat recovery steam generator.
- A heat storage unit is used for weakening the tie between the electricity and heat productions. The heat storage unit is a tank with hot water on top and cold water at the bottom. When the storage is charged, hot water is let in at the top and cold water is tapped from the bottom. When the storage is discharged, hot water is taken off from the top and cold water is fed at the bottom.
- A natural gas fired peak load boiler is utilized to meet the peak heat demand requirements at the customer.
- A cooling tower exists in the system which transfers the excess heat to the environment when it is necessary.

Table 4.1 Physical data for Case Study Plant

Parameter	**Value**
Storage tank length (m)	20
Storage tank diameter (m)	27
Maximum power of gas turbine (MW)	50
Minimum power of gas turbine (MW)	10
District heating supply temperature (^{0}C)	90
District heating return temperature (^{0}C)	70

Table 4.2: Temperature and pressure data for Case Study Plant

State	Substance	Temperature (K)	Pressure (kPa)
1	Air[a]	298.150	101.3
2	Air [a]	603.738	1013.0
3	Air [a]	850.000	962.3
4	Combustion products[b]	1520.000	914.2
5	Combustion products[b]	1006.162	109.9
6	Combustion products[b]	779.784	106.6
7	Combustion products[b]	426.897	101.3
8	Methane (Fuel)	298.150	1200
9	Water (superheated vapor)	703.15	8000
10	Water (superheated vapor)	703.15	8000
11	Water (superheated vapor)	703.15	8000
12	Water (superheated vapor)	647.54	500
13	Water (saturated vapor)	425.01	500
14	Water[c] (wet steam)	306.03	5
15	Water (saturated liquid)	306.03	5
16	Water (subcooled liquid)	307.95	8000
17	Water (saturated liquid)	425.12	500
18	Water (subcooled liquid)	426.90	8000
19	Water (subcooled liquid)	376.75	8000

[a] Molar analysis (%) : 77.48N_2, 20.59O_2, 0.03CO_2, 1.90H_2O(g)
[b] Molar analysis (%) : 75.07N_2, 13.72O_2, 3.14CO_2, 8.07H_2O(g)
[c] Quality x_{14}=0.758

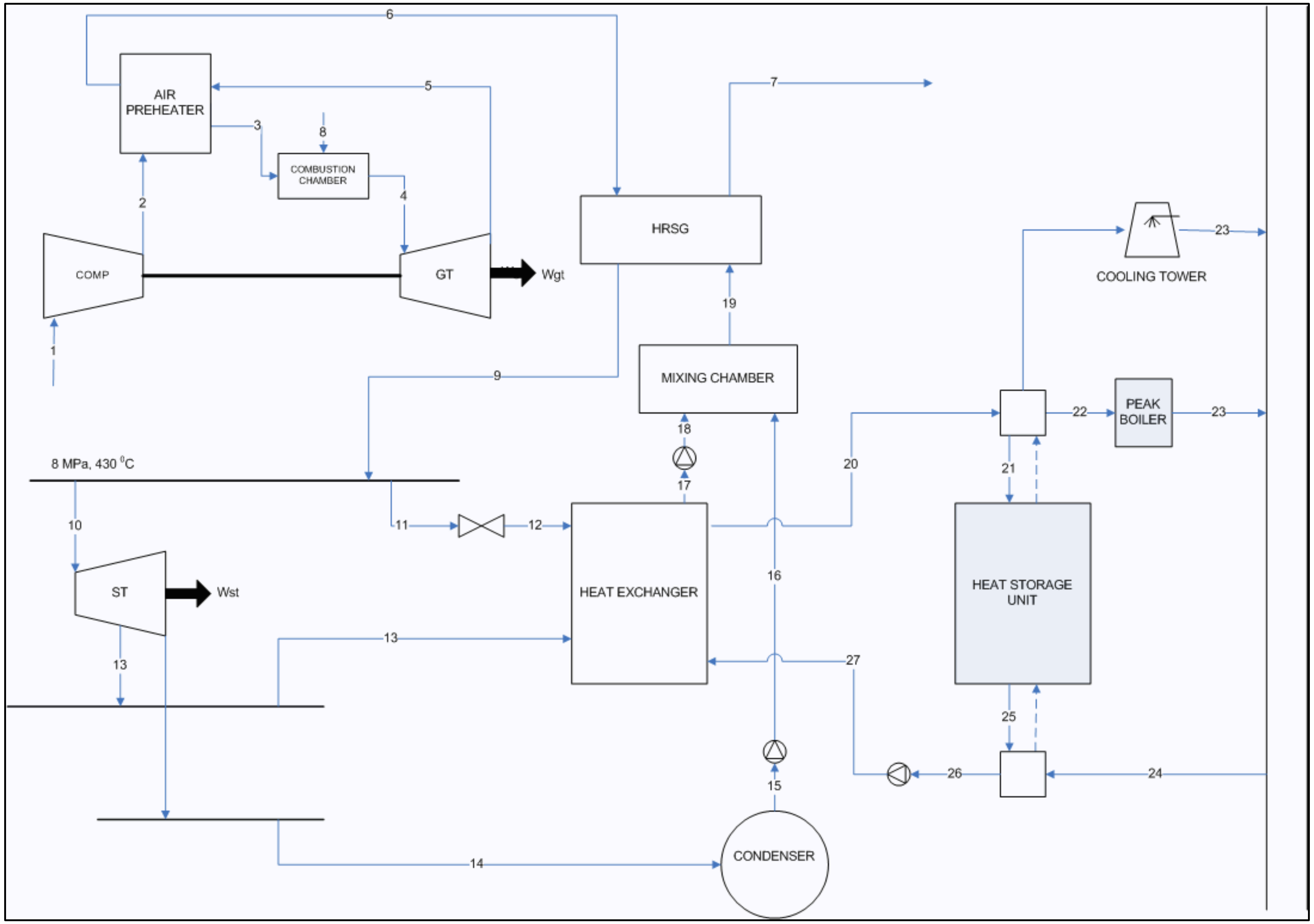


Figure 4.1 Schematic representation of cogeneration system selected as a case study

4.3 Description of the Plant Operation

- The plant operates to meet the heat demand. In case the heat produced by the gas and steam cycles is not sufficient for covering the total heat demand, the peak load boiler completes the deficiency.
- The plant operates in a competitive electricity market, in which the plant can sell electricity by means of bilateral contracts and through bidding to PMUM. In this context, the plant operator submits its load increment and load decrement bids to PMUM on a day-ahead basis. The state of the plant is its operational status and is determined according to the operational principles of PMUM. The system is subject to three options: i) increase in power output, ii) decrease in power output, iii) power output matching to bilateral contract requirement.
- The heat demand, the state of the electricity market and the electricity price are not known when the plant operator is subject to submit its load increment and load decrement bids to PMUM. These uncertainties are represented by probability density functions. Plant operation is then determined by a stochastic optimization approach.

4.4 Formulation of Optimization Problem

This section describes the input and output structure of the optimization problem as well as its mathematical formulation which forms the basis for computational algorithms and calculations. The inputs and outputs are tabulated in Table 4.3

Table 4.3 Input and outputs of problem

Inputs	Outputs
• Probability density functions for heat demand, electricity market price and state. • Amount of bilaterally contracted power and its price	• Load schedules of gas and steam turbines within the planning horizon. • Storage content of storage tank within the planning horizon. • Expected revenue

The objective of the operational plan is to maximize the expected revenue within the planning horizon. The expected revenue is expressed as

$$maxE\left[\sum_{k=1}^{K} r_{t+k\Delta t}\left(\dot{m}_{8,t+k\Delta t}, \dot{m}_{10,t+k\Delta t}, \breve{D}_{t+k\Delta t}, \check{C}_{P,t+k\Delta t}, \widetilde{ss}_{t+k\Delta t}\right)\right] \tag{4.1}$$

where

E: the expected operator,

t: reference time,

Δt: time interval (h),

k : time period (k th time period is the time interval from $t+\ (k-1)\Delta t$ until $t+k\Delta t$),

$\dot{m}_{8,t+k\Delta t}$: the amount of methane used by gas turbine within kth time interval,

$\dot{m}_{10,t+k\Delta t}$: the amount of steam going to the steam turbine within kth time interval,

$\breve{D}_{t+k\Delta t}$: heat demand within kth time interval (random variable),

$\check{C}_{P,t+k\Delta t}$: market price of electricity per MWh within kth time interval (random variable),

$\widetilde{ss}_{t+k\Delta t}$: system state, 0: load increment, 1: load decrement (random variable).

$r_{t+k\Delta t}$ is the revenue (profit) within time interval between $t+\ (k-1)\Delta t$ and $t+k\Delta t$.

The revenues from running plant consist of revenues from selling both power and heat to customers.

$$
\begin{aligned}
& r_{t+k\Delta t}\left(\dot{m}_{8,t+k\Delta t}, \dot{m}_{10,t+k\Delta t}, \breve{D}_{t+k\Delta t}, \check{C}_{P,t+k\Delta t}, \widetilde{ss}_{t+k\Delta t}\right) = \\
& \left[\, P_{bc}c_{bc} + (P_{t+k\Delta t} - P_{bc})\check{C}_{P,t+k\Delta t}\right]\Delta t \\
& + c_D \dot{Q}_D \Delta t \\
& - c^{(ng)} \dot{q}_{8,t+k\Delta t} \Delta t \\
& - c^{(ng)} H_{PB,t+k\Delta t} \\
& - c^{(m)} P_t \Delta t \\
& - c^{(c)} \dot{Q}_{excess} \Delta t
\end{aligned}
\tag{4.2}
$$

where

$P_{t+k\Delta t}$: total power generated by gas and steam turbines within kth time interval,

P_{bc}: bilateral contract power within the planning horizon (MW),

c_{bc}: bilateral contract electricity price within the planning horizon (\$/MWh),

c_D: price of thermal energy sold within the planning horizon (\$/MWh),

$c^{(ng)}$: unit cost of natural gas (\$/m^3) at pressure P_8,

$\dot{q}_{8,t+k\Delta t}$: volumetric flow rate of natural gas within kth time interval (m^3/s),

$H_{PB,t+k\Delta t}$: amount of gas used by peak boiler within kth time interval,

$c^{(m)}$: maintenance cost ($/MWh),

$c^{(c)}$: unit cooling cost of excess energy ($/MWh).

The natural gas is purchased from a gas distribution company. The price of gas is assumed constant within the planning horizon.

A maintenance cost associated with the amount of power is modeled as

$$\sum_{k=1}^{K} c^{(m)} \Delta t P_{t+k\Delta t} \tag{4.3}$$

The natural gas fired peak boiler which meets excess heat demand requirement is modeled. A constant unit cooling cost of excess energy is assumed.

Maximum and minimum power limits are considered in making decision. The shutdown of the plant is allowed in case the power level reaches to a pre-determined level. The startup costs are neglected.

The model employed for storage tank operation takes three types of operation modes into account.

1. Charging: In charging periods heat output is greater than heat demand. Feeding water is charged to the tank and the same amount of cold water is taken off from the tank bottom.

2. Discharging: In discharging periods heat output is smaller than heat demand. Hot water is taken off from the tank top and the same amount of return water is fed to the tank bottom.

3. Heat transfer: Heat transfer occurs in the periods when the tank is neither charged nor discharged. The explicit numerical approach

presented by Kostowski[2005] which is based on finite volume method, is implemented.

$$V_i c_i \rho_i \left(T_i^{k+1} - T_i^k\right) = \sum_j A_{ji} \frac{1}{R_{ji}} \left(T_j^{k+1} - T_j^k\right) \Delta t \quad (4.4)$$

where R_{ji} is the thermal resistance between volume elements i and j, T_i^k is the temperature of the volume element i at time k.

4.5 Comparison of Evolution Program and Stochastic Dynamic Programming Techniques

This section provides a sample problem to assess the performance of the evolution program and stochastic dynamic programming methods. The parameters used by evolution program and stochastic dynamic programming techniques are listed in Table 4.4. Storage tank content is used as state variable in stochastic dynamic programming technique. The sample problem is composed of three different scheduling periods. The operational parameters of the sample problem are tabulated in Table 4.5. The problem is solved by two techniques and the results are discussed.

Table 4.4 Parameters of optimization techniques

Parameter	**Value**
Generation Number	80
P_1 (Preferences Parameter)	0.1
P_0 (Preferences Parameter)	0.4
P_2 (Preferences Parameter)	0.8
Crossover Probability	0.3
Mutation Probability	0.3
Population Size	8
Simulation Number	15000
Number of States in each Stage (SDP)	30

Table 4.5 Operational Parameters of sample problems

Parameter	Value
Bilateral Contract Power (MW)	30
Bilateral Contract Price ($/MWh)	150
Exchange Rate ($/TL)	1.5
Natural gas price ($/m^3) at 1200kPa	0.25
Maintenance Cost ($/MWh)	4
Cooling Cost ($/MWh)	0.01
Initial Storage Content (MW)	79

Load Scheduling for One Hour:

In this example case, the uncertainties in heat demand, electricity price and state are represented by normal distributions. These uncertainties are kept small to enable comparison with deterministic solutions.

Heat demand probability density function is

$$f_{D^t}(d) = N(\overline{D}^t, \sigma_D{}^t) = \frac{1}{\sqrt{2\pi}\sigma_D{}^t} exp\left[-\frac{(d-\overline{D}^t)^2}{\sigma_D{}^{t^2}}\right] \tag{4.5}$$

where

$$\overline{D}^t = 70\ (MW), \qquad \sigma_D{}^t = 1\ (MW), \qquad t = 1$$

Electricity price probability density function is

$$f_{P^t,ss^t}(p, ss) = \begin{cases} 0, & ss = 0\ (load\ increment) \\ \frac{1}{\sqrt{2\pi}\sigma_P{}^t} exp\left[-\frac{(p-\overline{P}^t)^2}{\sigma_P{}^{t^2}}\right], & ss = 1\ (load\ decrement) \end{cases} \tag{4.6}$$

where

$$\overline{P}^t = 33.33\ (\$/MWh), \qquad \sigma_P{}^t = 1\ (\$/MWh), \qquad t = 1$$

According to the 3-sigma rule, heat demand is expected in the range of 70 ± 3 MW with a probability of 99.7 %. On the other hand, electricity oversupply situation is anticipated, which yields load decrement. Load decrement price is expected in the range of 33 ± 3 $/MWh with a probability of 99.7 %.

Since the probability density function for electricity price incorporates no expectation for load increment, the plant is subjected to perform either load decrement or operation based on the bilateral contract. The optimization techniques determine the optimal operation of the plant.

Based on the probability density function, the plant is subjected to operate between two limiting conditions:

1- Participation in PMUM by load decrement to zero power.

   In this case, the plant operator is paid by PMUM on the basis of its bilateral contract terms. The plant operator pays PMUM the amount calculated on the basis of the electricity price in PMUM.

   150[$/MWh]*30[MW] + (0 – 30)[MW]*33.33[$/MWh] = 3500[$]

2- Production on the basis of the bilateral contract without participation in PMUM.

   In this limiting case, the plant exactly produces the amount based on its bilateral contract.

   150[$/MWh]*30[MW] – 1415[$](fuel cost)-120[$] (maintenance cost) = 2964[$].

Figure 4.2 shows the change of the deterministic solutions by produced electricity together with a logarithmic trend line. These deterministic solutions are obtained based on the mean values of normal distribution functions as given by Equation 4.5 and Equation 4.6. As can be seen from the figure, maximum revenue is obtained when the load decrement offer is accepted and the plant generates no power. In this situation, heat demand is covered by the initially stored energy.

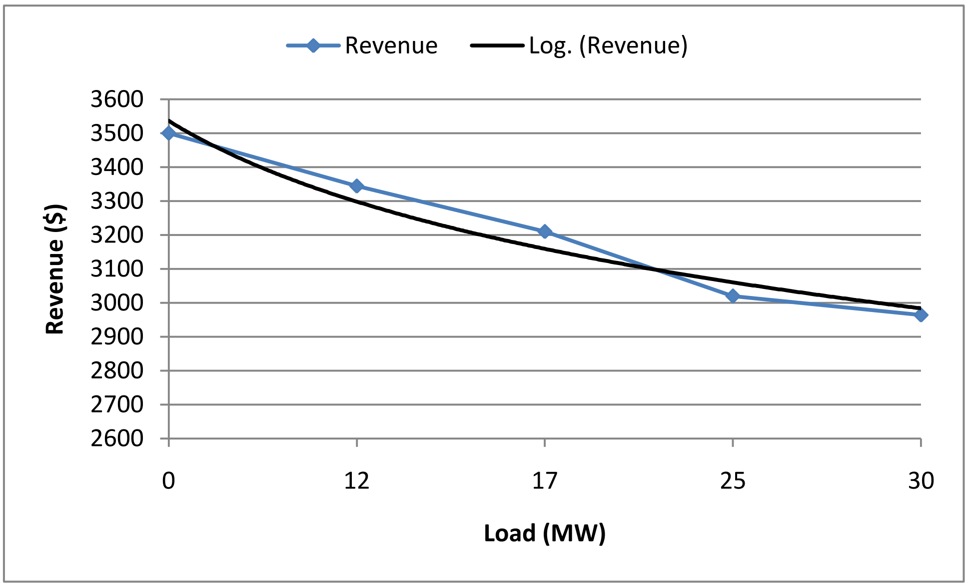


Figure 4.2 Revenue versus electricity produced for one hour load scheduling based on deterministic solution

The solutions by two stochastic optimization approaches are tabulated in Table 4.6. As it can be observed from Table 4.6, the optimal solutions do not represent any significant difference for the two techniques. This is attributed to the use of evolution programming technique for one hour load scheduling by SDP technique. The difference observed in expected revenues results from different random numbers employed in Monte Carlo integration. Both solutions are in accord with the deterministic solution. This is attributed to the fact that normal distribution tends towards deterministic case for small deviation values.

All dispatching units accepting load decrement pay market prices for buying electricity from PMUM. In order to execute the load scheduling plan resulting from stochastic load scheduling optimization, the generator should offer a load decrement price higher than 33.33 $/MWh.

Table 4.6 Solution summary for one hour load planning

Expected Decision Values	**Evolution Program**	**Stochastic Dynamic Programming**
GT Load (MW)	0.0	0.0
ST Load (MW)	0.0	0.0
Total Load (MW)	0.0	0.0
Heat Produced (MW)	0.0	0.0
Fuel Cost ($)	0.0	0.0
Maintenance Cost ($)	0.0	0.0
Storage Tank Use (MWh)	70 (Discharge)	70 (Discharge)
Expected Revenue ($)	3500	3502

Load Scheduling for Two Hours:

Heat demand probability density function

$$f_{D^t}(d) = N(\overline{D}^t, {\sigma_D}^t) = \frac{1}{\sqrt{2\pi}{\sigma_D}^t} exp\left[-\frac{(d-\overline{D}^t)^2}{{\sigma_D}^{t^2}}\right]$$

where (4.7)

$$\overline{D}^t = 70\,(MW), \qquad {\sigma_D}^t = 1\,(MW), \qquad t = 1$$

$$\overline{D}^t = 80\,(MW), \qquad {\sigma_D}^t = 1\,(MW), \qquad t = 2$$

Electricity price probability density function

$$f_{P^t,ss^t}(p, ss) = \begin{cases} 0, & ss = 0\;(load\ increment) \\ \frac{1}{\sqrt{2\pi}{\sigma_P}^t} exp\left[-\frac{(p-\bar{P}^t)^2}{{\sigma_P}^{t^2}}\right], & ss = 1\;(load\ decrement) \end{cases} \quad (4.8)$$

where

$$\bar{P}^t = 33.33\ (\$/MWh), \qquad \sigma_P{}^t = 1\ (\$/MWh), \qquad t = 1$$

$$\bar{P}^t = 20.00\ (\$/MWh), \qquad \sigma_P{}^t = 1\ (\$/MWh), \qquad t = 2$$

In this case, plant is expected to operate in load decrement mode along the two-hour period. During the second hour, expectation for heat demand is higher and the expectation for electricity price is lower as compared to the first hour. Under these circumstances, the expected solution for the plant operation is maximum benefit from the load decrement during the second hour when the electricity price is lower. This, in turn, necessiates heat storage during the first hour to cover the higher heat demand during the second hour.

