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UNIVERSIDADE DE COIMBRA

Faculdade de Ciências e Tecnologia

Departamento de Engenharia Eletrotécnia e de Computadores

Seyedmasoud Taheri

"The Use of Load Management Controls to Minimize Differences between Load Diagrams"

A thesis submitted in partial fulfillment for the Degree, Master of Science in Energy for Sustainability

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Specialization: ***Buildings and Urban Environment***

Under supervision of:

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October 2016

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Resumo

O Mercado das Energias tem evoluído de modo a fornecer energia elétrica ao consumidor de uma forma segura e fiável. De modo a atingir esse objetivo e manter um sistema com a dita fiabilidade, é necessário haver um equilíbrio entre produção e consumo, e/ou fornecimento e procura, a cada instância de tempo.

A Resposta Dinâmica dos Consumidores ("Demand Response") começa a ser um importante recurso que pode de forma ativa ser utilizada na operação e no funcionamento do Mercado das Energias de modo a melhorar a sua fiabilidade e eficiência, reduzir picos de consumo e as várias oscilações de preço. Com a introdução de redes elétricas inteligentes e com a implementação e desenvolvimento das tecnologias de informação, os consumidores podem ativamente participar em ações de Resposta Dinâmica e fazer uso dos seus recursos (consumos controlados, armazenamento e produção local).

O objetivo desta dissertação é de avaliar o impacto das ações de Resposta Dinâmica dos Consumidores na fiabilidade dos mercados das energias e encontrar uma solução que mantenha e preveja consumos no mercado diário e mercado intradiário equilibrado. Por conseguinte, foi implementada uma abordagem para identificar as ações de controlo, simular o seu impacto nos padrões de consumo de cargas e avaliar os efeitos das mudanças na procura. Para a abordagem implementada utilizou-se o algoritmo evolutivo NSGA-II em conjunto com outros modelos baseados no local para a identificação das ações de controlo e avaliação do impacto nos padrões de procura.

Nesta dissertação o software MATLAB serviu de via para a implementação da abordagem delineada. Os resultados deste trabalho mostram que é possível atenuar as diferenças entre as procuras de carga no mercado intradiário e as procuras de carga previstas para o mercado diário com a aplicação das devidas ações de gestão de procura de carga adequadas.

Palavras-Chave: Fiabilidade; Demand Response; Estratégia Evolutiva; Modelo Baseado no Local

Abstract

The Electricity markets have evolved in order to supply power to consumers in a secure and reliable way. In order to achieve this target and have a reliable system, it is necessary to be a balance between supply and demand at each period of time.

Demand Response is becoming important as a resource that can be actively used in the operation and functioning of the Electricity markets to improve the reliability and efficiency and also to decrease peak demand and price instability. By introducing smart grids and with the deployment and development of information and communication technologies, consumers can actively participate in demand response actions and use their resources (controllable demand, storage and site generation).

The objective of this thesis is to assess the impact of demand response actions on the reliability of electricity markets and find a solution for keeping the demand forecast in day-ahead market and intraday market balanced. Hence, an approach was implemented to identify the control actions, simulate their impact on consumption patterns of loads, and evaluate the effects of the changes on the demand .The implemented approach used NSGA- II evolutionary algorithm along with physically based models to identify the control actions and evaluate their impact on demand patterns.

In this thesis Matlab software was used in order to implement the approach. The results of this work show that it is possible to mitigate the differences between the load demands in intraday market and forecasted load demands in day-ahead market with the application of appropriate load demand management actions.

Key words: Reliability; Demand Response; Evolutionary Strategy; Physically Based Model

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Abbreviations

DSO – Distribution system operators

LSE – Load service entities

RTM – Real-time electricity markets

DR – Demand response

DLC – Direct Load Control

MIBEL – Iberian Electricity market

DAM – Day ahead market

IM – Intraday market

LMP – Locational marginal price

ISO-NE – New England independent system operator

PJM – Pennsylvania-New Jersey-Maryland

TOU – Time-of-use

RTP – Real-time pricing

CPP – Critical-peak pricing

DLC – Direct Load Control

I/C – Interruptible/curtailable

EDRP – Emergency Demand Response Program

CMP – Capacity Market Program

A/S – Ancillary Service

PBLM – Physically based load models

EMO – Evolutionary multi-objective optimization

LM – Load management

HV – High Voltage

LV – Low Voltage

GA – Genetic algorithm

NSGA – Non-dominating genetic algorithms

EA – Evolutionary algorithms

ALC – Aggregated Load Consumption

FLC – Freezer Load Consumption

CLD – Consumed Load Difference

LDF – Load Demand Forecast

NSPG – Number of sets per each load group

Chapter 1

Introduction

1.1 Background and Motivation

The structure of Electricity supply industry was changed because of the deregulation and liberalization of power systems. In traditional method, power demands were supplied whenever it was needed. In new method it is important to keep the system more efficient by keeping demand fluctuations as small as possible. To have a reliable operation it is necessary to be a balance between supply and demand in real time. Achieving this balance could have some difficulties because of rapid and unexpected changes which may occur between demand and supply levels for so many reasons such as outages and sudden load changes.

Renewable energy sources along with demand response programs are the cheaper resources available for operating the system according to this new method and they are increasingly becoming important in the past several years. Change of electricity consumption pattern by end-users in response to the changes in price of electricity is regarded as demand response. Demand response play an important role in competitive electricity markets and can have so many advantages such as improving market efficiency, reducing peak demand and price instability and enhancing the reliability. DR participation in system operation markets can be increased by using advanced smart grid infrastructures

DR can be used in electricity markets by implementing new rules and regulations in electricity markets. In the electricity market players can be divided into DR buyers which are usually retailers and distributors and DR sellers who are large customers or new market participants such as distribution system operators (DSOs), load service entities (LSEs), and DR aggregators which have the responsibility of managing customer responses.

Retailer obtains electricity from the wholesale market and sells it to the customers. The day-ahead market is a market in which the price of the electricity is calculated for the next day and the price of electricity is not the same for different periods of time usually each thirty minutes over twenty-four hours. Day-ahead market is the main source for retailer in some electricity markets and retailer buys electricity based on the amount of demand needed for the next day and the spot prices in day-ahead market. Retailer as a buyer needs to assess how much electricity is needed to meet the demand of the following day. The amount of power supplied by the retailer should match with the total demand of all consumers at each period. If there are some differences between them it should be balanced by adjusting them through intraday market. Prices in intraday market are different from the spot prices of day-ahead market and retailer prefers to compensate these difference by using demand response actions.

In this thesis we have tried to implement some load management programs to maintain the balance between demand forecast in day-ahead market and intraday demand forecast which is close to the real-time demand. To achieve this purpose we have used physically based load models which are freezers in this thesis and implemented some demand management actions to mitigate the differences. The main purpose of this thesis is to use different strategies and find out the best solution by using multi-objective optimization tool (NSGA- II).

1.2 Dissertation structure

This dissertation is divided into different chapters. Chapter 2 presents a general explanation about electricity markets and talks about some different markets around the world. It is made one brief reference to the evolution of the electricity sector, and some examples of existing markets. With regard to Chapter 3, demand response is dissected in literature, different classification of demand response and costumer participation in demand response activities is explained. Chapter 4 talks about the methodology of this thesis and refers to the existence of physically based models, mostly freezers. In addition, a small review about evolutionary and genetic algorithms is carried out. In the end of this chapter the problem which is going to be solved and the formulation needed for our work is mentioned. In chapter 5 the case study was analyzed, in order to verify the impact of load management strategies in our work. Finally, in Chapter 6 Conclusions that this work yielded are drawn, and some suggestions for future works are proposed.

Chapter 2

Electricity market

In the past, the electricity sector was based on vertically integrated monopolies consisting of independent generation, integrated transmission and distribution that usually owned by states or a single entity. During the last decades, the infrastructure of system operation and planning has been changed by restructuring and deregulation of power system [1]. The term ‘deregulation’ means that power market is neither owned nor run by the state (government) anymore. This deregulation changed the monopolistic structure and unbundled the main sections of integrated utilities (generation, transmission, distribution and retail supply) and let generation activities and electricity retailing take part in a competition market while the remaining parts of utilities remained regulated [2, 3]. Due to different market organizations in the electricity industry and different regulatory policies around the world, there is no single standard market model yet. Nevertheless, from the various electricity market models which are operating in different parts of the world, it is likely to classify two main types of market organizations namely pool (centralized markets) and bilateral contract (decentralized market models) or a combination of their variants [4]. In pool or centralized markets, the whole electricity is traded via the pool and most of the time, the supply side places the bid into the pool, while the demand is estimated by market operator. The pool can either run on a day-ahead market or a market which is similar to an intraday real-time market [4]. A bilateral contract or decentralized market is founded on a bilateral contracts among sellers (generators) and buyers (distribution companies) participating freely into bilateral contracts for electricity supply [4].

The wholesale electricity market is a mandatory pool where Energy is transacted. In this market energy and ancillary services are simultaneously traded in a day-ahead market and are dispatched on the available units [5]. These markets are organized with several generation companies. Generation companies compete to sell to all distributors or directly to customers and retailers if retail competition is allowed [3]. Retail competition is implemented to allow consumers to choose among different sellers (retail companies) or to buy directly from the wholesale market. The electrical energy is purchased from the wholesale market and it is sold to consumers who are not able to participate in the wholesale market. Retailers can compete with each other by offering cheaper prices and better services. The competitive wholesale markets provide stronger incentives for controlling construction and operating costs of new and existing generating capacity which lead suppliers to save costs. In addition, competition provides better incentives for network operators to ensure appropriate levels of service quality. Usually, the wholesale electricity market can be categorized as three market places according to different time scales.

2.1 Different types of markets

2.1.1 Day-ahead Market

The spot market is also called as day-ahead market is a forward market in which clearing prices are calculated for each hour of the next operating day based on generation offers, demand bids, bilateral transaction schedules and so on. Most of the electricity is traded majorly through day-ahead market. Therefore market operators need to submit their offers for all hours of the day-ahead and it should be a couple of hours ahead of time.

2.1.2 Intraday markets

Intraday market is a market that operates immediately after the time when clearing prices of Day-Ahead Auction is represented and it will be closed approximately near to real time, commonly 60 minutes or in some markets 45 minutes. In intraday market participants can benefit from more accurate forecasts.

2.1.3 Real-time electricity markets (RTM)

RTM is a balancing market where the clearing prices are calculated every 5 min based on the different criteria such as actual system operations security-constrained and economic dispatch [6]. The negative aspects of buying electricity at wholesale markets for the electricity end-users would be the market uncertainty along with the monetary risks of purchasing at real-time prices. The contributors within the wholesale market need to keep track of the market, which can be hard for them and needs unlimited accessibility to the revised market details. A further obstacle towards the contribution of the customers in wholesale electricity markets is considered the insufficient infrastructure of the essential systems (e.g., smart metering systems at the endpoints) in the majority of the electric power systems. Retail electricity providers take part in the wholesale market with respect to the end-users. They protect the end-users from economic negative consequences in the market and the real-time pricing difficulties, and they take the risks rather than end-users. This means that Retail markets are susceptible to financial risks due to the unpredicted price changes, price spikes, volatile loads and for these reasons they have to buy electricity at prices higher that their selling prices [7]. The risk of financial losses can be reduced by using different approaches such as well-designed demand response programs or using the distributed generation units. Demand response distributed energy sources can have various benefits such as lowering of electricity charges through changing the electricity consumption pattern to hours that the electricity prices are lower. Additionally Demand response programs perform a significant role in enhancing market efficiency, reducing peak demand and price instability and can have a predominant role in mitigating market and network problems. It can reduce retailer's risk whenever the prices are high by implementing smart controllers and using a proper method to manage them. Electricity retailers intend to implement DR in electricity markets in order to improve the security and reliability of the network and also to alleviate the risk of pool price volatilities.

2.2 Some Electricity Market Operators

2.2.1 Nord pool

Nord Pool is the Nordic commodity market for electricity which was established in 1992 as a consequence of the Norwegian energy act of 1991 that formally paved the way for deregulation.