Figures 4.3 and 4.4 illustrate the solutions for evolution program and stochastic optimization programming, respectively. As can be seen from these figures, the solutions found by the two techniques are in line with the expectations described above.

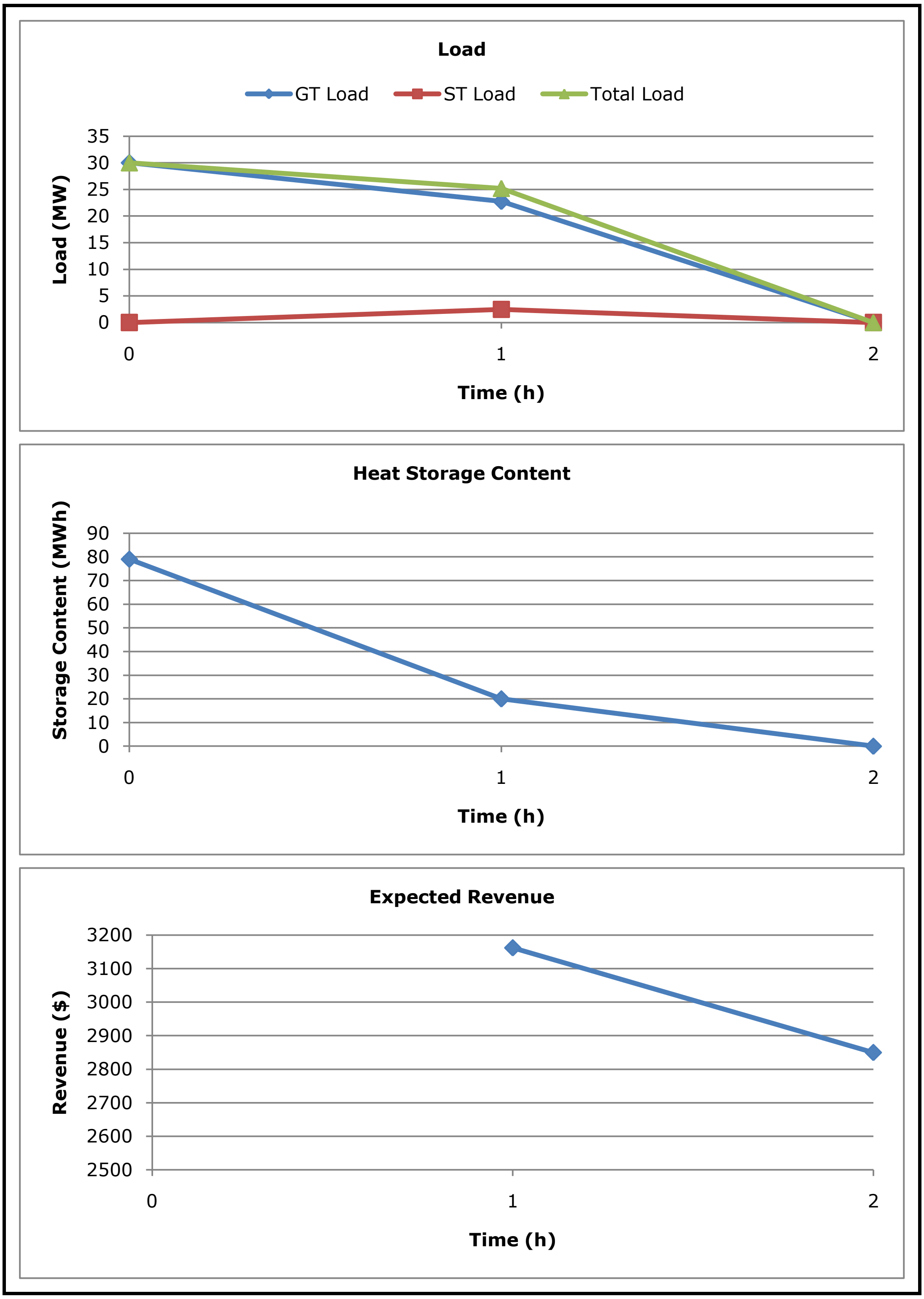


Figure 4.3 Evolution Solution 2 hours planning

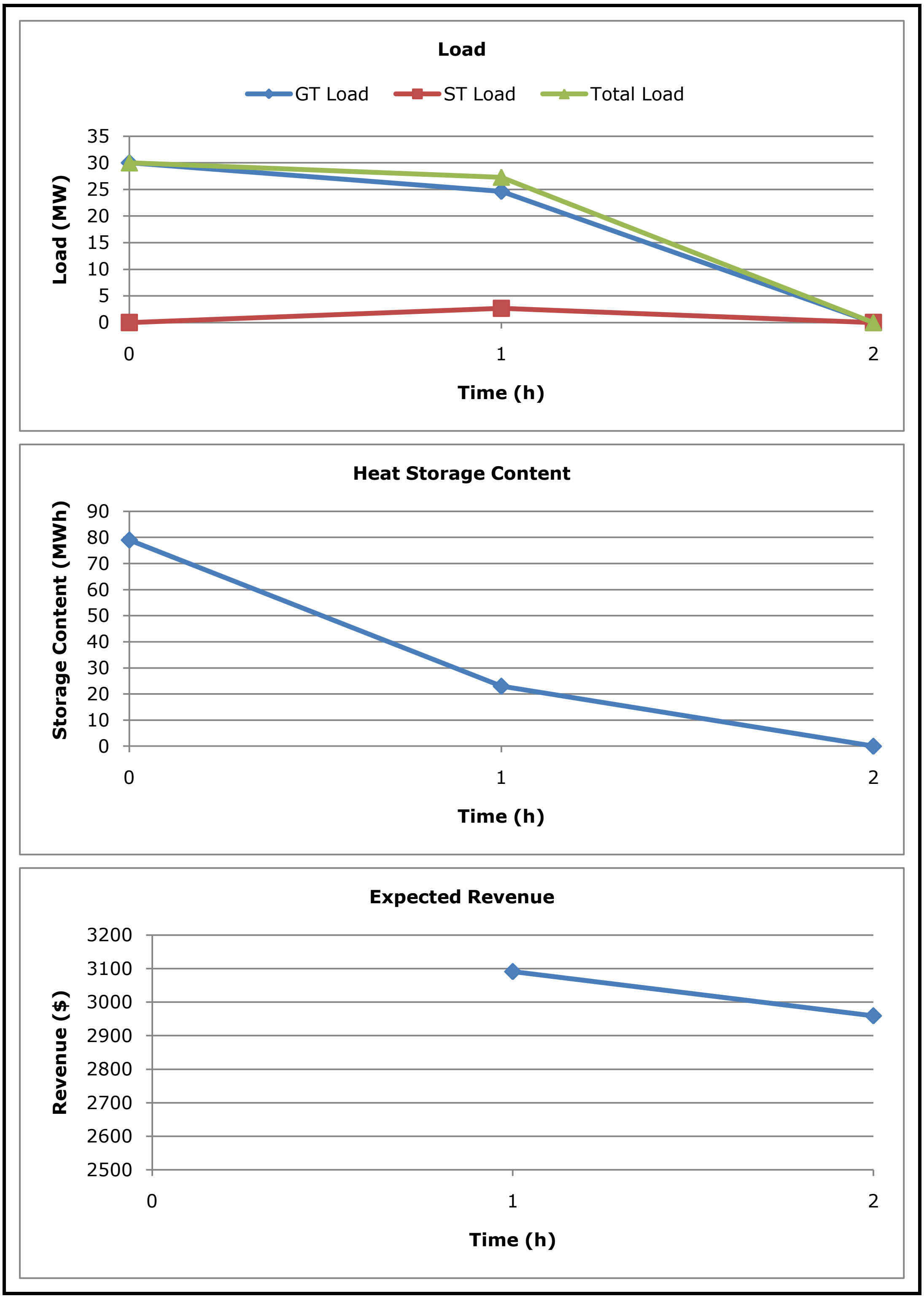


Figure 4.4 SDP Solution 2 hours planning

Load Scheduling for Three Hours:

Heat demand probability density function

$$f_{D^t}(d) = N(\bar{D}^t, {\sigma_D}^t) = \frac{1}{\sqrt{2\pi}{\sigma_D}^t} exp\left[-\frac{(d-\bar{D}^t)^2}{{\sigma_D}^{t^2}}\right]$$

where

$$\bar{D}^t = 70\ (MW), \quad {\sigma_D}^t = 1\ (MW), \quad t = 1$$
$$\bar{D}^t = 80\ (MW), \quad {\sigma_D}^t = 1\ (MW), \quad t = 2$$
$$\bar{D}^t = 40\ (MW), \quad {\sigma_D}^t = 1\ (MW), \quad t = 3$$

(4.9)

Electricity price probability density function

$$f_{P^t,ss^t}(p, ss) = \begin{cases} \frac{\alpha}{{\sigma_P}^t} exp\left[-\frac{(p-\bar{P}^t)^2}{{\sigma_P}^{t^2}}\right], \ ss = 0\ (load\ increment) \\ \frac{\beta}{{\sigma_P}^t} exp\left[-\frac{(p-\bar{P}^t)^2}{{\sigma_P}^{t^2}}\right], \ ss = 1\ (load\ decrement) \end{cases}$$

(4.10)

where

$\bar{P}^t = 33.33\ (\$/MWh),\ {\sigma_P}^t = 1\ (\$/MWh),\ \alpha = 0,\quad \beta = 1/\sqrt{2\pi},\quad t = 1$

$\bar{P}^t = 20.00\ (\$/MWh),\ {\sigma_P}^t = 1\ (\$/MWh),\ \alpha = 0,\quad \beta = 1/\sqrt{2\pi},\quad t = 2$

$\bar{P}^t = 100.0\ (\$/MWh),\quad {\sigma_P}^t = 1\ (\$/MWh),\quad \alpha = 1/\sqrt{2\pi},\ \beta = 0,\quad t = 3$

This case, in addition to the characteristics assumed for the first two hours as described above, incorporates an expectation for the load increment for the third hour. This expectation, necessiating maximum amount of load increment for the third hour, results in excess heat which needs to be transferred via the cooling system. Therefore, the plant operator has to consider the cooling related costs in determining the operational plan.

The solutions determined by the evolution program and stochastic optimization programming are shown in Figure 4.5. and Figure 4.6 in respectively. The solutions found by the two techniques are in paralel to the expectations described above.

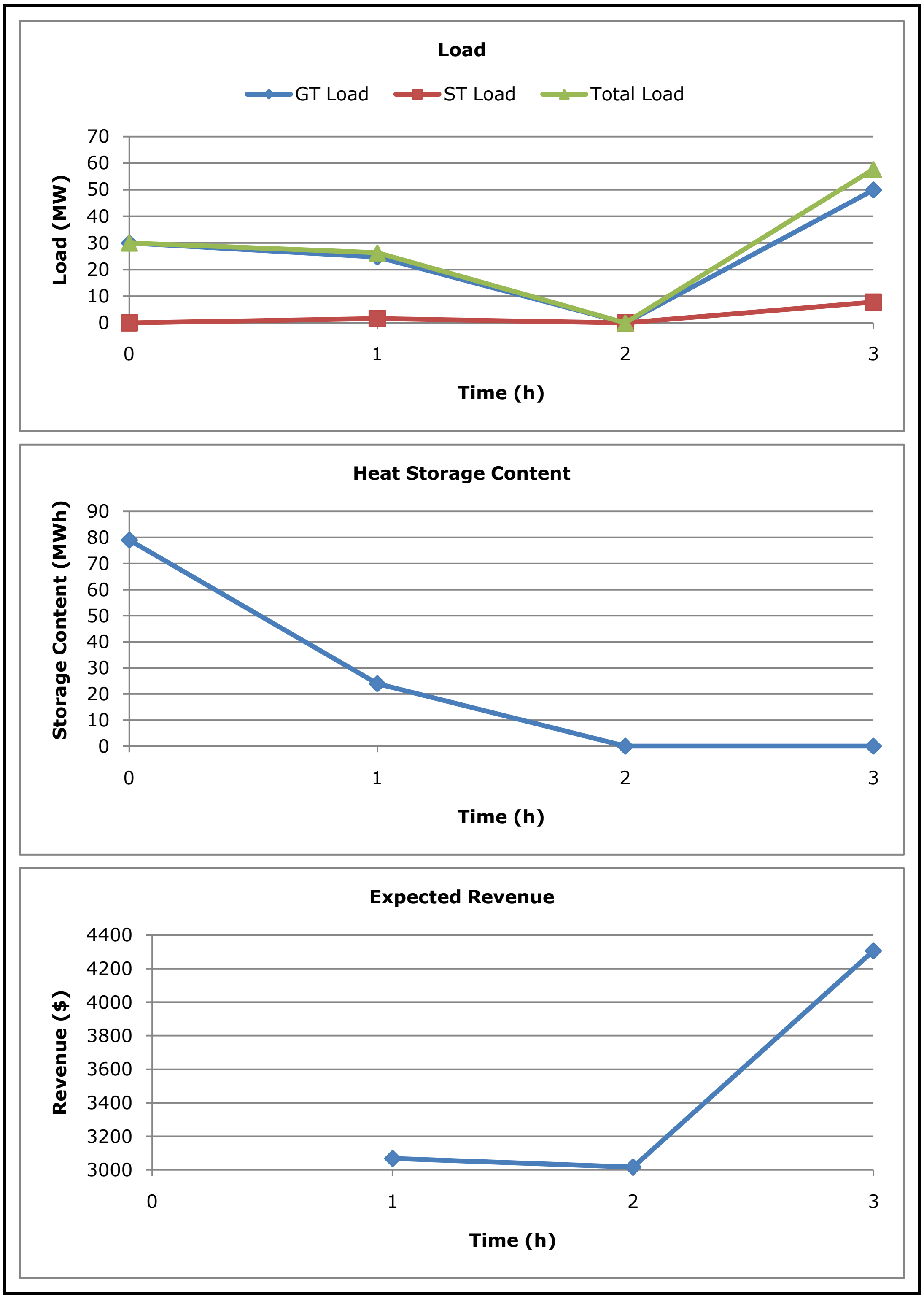


Figure 4.5 Evolution Solution 3 hours planning

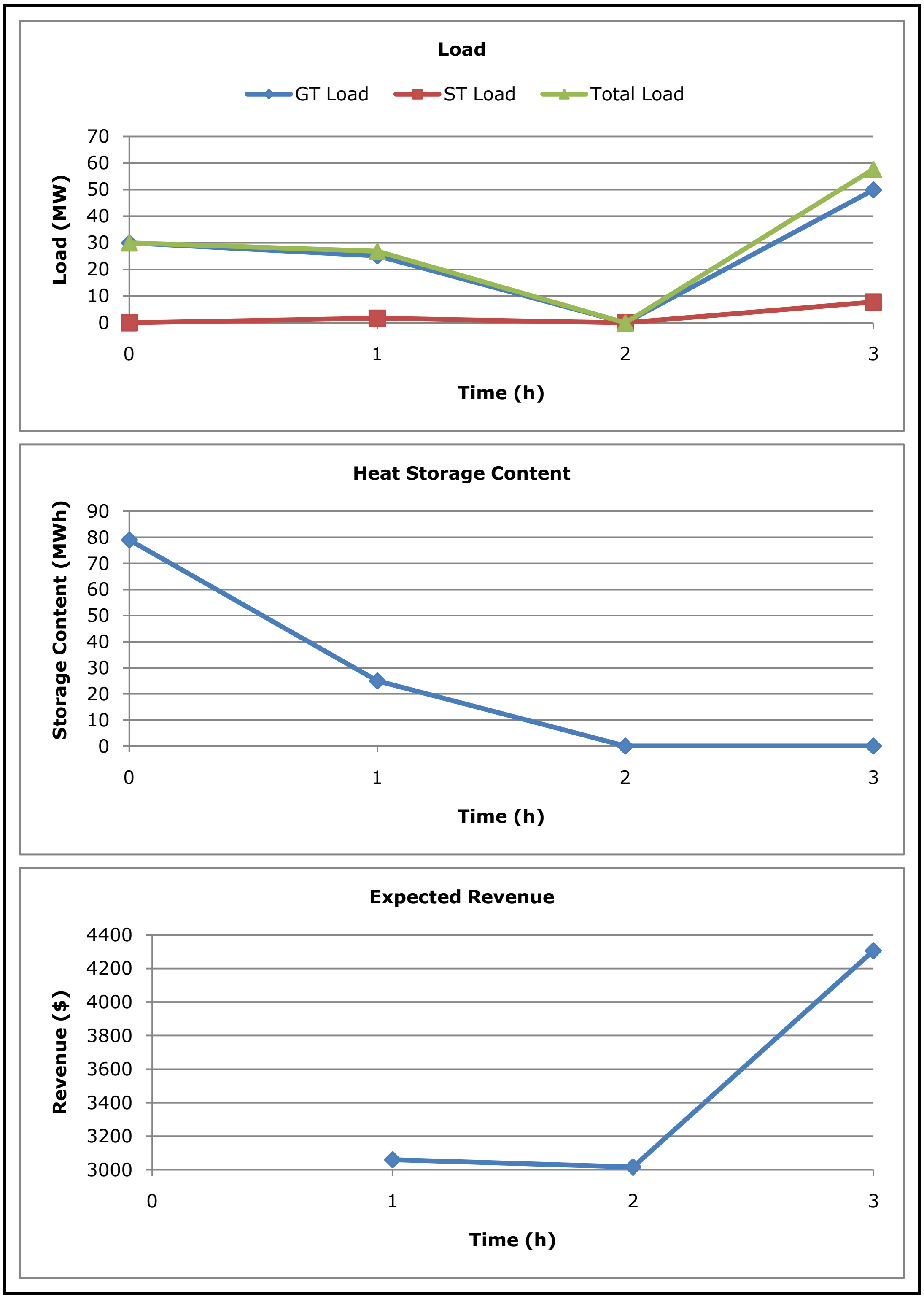


Figure 4.6 SDP Solution 3 hours planning

The solutions provided by the two techniques do not show any significant difference for all cases presented in this section. The expected revenues calculated by the two techniques do not differ significantly, as presented in Table 4.7.