- **Elspot Market**

The Elspot market is a day-ahead auction market for Nord Pool Spot where electrical power is traded for delivery during the next day [8]. Prices calculated based on supply, demand and transmission capacity (how much power can be moved from one area to another). Market participants can submit offers to sell or bids to buy physical electricity for the following day [9]. Players who want to trade power on the Elspot market and participants who want to sell power to Elspot have to send their purchase orders and sale offers to Nord Pool not later than 12:00 CET. Figure 2.1 demonstrates different actions taken by market participants in Elspot market.

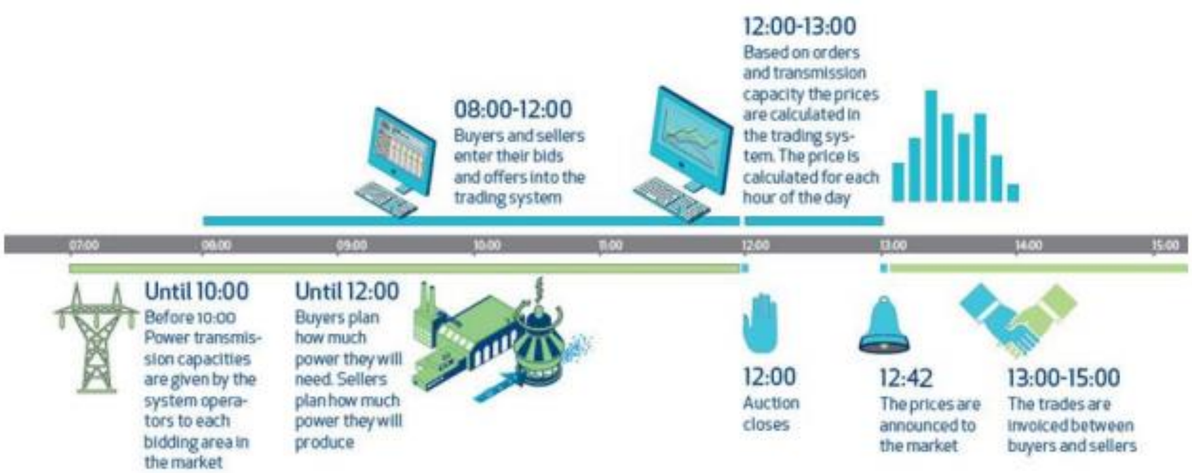


Figure 2.1: *Elspot trading – daily routines [8]*

- **Elbas Market**

The Elbas market is an intraday market for Nord Pool where the actual generation (or consumption) during the day are adjusted. Participants are allowed to trade physical electricity for the next day at 14:00, when the spot prices are available for the next day. Trades are allowed up to one hour before the operation hour. Elbas trading schedule continuous adjustment trading in hourly contracts can be performed until one hour before the delivery hour. New contracts are opened after the day-ahead Elspot prices have been set. Before 2 p.m. the remaining hours of the current day are tradable and then day-ahead contracts are open for trading. The objective of Nord Pool financial market is to provide an efficient market, with excellent liquidity and a high level of security to offer a number of financial power contracts that can be used profitably by a variety of customer groups [10].

2.2.2 MIBEL

The Iberian Electricity market (MIBEL) is an agreement between the governments of Portugal and Spain with the aim of promoting the integration of both countries' electrical systems. The consequence of this cooperation has been very constructive and fruitful and has made an important step in building the Internal Energy Market in addition to its contribution towards establishing an electricity market at the Iberian level [11]. MIBEL includes a Day-Ahead Market (DAM) and Intraday Market (IM) located in Spain and managed by OMIE and Derivative/forward Market located in Portugal and managed by OMIP and also an ancillary services market that balances the stability between electricity production and consumption and operates in real time. DAM (Day-Ahead Market) is the predominate market which takes part in energy transactions the day before the delivery day. It has 24 simultaneous auctions, one for each hour of the next day. The closing hour of the day-ahead market is 10.00 am on the day before supply; clearing prices are published at 11.00 am. Intraday market runs just before and through the delivery day. In this markets electricity is either sent or bought by Generation Companies so they can role both as buyers or sellers of energy. It has the same function as the DAM has and Generation Companies implement it to change the DAM resulting generation scheduling. It is worth bearing in mind that a unit can only submit buy or sell offers in one hour, not both of them simultaneously, although this role can change during the different hours [12].

2.2.3 PJM

The Pennsylvania-New Jersey-Maryland (PJM) operates the wholesale electricity market of the 13 states of U.S. and Columbia District. It mainly operates as a day-ahead energy market and a real-time energy market. In these markets customers are allowed to participate directly in real time [13] and day-ahead markets. In day-ahead market participants can buy and sell energy at binding day-ahead prices and also transmission customers are allowed to schedule bilateral transactions at binding day-ahead congestion charges based on the differences in Locational Marginal Price (LMP) between the transaction source and sink locations [6]. It means that PJM will pay LMP to customers whenever the LMP in the given zone is higher than a trigger point and if the LMP is below or equal to a trigger point, customers will receive the difference between the LMP and the generation and transmission components of the customer's bill [13].

2.2.4 New England Market

The New England electricity market has designed a real-time demand response program for customers in which customers are able to decrease their electricity consumption within 30 hours or two hours when it is needed and New England independent system operator (ISO-NE) asks for it. The request by ISO-NE is named as "reliability events." In order to contribute in the real-time demand response program customers need to install special metering and communication systems which are able to record participant's electricity consumption in five-minute intervals. The purpose of ISO-NE's price program is to reduce the severe consequences of real-time market price volatility, while its reliability programs are intended to provide a stock of resources that help avoid electricity shortages [14].

Chapter 3

Demand Response

There is a growing consensus that insufficient levels of demand response exist in the Europe electric power system. The disconnection between short-term electricity production costs and time-averaged, fixed retail rates paid by most consumers leads to an inefficient use of resources. An important benefit of demand response is avoided need to build power plants to serve heightened demand that occurs in just a few hours per year. To meet the above requirements, tremendous research is being carried out to build new electric grids. Electrical Grid is a network of horizontal and perpendicular lines cross each other to connect synchronized power providers and consumers by transmission and distribution lines together. Electricity is produced in these grids by using centralized power plants of hydraulics, combined heat, nuclear, and fossil fuel based plants [15]. There is no bidirectional communication between supplier and demand side and power flow is almost unidirectional [16] as shown in Figure 3.1:

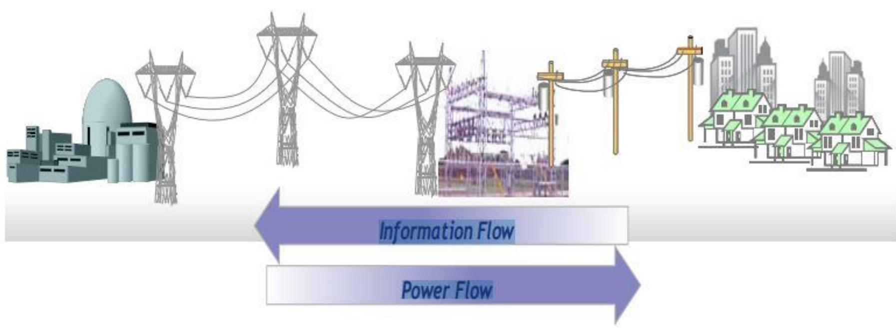


Figure 3.1: *Power and Information Flow in Traditional Utility Environment [16]*

Smart grid is a new concept of electrical grid seeks to improve operation, maintenance and reliability of the network through delivering electricity in a controlled and smart way from electricity supplier to a consumer. Smart grid as an intelligent grid can store, communicate and make decisions by collecting data from electric meters. By emerging smart metering infrastructure to the smart grid it is possible for residential users to control their electricity costs [17] and have a bidirectional communication with the utility operator. Bidirectional communication and smart metering infrastructure are two key technical drivers for introducing demand response into smart grids [18].

Figure 3.2*: Power and Information Flow under Smart Grid [16]*

Demand response can be defined more specifically as Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized [19]. DR can play an important role for securing network reliability and controlling the price volatilities in wholesale market. DR programs are able to change electricity consumption patterns of end-use customers who are intended to change the timing, level of instantaneous demand, or the total electricity consumption [20]. DR lets customers to have interaction with utility and respond to them whenever it is necessary. The collaboration between customers and utility will have short impacts on the electricity markets and lead to economic benefits for both sides. Furthermore DR can enhance the reliability of the power systems and have long-term consequences such as lowering peak demand, decreasing overall plant and capital cost investments and postponing the need for network upgrade [7]. Lowering peak demand can have some advantages through lowering the quantity of generation and transmission assets needed to supply electrical service. Decreasing the demand in response to high charges reduces the expenses of energy production and keeps the expenses at the same level in energy spot markets. Reduced demand in reaction to system reliability troubles improves operators' capability to control the electric grid—the network that transmits power from generators to customers—and reduces the possibility of sudden shut down or complete power cut [5].

There are three general ways by which a customer can participate in demand response options. every of these actions involves price and measures taken by the client [21].

- **Foregoing:** Reducing their energy consumption through load curtailment strategies at times the price of electricity is high; for instance changing the thermostat set point of refrigerators or air conditioners that can have some uncomfortable results for a short period
- **Shifting:** Moving energy consumption to a different time period by rescheduling consumption from high peak period to another time; for example instead of using their washing machines during the high price periods users can postpone it to another time.
- **Onsite generation:** customers can use some distributed energy resources or emergency generators to limit their dependence on the main grid and to supply some of their needs, For instance, they can install some solar panels or some electricity storages in order to have less dependency to the power system.

Customer’s contribution in demand reduction will depend on the contract with the utility or electricity suppliers and can be either directly or through an intermediary. Different price based or incentive based plans are useful for this issue. For household clients, using the demand response signal needs accomplishing a number of available actions including dimming or switching off non-critical lights, adjusting the thermostat set-points, or switching off non-critical equipment Regardless of the plan which is adopted, the customer’s contribution are typically considered either on/off services from where the load is cut down or turned off totally (worst case), smooth decrease in consumption at its own discretion, or shifting the loads from peak hours to non-peak hours.

3.1 Quantifying the Benefits of Demand Response

- Quantifying the potential nation-wide benefits of demand response is a difficult undertaking requiring the following key information and assumptions:
- Demand Response Options—the types of time-varying rates and demand response programs currently offered (or potentially available)
- Customer Participation—the likelihood that customers will choose to take part in the offered programs
- Customer Response—documenting and quantifying participants’ current energy usage patterns, and determining how participants adjust that usage in response to changes in prices or incentive payments

- Financial Benefits—developing methods to quantify the short- and long-term resource savings of load response under varying market structures
- Other Benefits—identifying and quantifying any additional benefits provided by demand response resources (e.g., improved reliability); and
- Costs—establishing the costs associated with achieving demand response

In the literature Demand response can be classified differently. Based on [19] DR can be separated into two categories, price (Time) -based programs and incentive-based programs, while in [22] in addition to the first two groups, an extra group has been added named as Demand reduction bids.

3.2 Classifying Demand Response Options

Price-based or time-based demand response programs depend on costumer's choice. The price of electricity varies over the time in order to motivate consumers to change and decrease their consumption patterns. Time-of-use (TOU), real-time pricing (RTP) and critical-peak pricing (CPP) are three different tariffs included in this program. Incentive-based programs relies on customer's reaction to financial rewards given by electricity utility during the period of high peak demand in order to curtail their consumption [23]. Direct Load Control (DLC), Interruptible/curtail able service (I/C), Emergency Demand Response Program (EDRP), Capacity Market Program (CMP), Demand Bidding/Buy Back and Ancillary Service Markets (A/S) are some common demand response programs related to Incentive-based programs [24]. In demand reduction bids customers place their reduction bids to the aggregators or to the utilities when the prices are high and they wish to be curtailed [22]. Table 3-1 gives a brief explanation of each demand response programs.