Although the calculation times for the first hour case are similar, the stochastic dynamic programming technique proves to yield shorter computational times as the planning horizon extends. This is attributed to the fact that evolution program considers all time intervals together. This approach results in increase in the number of stochastic variables. For example, number of stochastic variables is 9 for the three hours planning case. As the number of stochastic variables increases, the number of simulations required for the convergence of the Monte Carlo integral also increases. This causes a substantial increase in CPU time. On the other hand, stochastic dynamic programming technique solves the problem by one hour solution periods. This type of solution approach decreases the number of Monte Carlo simulations, and consequently the CPU time. Table 4.7 presents the CPU times for the two techniques employed for the three different cases developed and explained in this section.

In the remainder of the thesis, analyses are performed by SDP technique.

Table 4.7 Comparison of Evolution Program and SDP Solutions

Planning Horizon (hours)	**Evolution Program**		**Stochastic Dynamic Programming**	
	Expected Revenue ($)	CPU Time (s)	Expected Revenue ($)	CPU Time (s)
1	3500	40	3502	45
2	6012	8472	6050	1246
3	10391	18972	10383	2855

4.6 Parameter Analysis

Stochastic Dynamic Programming technique utilizes an evolution program for optimization of each state. In this section, parameter analysis of the evolution program is performed. Evolution program is a random search technique based on genetic algorithm method. Genetic algorithms have the ability to enhance the quality of solution by tuning. The four major parameters genetic algorithms use for tuning are generation number, population size, mutation probability, and crossover probability. During the course of parameters analysis, one parameter is changed while the others are kept constant.

As can be seen from Figure 4.7, increasing generation number further than 20 does not improve revenue. On the contrary, CPU time increases in parallel to the number of generations.

The parameter analysis for population size is shown in Figure 4.8. Although the increase in population size generally increases the probability for better solutions, in the problem under consideration maximum revenue is obtained when the population size is 8.

The results of the parameter analysis for mutation probability and cross-over probability are presented in Figure 4.9. and Figure 4.10 respectively. As can be seen from these figures, revenue is maximized when the mutation probability is 0.1 and the crossover probability is 0.3.

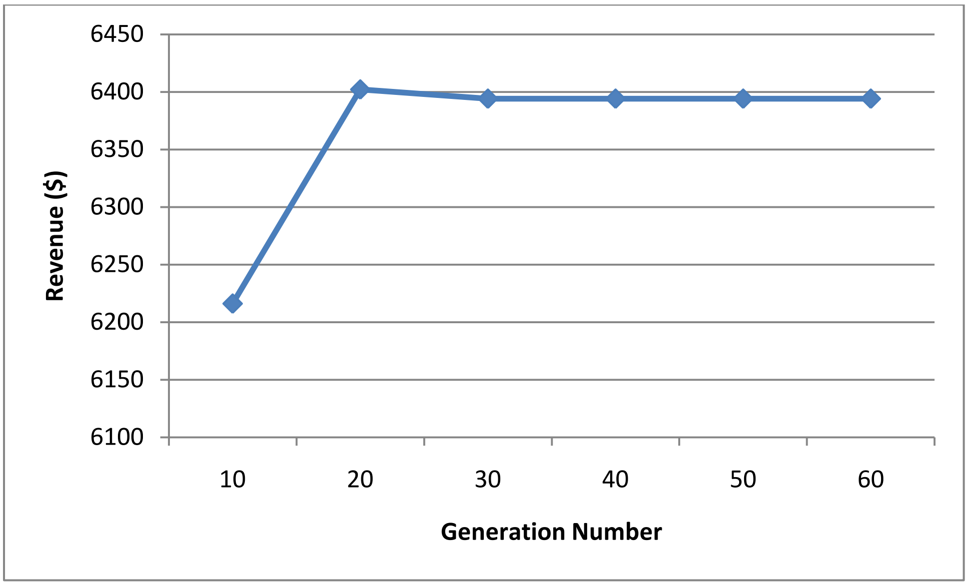


Figure 4.7 Revenue versus generation number

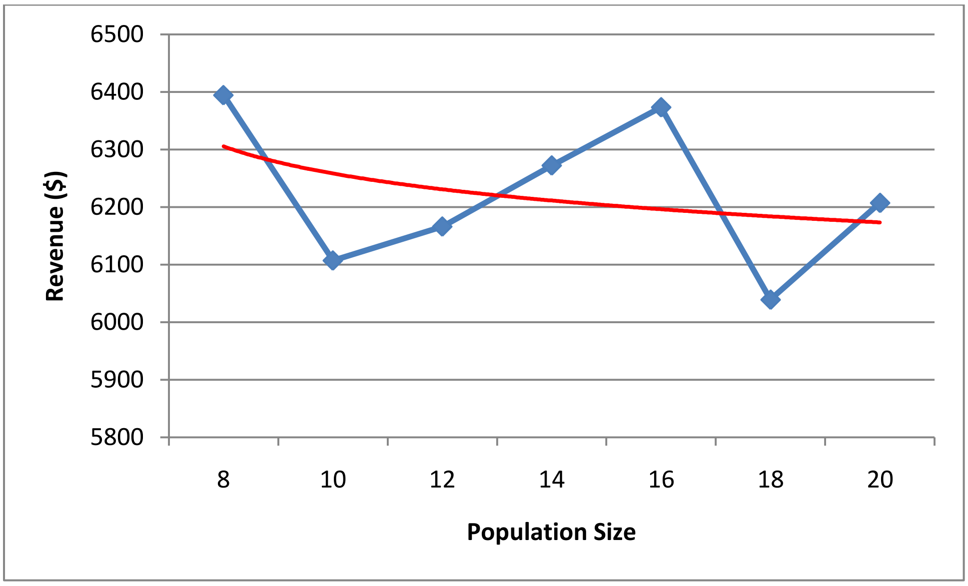


Figure 4.8 Revenue versus population size

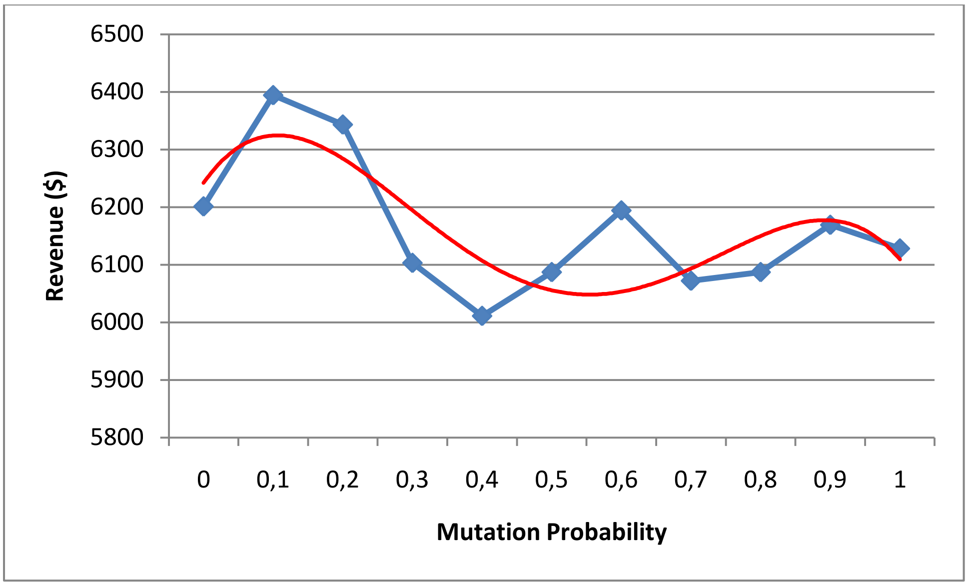


Figure 4.9 Revenue versus mutation probability

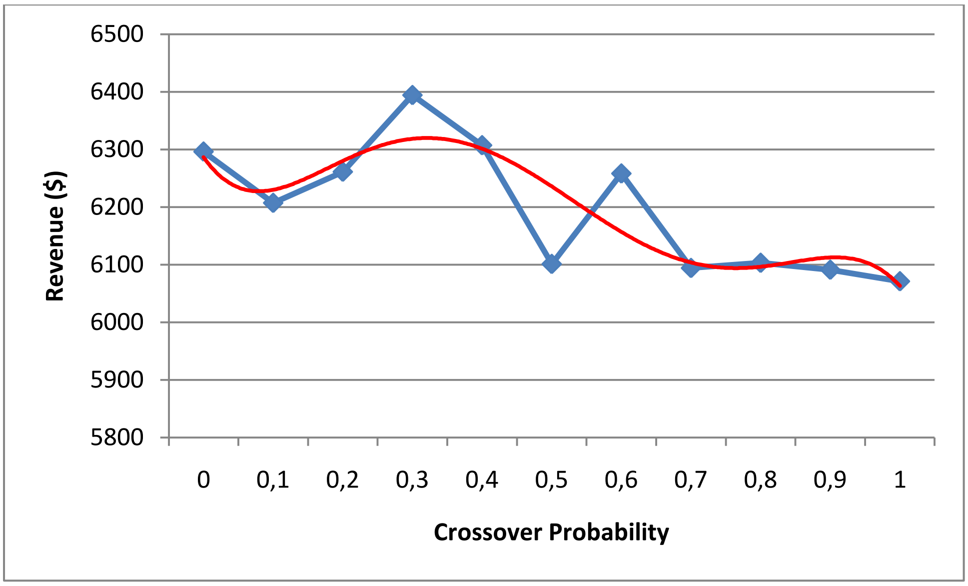


Figure 4.10 Revenue versus crossover probability

4.7 Effect of Uncertainty in Heat Demand

In this analysis, effect of the degree of uncertainty on stochastic load scheduling is investigated. One hour load scheduling is used. Initial storage content of the heat storage tank is assumed to be 79 MW.

Heat demand probability density function is

$$f_{D^t}(d) = N(\bar{D}^t, {\sigma_D}^t) = \frac{1}{\sqrt{2\pi}{\sigma_D}^t} exp\left[-\frac{(d-\bar{D}^t)^2}{{\sigma_D}^{t^2}}\right] \quad (4.11)$$

where

$$\bar{D}^t = 70\ (MW), \quad t = 1$$

Electricity price probability density function is

$$f_{P^t, ss^t}(p, ss) = \begin{cases} 0, & ss = 0\ (load\ increment) \\ \frac{1}{\sqrt{2\pi}{\sigma_P}^t} exp\left[-\frac{(p-\bar{P}^t)^2}{{\sigma_P}^{t^2}}\right], & ss = 1\ (load\ decrement) \end{cases} \quad (4.12)$$

where

$$\bar{P}^t = 33.33\ (\$/MWh), \qquad {\sigma_P}^t = 1(\$/MWh), \qquad t = 1$$

Standard deviation of heat demand ${\sigma_D}^t$ is varied to analyze the effect of uncertainty in heat demand. Figure 4.11 illustrates load and revenue changes obtained by stochastic load scheduling with respect to uncertainty of heat demand. For the cases of small uncertainty in heat demand, optimal solution is load decrement. Beyond a standard deviation of 3.2, heat demand can only be covered by supplementary firing. Therefore, the solution suggests generation of electricity as per the bilateral contracting instead of participating in PMUM.

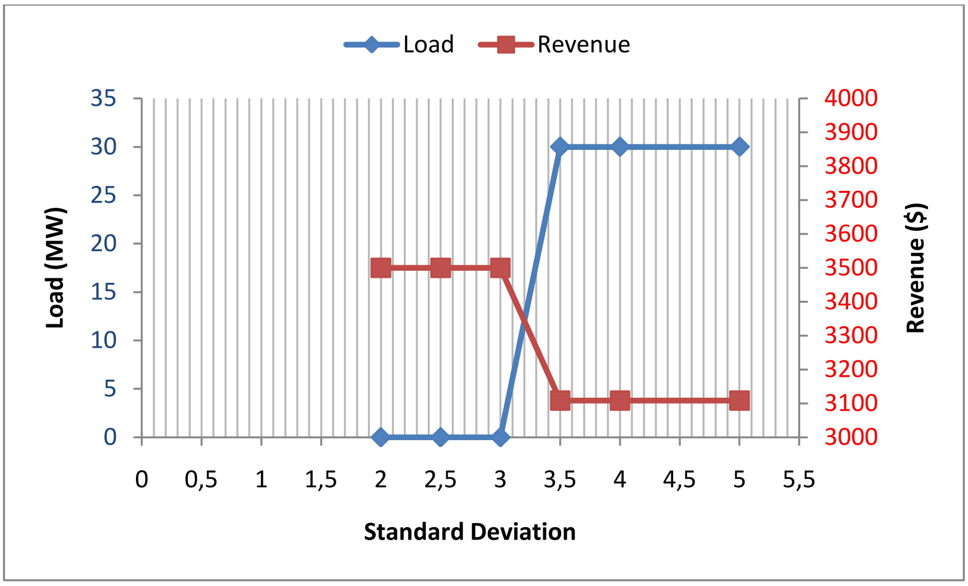


Figure 4.11 Effect of uncertainty in heat demand on load scheduling

4.8 Load Scheduling for a Typical Day

The aim of this scenario is to solve a load scheduling problem for a typical day. Normal distribution is selected to represent the probability density distribution of electricity system price for each hour. Real hourly electricity price values are used as mean values of distributions. The value of standard deviation is assumed as 5 for each distribution. Similarly, heat demand probability density function is assumed as normal distribution. Hourly data for a typical day is tabulated in Table 4.8. Initial storage content of the heat storage tank is assumed to be 131 MW. The bilateral contract price is assumed to be 250 $/MWh for each hour within the planning horizon.

Solution of stochastic load scheduling problem for the case study is presented in Figure 4.12. During the period of 9-24 hours, plant is expected to operate in load increment. In this case, plant output is increased over the bilateral contract power (30 MW).

Table 4.8 Hourly data for a typical day

Hour	System State	System Price ($/MWh)[a]	Heat Demand (MW)
1	Load Increment	87.87	23.19
2	Load Increment	79.27	23.19
3	Load Decrement	49.90	22.74
4	Load Decrement	46.85	24.72
5	Load Decrement	46.57	24.06
6	Load Decrement	49.90	24.30
7	Load Decrement	51.65	22.08
8	Load Decrement	57.03	22.08
9	Load Increment	96.41	22.08
10	Load Increment	97.42	24.30
11	Load Increment	97.42	26.49
12	Load Increment	97.67	24.30
13	Load Increment	96.65	22.08
14	Load Increment	96.92	22.08
15	Load Increment	97.40	22.08
16	Load Increment	97.40	22.08
17	Load Increment	99.08	23.19
18	Load Increment	112.77	22.74
19	Load Increment	103.83	24.06
20	Load Increment	97.39	21.42
21	Load Increment	96.76	20.52
22	Load Increment	96.00	21.63
23	Load Increment	93.70	19.65
24	Load Increment	79.27	22.29

[a] Exchange Rate ($/TL) = 1.5 (December 2009)

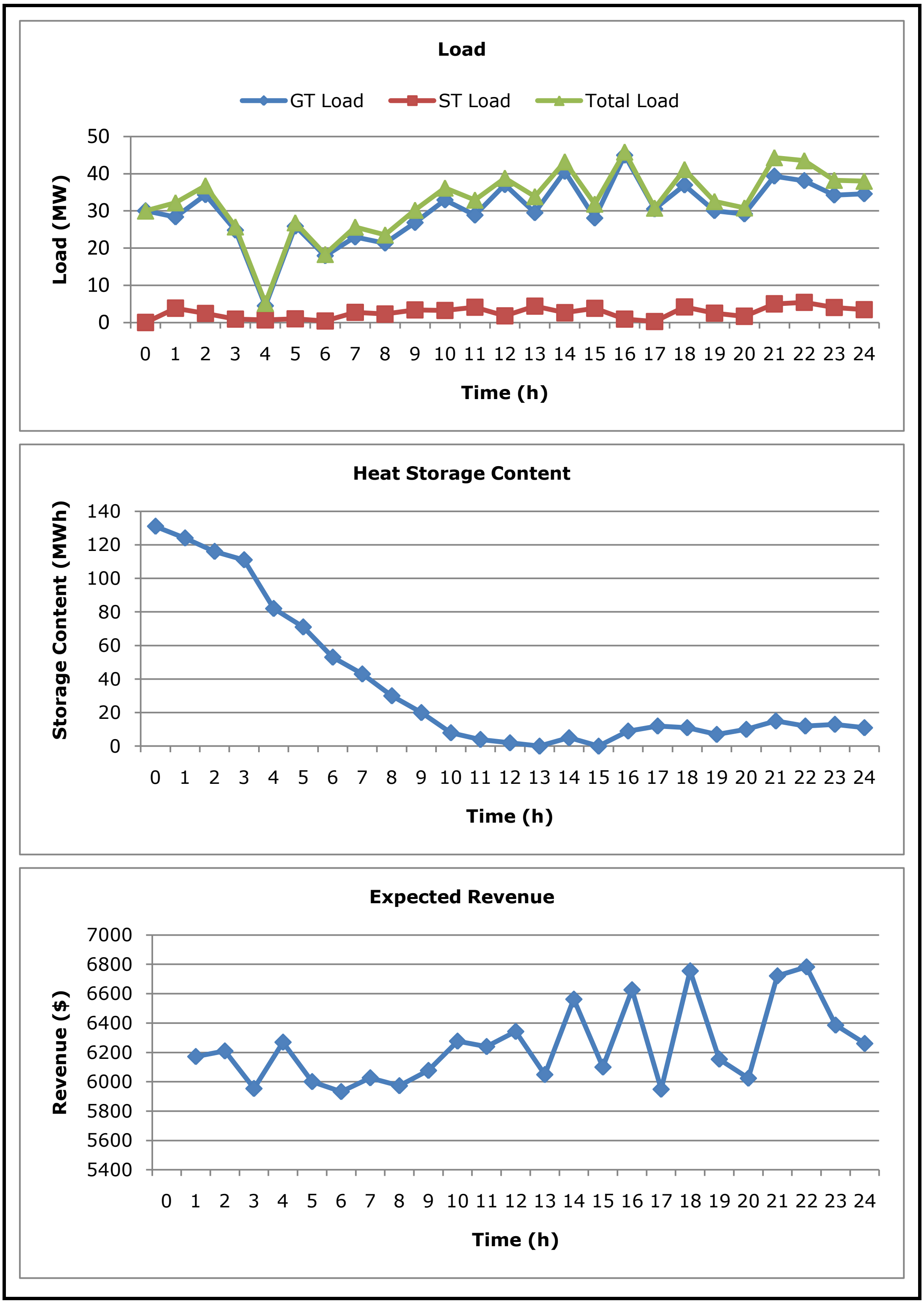


Figure 4.12 SDP Solution 24 hours planning for a typical day

4.9 Heat Storage Capacity

In this section, effect of the storage tank volume on the revenue is analyzed. The analysis is performed for the typical day based on the data given in Table 4.8. Load scheduling problem is solved for different values of storage tank volume. Revenue reaches a plateau at a certain value of storage capacity, as illustrated in Figure 4.13.

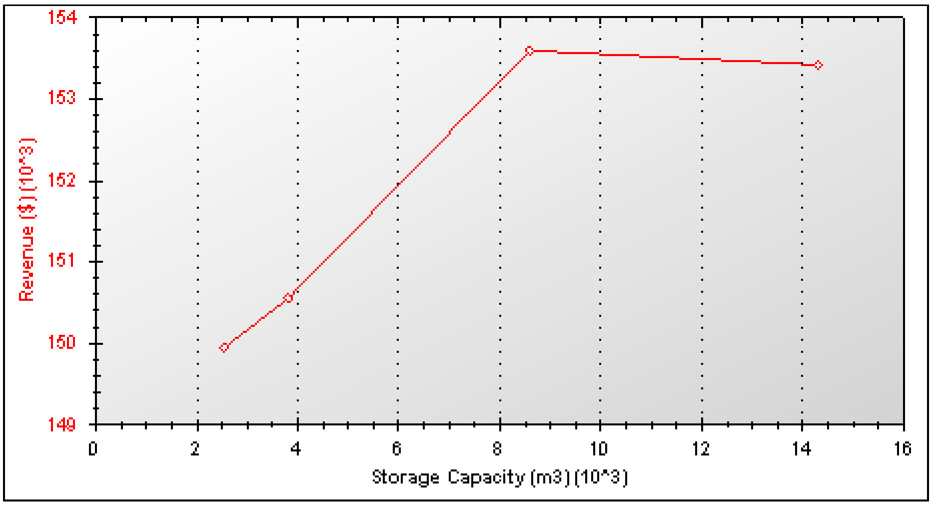


Figure 4.13 Effect of storage capacity on revenue for the typical day

The analyses for the storage capacity are also performed to investigate the effect of seasons. In this respect, the characteristic data, comprising PMUM data for market together with heat demand data from Bilkent Cogeneration Plant and relevant meteorological data, are used to represent each of the four seasons in a year. Figure 4.14 illustrates the effect of seasons on the storage capacity. In summer season, heat demand is lower than other seasons. However, the electricity peak demand is relatively higher (Güray [2009]). This can be attributed to the use of air-conditioning equipment. Therefore, the plant tends to operate at high power rates and uses storage capacity to compensate for the cooling requirement of excess heat. The annual pattern is given in Figure 4.15. Revenue reaches a plateau at a certain value of storage capacity. This can be explained by the characteristics of other three seasons, as Figure 4.15 illustrates the annual pattern found by the superposition of four seasons.

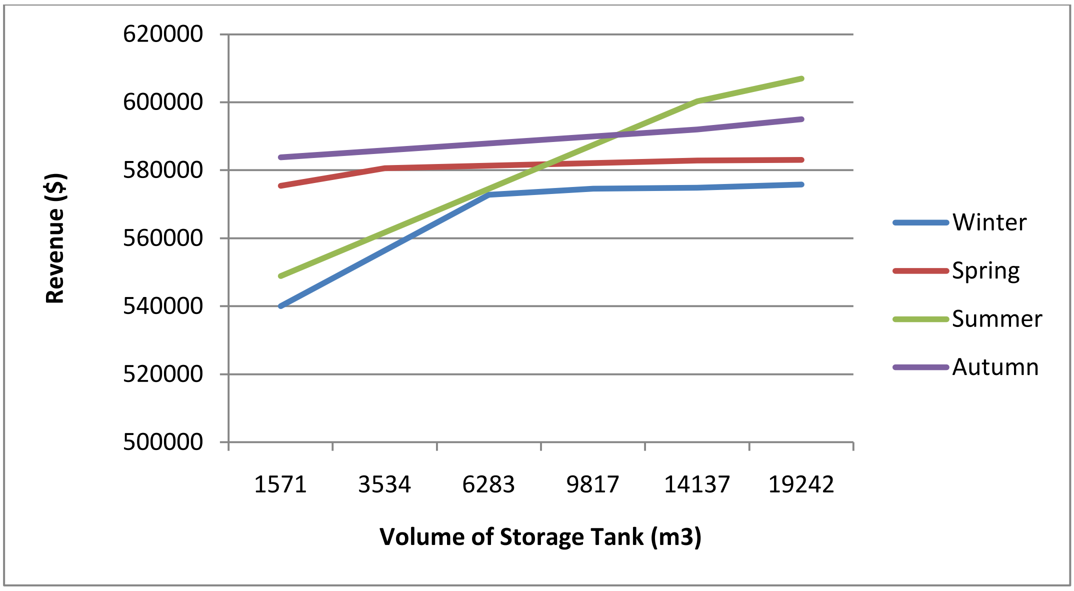


Figure 4.14 Effect of storage capacity on revenue

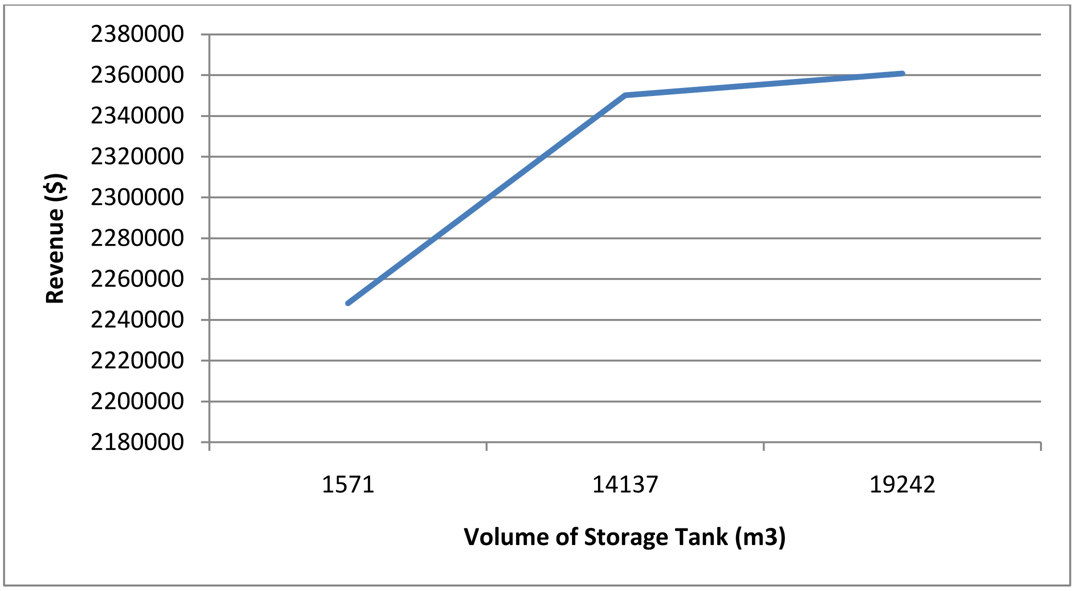


Figure 4.15 Effect of storage capacity on revenue on an annual basis

4.10 Stochastic Load Scheduling based on Thermoeconomics

Thermoeconomics is the branch of thermal sciences that combines a thermodynamic analysis with economic principles. It provides the understanding of an energy conversion system with information which is not available through conventional thermodynamic analysis and economic evaluation. Thermoeconomics is based on exergy costing which is the only rational approach for assigning costs to the interactions that a thermal system experiences with its surrounding and to the sources of inefficiencies within it (Lazzaretto [1999]). Exergy costing provides a set of indicators which provides information on the impact on resources (Valero [2006]).

In exergy costing a cost is associated with each exergy stream. Equations through 4.13-4.16 cost rates are formulated for entering and exiting streams of matter with associated rates of exergy transfer $\dot{E}_i$ and $\dot{E}_e$, power $\dot{W}$, and the exergy transfer rate associated with heat transfer $\dot{E}_q$ respectively.

$$\dot{C}_i = c_i\dot{E}_i = c_i(\dot{m}_i e_i) \tag{4.13}$$

$$\dot{C}_e = c_e\dot{E}_e = c_e(\dot{m}_e e_e) \tag{4.14}$$

$$\dot{C}_w = c_w\dot{W} \tag{4.15}$$

$$\dot{C}_q = c_q\dot{E}_q \tag{4.16}$$

Here c_i, c_e, c_w, and c_q denote average costs per unit of exergy in dollars per gigajoule ($/GJ). Exergy costing is applied for each component separately. For kth system component operating at steady state with a number of entering and exiting streams as well as both heat and work interactions with surroundings the relevant cost balance is

$$\sum_e \dot{C}_{e,k} + \dot{C}_{w,k} = \dot{C}_{q,k} + \sum_i \dot{C}_{i,k} + \dot{Z}_k \tag{4.17}$$

where $\dot{Z}_k$ is the appropriate charge due to capital investment plus operating and maintenance expenses. The cost rates associated with capital investment and operating and maintenance are calculated by dividing the annual contribution of capital investment and the annual operating and maintenance costs by the number of time units.

In analyzing a component, the costs per exergy unit are assumed known from the components they exit. As a rule, n-1 auxiliary relations are required for components with n exiting energy streams. This task is accomplished with the aid of F and P rules (Lazzaretto [1999]). The F rule states that the total cost associated with this removal of exergy from a stream must be equal to the cost at which the removed exergy is supplied to the same stream in upstream component when for this stream the exergy difference between inlet and outlet is considered in the definition of fuel. The P rule refers to the supply of exergy to an exergy stream within the component being considered. The P rule states that each exergy unit is supplied to any stream associated with the product at the same average cost. Since the total number of exiting exergy streams is equal to the sum of the number of exiting streams included in product definition and the number of exiting streams included in fuel definition, the F and P rules together provide the required auxiliary equations.

The principles of exergy costing are explained below which is based on an example concerning a simple adiabatic turbine in Figure 4.16. For this case, Equation 4.17 reduces to

$$\dot{C}_e + \dot{C}_w = \dot{C}_i + \dot{Z} \tag{4.18}$$

where $\dot{Z}$ represents the sum of charges associated with turbine's capital investment and operating and maintenance costs. With Equations 4.13, 4.14, and 4.15 Equation 4.18 becomes

$$c_e \dot{E}_e + c_w \dot{W} = c_i \dot{E}_i + \dot{Z} \tag{4.19}$$

where $\dot{W}$, $\dot{E}_i$, and $\dot{E}_e$ are known based on a prior exergy analysis. $\dot{Z}$ is known from a previous economic analysis. The cost per exergy unit of steam entering the turbine c_i can be determined from the application of exergy costing to the components upstream of the turbine. To determine unknown exergy unit costs c_e and c_w, one auxiliary relation is required. According to F rule the cost per unit exergy of working fluid remains constant which is

$$c_e = c_i \tag{4.20}$$

In this study, stochastic load scheduling problem for the case study cogeneration plant is solved on the basis of thermoeconomics. Cost balances and auxiliary equations are formulated for major components of the plant and are presented in Table 4.9. Resulting system of linear equations is solved to determine unknown cost flow rates and unit costs for each hour within the planning horizon. Exergy values of the streams used in the equations are given in Table 4.10. Finally, cost rates of products are obtained.

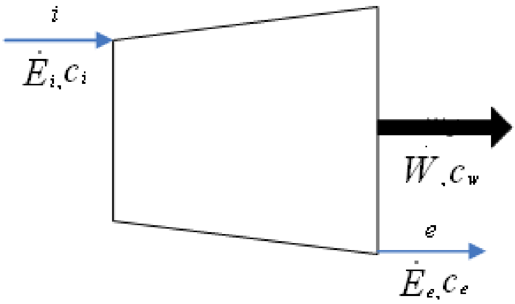


Figure 4.16 Simple steam turbine at steady state

Equation 4.3 which represents the revenues from running plant consists of revenues from selling both power and heat to customers is modified to incorporate the exergy related cost terms.

$$r_{t+k\Delta t}(\dot{m}_{8,t+k\Delta t}, \dot{m}_{10,t+k\Delta t}, \breve{D}_{t+k\Delta t}, \check{C}_{P,t+k\Delta t}, \widetilde{ss}_{t+k\Delta t}) =$$

$$[P_{bc}c_{bc} + (P_{t+k\Delta t} - P_{bc})\check{C}_{P,t+k\Delta t}]\Delta t$$

$$+ c_D \dot{Q}_D \Delta t$$

$$-\acute{C}_{gt}\Delta t \qquad (4.21)$$

$$-\acute{C}_{st}\Delta t$$

$$- c^{(ng)} H_{PB,t+k\Delta t}$$

$$- c^{(c)} \dot{Q}_{excess}\Delta t$$

where $\acute{C}_{gt}$ and $\acute{C}_{st}$ are final cost flow rates of final products.

The charges due to capital investment plus operating and maintenance expenses are calculated by using purchased equipment costs. These costs are tabulated in Table 4.11.

The following assumptions are made in formulating cost balances and auxiliary relations:

- A zero unit cost is assumed for air entering the air compressor.
- The cost rate of stream 8, which is supplied to the total system from outside, is obtained by the amount and price of natural gas used within a certain hour of planning.
- Power requirement of pumps are met by steam turbine.
- Losses during the transmission of power from the steam turbine to pumps are ignored.
- The annual carrying charges and operating and maintenance costs are apportioned among the system components according to the contribution of each component to the sum of purchased equipment costs.

Table 4.9 Cost balance and auxiliary equations for the components of case study cogeneration plant

Component	Cost balance and auxiliary equations
Air compressor	$\dot{C}_2 - \dot{C}_{ac} = \dot{Z}_{ac}$ $\dot{C}_1 = 0$ (assumption)
Air preheater	$\dot{C}_3 + \dot{C}_6 - \dot{C}_2 - \dot{C}_5 = \dot{Z}_{ph}$ $\dot{E}_5\dot{C}_6 - \dot{E}_6\dot{C}_5 = 0$ (F rule)
Combustion Chamber	$\dot{C}_4 - \dot{C}_3 = \dot{Z}_{cc} + \dot{C}_8$
Gas Turbine	$\dot{C}_4 + \dot{Z}_{gt} = \dot{C}_5 + \dot{C}_{ac} + \dot{C}_{gt}$ $\dot{E}_4\dot{C}_5 - \dot{E}_5\dot{C}_4 = 0$ (F rule) $\dot{W}_{gt}\dot{C}_{ac} - \dot{W}_{ac}\dot{C}_{gt} = 0$
Heat Recovery Steam Generator	$\dot{C}_7 + \dot{C}_9 = \dot{C}_6 + \dot{C}_{19} + \dot{Z}_{hrsg}$ $\dot{E}_6\dot{C}_7 - \dot{E}_7\dot{C}_6 = 0$ (F rule)
Steam Turbine	$\dot{C}_{13} + \dot{C}_{14} + \dot{C}_{st} + \dot{C}_{pump,1} + \dot{C}_{pump,2} - \dot{C}_{10} = \dot{Z}_{st}$ $\dot{E}_{13}\dot{C}_{10} - \dot{E}_{10}\dot{C}_{13} = 0$ (F rule) $\dot{E}_{14}\dot{C}_{10} - \dot{E}_{10}\dot{C}_{14} = 0$ (F rule)
Throttling Valve	$\dot{C}_{11} - \dot{C}_{12} = \dot{Z}_{th}$
Pump 1	$\dot{C}_{16} - \dot{C}_{15} - \dot{C}_{pump1} = \dot{Z}_{pump1}$ $\dot{W}_{st}\dot{C}_{pump1} - \dot{W}_{pump1}\dot{C}_{st} = 0$
Pump 2	$\dot{C}_{18} - \dot{C}_{17} - \dot{C}_{pump2} = \dot{Z}_{pump2}$ $\dot{W}_{st}\dot{C}_{pump2} - \dot{W}_{pump2}\dot{C}_{st} = 0$

Table 4.10 Exergy data for the case study cogeneration system[a]

State	Substance	$\dot{e}^{PH}$ (kJ/kg)	$\dot{e}^{CH}$ (kJ/kg)	$\dot{e}$ (kJ/kg)
1	Air[b]	0.0000	-0.4277	-0.4277
2	Air [b]	301.7035	-0.4277	301.2758
3	Air [b]	459.4695	-0.4277	459.0418
4	Combustion products [c]	1087.9241	3.9444	1091.8685
5	Combustion products [c]	413.4394	3.9444	417.3838
6	Combustion products [c]	230.1512	3.9444	234.0956
7	Combustion products [c]	25.8950	3.9444	29.8394
8	Methane (Fuel)	381.9356	51383.6409	51765.5765
9	Water	1291.6000	2.4979	1294.0979
10	Water	1291.6000	2.4979	1294.0979
11	Water	1291.6000	2.4979	1294.0979
12	Water	923.5494	2.4979	926.0473
13	Water	676.3952	2.4979	678.8931
14	Water [d]	48.1054	2.4979	50.6033
15	Water [e]	0.4864	2.4979	2.9843
16	Water	8.5164	2.4979	11.0143
17	Water	90.1524	2.4979	92.6503
18	Water	98.3624	2.4979	100.8603
19	Water	44.9912	2.4979	47.4891

[a] Standard chemical exergies are from Bejan [1996] Model I.
[b] Molar analysis (%) : 77.48N_2, 20.59O_2, 0.03CO_2, 1.90H_2O(g)
[c] Molar analysis (%) : 75.07N_2, 13.72O_2, 3.14CO_2, 8.07H_2O(g)
[d] Quality x_{14}=0.758
[e] $h_0 = 104.88$ kJ/kg and $s_0 = 0.3674$ kJ/kg.K

Table 4.11 Estimate of Purchased Equipment Costs (PECs) for case study cogeneration system (all costs are expressed in thousands of dollars) [a]

Component	Purchased Equipment Cost ($)
Air compressor	6,209
Air preheater	1,270
Combustion chamber	562
Gas turbine	6,218
Heat recovery steam generator	1,648
Process heater	482
Steam turbine	2,193
Expansion valve	244
Pump 1	76
Pump 2	99
Mixing chamber	18
Condenser	16
Storage unit	614
Other plant equipment	1,100

[a] PECs are calculated according to relations in terms of technical characteristics in Bejan [1996], Vieira [2006], Silveira [2003], Kostowski [2005].

Load scheduling problem, which is solved by energy analysis in Section 4.6 for a cogeneration system selected as a case study, is analyzed and solved by exergy analysis. The results of the analyses are presented in Figure 4.17. Total load and the storage content exhibit similar patterns with the energy analysis case. Figure 4.18 illustrates the share of steam turbine in total electricity production for the energy and exergy-costing analyses. Exergy-costing analysis based solution yield larger utilization values for steam turbine along the 24 hours period. As the cost rate of electricity generated by the gas turbine is considerably higher than the cost rate of electricity generated by the steam turbine, the plant tends to utilize the steam turbine more effectively. This effect is highlighted by the polynomial fitting, as presented in Figure 4.18.