<table>
<tr><td colspan="2">Demand Response Options
Policymakers have several tariff and program options for eliciting demand response. The most commonly implemented options are described below.</td></tr>
<tr><td>Tariff Options
("price-based" demand response)

Time-of-use (TOU): a rate with different unit prices for usage during different blocks of time, usually defined for a 24-hour day. TOU rates reflect the average cost of generating and delivering power during those time periods. TOU rates often vary by time of day (e.g., peak vs. off-peak period), and by season and are typically pre-determined for a period of several months or years. Time-of-use rates are in widespread use for large commercial and industrial (C/I) customers and require meters that register cumulative usage during the different time blocks.

Real-time pricing (RTP): a rate in which the price for electricity typically fluctuates hourly reflecting changes in the wholesale price of electricity. RTP prices are typically known to customers on a day-ahead or hour-ahead basis.

Critical Peak Pricing (CPP): CPP rates include a pre-specified high rate for usage designated by the Utility to be a critical peak period. CPP events may be triggered by system contingencies or high prices faced by the utility in procuring power in the wholesale market, depending on the program design. CPP rates may be super-imposed on either a TOU or time-invariant rate and are called on relatively short notice for a limited number of days and/or hours per year. CPP customers typically receive a price discount during non-CPP periods. CPP rates are not yet common, but have been tested in pilots for large and small customers in several states
(e.g., Florida, California, and North and South Carolina).</td>
<td>Program Options
("incentive-based" demand response)
Direct load control: a program in which the utility or system operator remotely shuts down or cycles a customer's electrical equipment (e.g. air conditioner, water heater) on short notice to address system or local reliability contingencies. Customers often receive a participation payment, usually in the form of an electricity bill credit. A few programs provide customers with the option to override or opt-out of the control action. However, these actions almost always reduce customer incentive payments. Direct load control programs are primarily offered to residential and small commercial customers.

Interruptible/curtailable (I/C) service:
Programs integrated with the customer tariff that provide a rate discount or bill credit for agreeing to reduce load, typically to a pre-specified firm service level (FSL), during system contingencies. Customers that do not reduce load typically pay penalties in the form of very high electricity prices that come into effect during contingency events or may be removed from the program. Interruptible programs have traditionally been offered only to the largest industrial (or commercial) customers.

Demand Bidding/Buyback Programs:
programs that (1) encourage large customers to bid into a wholesale electricity market and offer to provide load reductions at a price at which they are willing to be curtailed, or (2) encourage customers to identify how much load they would be willing to curtail at a utility-posted price. Customers whose load reduction offers are accepted must either reduce load as contracted (or face a penalty).

Emergency Demand Response Programs: programs that provide incentive payments to customers for measured load reductions during reliability-triggered events; emergency demand response programs may or may not levy penalties when enrolled customers do not respond.

Capacity Market Programs: these programs are typically offered to customers that can commit to providing pre-specified load reductions when system contingencies arise. Customers typically receive day-of notice of events. Incentives usually consist of up-front reservation payments, determined by capacity market prices, and additional energy payments for reductions during events (in some programs). Capacity programs typically entail significant penalties for customers that do not respond when called.

Ancillary Services Market Programs:
These programs allow customers to bid load curtailments in ISO/RTO markets as operating reserves. If their bids are accepted, they are paid the market price for committing to be on standby. If their load curtailments are needed, they are called by the ISO/RTO, and may be paid the spot market energy price.</td></tr>
</table>

Table 3-1: *Common types of demand response programs [22]*

Chapter 4

Methodology

Demand response needs some improvements of control mechanism to let end-use costumers change the electricity consumption as a result of price variations over the time. Presence of controllable loads are necessary in order to implement the control mechanism. Controllable loads include different range of loads such as refrigerators, freezers, washing and dishing machines, air conditioners, coolers, heaters, water heating and so on. These loads can be either interrupted or shifted by utilities and the load curve can be changed by decreasing demand.

The activities used to change these controllable loads are generally called Load Management (LM) Programs. LM programs can change the usual working cycles of loads by using appropriate power curtailment actions [25]. Direct Load Control (DLC) and Interruptible Load Management are the most common programs used in LM programs. DLC can reshape load consumption of end-users by changing the demand of controllable load without having remarkable impact on their life style. LM programs can use thermostatic loads which are able to change the power demand of loads by adjusting different thermostat points. Temperature of the fluid being heated or cooled defines the demand of these loads [26]. For a cooling device whenever the temperature is higher than the above limit of dead band the power will be connected and whenever the temperature is below the lower limit of dead band the power will be disconnected and it is opposite for a heating device. In these specific types of loads the demand pattern will be changed as soon as the regular working cycle is changed by an external action [27].

4.1 Physically based load models

Since LM programs will change the normal behavior of loads it is important to use models which are capable to capture these kinds of behaviors. In order to evaluate the impacts of load management strategies it is necessary to use tools for monitoring the result of actions. Physically based load models (PBLM) are models that let you know, at any time the value of each variable interest. By using these models, operation equipment can be simulated and also it is possible to evaluate the impact of LM actions. PBLMs can recreate the demand of end-use loads such as thermostatic loads by simulating the physical phenomena happening in these sort of loads and also replicating thermostatic behaviors influencing the demand of these loads. By using some software tools it is possible to simulate the load diagram and assess the results both with and without implementing load control strategies. An important feature that modeling tools should be capable of is that they can simulate the demand of group of end-use loads because usually load control strategies are applied over group of loads [26, 27].

The loads that are used in this thesis are freezers and the operation of these loads can be controlled by changing the thermostat point. Thermostat allows certain range of temperatures and determines the operational status of loads and turn them on/off. In thermostatic loads like freezers both parameterizing thermostat and cutting actions can be implemented. In this thesis simultaneous control both with changing the thermostat set points and direct load control (DLC) has been used which means that loads consumption pattern is changed by altering the thermostat values of the freezers and switching ON/OFF of them. The reason for choosing this type of PBLM is due to their availabilities in all homes and many other places which lead to have a better assessment of load management strategies. The other reason is that these types of loads are operating during the 24 hours a day and they are a resource with high temporal availability. In order to simulate these loads, a PBLM which has been created and validated experimentally in [28] has been used.

4.2 Optimization and Evolutionary Algorithms

Optimization is a technique used to select a number of probable solutions which match extreme values of one or more objectives. The necessity for discovering such ideal solutions within a problem originates mainly out of the excessive reason for either designing a solution for minimum possible cost of fabrication, or for optimum possible reliability, or others. As a result of such extreme properties of optimal solutions, optimization methods are so important in practice, predominantly in engineering design, scientific experiments and business decision–making. Single-objective optimization refers to a procedure to find the optimal solution for an optimization problem which has only one objective function. When the optimization problem is related to more objective functions, it is a needed to find more than one optimum solution and this optimization problem is called multi-objective optimization [29]. Typically optimization problems have multiple objectives. In most cases these objectives are contradicting, it means that by optimizing one objective another objectives will become poor.

Evolutionary algorithms are stochastic search techniques that imitate the metaphor of natural biological evolution. Evolutionary algorithms work on a population of potential solutions by using a theory that is based on the survival of the fittest to produce better estimates to a solution. Every single generation, a completely new number of estimates is created by the whole process of selecting individuals according to their amount of fitness inside the problem domain and breeding them together using operators given from natural genetics. This approach results in the evolution of populations of individuals which are more appropriate for their environment comparing to those were just created from natural adaptation [30].

The genetic algorithm (GA) is definitely an evolutionary algorithm that utilizes genetic operators to acquire optimal solutions with no presumptions concerning the search space. Genetic Algorithms (GAs) are search methods of probabilistic nature, which were inspired by the principles of genetics and natural selection. The process of natural evolution, according to the assumptions made by Darwin, involves two basic processes: the selection and reproduction with variation. The process of selection responsible for ensuring that individuals are better adapted to the environment (the fittest) and they have a greater chance of survival. The variation associated with reproduction and mutation ensures that the descendants that are being generated, will not be an exact copy of their parents. The combination of these two processes allows the development of individuals, over successive generations, occurs in a gradual manner [31].

GA deals with a population of possible solutions and due to this fact, it can be used in multi-objective optimization problems to collect several solutions at the same time. GA based multi-objective optimization strategies were implemented nicely in order to look for a group of Pareto-optimal solutions during the past decade and far beyond. Evolutionary multi-objective optimization (EMO) methodologies have proved their advantages in looking for a well-incorporated and well-distributed group of near Pareto-optimal solutions during the 15 years or even more. As a result of so many widespread studies and accessible source codes either commercially or without restraint, the EMO strategies was used widely in a variety of problem-solving projects and have received significant amounts of interest even from the classical multi-criterion optimization and decision-making communities. Non-dominating sorting GA (NSGA-II) is just about the most popular strategies to producing the Pareto frontier. The NSGA-II algorithm ranks the individuals by considering dominance. NSGA-II works by using elitism along with a phenotype crowd comparison operator that maintains diverseness without revealing any extra variables [32]. The main feature of NSGA-II could be as below:

- It is a sorting non-dominated technique and it sorted individual based on the level of non-domination;
- Elitism is implemented and it stores all non-dominated solutions, and it enhance convergence properties;
- a suitable automatic mechanics is adapted based on the crowding for ensuring diversity and spread of solutions;
- Constraints are implemented using a modified definition of dominance without the use of penalty functions [33].

4.3 Problem

As mentioned before retailer can take advantages of demand response programs in order to decrease financial risks and some other market problems. The retailer buys electivity from the market and sell the power to the consumers. The day-ahead market (called spot market) is mentioned in this work because it is expected to be the main market for many retailers. In the day-ahead market a buyer, typically a utility/retailer, needs to assess how much energy is required for the following day and a seller needs to decide how much energy can be provided. Bids are placed for each hour of the next day and clearing prices are calculated. The orders placed in the day-ahead market are not always equal to the demands needed to be physically delivered in the next day. This differences can be balanced by giving a new forecast through intra-day market which is closer to the actual demand. The differences between demands of day-ahead market and intra-day demands can be resolved whether by purchasing an extra energy which is costly or by using Load Managements (LM) programs.

LM programs can implement load control strategies to mitigate these differences. The load strategy going to be used in this research is based on load on/off pattern or thermostatic loads management and the load models in this research are physically-based load models (Freezers). It means that by applying load curtailments or by changing the input temperature of Freezers in large numbers, the consumption pattern will be changed. The main purpose of this research is to use different strategies and find out the best solution by using evolutionary algorithms (EA). EA identifies a set of solutions which are then decodified into load control strategies. Freezers implement these strategies and then the load pattern is simulated under this control strategy. Then the obtained result is used by EA to identify the next generation. This cycle repeats until a stop condition is reached. Figure 4.1 demonstrates the iterative process.

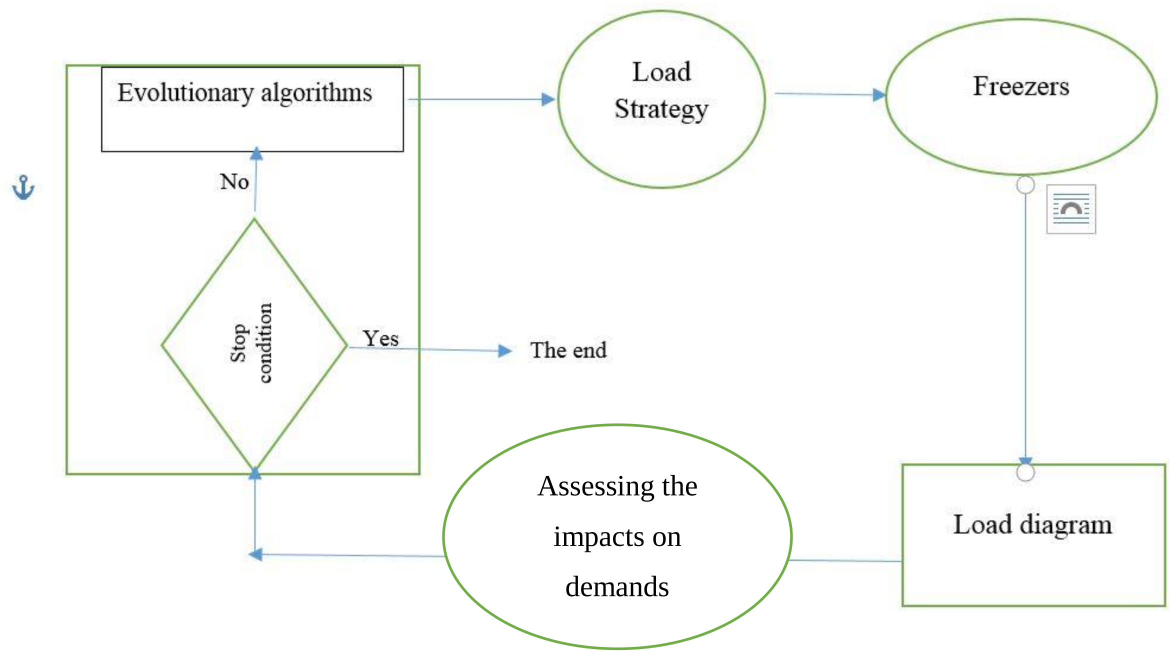


Figure 4.1: *iterative process of load management simulation*

4.4 Mathematical Formulation

In order to assess the impact of demand management actions in a real situation, we used a substation load diagram with a transformation ratio High Voltage (HV) / Low Voltage (LV), in kV, of 60/15, an installed capacity of 60 MVA and a total number of consumers of 35950. This load diagram includes two different consumption patterns; one of these patterns is considered as day-ahead forecasted load demands and the other one is considered as an intraday forecast which is closer to actual demands.