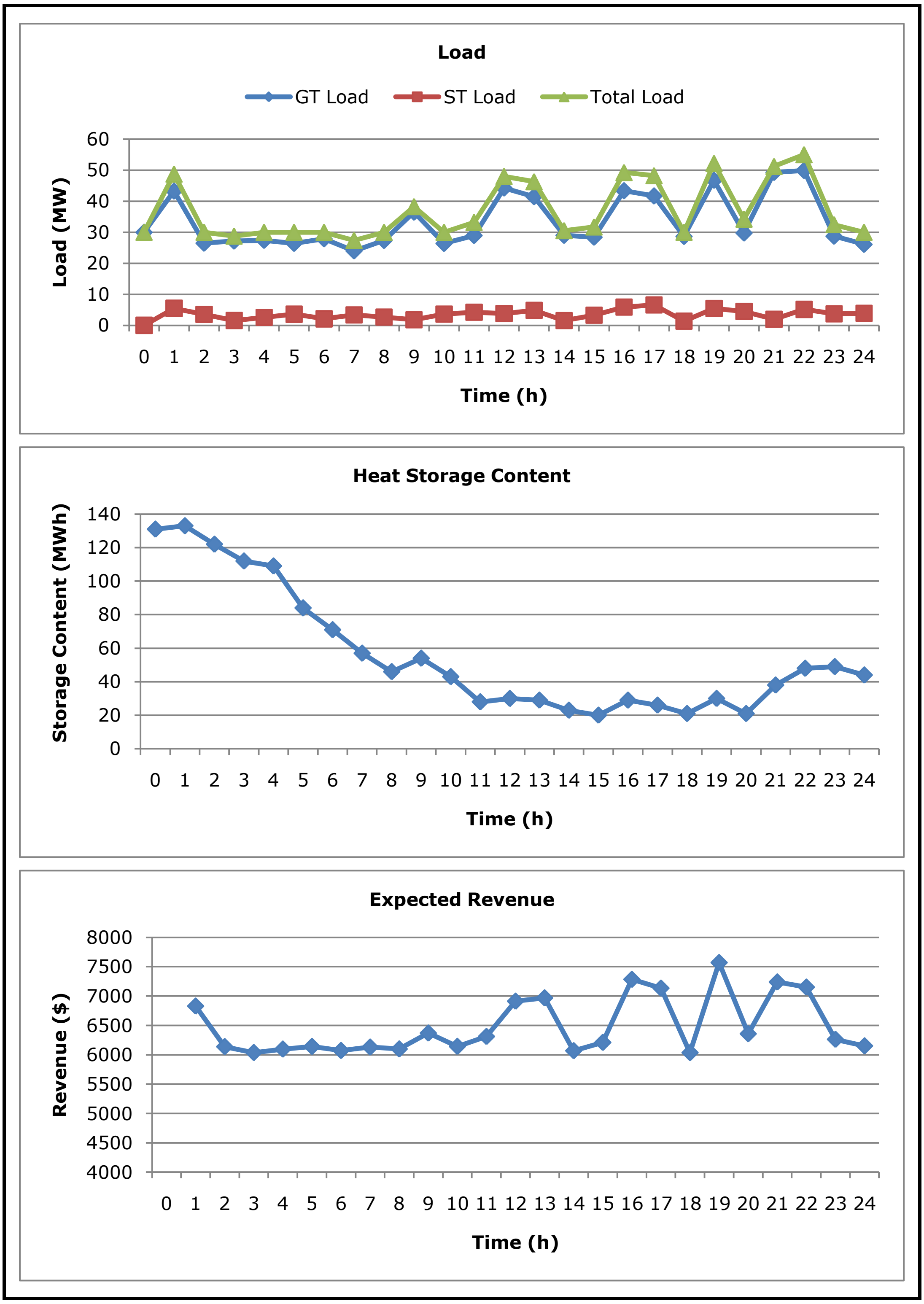


Figure 4.17 24 hours load scheduling based on exergy costing

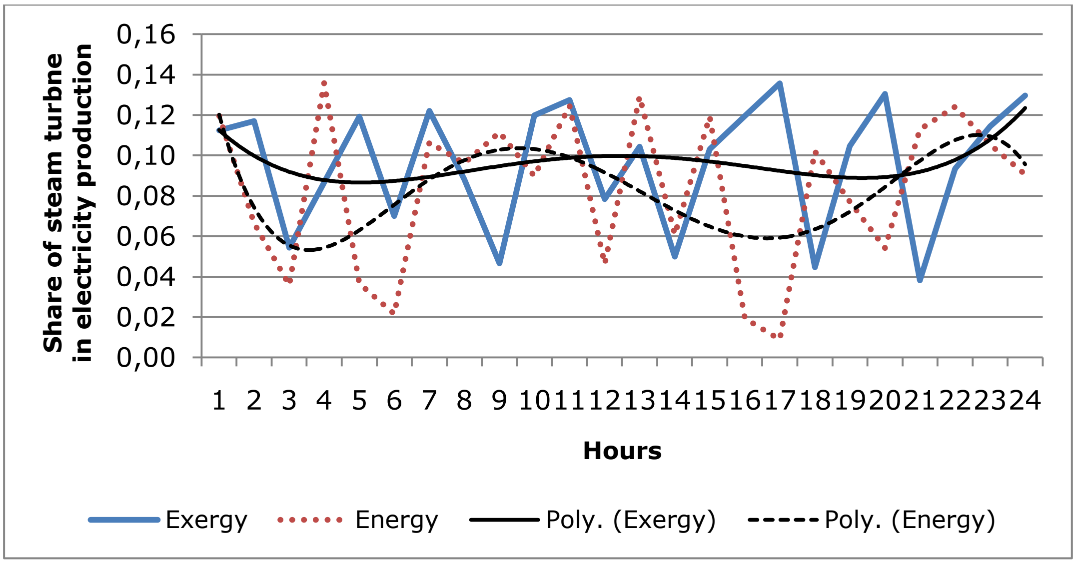


Figure 4.18 Comparison of steam turbine use in energy and thermoeconomics approach

CHAPTER 5

PROBABILITY DENSITY ESTIMATION

In this chapter, an approach is proposed to estimate the probability density functions for heat demand and the revenue from selling electricity for each hour within the planning horizon using the heat demand and electricity price data in the past. The approach is coupled with stochastic load scheduling analysis which requires hourly probability density functions to evaluate uncertainties in heat demand and the revenue from selling electricity in scheduling horizon.

5.1 Overview of Probability Density Estimation

Probability density estimation falls into two general types: nonparametric approach and parametric approach. In nonparametric probability density estimation approach, density is determined according to a formula involving the data points available. The kernel density estimator and k-nearest neighbor technique are the most common nonparametric methods. Nonparametric probability density approach is data driven and does not require selecting a multivariate probability distribution and verifying its fitness to the particular data. Nonparametric density estimation belongs to the class of ill-posed problems in sense that small changes in the data can lead to large changes in the estimated density. Therefore it is important to have methods that are robust to slight changes in the data. Parametric techniques for probability density estimation assume a model of suitable functional form with parameters to be adjusted so that it approximates the distribution of the data. The most widely used parametric approach for density is based on Gaussian mixtures which have been shown to exhibit the universal approximation property. Efficient procedures for likelihood maximization are present for this model in the literature.

Charytoniuk [1998] presented the application of nonparametric regression for short-time load forecasting which allows the load forecast to be calculated directly from historical data as a local average of observed past loads with the size of the local neighborhood (in terms of time, temperature and other relevant factors) and the specific weights on the loads defined by a multivariate product kernel.

Charytoniuk [1999] presented an application of probability density function (PDF) with nonparametric estimation technique in order to model relationships between customer electricity demand, temperature, and time. Approach enables effective use of electricity demand survey data to build a demand model that expresses both the random nature of electricity demand and its temperature dependence and allows a PDF estimated from a sample without making any assumption on population properties. Loads of power distribution systems are not known certainly because of the limited monitoring and the loads should be forecasted by using the information on customers and weather conditions. Effective utilization of demand survey data for building a demand model which expresses both the random demand nature and its temperature dependence is estimated by a nonparametric density estimator and this dependence is used for demand forecast based on energy usage and outside temperature. This approach allows using the data regardless of the type of its load distribution which brings the advantage of eliminating the need for a multivariate distribution for fitting the data.

Chen [2006] proposed a heuristic method to estimate the steady state density of a stochastic process. The proposed procedure computes sample densities only at certain points by a nonparametric method and uses Lagrange interpolation to estimate density. The method does not require users to have a priori knowledge of values that the data might assume. It applies classical statistical techniques directly and do not require more advanced statistical theory. Therefore, the algorithm is easy to understand, and simple to implement.

Many of proposed methods using neural networks in the literature are similar to existing conventional methods, but developed in a neural network framework. Traven [1991] and Cwik [1996] proposed methods on the basis of parametric approach. Schioler [1997] designed a neural network structure for estimating conditional distributions, is based on nonparametric approach. Magdon-Ismail [1998] developed semi-parametric methods for density estimation implemented using multilayer neural networks. Miller [1998] proposed an algorithm using a principle of entropy maximization which is closely related to the maximum likelihood approach for estimating probability density functions. The algorithm has been implemented by neural networks. Morad [2000] used the expectation maximization algorithm to iteratively find the maximum likelihood estimate of the missing values and the parameters of the probability density function. In the study, an unsupervised method of learning probability density function parameters in the framework of mixture densities from incomplete data is developed. Likas [2001] presented an approach based on the use of multilayer neural networks with sigmoid hidden units for the estimation of probability density functions given a set of observations.

5.2 Artificial Neural Networks

An artificial neural network (ANN), commonly referred to as "neural network (NN)" is a mathematical model that approximates the operation of the biological neural networks (Hertz [1991] and Haykin [1999]). Neural networks involve a network of simple computing cells referred to as "neurons" or "processing units". Each neuron is connected to other neurons by "synapses". Neural networks perform useful computations through a process of learning which aims to acquire knowledge. Synaptic weights which are connection strengths between neurons are used to store acquired knowledge. Supervised learning and unsupervised learning are the major learning ways of learning. Supervised learning is performed on the basis of direct comparison of the output of the network with known correct output. The supervised learning is commonly applied successfully to pattern recognition and regression. However, in the case of unsupervised learning the only available information is in the correlations of the input data and the network is expected to create categories from these correlations and, to produce output signals corresponding to the input category. Tasks that fall within the application of the unsupervised learning are in general estimation problems including clustering and the estimation of statistical distributions.

Multilayer feedforward networks, commonly referred to as "multilayer perceptrons (MLPs)", are applied successfully to solve some difficult and diverse problems by training them in a supervised learning. A multilayer perceptron is a feedforward artificial neural network model maps a set of input data onto a set of appropriate output. The network consists of a set of sensory units that constitute the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. Figure 5.1 illustrates a multilayer feedforward neural network with one hidden layer. The input signal propagates forward through the network in a forward direction, on a layer-by-layer basis. When the input signal arrives at the output end of the network, an error signals originates and propagates backward through the network. During the backward pass the synaptic weights are adjusted to make the actual response of the network move closer to the desired response in statistical sense. This method is referred as to "back-propagation algorithm" (Haykin [1999]).

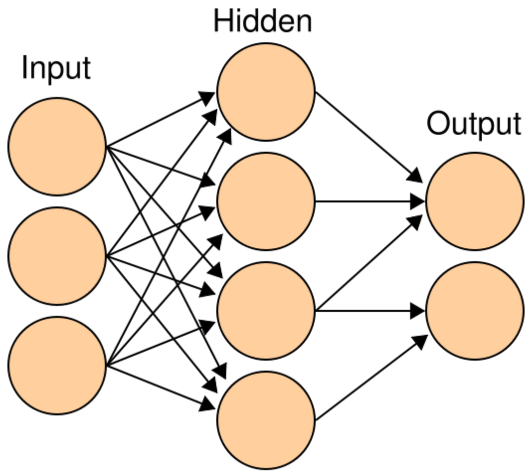


Figure 5.1 A multilayer feedforward neural network

5.3 MLP for Probability Density Estimation

Probability density function is defined on a compact subset. The function:

$$p_N(x,p) = \frac{N(x,p)}{\int N(z,p)\,dz} \qquad (5.1)$$

where $\mathrm{N(x,p)} \geq 0\ (\mathrm{x} \in S)$ is the output of an multilayer perceptrons (MLP) with parameter vector p for a given input x. A network architecture for probability density function approximation is proposed in Likas [2001]. The proposed network architecture consists of d input units, one hidden layer with H hidden units having the logistic activation function, and of one output unit with exponential activation function:

$$N(x,p) = exp\left(\sum_{i=1}^{H} v_i \sigma(o_i)\right) \tag{5.2}$$

where

$$o_i = \sum_{j=1}^{d} w_{ij}\, x_j + u_i \tag{5.3}$$

and

$$\sigma(z) = 1/\big(1 + exp(-z)\big) \tag{5.4}$$

$\sigma(z)$ is the logistic (sigmoid) activation function. The adjustable parameters of the network denoted as a vector $\vec{p}$ are w_{ij}, u_i, and v_i $(i = 1, \cdots, H,\ j = 1, \cdots, d)$. The network is trained to find the optimum parameter vector $\vec{p}$, so that negative log-likelihood of the data is minimum.

The logistic function provides necessary nonlinearity. The use of the logistic function is also biologically motivated, since it attempts to account for the refractory phase of real neurons (Haykin [1999]).

Negative log-likelihood of the set of n observations x_k is given by

$$L(p) = -\sum_{k=1}^{n} log p_N\,(x_k, p) \tag{5.5}$$

which can also be written as

$$L(p) = -\sum_{k=1}^{n} logN\,(x_k, p) + nlog\int_S N(x,p)\,dx \tag{5.6}$$

Likas [2001] proposed a preprocessing stage to obtain a good starting point for minimization of the likelihood. The proposed preprocessing stage performs supervised training of the MLP by constructing a training set using Parzen estimation method based on Gaussians:

$$\hat{p}(y_l) = \frac{1}{N}\sum_{i=1}^{n}\frac{1}{(2\pi)^{1/2}\sigma}exp\left(-\frac{|x_i - y_l|^2}{2\sigma^2}\right) \quad (5.7)$$

Using the above non-parametric specification, training set with M pairs $(y_l, \hat{p}(y_l))$ $(l = 1, \cdots, M)$ is constructed. The set is used to train MLP by minimizing the error function:

$$E(p) = \sum_{l=1}^{M}\left(N(y_l, p) - \hat{p}(y_l)\right)^2 \quad (5.8)$$

The preprocessing stage provides that the network output diminishes near the boundary of domain which is specified by the set of training points.

In Likas [2001], a gradient descent method is employed to find optimum parameter vector in Equation (5.8). The gradient descent method is combined with a moving grid approach including an intelligent selection scheme which is used to compute the integral in Equation (5.8).

In this study, the network architecture proposed in Likas [2001] is implemented. MLP training in both preprocessing stage and the likelihood minimization phase is performed using genetic algorithm. Monte Carlo integration is employed while evaluating the integral in the likelihood minimization phase.

5.4 Verification of MLP Estimator

A set of experiments with data constructed independently from known distributions is conducted to verify the model developed in this study. In experiments, the unknown probability density functions presented in Likas [2001] are used. The accuracy of solutions is compared with known distribution used to generate data. In all experiments, 5000 data points drawn independently from known distribution are used as training set. 10 sigmoid hidden units are used in MLPs. The value of parameter σ is assumed as 0.1 in all experiments. The optimal log-likelihood $\tilde{L}$ for a known distribution g and a set of samples $x_k(k = 1, \cdots, n)$ is calculated according to the formula:

$$\tilde{L}(x_1, \cdots, x_n) = \sum_{k=1}^{n} log\big(g(x_k)\big) \tag{5.9}$$

Experiment 1:

In this experiment the following probability density distribution which is mixture of two uniform and two Gaussian distributions is used to construct sample data.

$$g(x) = 0.25N(-7, 0.5) + 0.25U(-3, -1) + 0.25U(1,3) + 0.25N(7, 0.25) \tag{5.10}$$

with $\tilde{L} = -10477$. As Figure 5.2 illustrates, MLP estimator provides a good approximation to $g(x)$.

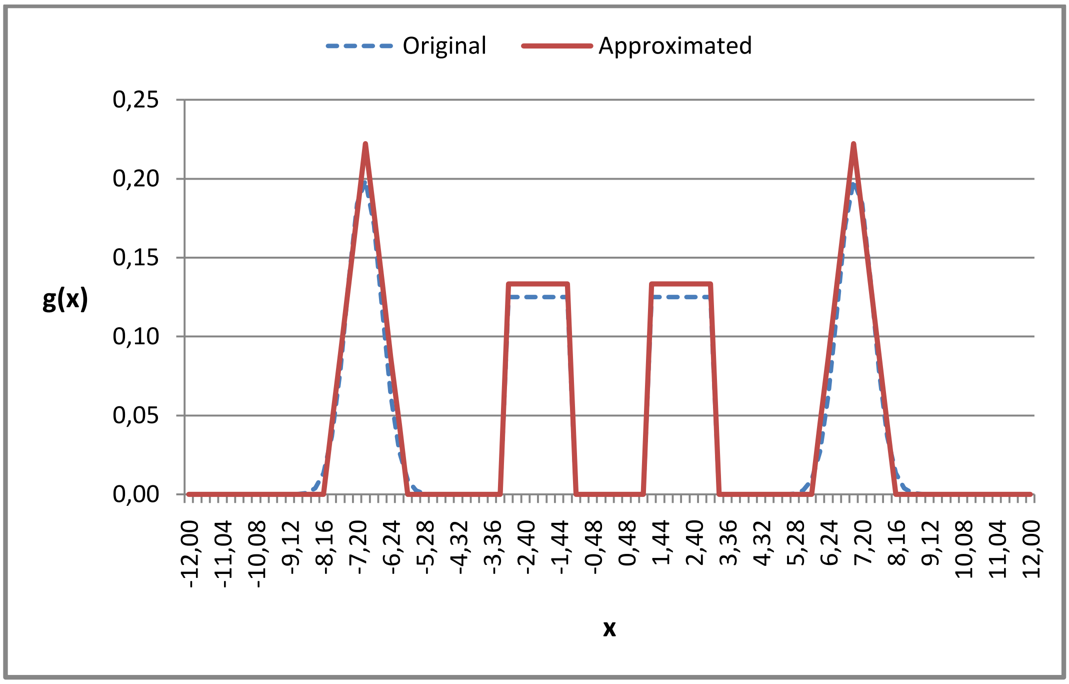


Figure 5.2 Approximation of experiment 1 density

Experiment 2:

In this experiment, the unknown probability density function is as follows:

$$g(x) = \begin{cases} 0, & x < 0 \; or \; x \geq 3+\sqrt{2} \\ (2 - x/2)/6.5523, & 0 \leq x \leq 2 \\ (2-(x-3)^2)/6.5523, & x < 0 \; or \; x \geq 3+\sqrt{2} \end{cases} \quad (5.11)$$

with $\tilde{L} = -7166$. Figure 5.3 displays the solution obtained using MLP estimator and the original distribution. The likelihood of the obtained solution is -7225 for the MLP approach.

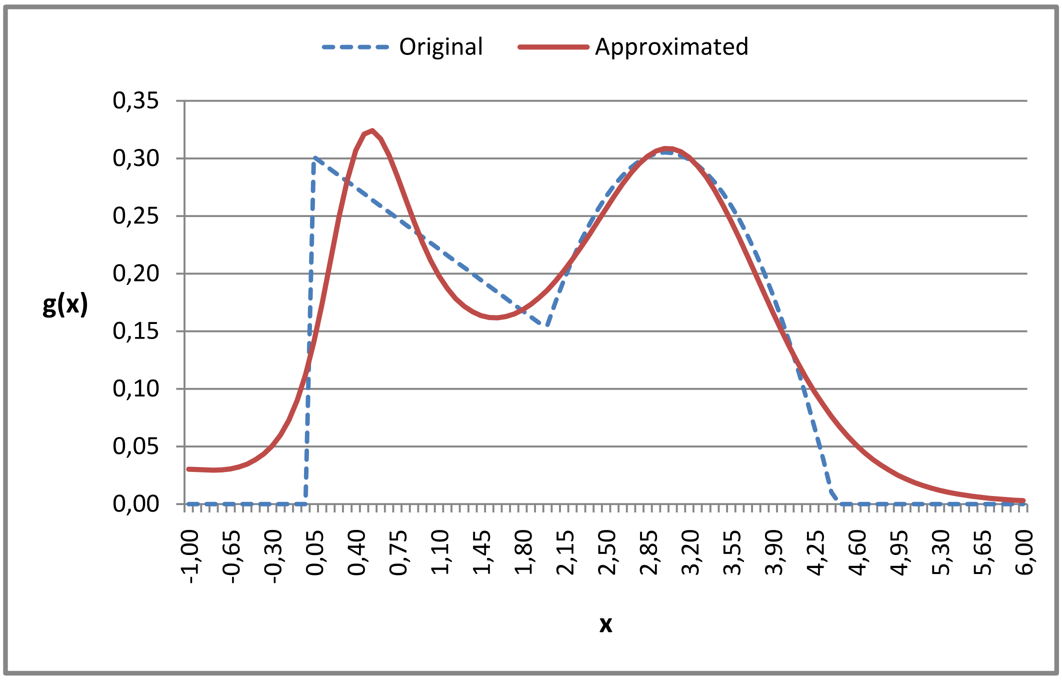


Figure 5.3 Approximation of experiment 2 density

Experiment 3:

In this experiment, uniform distribution $g(x) = U(-5,5)$ with $\tilde{L} = -11515$ is used as unknown probability density function. Figure 5.4 illustrates the solution obtained using MLP estimator and the original distribution. The likelihood of the obtained solution is -11871 for the MLP approach. The MLP approach is able to approximate uniform distribution.