The above-mentioned load diagrams are shown in figure 4.2; as it can be seen, there are two different forecasts in two different instants of time.

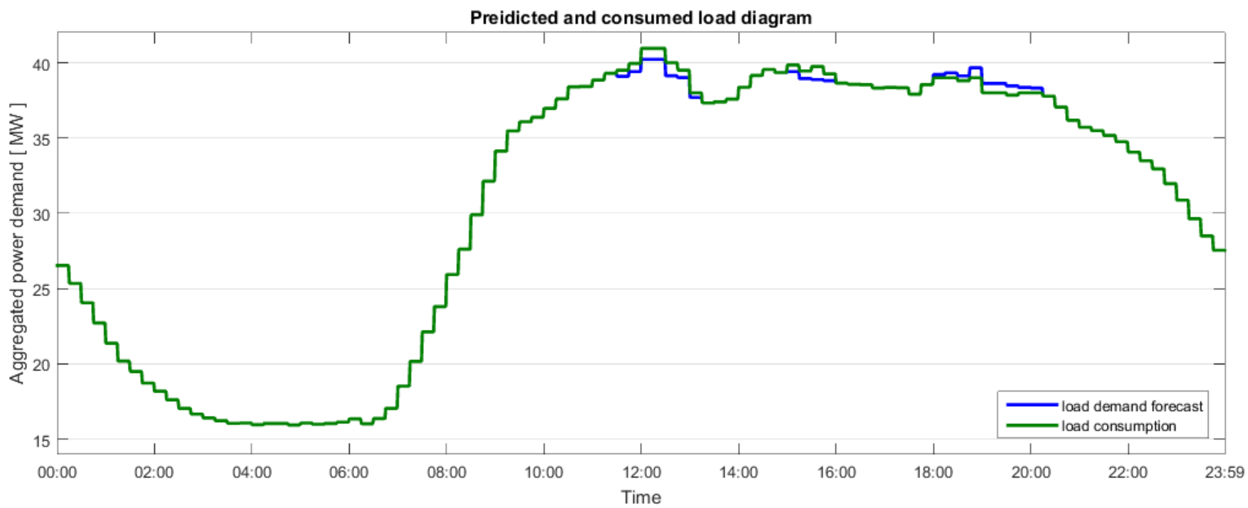


Figure 4.2*: Aggregated load diagrams, forecasted in two different instants of time*

We notice that they just differ for following three time durations:

- between 11:30 to 13:15 which the consumption is more than forecast
- between 15:00 to 16:00 which the consumption is more than forecast
- between 18:00 to 20:15 which the consumption is less than forecast

These parts of the diagrams are shown graphically in figure 4.3. The main objective is to identify LM actions that allow minimizing the differences between these two curves.

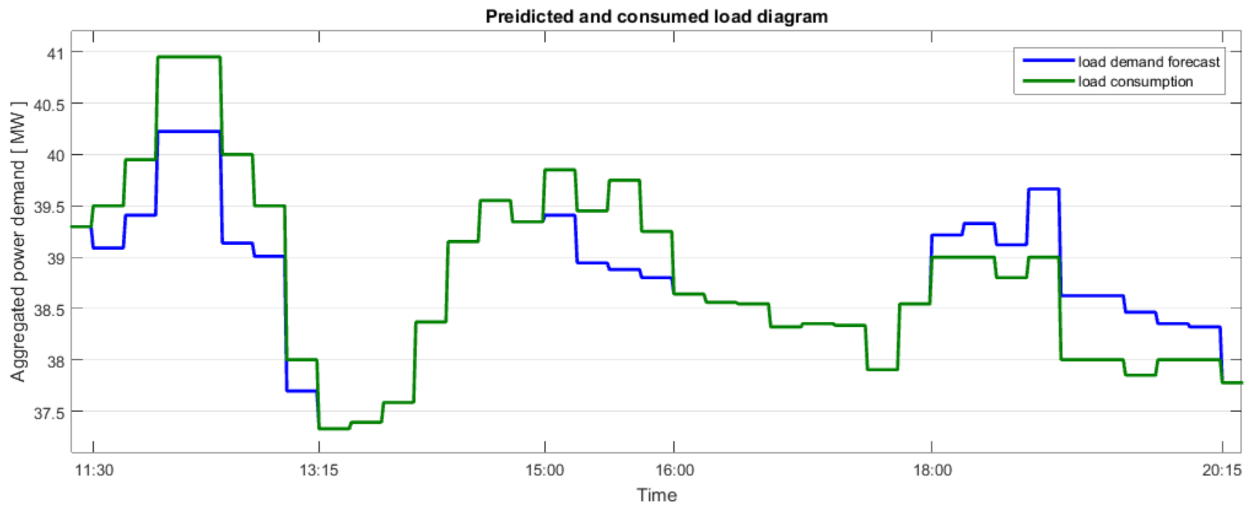


Figure 4.3*: Enlargement of the aggregated load diagrams between time duration 11:30 to 20:15*

In this study, two objective functions and three types of decision variables are considered which are explained in the following three subsections.

4.4.1. Objective 1

The 1st objective is to minimize the differences between aforesaid two load diagrams, i.e., the day-ahead forecasted load demands and the intraday forecast which is close to actual load demands. In this regard, we consider time varying "thermostat set points" for freezers. Hence the thermostat set points of each group of freezers, with group index "j" at time instant "i," can be represented with [Tminj + xij, Tmaxj + xij] in which "xij" varies in [-2, 2]. The objective is to find "xij" in such a way that minimize the differences between the two load diagrams.

j	index for group of loads (index for group of freezers)
Ng	number of load groups (in this study, Ng = 8)
$Tmin_j$	initial minimum thermostat set point of load group j
$Tmax_j$	maximum thermostat set point of load group j
i	index for time grid node under consideration
N	number of time grid nodes the load diagram is discretized (in this study, N = 1440)
t_i	time instant at grid node i (in this study, $t_i = i - 1$)
x_{ij}	the difference between proposed thermostat set points and initial thermostat set points for load group j at time instant i; it varies between -2°C to +2°C

DLC_{ij} the ON/OFF state of freezer for load group j at t_i which can be decided by operator as a part of load management and called Direct Load Control; it switches between 0 and 1

DLC_{ij}^0 the ON/OFF state of freezer for load group j at t_i with no LM action

We assume the "blue color diagram" is the load demand forecast, and the "green color diagram" is the consumed load. Therefore, in the computer simulation when "xij = 0" for i = 1, 2, …, N and j = 1, 2, …, Ng, the freezer load consumption diagram plus an unknown load consumption from other load groups should be identical to the consumed load diagram, i.e., green color diagram.

In order to express the objective function for minimization of the differences between load consumption and load demand forecast suppose:

ALC_i Aggregated Load Consumption at t_i (load value on green color diagram at t_i)
FLC_{ij} Freezer Load Consumption for load group j at t_i
CLD_i Consumed Load Difference at t_i
LDF_i Load Demand Forecast at t_i (load value on blue color diagram at t_i)
e_i The difference between load consumption and load demand forecast at t_i

Then we can calculate the differences between load consumption and load demand forecast as followings:

$$CLD_i = ALC_i - \sum_{j=1}^{Ng} FLC_{ij}(x_{ij} = 0, DLC_{ij}^0)$$

$$e_i = LDF_i - [\sum_{j=1}^{Ng} FLC_{ij}(x_{ij}, DLC_{ij}) + CLD_i] =$$
$$= LDF_i - \left[\sum_{j=1}^{Ng} FLC_{ij}(x_{ij}, DLC_{ij}) + ALC_i - \sum_{j=1}^{Ng} FLC_{ij}(x_{ij} = 0, DLC_{ij}^0)\right]$$

Now to minimize the differences between load consumption and load demand forecast, we can consider a non-negative function as objective function; for example, the summation of weighted absolute differences:

$$\text{objFunc1} = \sum_{i=1}^{N} p_i |e_i| = \sum_{i=1}^{N} p_i \left| LDF_i - \left[\sum_{j=1}^{Ng} FLC_{ij}(x_{ij}, DLC_{ij}) + ALC_i - \sum_{j=1}^{Ng} FLC_{ij}(x_{ij} = 0, DLC_{ij}^0)\right]\right|$$

In which, p_i denotes to a suitable weighting function in order to account the relative importance of the differences between load consumption and load demand forecast at t_i.

In the above formulation, the number of considered xij decision variables is N*Ng (in this study, N = 1440, Ng = 8). However, if we assume the thermostat set points vary just after each "dtThermostat" minutes, then the number of decision variables will be reduced to (N/dtThermostat)*Ng (in this study, dtThermostat = 15).

4.4.2. Objective 2

The 2nd objective is to minimize causing discomfort. For this purpose the indicator considered is the number of minutes that the thermostat set points go "dTemp" beyond initial thermostat set points (in this study, dTemp = 0.5°C). This objective function can mathematically be expressed with following equation:

$$\text{objFunc2} = NSPG.dtThermostat.\sum_{i=1}^{N/dtThermostat}\sum_{j=1}^{Ng}\sum_{k=1}^{nLoads_j} H\left(\left|x_{ijk}\right| - dTemp - 0.1\right)$$

In which:

nLoadsj	number of freezers of load group j
NSPG	number of sets per each load group

And "H" denotes to Heaviside step function:

$$H(x) = \begin{cases} 0 & x < 0 \\ 1 & x \geq 0 \end{cases}$$

4.4.3. Decision Variables

In this study, following three types of decision variables are considered:

x_{ij} the difference between proposed thermostat set points and initial thermostat set points for load group j at time instant i; it varies between -2°C to +2°C

nVars1 = number of xij = (N/dtThermostat)*Ng = (1440/15)*8 = 768

DLC_{ij} the ON/OFF state of freezer for load group j at t_i which can be decided by operator as a part of load management and called Direct Load Control; it switches between 0 and 1

nVars2 = number of DLC_{ij} = N*Ng = 1440*8 = 11520

NSPG number of sets per each load group

nVars3 = number of NSPG = 1

Chapter 5

Case study

5.1. Description of the system

In realization of this case study, the system considered consisted of some controllable loads, i.e., freezers, and some uncontrollable loads. The controllable loads are described in section 5.2. The aggregated load diagrams considered described in chapter 4.

The parameters of controllable loads, presented in table 5.1, are used as input to a physically-based model computer simulation to obtain the controllable load diagram. The result is shown in figure 5.1 graphically.