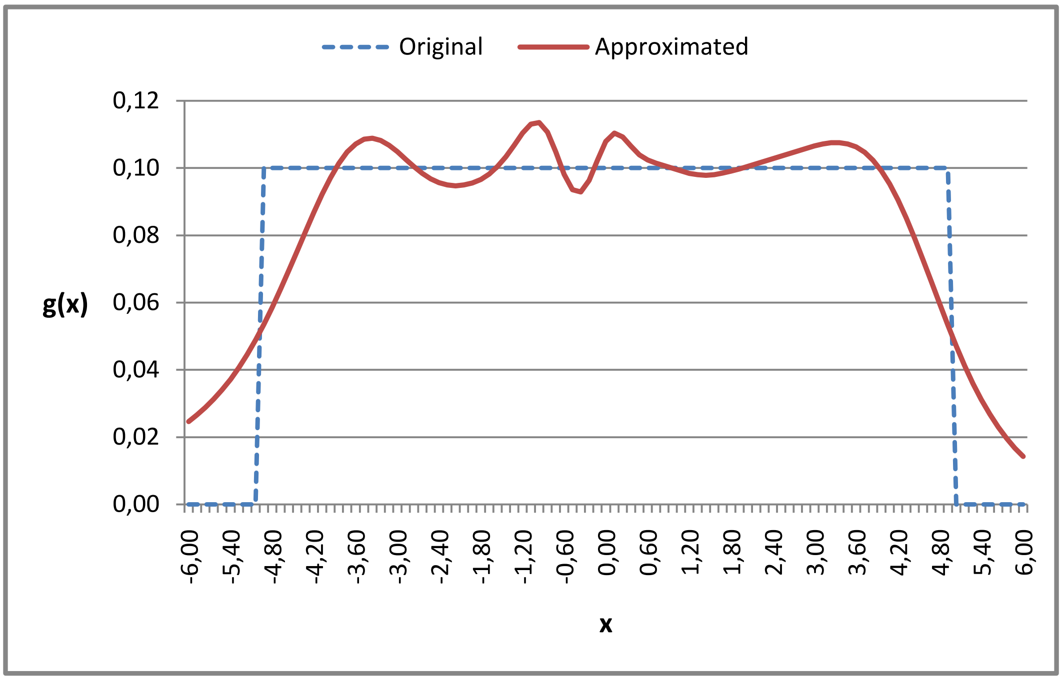


Figure 5.4 Approximation of experiment 3 density

Experiment 4:

In this experiment, the probability density function to be approximated is as follows:

$$g(x, y) = U(0, 0.2)U(0, 0.2) \quad (5.12)$$

with $\tilde{L} = -16094$. The likelihood of the obtained solution is -16686.

5.5 Heat Demand Probability Density Function Estimation

Weather conditions constitute an important element which should be taken into consideration while estimating heat demand. Demand for a heating system mainly depends on outside temperature. Other meteorological phenomena such as solar radiation, force and direction of wind, precipitation also have certain influence on instantaneous demand for heat power. Wojdyga [2008] outlined the important factors pertaining to the relationship between heat demand and weather conditions. Analytical calculation of the influence of weather changes is in principle impossible, due to the chaotic nature of weather related events. Discrepancies relating to heat demand at the same outside temperature are significant and can reach to 20–25% depending on wind force, insolation and cloudiness. Temporary fluctuations can even be larger. The influence of solar radiation on lowering heat demand in a heating season, in particular in the coldest months, is not large. However, this phenomenon lowers heat demand for the whole system The behavior of the residents has also a big influence on the heat demand, as mentioned by Bakker [2008].

In this study, an approach is proposed to yield a pdf with relation to heat demand and temperature. The approach is based on MLP with 10 sigmoid hidden units. In the context of the available data set, outdoor temperature is considered as the major factor determining the heat demand, whereas other factors are assumed to constitute the uncertainty. Training and validation of the pdf are performed by using the district heat demand data obtained from Bilkent Cogeneration Plant together with the meteorological data in the past for the same time period. The hourly heat demand pdfs, which are required by the stochastic load scheduling, are obtained by substituting the meteorological temperature data forecasts.

Table 5.1 presents mean values for the estimated pdfs and real demand data. Estimated pdfs are in accord with the real data. Figures 5.5-5.8 show estimated heat demand pdfs for each hour of the planning horizon.

Table 5.1 Comparison of estimated and real heat demand values

Hour	Mean Value of Estimated Heat Demand (MW)	Real Demand (MW)
1	18,89	24,60
2	19,23	24,60
3	19,23	26,10
4	19,42	22,80
5	19,42	21,90
6	18,74	22,20
7	18,45	24,60
8	17,97	23,40
9	17,53	23,10
10	17,26	22,50
11	16,95	23,40
12	16,61	24,30
13	16,23	18,60
14	15,83	17,10
15	15,83	18,00
16	15,83	17,70
17	16,23	16,80
18	16,61	15,60
19	16,61	13,50
20	17,26	14,10
21	16,95	14,10
22	17,53	15,00
23	17,97	24,60
24	17,77	24,90

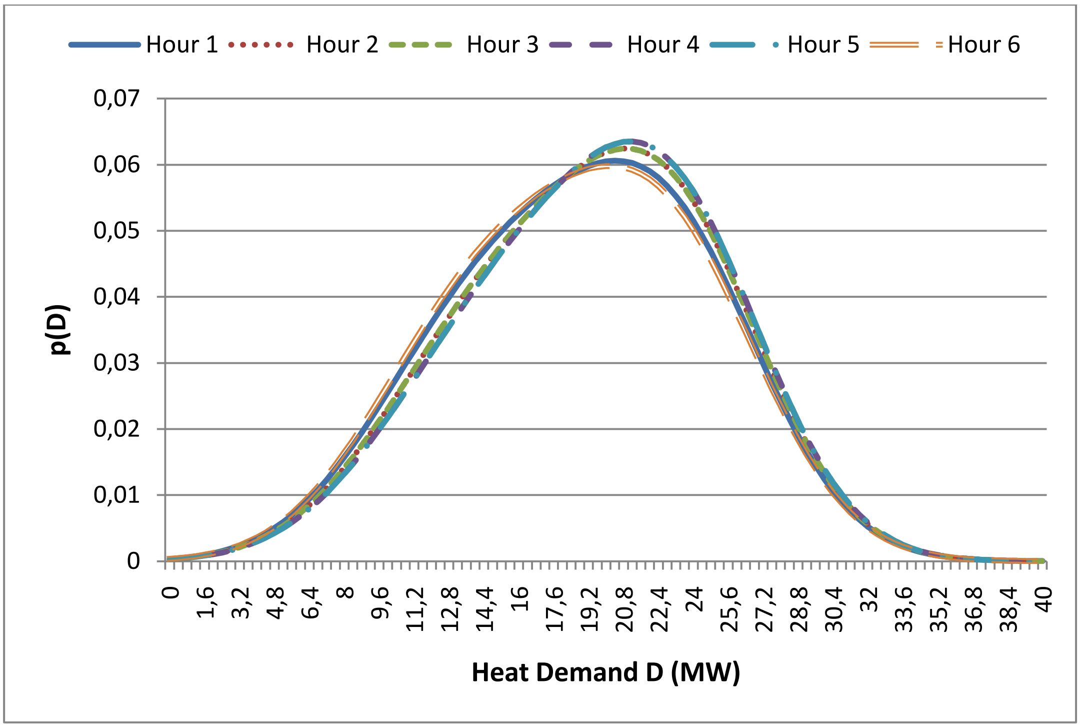


Figure 5.5 Heat demand pdfs for hours 1-6

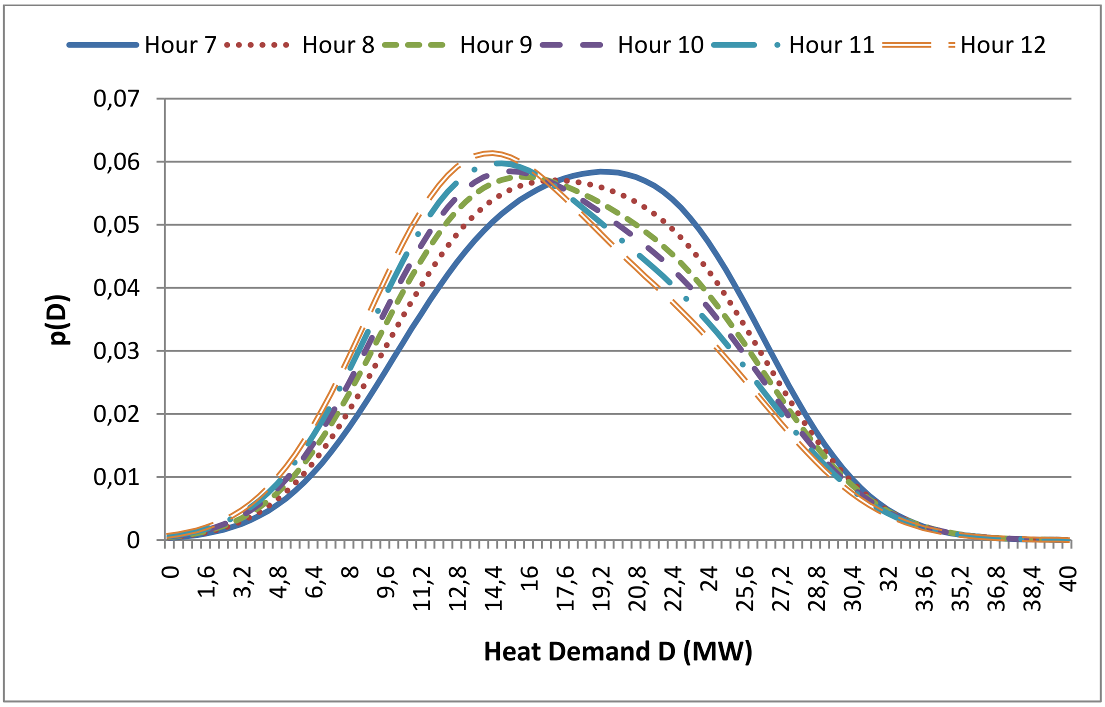


Figure 5.6 Heat demand pdfs for hours 7-12

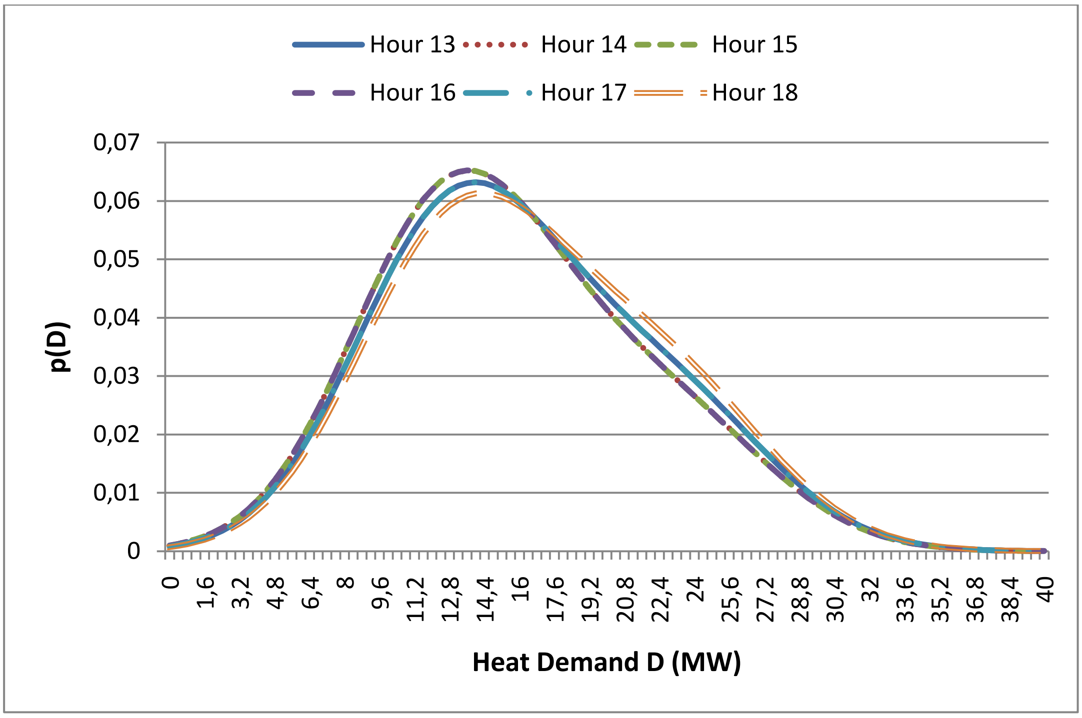


Figure 5.7 Heat demand pdfs for hours 13-18

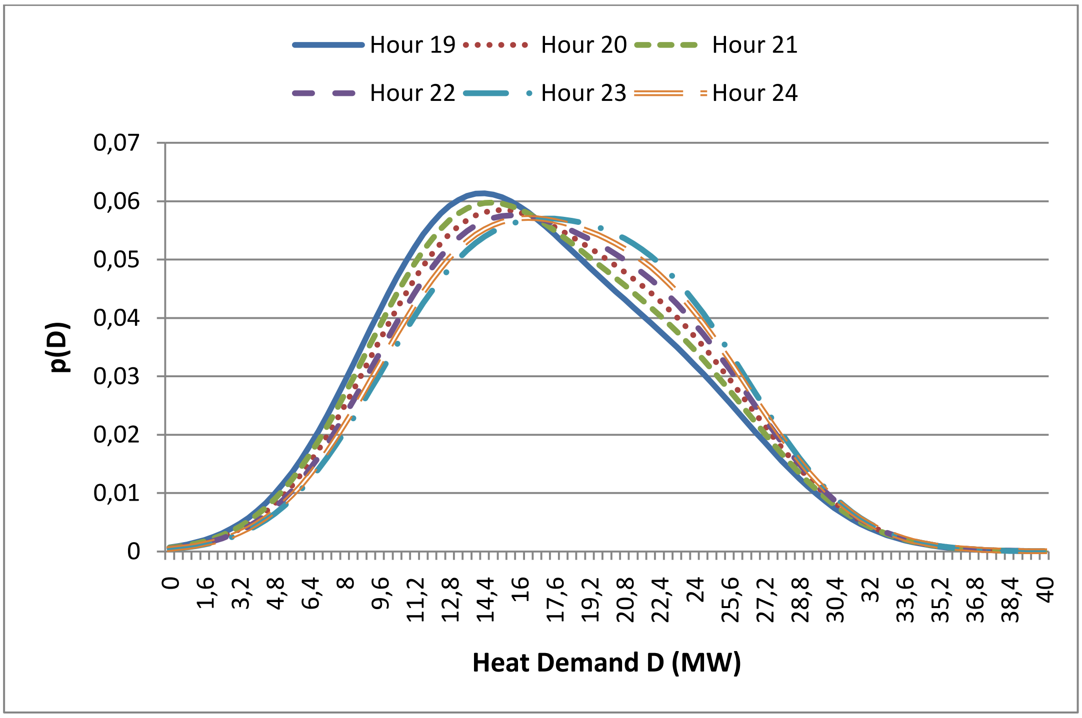


Figure 5.8 Heat demand pdfs for hours 19-24

5.6 Electricity Market Price and State Probability Density Function Estimation

Combined pool/bilateral markets in Turkey are operated by PMUM, and were commenced trading in 2006. Trading is executed day-ahead in double-sided call auction. Thereby participants submit bids for purchase and sale of hourly contracts for the following day together with its MW bilateral commitments. The bids are collected in a closed order book. Every trading day at noon the individual supply and demand curves are aggregated to a single supply and demand curve. The intersection between two curves represents the balance between purchase and sale bids and determines the uniform market-clearing price.

The dynamics of prices on spot electricity markets exhibits dependence on seasons, high volatilities, mean-reversion which is the tendency of prices to fluctuate around an equilibrium mean, and price spikes (Swider [2007]). The dependence on seasons is explained by the impact of climatic conditions that causes a different final electric usage. A major reason for high volatilities is the non-storability of electricity. In peak demand hours, prices may increase due to capacity shortages. Historical prices, bidding strategies, operating reserves affect the formation of electricity market price (Catalao [2007]). The electricity pool price in the hours included in the ‘‘weekday’’ set is known to depend strongly on labor days and weekends (Gareta [2006]).

The pdf estimation of electricity market price is crucial in a competitive electricity market for all market players. A prior knowledge of the electricity market price and state is important for risk management and may represent an advantage for a market player facing competition. For companies trading in electricity markets, the ability to forecast prices means that the company is able to strategically set up bids for the spot market in the short term.

In this study, an approach based on MLP is proposed to yield a pdf with relation to time series of electricity market price and state including current time, previous hour, previous day, day of week, weekend, and hour of day. Training and validation of the pdf are performed by using the electricity market data obtained from PMUM. 20 sigmoid units is used in the design of MLP.

System state variable $\widetilde{ss}$ which indicates whether or not the market is oversupplied is added as input parameter to electricity price probability density estimation model. Then the electricity price probability density function becomes:

$$\Phi = \Phi\left(\check{C}_{P,t}, \check{C}_{P,t-1}, \check{C}_{P,t-24}\ \widetilde{ss}_t, \widetilde{ss}_{t-1}, \widetilde{ss}_{t-24}, dow, weekend, hod\right) \quad (5.13)$$

where

$\check{C}_{P,t}$: market price at hour t,

$\check{C}_{P,t-1}$: previous hour market price,

$\check{C}_{P,t-24}$: previous day market price (the same hour),

$\widetilde{ss}_t$: system state at hour t 0: load increment (shortage) 1: load decrement (oversupply)

$\widetilde{ss}_{t-1}$: previous hour system state 0: load increment (shortage) 1: load decrement (oversupply)

$\widetilde{ss}_{t-24}$: previous day system state 0: load increment (shortage) 1: load decrement (oversupply)

dow: day of week.

$weekend$: 1: weekend 0: week day

hod: hour of day (0-23)

$\Phi = \Phi\left(\check{C}_{P,t}, \widetilde{ss}_t\right)$ is obtained by substituting the known variables into Equation (5.13) and normalizing it. This distribution can be used in stochastic load scheduling problem.