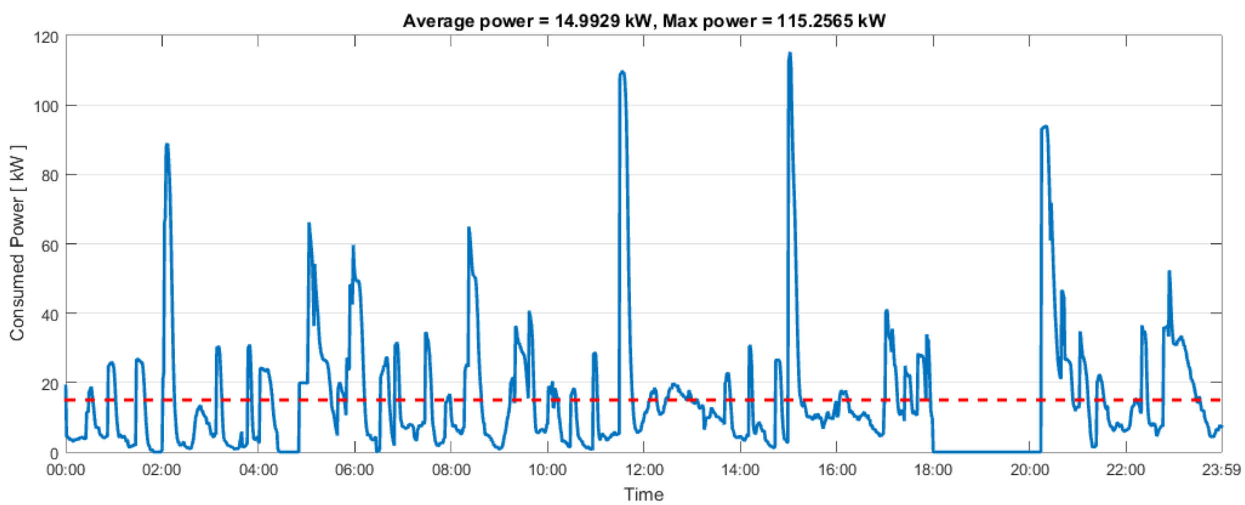


***Figure 5.1**: Total controllable load diagram assuming NSPG = 1*

The red line shown in figure 5.1 corresponds to the average value of controllable power which is 15 kW approximately, considering "NSPG = 1." If we consider "NSPG = 30" then the average controllable power is 450 kW approximately. This means that the amount available for inspection at each instant of time fluctuates around 450 kW. It should be noted that this value is in continuous operation and is available all day when the control actions are considered randomly.

To determine the number of loads to consider, the variable "NSPG" is considered which the computer program will find it. Once we find this variable, then it's enough to multiply it to "nLoads" to find the number of loads considered (in this study, nLoads = 2000). To simulate the operation, “Ng” groups of loads have been considered, each containing “$nLoads_j$” sets of “NSPG” equal loads (in this study, Ng = 8, $nLoads_j = 250$ for j = 1,2,…,Ng). In section 5.2 the parameters used in each of these groups of loads are presented.

The uncontrollable load diagram is shown in figure 5.2. It’s obtained by subtracting the controllable load diagram which is NSPG times of the diagram shown in figure 5.1, from the aggregated load diagram shown (with green color) in figure 4.2.

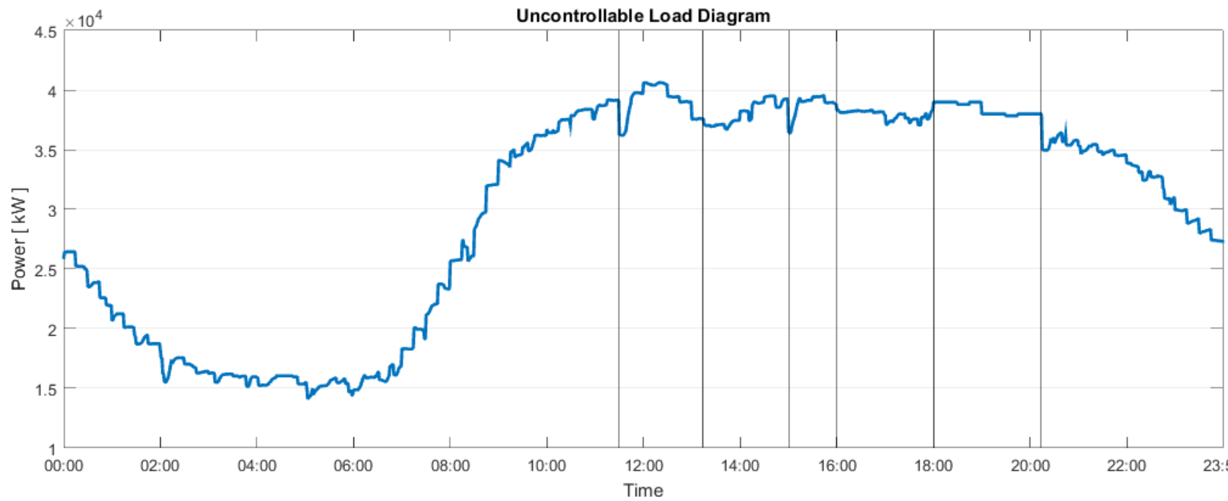


Figure 5.2: *Uncontrollable load diagram assuming NSPG = 21*

5.2. Controllable Loads

The parameters of controllable loads (freezers), is presented in table 5.1. As we neither know the number of controllable loads nor want to estimate manually, we considered it unknown and allowed the optimization algorithm to find it introducing a decision variable; refer to last column of table 5.1 which shows the total number of controllable loads are 2000*NSPG, in which “NSPG” is an unknown positive integer number.

Table 5.1: *The parameters of controllable loads*

Group No., j	Tmin	Tmax	DLC	Tamb	P	COP	MCP	Rterm	Scheduling time	nLoads / NSPG
1	-24.25	-20	1	22	90	1.5	27657	12.1341	1440	250
2	-24.25	-20.75	1	20	105	1.3	28349	13.8381	1440	250

Group No., j	Tmin	Tmax	DLC	Tamb	P	COP	MCP	Rterm	Scheduling time	nLoads / NSPG
3	-23	-20.5	1	23	100	1.3	26993	10.5151	1440	250
4	-23.25	-19.85	1	22	80	1.5	29363	9.3019	1440	250
5	-22.25	-19.85	1	24	110	1.5	30097	11.1995	1440	250
6	-23.45	-18.85	1	22	85	1.5	30859	13.7986	1440	250
7	-24.25	-19.85	1	23	85	1.5	31649	23.2815	1440	250
8	-24.25	-18.85	1	23	90	1.3	30097	20.88	1440	250

In which:

- Tmin and Tmax - Minimum and maximum of freezer thermostat temperatures set points of each load group
- DLC - Initial direct load control of each load group at each time instant, which can take the values 0 and 1. When the freezer is "ON," the value of the variable is 1, and when the curtailment action is applied to the freezer, i.e., the freezer switches "OFF," the value of the variable changes to 0. Although all the initial DLC shown in this table have the value 1, but in the computer simulation for the controllable part of load demand forecast, the initial DLC values considered are some randomly generated 1 or 0 numbers. The reason is explained in section 5.5
- Tamb - Room temperature of each load group
- COP - The freezer coefficient of performance of each load group
- nLoads - Number of freezers of each load group
- NSPG - Number of sets per each load group

5.3. Genetic Algorithm and its Parameters Setting

As mentioned in section 4.2, Genetic algorithms are stochastic parallel search algorithms based on the principle of evolution and natural selection [34]. They have proven to be robust search algorithms [35]. The implementation of GA in a specific problem starts with six fundamental issues: encoding of solution, creation of initial population, fitness evaluation, selection of parents, generation of children by genetic operators, and termination criteria.

Genetic parameters (population size, crossover probability, and mutation probability) should be carefully selected for optimal performance [36]. The choice of these parameters is problem specific and no exact rule exists to determine a suitable combination of these parameters [37]. A joint effect of population size, crossover probability, mutation probability, and number of crossover points in each recombination influences the performance. Goldberg has suggested a population size equal to $1.65x2^{0.21L}$ where L is the length of the chromosome for optimal performance [38]. The formula suggested by Goldberg is not applicable for our case since it provides almost an infinite population size. Schaffer et al. have concluded that a small population size 20 to 30, a crossover probability in the range 0.75 to 0.95, and a mutation probability in the range 0.005 to 0.01 perform well [39].

In this case study, the identification of the appropriate set of parameters used in the genetic algorithm is taken after a long simulation work.

The population size of 20 individuals is used. This value was found to have a good compromise between the need of diversity and the computational effort required. The parameters used in this case study are summarized in the table 5-2.

***Table 5-2**: Parameters used in this case study*

Parameter	Value / Type
Number of decision variables	12289
Population size	20 binary chromosomes
Selection type	Tournament
Tournament size	2
Crossover type	Single point
Crossover fraction	0.8
Mutation type	Uniform
Mutation rate	0.01
Pareto fraction	1
Genome (or chromosome) length	16142 binary gens
Number of load groups	8
Total number of loads	2000*NSPG
Temperature threshold, dTemp	0.5ºC
Max number of generations, maxIter	1500
Termination tolerance on fitness value, tolFun	10^{-10}

A suitable weighting function that denoted by “p_i” in section 4.4.1 is considered, which is shown in figure 5.3.

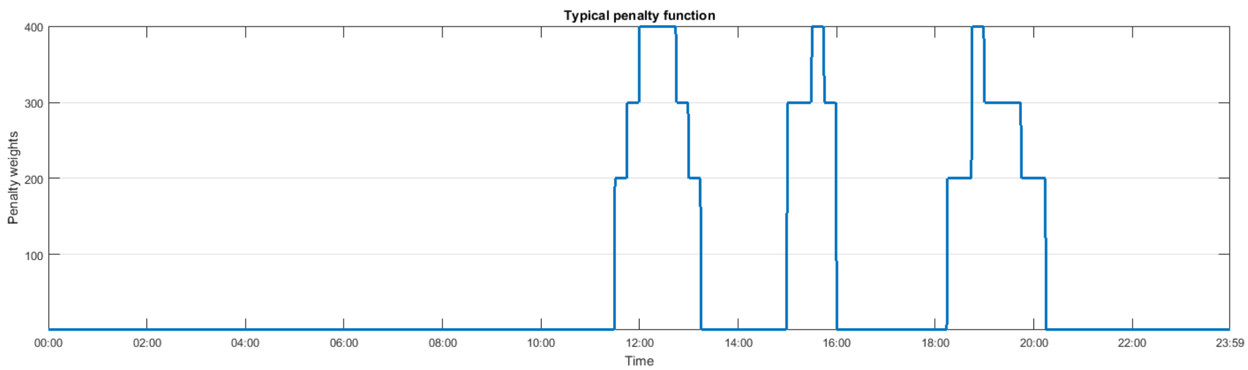


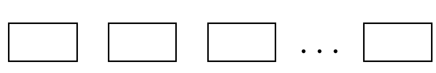
Figure 5.3*: Weighting function, p_i, considered for “objFunc1”*

In order to account the discomfort, it is defined that a load is in discomfort when thermostat set points exceed 0.5°C beyond initial thermostat set points.

Two stop conditions are defined: maximum number of iterations, “maxIter,” and the tolerance on fitness function value, “tolFun.” The maximum number of iterations for this case study is considered is 1500. As the average change in the spread of Pareto solutions became less than “tolFun” at iteration 1483, the algorithm found good compromise solutions and the minimization terminated. Increasing the number of iterations and decreasing the tolerance on fitness function value does not lead to an increase in the quality of obtained solutions.

5.4. Binary encoding of solution

A binary chromosome is constructed of series of chromosome slices or binary substrings that each one of the chromosome slice itself may be constructed from series of smaller chromosome slices or binary substrings. Each chromosome slice in general can be presented similar to the following sketch:

A Chromosome Slice: 

Gen's number:	1	2	3	. . .	m_j

"m_j" is the number of gens or bits in the j^{th} substring. Each gen or bit can take the value 0 or 1.
Each chromosome slice with "nVars" variable which each variable defined with "m_j" gens can be represented similar to the following sketch:

		. . .				. . .		. . .			. . .	
1	2	. . .	m_j	1	2	. . .	m_j	. . .	1	2	. . .	m_j
1				2				. . .	nVars			

What explained above is called "binary encoding." Binary encoding is the most common, mainly because first works about GA used this type of encoding.

5.5. Mapping from a binary string to a real number

As mentioned in section 4.4.3, in this study three types of decision variables are considered. Two types of these decision variables are real-valued variables which fed as inputs to the objective functions. Therefore we have to change the generated binary strings to real numbers as inputs of objective functions. A simple way is first to decode a chromosome slice or binary substring as an unsigned integer (or decimal value) and then map them to real values. Therefore we get the minimum value when all gens are 0:

Chromosome Slice L:	0	0	0	. . .	0

Decimal value: $0\times 2^0 + 0\times 2^1 + 0\times 2^2 + \cdots + 0\times 2^{m_j-1} = 0$

m_j is the number of gens or bits in the j^{th} substring.

We also get the maximum value when all gens are 1:

Chromosome Slice R:	1	1	1	. . .	1

Decimal value: $1\times 2^0 + 1\times 2^1 + 1\times 2^2 + \cdots + 1\times 2^{m_j-1} = 2^{m_j} - 1$

Therefore, the decoded unsigned integer values are in range $[0,\ 2^{m_j}-1]$. Now we map the decoded unsigned integer values linearly from $[0,\ 2^{m_j}-1]$ to $[a_j,\ b_j]$:

$$r_j = a_j + \frac{b_j - a_j}{2^{m_j}-1} u_j$$

In which, uj is the decimal value of the j[th] substring.

With this manner, we can control the range and precision of the decision variables carefully.

As it can be seen, in the representation of encoded decision variables into binary strings, length of the strings depends on the required precision.

If we consider all possible decimal numbers which can be generated using this decoding scheme as a arithmetic sequence, the common difference of successive members is equal to $\frac{b_j - a_j}{2^{m_j}-1}$.

Therefore if we consider d places after the decimal point as the required precision, then:

$$\frac{b_j - a_j}{2^{m_j}-1} \le 10^{-d} \Rightarrow (b_j - a_j)\times 10^d \le 2^{m_j}-1$$

$$\frac{b_j - a_j}{2^{m_j-1}-1} \ge 10^{-d} \Rightarrow (b_j - a_j)\times 10^d > 2^{m_j-1}$$

Therefore:

$$2^{m_j-1} < (b_j - a_j)\times 10^d \le 2^{m_j}-1$$

In the other words, if we consider d places after the decimal point as the required precision, then the precision requirement implies that the range of domain of each variable should be divided into at least $(b_j - a_j)\times 10^d$ size ranges. Hence, the required bits denoted with m_j for a variable is calculated as following [40]:

$$2^{m_j-1} < (b_j - a_j)\times 10^d \le 2^{m_j}-1$$

For our case, each chromosome consisted of 3 types of decision variables:

1) Variables for ON/OFF of the freezers, denoted by DLC

2) Variables for changing the thermostat set points, denoted by X

3) A variable to find required number of freezers, denoted by NSPG

X	DLC	NSPG
4608 bits	11520 bits	14 bits

As for direct load control (DLC), we need just switch between ON (1) and OFF (0), 1 bit for each decision variable is enough, therefore we should totally consider 1*nVars2 = 1*11520 = 11520 bits for DLC.

For X, the domain of variable is [-2.0, 2.0] and if we consider d = 1 place after the decimal point, then from the above formula, we can find $m_j = 6$, hence the total length of bits to construct X is m_j*nVars1 = 6*768 = 4608 bits.

For number of sets per each load group (NSPG), we considered [1, 10000] as the domain of variable. Similarly for maximum precision of 1, we should consider 14*nVars3 = 14*1 = 14 bits.

5.6. Simulation Detailed Analysis Results

In this section we present a detailed analysis of the results obtained in the simulations performed using the parameters listed in the previous subsections.

The binary code option of MATLAB "GAMULTIOBJ" is used to find the Pareto fronts [41]. This multi-objective GA function uses a controlled elitist genetic algorithm (a variant of NSGA-II) [29].

The figure 5.4 presents the evolution of the Pareto fronts in three specific numbers of iterations. As it can be seen clearly, the overall status of Pareto fronts evolving when the number of iterations increases; this is what we expect in an evolutionary algorithm.

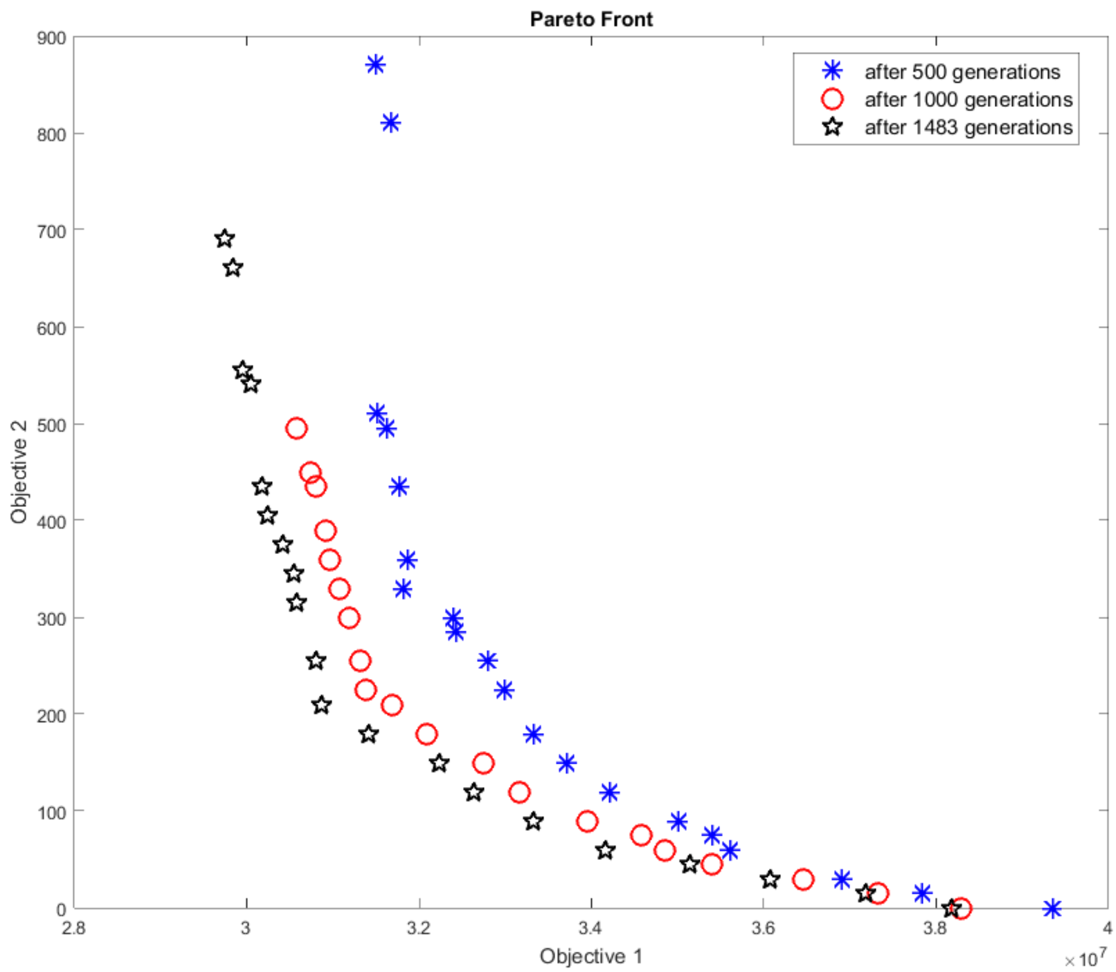


Figure 5.4: *Evolution of the Pareto fronts*

Figure 5.5 shows the results of the solutions obtained at the end of the simulation; all the solutions selected by the algorithm are the dominated solutions.

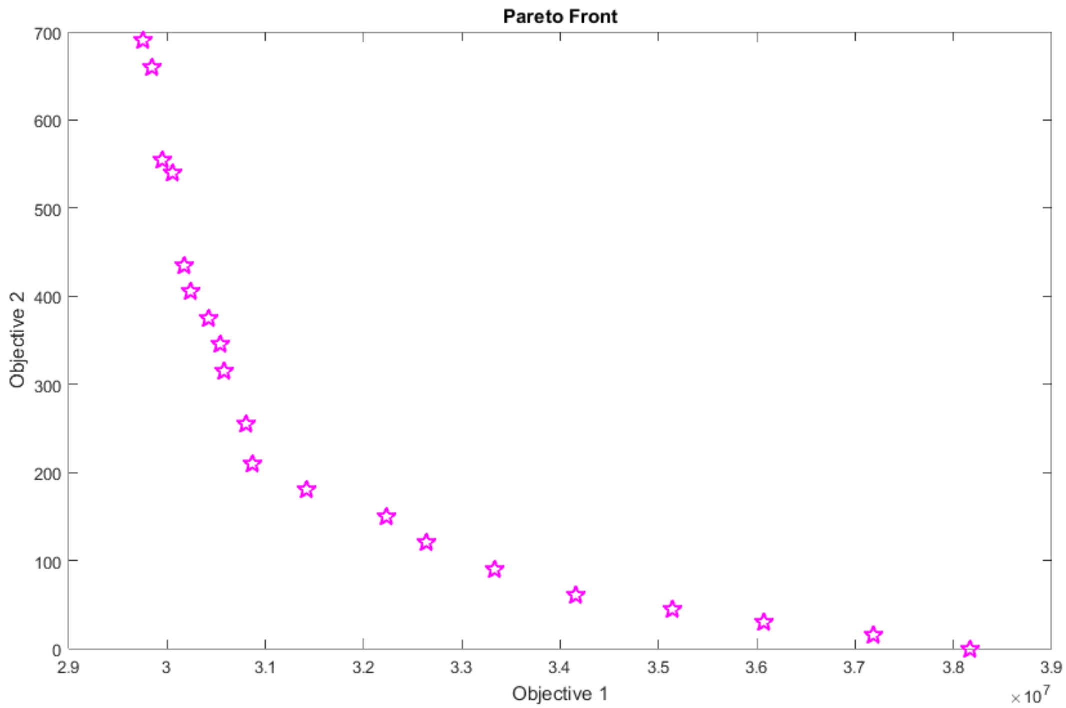


Figure 5.5: *Solutions selected by algorithm*

The numerical values of the chosen dominated solutions are also presented in the table 5-3.

Table 5-3: *Selected solutions*

	Objective 1 [kW]	**Objective 2 [min]**
Solution 1	33331559.6	90
Solution 2	34154976.6	60
Solution 3	31420882.2	180
Solution 4	35136083.2	45
Solution 5	36069712.2	30
Solution 6	37184178.8	15
Solution 7	38172866.6	0
Solution 8	32636487.7	120
Solution 9	32229483.3	150
Solution 10	29748525.0	690
Solution 11	30171450.0	435
Solution 12	30418002.0	375
Solution 13	30053195.2	540
Solution 14	29843813.3	660

	Objective 1 [kW]	Objective 2 [min]
Solution 15	30240917.8	405
Solution 16	30572935.6	315
Solution 17	30866360.7	210
Solution 18	30542802.0	345
Solution 19	30800407.4	255
Solution 20	29947732.8	555

Observing figure 5.5 and table 5.3, it can be seen that the worst value recorded for 1st objective is 38172866.6 which its associated discomfort value is 0. Therefore the worst value for the 1st objective (highest value) is recorded when the value of discomfort is the best (the smallest value).

The best value recorded for 1st objective is 29748525.0, corresponding to an improvement of 26.1% relative to the value recorded without load demand management actions. This case associated with the worst value of discomfort. It can be concluded that, when there is an improvement in the value of 1st objective, the 2nd objective, i.e., discomfort, tends to worsen, i.e., increase. This is what we expect in multi-objective optimization.

Figure 5.6 represents the number of non-dominated solutions during the iterative process. As it can be seen, from iteration number 1337 onward till the end of process, the number of non-dominated solutions is constant, i.e., equal to 20.