The approach is tested for a selected day. Table 5.2 presents mean values for the estimated pdfs and real data for electricity price and state for 29.03.2008. The estimated values include load increment and load decrement pdfs for each hour. The estimated pfds are in general accord with the real data. The estimated electricity price pdfs for each hour of the planning horizon are illustrated for both load increment and load decrement states in Figures 5.9-5.16. The estimated values provide good approximation to the real values except for hours 3, 4, and 5. As the probabilities for both states are rather significant in these hours, deviations from the real values are more evident as compared to other hours of the day.

Table 5.2 Comparison of estimated and real electricity price values

Hour	Real Electricity Price (TL/MWh)	Estimated Electricity Price	
		Probability	Mean Value Price (TL/MWh)
1	162.35 (Load Inc.)	0.93 0.07	160.07 (Load Inc.) 67.20 (Load Dec.)
2	160.96 (Load Inc.)	0.98 0.02	152.68 (Load Inc.) 79.94 (Load Dec.)
3	160.16 (Load Inc.)	0.92 0.08	139.86 (Load Inc.) 92.43 (Load Dec.)
4	128.90 (Load Inc.)	0.81 0.19	160.16 (Load Inc.) 87.03 (Load Dec.)
5	75.50 (Load Dec.)	0.77 0.23	156.80 (Load Inc.) 94.30 (Load Dec.)
6	77.04 (Load Dec.)	0.01 0.99	170.44 (Load Inc.) 79.56 (Load Dec.)
7	56.69 (Load Dec.)	0.01 0.99	153.58 (Load Inc.) 63.72 (Load Dec.)
8	143.93 (Load Inc.)	0.95 0.05	149.80 (Load Inc.) 48.39 (Load Dec.)
9	170.44 (Load Inc.)	0.99 0.01	167,78 (Load Inc.) 66.57 (Load Dec.)

Table 5.2 (continued) Comparison of estimated and real electricity price values

Hour	Real Electricity Price (TL/MWh)	Estimated Electricity Price	
		Probability	Mean Value Price (TL/MWh)
10	170.44 (Load Dec.)	0.99 0.01	171.01 (Load Inc.) 67.31 (Load Dec.)
11	171.10 (Load Inc.)	0.99 0.01	171.14 (Load Inc.) 67.54 (Load Dec.)
12	171.10 (Load Inc.)	0.99 0.01	171.20 (Load Inc.) 67.59 (Load Dec.)
13	170.44 (Load Inc.)	0.99 0.01	171.22 (Load Inc.) 67.70 (Load Dec.)
14	170.44 (Load Inc.)	0.99 0.01	171.30 (Load Inc.) 67.76 (Load Dec.)
15	170.44 (Load Inc.)	0.99 0.01	171,42 (Load Inc.) 67.81 (Load Dec.)
16	170.44 (Load Inc.)	0.99 0.01	171.58 (Load Inc.) 67.87 (Load Dec.)
17	170.34 (Load Inc.)	0.99 0.01	171.78 (Load Inc.) 67.94 (Load Dec.)
18	175,28 (Load Inc.)	0.99 0.01	173.90 (Load Inc.) 67.59 (Load Dec.)
19	175.28 (Load Inc.)	0.99 0.01	174.80 (Load Inc.) 67.72 (Load Dec.)
20	175.45 (Load Inc.)	0.99 0.01	175.19 (Load Inc.) 67.82 (Load Dec.)
21	175.28 (Load Inc.)	0.99 0.01	175.38 (Load Inc.) 67.90 (Load Dec.)
22	175.28 (Load Inc.)	0.99 0.01	175.50 (Load Inc.) 67.97 (Load Dec.)
23	162,58 (Load Inc.)	0.99 0.01	162.87 (Load Inc.) 69.20 (Load Dec.)
24	162,52 (Load Inc.)	0.99 0.01	162.29 (Load Inc.) 68.49 (Load Dec.)

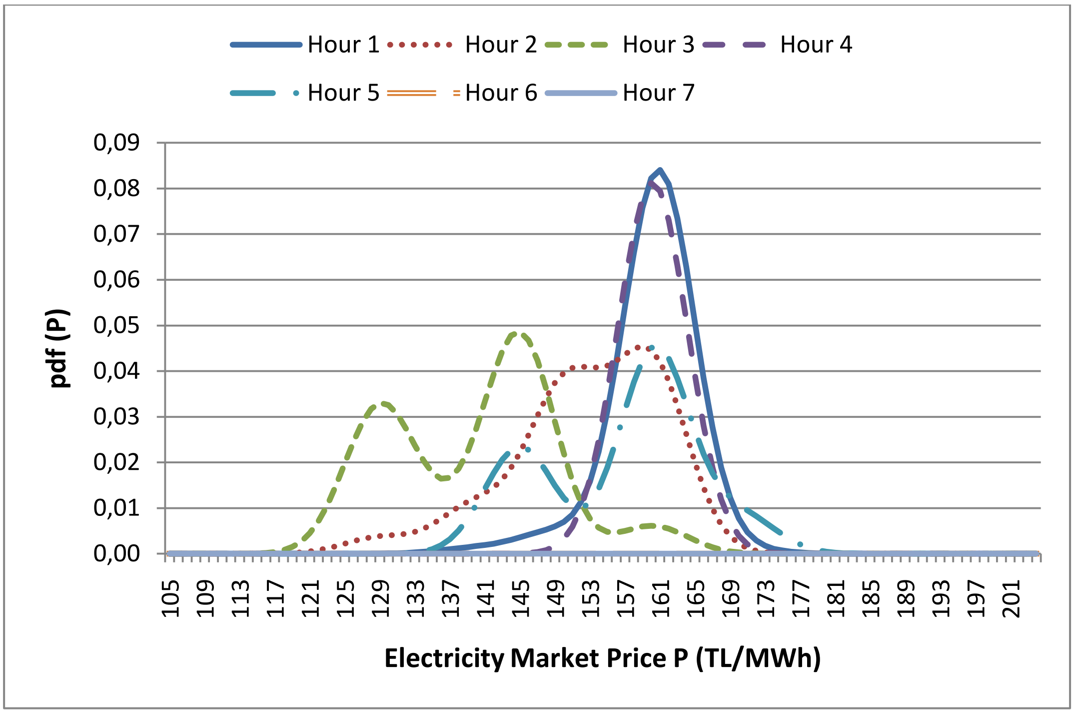


Figure 5.9 Load increment electricity price pdfs for hours 1-7

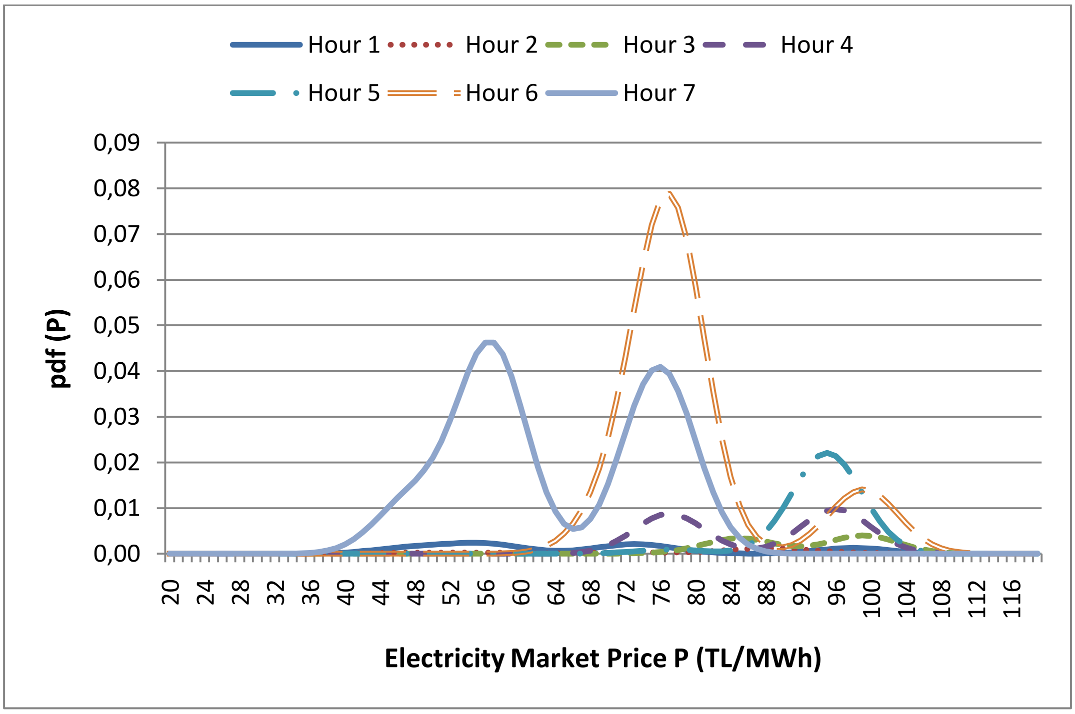


Figure 5.10 Load decrement electricity price pdfs for hours 1-7

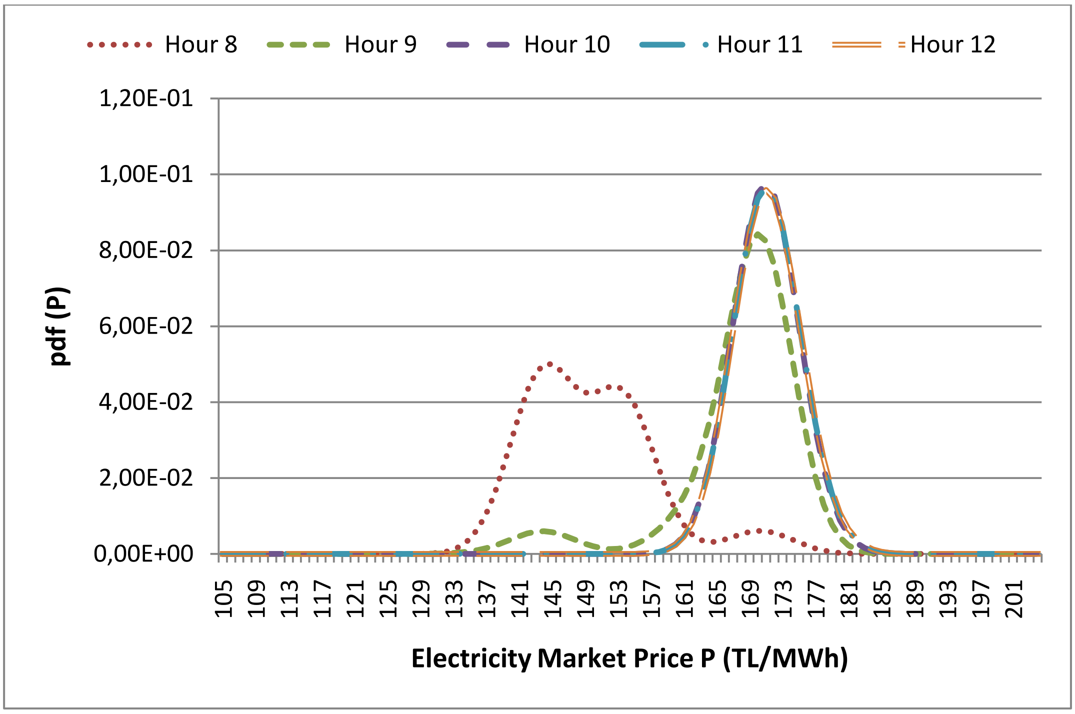


Figure 5.11 Load increment electricity price pdfs for hours 8-12

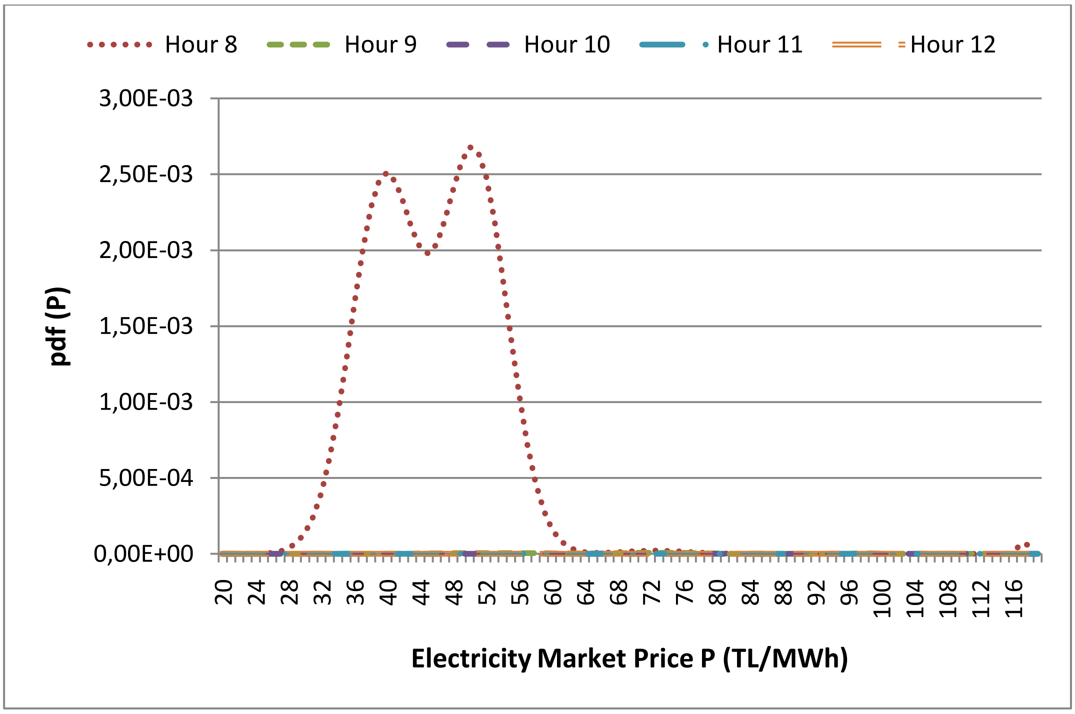


Figure 5.12 Load decrement electricity price pdfs for hours 8-12

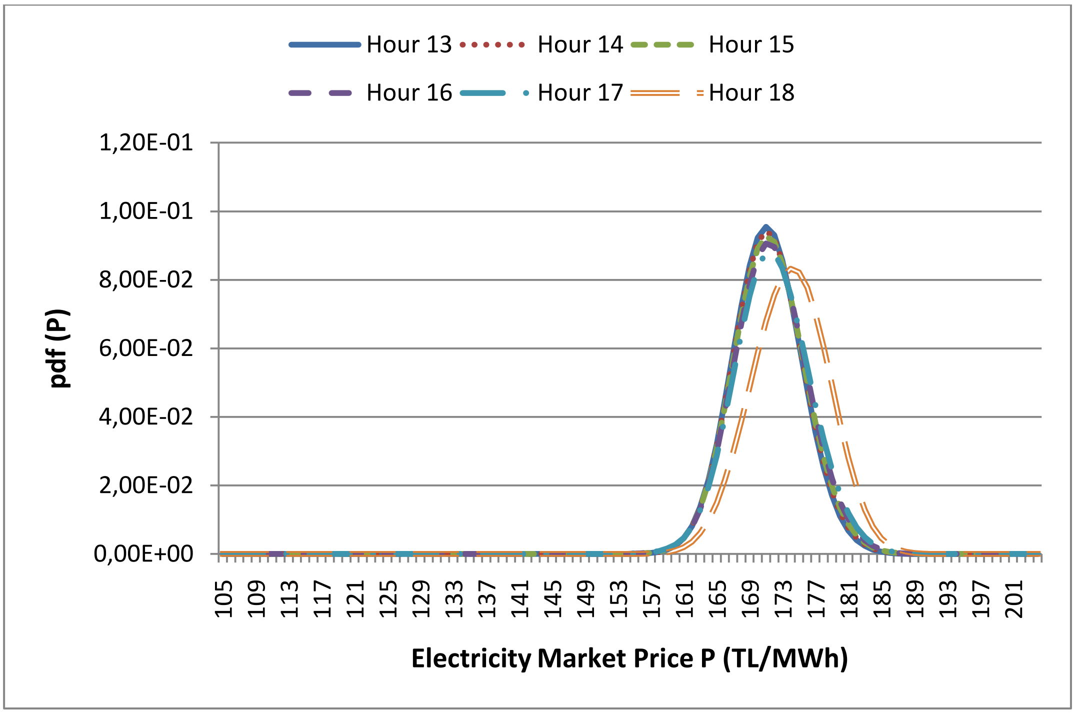


Figure 5.13 Load increment electricity price pdfs for hours 13-18

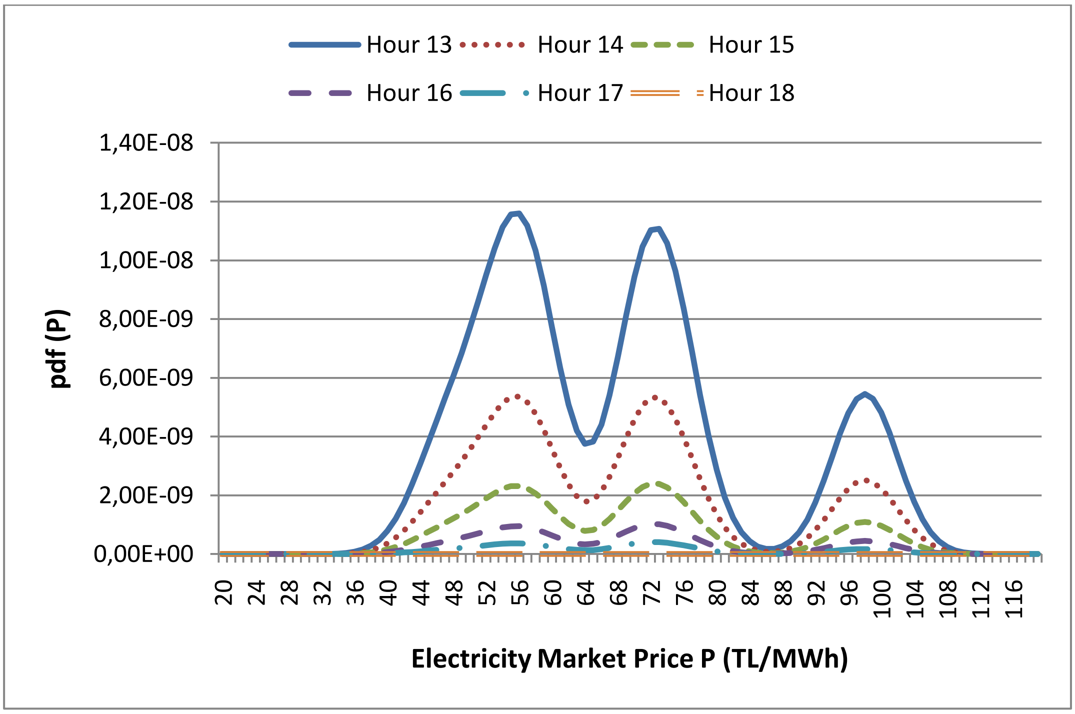


Figure 5.14 Load decrement electricity price pdfs for hours 13-18

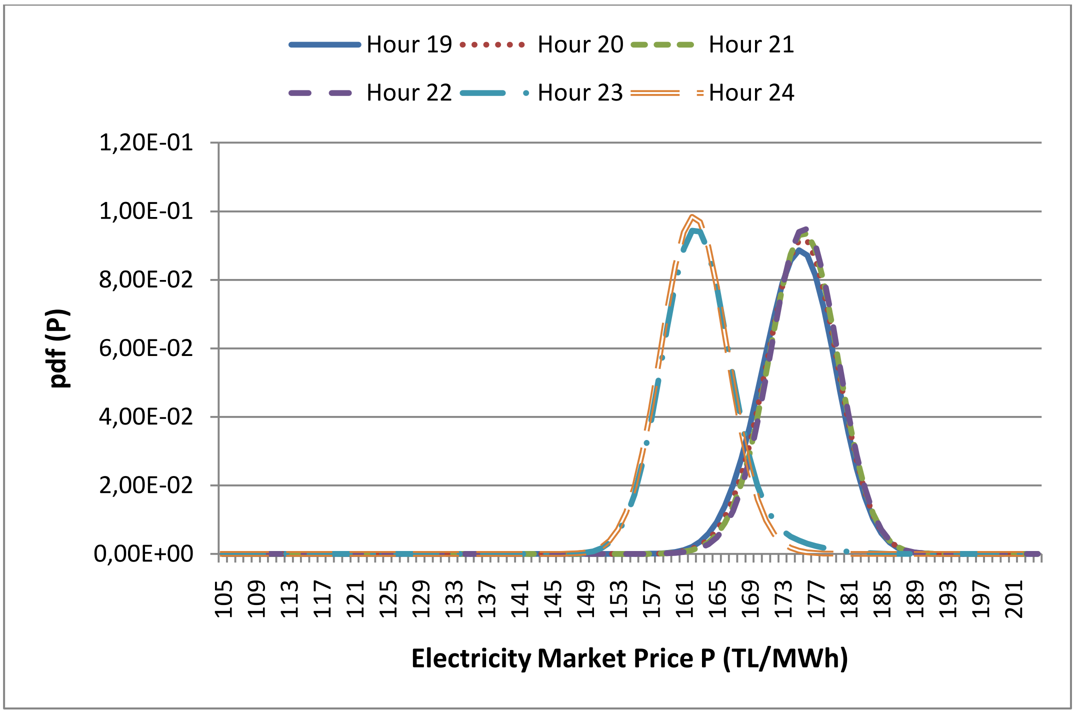


Figure 5.15 Load increment electricity price pdf for hours 19-24

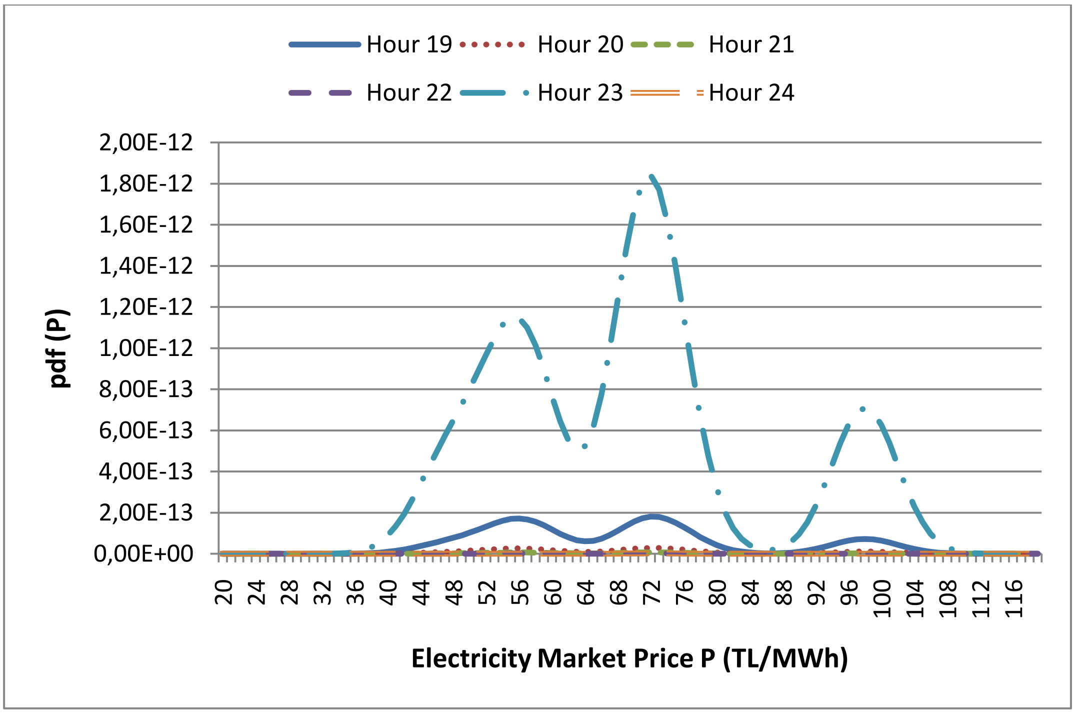


Figure 5.16 Load decrement electricity price pdf for hours 19-24

CHAPTER 6

CONCLUSIONS

In this study, a stochastic approach is developed for load scheduling of cogeneration plants. The approach takes the uncertainties in heat demand and electricity market into consideration. The effect of storage volume is also investigated in this context.

The cogeneration plant modeled and analyzed in this study is characterized by two main interactions with the external system. The plant is subject to cover the heat demands in the district heating system and is able to sell its electricity output to the electricity market. Electricity output of the plant can be sold in the market in two mechanisms: bilateral contracting and day ahead market. The heat storage unit provides flexibility in scheduling heat and power outputs.

The load scheduling problem which is characterized by a number of uncertainties is modeled and analyzed in the context of stochastic optimization. Stochastic optimization employed in this study aims at finding an optimal load plan for each hour in the planning horizon. In this regard, probability density functions are used to represent the uncertainties in each hour. The optimal load plan is targeted by achieving maximum revenue. Revenue is defined in the purposes of this study as the sales revenues minus total cost associated with the plant operation.

Heat demand possesses a number of uncertainties due to meteorological parameters as well as the customer behavior. The plant is subject to operate according to the obligations by the market operator. This introduces another dimension of uncertainty in terms of the plant operation. The electricity price is also uncertain as a result of the working principles of the electricity market driven by supply and demand balance. The stochastic optimization method developed in this study addresses these uncertainties in an effective manner.

Stochastic optimization problem is solved by stochastic programming approach. The Gen's Evolution Algorithm, which is one of the conventional stochastic programming techniques, did not result in accurate solutions in reasonable computational times. Therefore, a hybrid technique that combines a genetic algorithm based evolution algorithm with a stochastic dynamic programming technique is developed. The study proves that the hybrid technique developed is

effective in providing solutions to the stochastic load scheduling problem. This is attributed to the powerful search capabilities of evolution programming coupled with the effectiveness of stochastic dynamic programming.

The optimization problem, which aims to maximize the revenue, is modeled by thermodynamic analyses. In this context, the study introduces two objective functions: energy based optimization, exergy-costing based optimization. In the energy based optimization, the cost of electricity generated by steam and gas turbines do not represent any difference. The exergy-costing based optimization is able to account cost values differently for steam and gas turbines. Exergy-costing based optimization tends to utilize the steam turbine up to the largest possible extent.

The volume of heat storage unit is an important parameter in the context of the uncertainties addressed in this study. Load scheduling problem is solved for different values of storage tank volume to assess the importance of storage volume linked to variations in demand. The analyses, illustrating the change in revenue with respect to storage volume on daily and seasonally bases, determine optimal storage volumes.

Predictions for the uncertain parameters over the planning horizon are introduced in terms of heat demand and electricity price pdfs. This approach enables decision maker to perform what if analyses to address uncertainties for different scenarios. This type of approach builds on uniform distributions for maximum uncertainty and on normal distributions for minimum uncertainty. In this study, a method based on neural networks for pdf estimation is proposed for obtaining more realistic pdfs.

Validation of the stochastic optimization technique, which is developed for load scheduling of a cogeneration plant selected as a case study, is not possible in practice, since there exists no operational data for a one to one similar cogeneration plant. However, the stochastic problem can be converged to a deterministic problem by reducing the degree of uncertainty in the optimization analysis. For this purpose, the uncertainties for heat demand, electricity market price and state are kept small for enabling comparisons with deterministic solutions. As demonstrated in Figure 4.2, the stochastic solution is in line with the deterministic solution for one hour load scheduling problem. The stochastic optimization technique requires pdfs for heat demand, electricity market price and state. Comparisons of the mean values of estimated pdfs with real data is considered as an effective indicator for validation purposes. Comparison shows that the difference between the mean values and real data changes between 3%-30% for heat demand, as shown in Table 5.1. Regarding the electricity market price and state, mean values and real data are generally in accordance, as shown in Table 5.2. These analyses for validation indicate that the developed technique in this study can be applied for the effective operation of cogeneration plants.

The MLP application, a neural network technique, for probability density estimations to heat demand and electricity pool proves that the pdf estimation is possible by appropriate training of the neural network. However, lack of sufficient data stands as a weak point of this technique. It is also concluded that this kind of computational model should be revised every year in order to ensure its reliability.

For future work, costs related to environmental impacts can be incorporated into the revenue maximization problem. In this context, carbon prices and taxes can be considered as extra parameters for load scheduling of cogeneration plants. Effect of environmental costs on determination of optimum heat storage volumes can be a useful extension of the current study.

This study proposed a novel approach in analyzing uncertainties in terms of heat demand and electricity prices. This approach can further be improved in order to include the uncertainties in fuel prices. Development of a spot heat market can also introduce a new element of uncertainty in load scheduling of cogeneration plants.

BIBLIOGRAPHY

Bakker,V., Molderink,A., Hurink,J., Smit, G., *Domestic heat demand prediction using neural networks*, 19th International Conference on Systems Engineering, 2008.

Barelli,L., Bidini,G., Pinchi,E.M., *Implementation of a cogenerative district heating: Optimization of a simulation model for the thermal power demand*, Energy and Buildings vol.38, pp.1434–1442, 2006.

Bejan, A., Tsatsaronis, G., Moran, M., *Thermal Design and Optimization*, John Wiley & Sons, Inc., 1996.

Bellman,R., *Dynamic Programming*, Princeton University Press, Princeton, 1957.

Bogdan,Z., Kopjar,D., *Improvement of the cogeneration plant economy by using heat accumulator*, Energy vol.31, pp. 2285–2292, 2006.

Catalao,J.P.S., Mariano,S.J.P.S., Mendes, V.M.F, Ferreria, L.A.F.M , *Short-term electricity prices forecasting in a competitive market: A neural network approach* , Electric Power Systems Research vol.13, pp. 1297-1304, 2007.

Charytoniuk,W., Olinda,P.V., *Nonparametric regression based short-term load forecasting*, IEEE Transactions on Power Systems vol.77, no.3, 1998.

Charytoniuk,W., Chen,M.S., *Demand forecasting in power distribution systems using nonparametric probability density estimation*, IEEE Transactions on Power Systems vol.14, no.4, 1999.

Chen,E.J., Kelton,W.D., *Empirical evaluation of data-based density estimation*, Proceedings of the 2006 Winter Simulation Conference 2006.

Cwik,J., Koronacki,J., *Probability density estimation using a Gaussian clustering algorithm*, Neural Computing & Applications vol.4, no.3, 1996.

Domaski, R., Fellah, G., *Thermo economic analysis of sensible heat, thermal energy storage systems*, Applied Thermal Energy vol. 18, No. 8, pp. 693-704, 1998.

Dotzauer, E., *An introduction to short-term scheduling of power and cogeneration systems*, Research Report 2001-1 Department of Mathematics and Physics Malardalen University Sweden , 2001.

Dreyfus, S.E., *Dynamic Programming and the Calculus of Variations*, A Report Prepared for United States Air Force Project Rand, 1965.

Energy Market Regulatory Authority, http://www.epdk.org.tr/english/regulations/electricity.htm, last visited on day December 2009.

Gamou,S., Yokoyama,Y., Ito,K., *Optimal unit sizing of cogeneration systems in consideration of uncertain energy demands as continuous random variables*, Energy Conversion and Management vol.43, pp. 1349–1361, 2002.

Gareta,R., Romeo,L.M., Gil,A., *Forecasting of electricity prices with neural networks*, Energy Conversion and Management vol.47, pp. 1770–1778, 2006.

Gen, M., *Genetic Algorithms and Engineering Design*, John Wiley & Sons, New York, 1997.

Gül, Ö., *Overview of Electricity Deregulation*, Power Quality and Energy Efficiency Studies in Turkey, 9th International Conference: Electric Power Quality and Utilization, October 2007.

Güray, B.Ş., *A Unique Challenge*, Power Engineering International, February 2006.

Güray, B.Ş., *Elektrik Sektöründe Arz-Talep Analizleri, Beklentiler ve Hedefler*, 11. Uluslararası Enerji Arenası, November 2009.

Handschin, E., Neise, F., Neumann, H., Schultz, R., *Optimal operation of dispersed generation under uncertainty using mathematical programming*, Electrical Power and Energy Systems vol. 28, pp. 618–626, 2006.

Hasnain,S.M., *Review on sustainable thermal energy storage technologies, Part I: Heta storage materials and techniques*, Energy Conversion and Management vol. 39 no.11, pp. 1127-1138, 1998.

Haykin,S., *Neural networks: a comprehensive foundation*, Prentice Hall, 1999.

Hertz,J., *Introduction to the theory of neural computation*, Westview Press, 1991.

International Energy Agency, *Combined Heat and Power*, IEA Publications, 2008.

International Energy Agency, *Cogeneration and District Energy*, IEA Publications, 2009.

Khan, K. H., Rasul, M. G., Khan, M. M. K., Energy conservation in buildings: cogeneration and cogeneration coupled with thermal-energy, storage, Applied Energy vol. 77, pp.15–34, 2004.

Kostowski, W., Skorek, J., *Thermodynamic economic analysis of heat storage application in co-generation systems*, International Journal of Energy Research vol.29, pp. 177-188, 2005.

Lazzaretto, A., Tsatsaronis,G., *On the Calculation of Efficiencies and Costs in Thermal Systems*, Proceedings of ASME, AES-vol.39, 1999.

Likas, A., *Probability density estimation using artificial neural networks,* Computer Physics Communications vol.135, pp. 167–175, 2001.

Lin, F., Yi,J., *Optimal operation of a CHP plant for space heating as a peak load regulating plant*, Energy vol.25, pp. 283–298, 1998.

Lund, H., Andersen, A. N., *Optimal designs of small CHP plants in a market with fluctuating electricity prices*, Energy Conversion and Management vol. 46, pp. 893–904, 2005.

Magdon-Ismail M., *Supervised learning in probabilistic environments*, California Institute of Technology, 1998.

Marbe, A., Harvey, S., Berntsson, T., *Technical, environmental and economic analysis of co-firing of gasified biofuel in a natural gas combined cycle (NGCC) combined heat and power (CHP) plant*, Energy vol.31, pp.1614–1631, 2006.

Melanie, Mitchell, *An Introduction to Genetic Algorithms*, A Bradford Book The MIT Press, 1999.

Michalewicz, Z., *Genetic Algorithms + Data Structures=Evolution Programs*, Springer, 1996.

Michalewicz, Z., Fogel, D.B., *How to Solve It: Modern Heuristics*, Springer, 2002.

Miller, B.L., Goldberg, D.E., *Genetic algorithms, tournament selection, and the effects of noise*, IlliGAL Report No. 95006, 1995.

Miller, G., Horn, D, *Probability density estimation using entropy maximization*, Neural Computation vol. 10, no. 7, pp.1925-1938 1998.

Morad, K., *Probability density estimation using incomplete data,* ISA Transactions vol. 39 pp. 379-399, 2000.

Nielsen,H.A.,Nielsen,T.S.,Madsen,H., *Load scheduling for decentralized CHP plants*.

Peter, Kall and Stein, W. Wallace, *Stochastic Programming*, John Wiley & Sons, Chichester, 1994.

Pharr, Matthew M., *Monte Carlo Solution of Scattering Equations for Computer Graphics*, Stanford University, 2005.

Rao, Singiresu S., *Engineering Optimization*, John Wiley & Sons, New York, 1996.

Rolsman, B., *Combined heat-and-power plants and district heating in a deregulated electricity market* , Applied Energy vol. 78, pp. 37–52, 2004.

Rosen, M.A., Martinaitis, V., Andersen, A.N., Katz, J*., The exergy of stratified thermal energy storages*, Solar Energy vol.71, no.3, pp.173-185, 2001.

Schioler,H., Kulczyki,P., *Neural network for estimating conditional distributions*, IEEE Transactions on Neural Networks vol. 8, no. 5 pp.1015-1025, 1997.

Silveira, J.L., Tuna, CE.., *Thermoeconomic analysis method for optimization of combined heat and power systems. Part I*, Progress in Energy and Combustion Science vol. 29, pp.479-485, 2003.

Sivanandam, S.N., Deepa, S.N., *Introduction to Genetic Algorithms*, Springer, 2008.

Soong, T.T., *Probability and Statistics for Engineers*, John Wiley & Sons, Chichester, 2004.

Stoft S., *Power System Economics*, IEEE Press John Wiley & Sons, 2002

Streckiene,G., Martinaitis,V., Andersen,A.N., Katz,J., *Feasibility of CHP-plants with thermal stores in the German spot market*, Applied Energy vol. 86, pp.2308-2316, 2009.

Swider,D., Weber,C., *Extended ARMA models for estimating price developments on day-ahead electricity markets*, Electric Power Systems Research vol. 77, pp.583-593, 2007.

Takahashi,K.,Ishizaka,T., *Application of cogeneration sytem performance*, Applied Energy vol.61, pp. 147-162, 1998.

Terzi, Ü., *Geçiş Dönemi Dengeleme ve Uzlaştırma Uygulamaları*, Türkiye Kojenerasyon Derneği İTÜ, 2005.

Traven,H., *A neural network approach to statistical pattern classification by semiparametric estimation of probability density* *functions,* IEEE Transactions on Neural Networks, vol. 2, no. 3 pp. 366-377, 1991.

Valero, A., *Exergy accounting: Capabilities and drawbacks,* Energy vol. 31, pp. 164-180, 2006.

Veach, Eric, *Robust Monte Carlo Methods for Light Transport Simulation,* Stanford University, 1997.

Vieira, L.S., Donatelli, J.L., Cruz, M.E., *Mathematical exergoeconomic optimization of a complex cogeneration plant aided by a professional process simulator,* Applied Thermal Engineering vol. 26, pp. 654-662, 2006.

Weinzierl Stefan, *Introduction to Monte Carlo Methods*, NIKHEF Theory Group, Amsterdam, 2000.

Weise, Thomas, *Global Optimization Algorithms – Theory and Applications*, Online available as e-book at http://www.it-weise.de/, 2009.

Wojdyga,K., *An influence of weather conditions on heat demand in district heating systems,* Energy and Buildings vol.40, pp. 2009–2014, 2008.

Wu, D.W., Wang, R.Z., *Combined cooling, heating and power*: A review Progress in Energy and Combustion Science vol.32, pp. 459–495, 2006.

Zubair, S.M., Nakla, M.E., Shuja, S.Z., *Thermo economic design and analysis of a sensible-heat thermal energy storage system with Joulean heating of the storage element*, Exergy, an International Journal vol. 2, pp. 237-247, 2002.

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