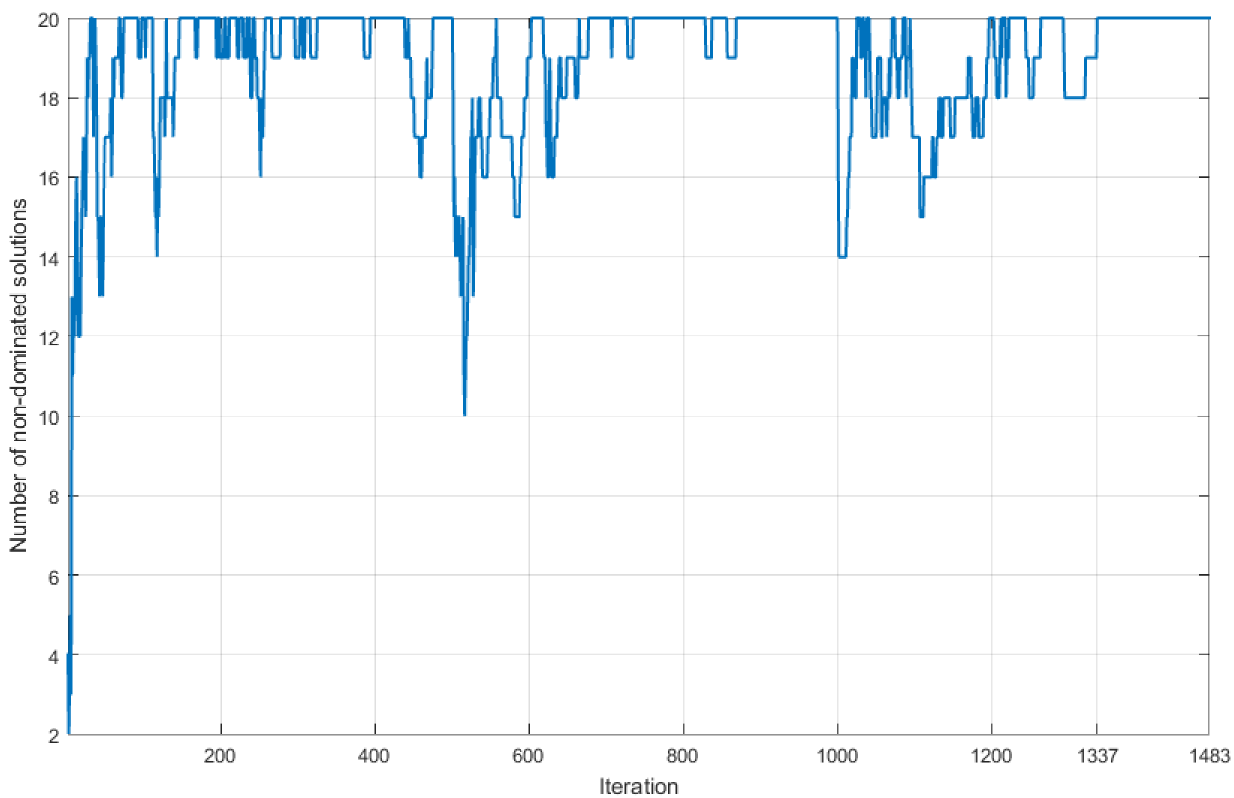


Figure 5.6*: Number of non-dominated solutions in each iteration*

In following pages, the results of one of the selected solutions, labeled as LM 10, are presented.

Figures 5.7 and 5.8 represents the actions applied to the loads of each 8 groups of freezers with enlargement of direct load control actions between 11:30-13:15, 15:00-16:00 and 18:00-20:15 of load group 8.

In figure 5.7 the action taken for changing the thermostat set points are shown. The red dotted lines are the margins of discomfort; therefore any taken actions located outside of those lines are considered as discomfort.

Figure 5.8 is the direct load control actions taken with enlargement of the graph of load group 8 between 11:30-13:15, 15:00-16:00 and 18:00-20:15. Note that as each of the two aggregated forecast graphs in two different time instants passes through the other one in three time periods with both positive and negative deviations, therefore the controllable part of load demand forecast is considered with some randomly generated ON/OFF-states. Hence all DLC actions presented on the graphs are not the actions taken for load demand management; few of them initially, i.e., before optimization, existed.

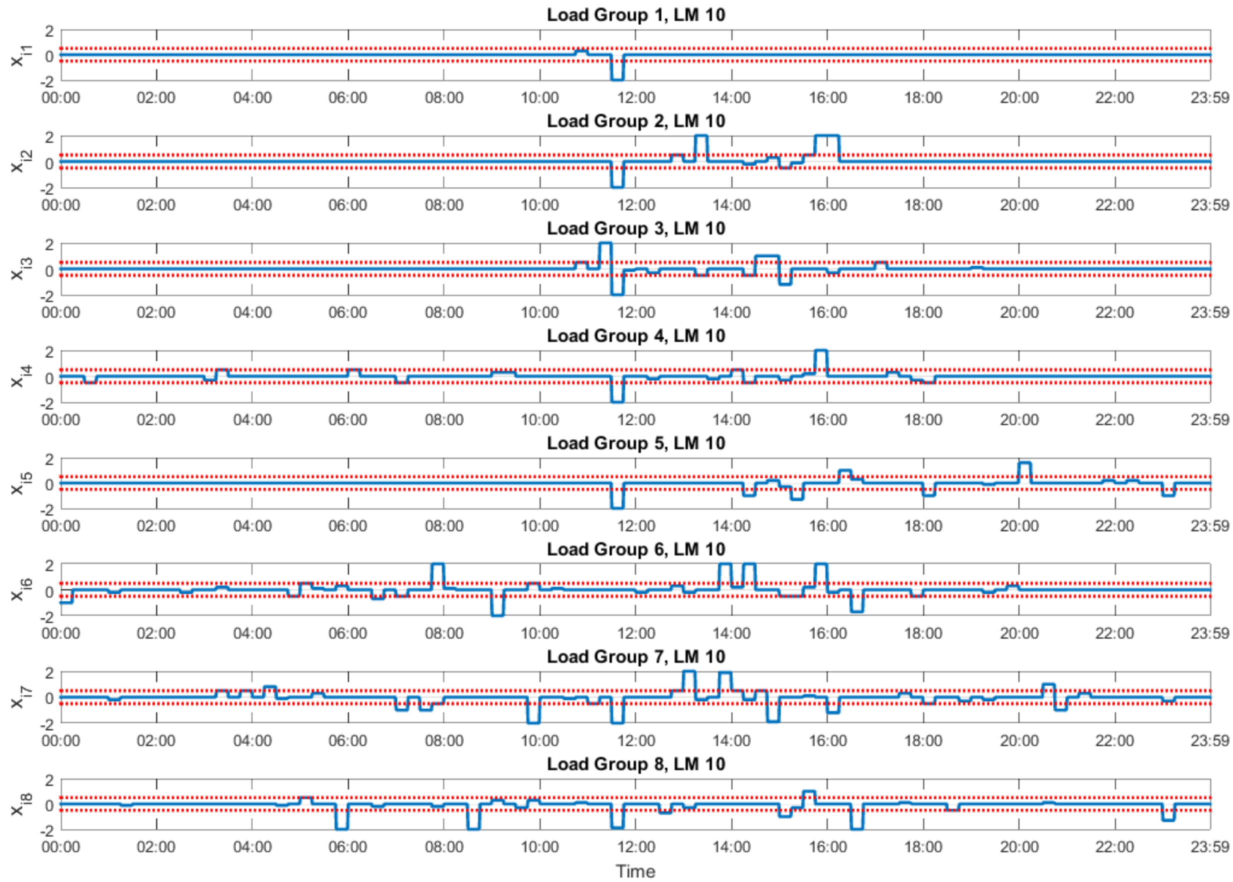


Figure 5.7*: Sample of actions taken to change the thermostat temperature set points applied to each load groups with margins of discomfort shown by red dotted lines*

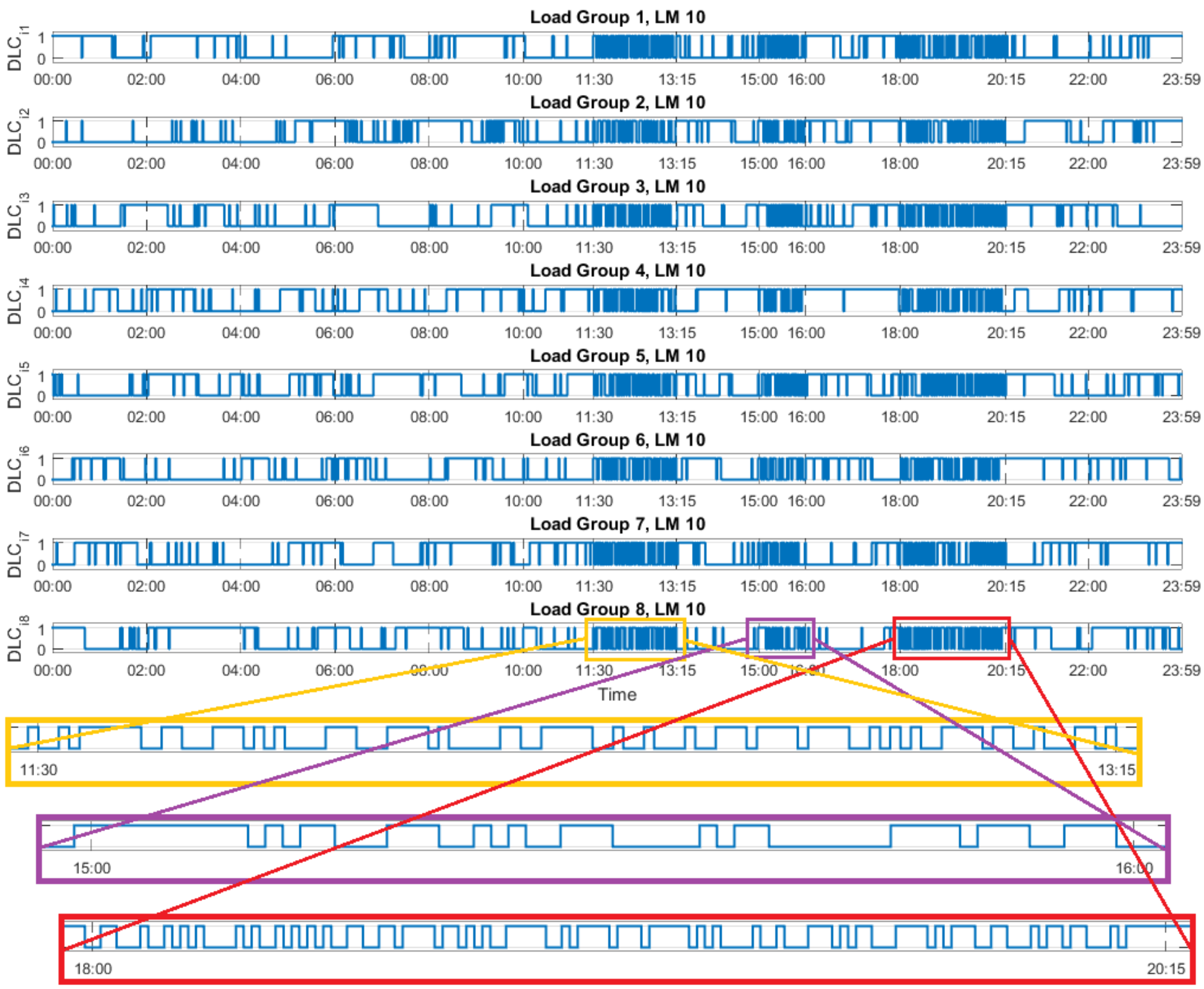


Figure 5.8*: Sample of DLC actions applied to each load groups, with enlargement between 11:30-13:15, 15:00-16:00 and 18:00-20:15 of load group 8*

Figure 5.9 represents the two initial forecasts superimposed with the final loading diagram with load demand management LM 10.

Figure 5.9*: The initial forecasts superimposed with the final loading diagram with load demand management LM 10, with enlargement between 11:30-20:15*

As it can be seen, the aggregated load consumption with load management strategies (red graphs) fluctuates on load demand forecast (blue graph). This is what we expected because of the nature of Monte-Carlo physically-based simulation which is the case we used here to simulate the freezers model.

The data from aforesaid diagrams are organized to obtain the initial and final load duration curves and final controlled load diagram which are shown in the figures 5.10 and 5.11 respectively. As it can be seen, the load duration graph with LM 10 (red graph) is passing through the two other graphs, which is showing good match with what we desired.

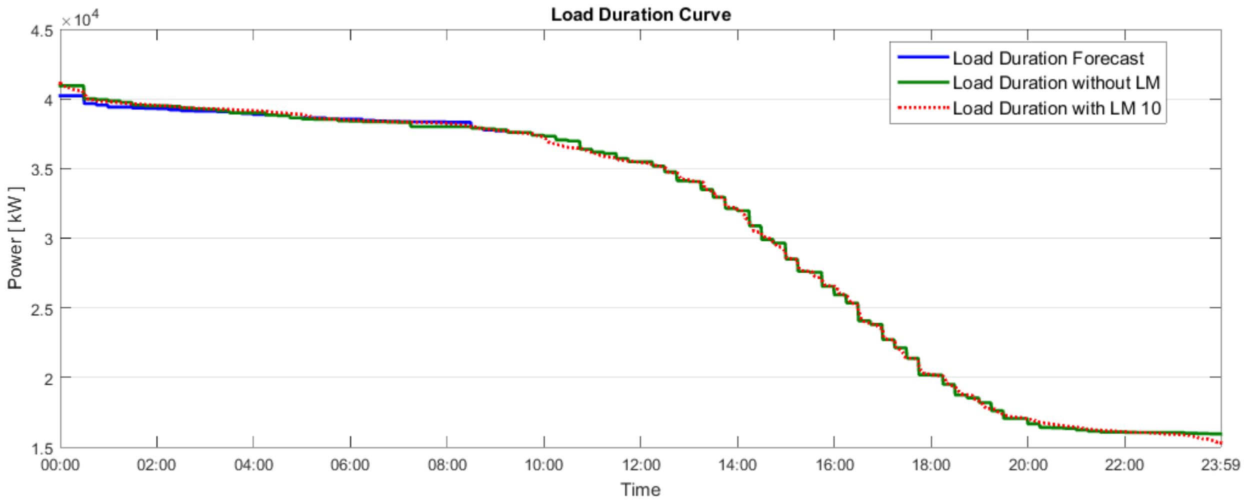


Figure 5.10*: Initial and final load duration curves*

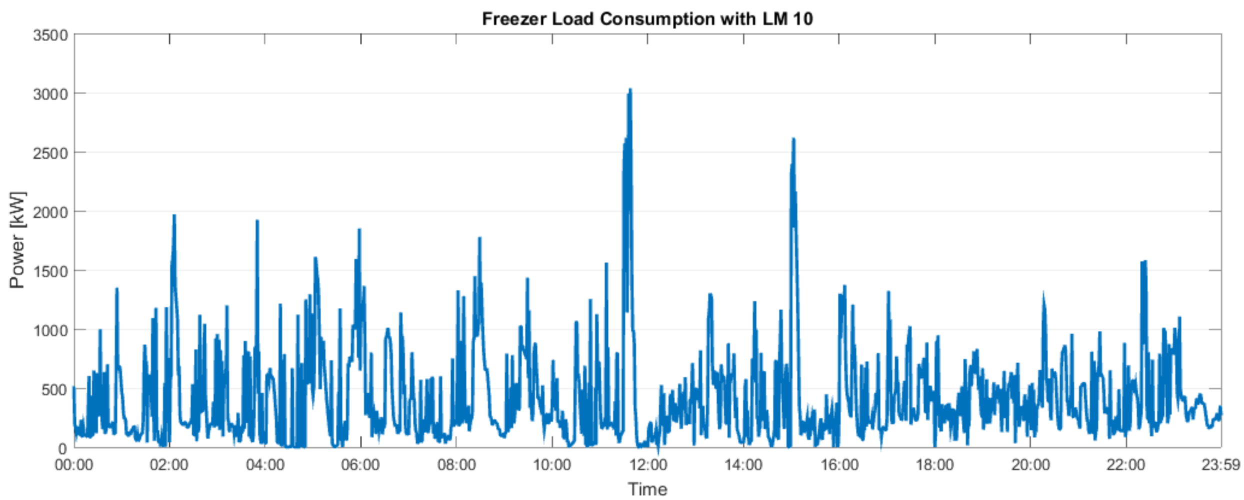


Figure 5.11*: Final controlled load diagram*

There are another check points pertaining to the three time durations in which the two aggregated forecast graphs in two different time instants deviate each other. The mentioned three time durations are listed in section 4.4 and shown graphically in figure 4.3. As stated before, the first objective was to identify LM actions that minimize the differences between the two aggregated forecast curves in two different time instants, especially in the mentioned three time durations shown in figure 4.3.

The freezer load consumption with load demand management actions should be reduced or increased in each of these three time periods. Figure 5.9 is showing a comparison load diagrams with and without management actions; the green color graph is the aggregated load consumption without any load management action, and the red color dotted graph is the aggregated load consumption with load management actions LM 10. Here the increase or decrease in load consumption of each of the mentioned 3 time durations is reported:

- For time period 11:30 to 13:15, we were looking for decreasing in the freezer load consumptions with load management actions. Calculation is showing 18952 kW decrease in the freezer load consumptions with LM 10.
- For time period 15:00 to 16:00, we were looking for decreasing in the freezer load consumptions with load management actions. Calculation is showing 13958 kW decrease in the freezer load consumptions with LM 10.
- For time period 18:00 to 20:15, we were looking for increasing in the freezer load consumptions with load management actions. Calculation is showing 51452 kW increase in the freezer load consumptions with LM 10.

Similarly the combination of all time periods and selected solutions are checked; all of these checks for all selected solutions are passed.

According to these solutions, the calculated "NSPG" for all selected solutions is equal to 27; therefore the required total number of freezers for all selected non-dominated solutions can be calculated simply: 27*2000 = 54000 sets.

Above-mentioned analysis on graphs and numerical values, considering what are explained above shows; the solutions we obtained are in line with what we desired.

5.7. Sensitivity Analysis

As it can be seen from above sections, the method used in this work, is a highly configurable algorithm. Therefore, this section is provided to study the effect of changing some of the parameters in the final results of the algorithm. The different parameters used for this study are summarized in table 5.4.

Table 5.4: *Parameters used in 7 simulations for sensitivity analysis*

	Population size	Tournament size	Crossover type	Crossover fraction	Mutation rate	tolFun
Case 1	20	2	Single point	0.8	0.01	10^{-10}
Case 2	10	2	Single point	0.8	0.01	10^{-10}
Case 3	20	4	Single point	0.8	0.01	10^{-10}
Case 4	20	2	Single point	0.9	0.01	10^{-10}
Case 5	20	2	Two points	0.8	0.01	10^{-10}
Case 6	20	2	Single point	0.8	0.005	10^{-10}
Case 7	20	2	Single point	0.8	0.01	10^{-6}

As it's shown in table 5.4, for this sensitivity analysis, 7 simulation cases with different sets of parameters are carried out. "Case 1" is the main case which is discussed in the previous sections. The other parameters for all cases are set according to what listed in table 5.2.

In order to compare the results of these 7 simulations, the resultant Pareto fronts are plotted in figure 5.12.

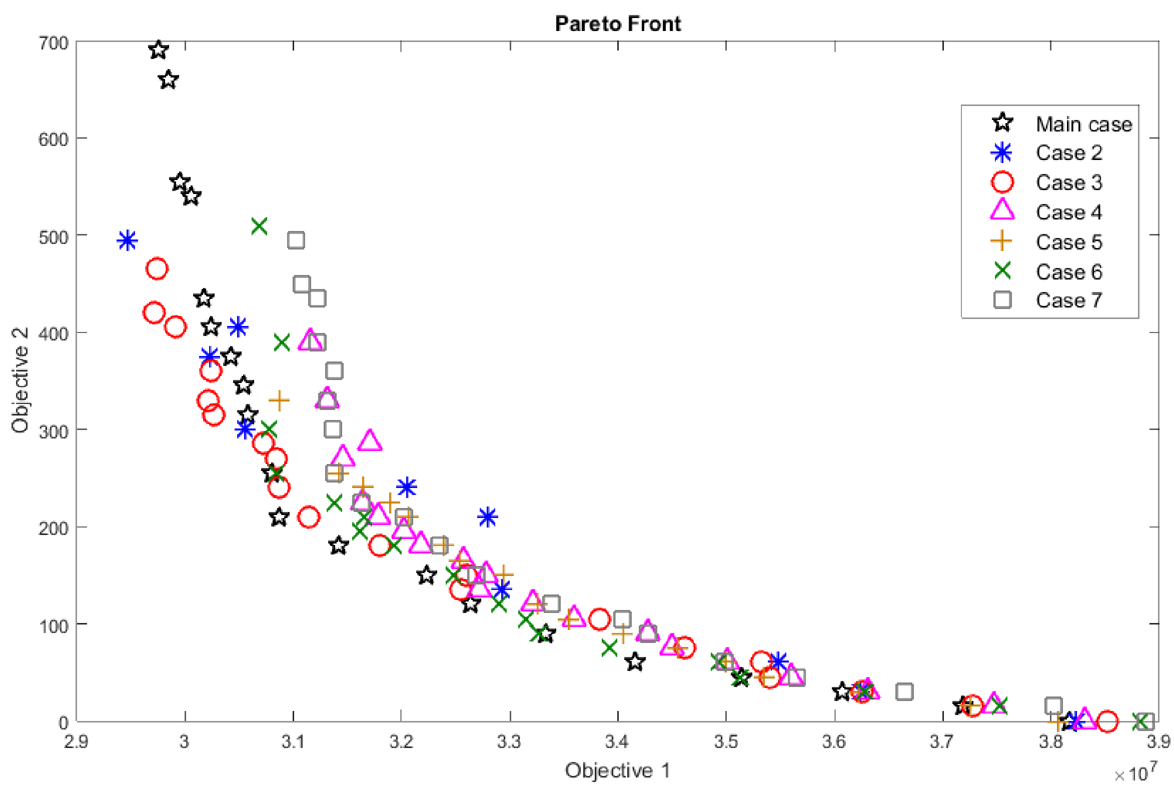


Figure 5.12: *Pareto fronts of 7 simulations with parameters mentioned in table 5.4*

As it can be seen in figure 5.12 the results generally are not much different. Note that this sensitivity analysis is only a small portion of whole simulations conducted to identify the optimal set of parameters used in main case, i.e., “case 1.”

Chapter 6

Conclusions and future works

The aim of this thesis was to identify suitable load management actions for groups of freezers to obtain positive impact on the purchased energy from day-ahead energy market to minimize purchasing extra energy in the next day which is costly. To achieve this aim, we tried to minimize the differences between the actual load demands and the forecasted load demands. It was also necessary to minimize the undesirable discomfort causing to the consumers. For this purpose, we used a validated physically-based model allowing the simulation of a specified type of loads and developed a code in MATLAB, which uses a non-dominated sorting genetic algorithm (NSGA-II) to identify the best load demand management actions to be applied to loads of each group, at each time instant. The load management actions considered in this study is combination of changing the thermostat set points and power-curtailment. According to this study, it is possible to reduce the differences between the actual load demands and the forecasted load demand with the application of appropriate load demand management actions, which will cause undesirable discomfort to the customers. Like any research work, there are several areas that the work developed and presented in this thesis can be continued.

Using a tool developed for various types of loads could provide more options to obtain positive impact on the purchased day-ahead energy, and r reducing the associated discomfort caused to consumers. Therefore it would also be interesting to do similar study with representation of other forms of the controllable loads.

In this study, just two conflicting objectives are considered. It may be more interesting to repeat similar studies with different objectives which the consumers are interested in, such as optimization of loss factor, ON/OFF cycles, coincidence factor, etc.

In this study, MATLAB is used to provide a computer code for simulation. It seems there is a need for some system-independent tool with suitable speed to do such calculations to identify appropriate load management actions.

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