OPTIMAL ENERGY MANAGEMENT OF POWER SYSTEMS AND MICROGRIDS INCORPORATING DEMAND RESPONSE PROGRAMS

by

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SUMMARY

OPTIMAL ENERGY MANAGEMENT OF POWER SYSTEMS AND MICROGRIDS INCORPORATING DEMAND RESPONSE PROGRAMS

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The energy management of today's power system is of utmost importance because of the increasing complexity of today's power system operations. One of the core energy management functions is determining the optimal dispatch of conventional generators whilst minimizing or maximizing some pre-determined objective function which can either be minimizing costs, minimizing emissions or maximizing profit. These problems have been explicitly defined as the Dynamic Economic Emissions Dispatch (DEED) which is concerned with determining the optimal dispatch of generators whilst minimizing costs and minimizing emissions and the Profit Based Dynamic Economic Emissions Dispatch (PBDEED) which determines the optimal dispatch of generators whilst minimizing costs, emissions and maximizing profit.

In this thesis, both the DEED and PBDEED are integrated with Demand Response (DR) programs. Integrating DR programs into the DEED and PBDEED problem instead of considering both problems independently is meant to introduce optimality into both the supply side and demand side of the power system. The DR programs used in this work are a Game

Theory DR (GTDR) program which is an Incentive Based DR (IB-DR) program and a Time of Use DR (TOU-DR)program which is a Price Based DR (PB-DR) program.

A Model Predictive Control (MPC) strategy is further deployed to solve the GTDR-DEED and GTDR-PBDEED models and obtained results show that for GTDR-DEED, MPC yields higher customer energy curtailment when compared to the open loop controller whilst obtained results also show that MPC shows better robustness against uncertainties and disturbances.

Finally, the GTDR program is integrated with a microgrid which is powered by conventional generators and Renewable Energy Sources (RES). The microgrid is in the grid connected mode and power can be traded between the main grid and the microgrid. Again, the results obtained from the optimal energy management of the microgrid collaborate results obtained in the main grid and show that integrating demand response programs into the energy management problem are mutually beneficial to utility and consumers alike and can bring about desired demand reduction in the power system.

OPSOMMING

OPTIMALE ENERGIEBESTUUR VAN KRAGSTELSELS EN MIKRONETWERKE MET AANVRAAGTERUGVOERPROGRAMME

deur

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Sleutelwoorde:	dinamiese ekonomiese emissieversending, aanvraagterugvoer, spelteorie, prysgebaseerde dinamiese ekonomiese emissieversending, model van voorspellende beheer, mikronetwerk, multidoelwitoptimalisering, interaktiewe beheerstrategie, beswaarde sombenadering, lasbeperking, hernubare energie, wiskundige modellering, sonenergie, windenergie

Die energiebestuur van hedendaagse kragstelsels is van die uiterste belang as gevolg van die toenemende kompleksiteit van eietydse kragstelselbedrywighede. Een van die wesenlike energiebestuurfunksies is die bepaling van die optimale versending van konvensionele kragopwekkers, terwyl een of ander voorafbepaalde funksie maksimeer of minimeer word; naamlik die vermindering van koste of emissies of die verhoging van wins. Hierdie probleme is uitdruklik gedefinieer as dinamiese ekonomiese emissieversending (DEED), wat betrokke is by die bepaling van die optimale versending van kragopwekkers terwyl koste en emissies minimeer word, en winsgebaseerde dinamiese ekonomiese emissieversending (PBDEED), wat die optimale versending van kragopwekkers bepaal terwyl dit koste en emissies minimeer en wins maksimeer.

In hierdie tesis is sowel die DEED as die PBDEED geïntegreer met die aanvraagterugvoerprogramme (DR-programme). Die integrasie van DR-programme in die DEED-en PBDEED-

probleem in plaas daarvan om beide probleme onafhanklik te oorweeg, is bedoel om optimaliteit te bewerkstellig in sowel die aanbod-as aanvraagkant van die kragstelsel. Die DR-programme wat hier gebruik word, is ’n aansporinggebaseerde (IB-DR) spelteorie- DR-program (GTDR) en ’n prysgebaseerde, tyd-van-gebruik- DR-program (TOU-DR).

’n Strategie vir ’n model van voorspellendebeheer (MPC) is verder ontplooi om die GTDR-DEED en GTDR-PBDEED modelle op te los en die resultate wat verkry is, toon dat vir GTDRDEED, MPC hoër kliënt-energiebeperking lewer in vergelyking met die oopbaankontroleerder, terwyl MPC beter robuustheid teen onsekerhede en versteurings toon.

Ten slotte is die GTDR-program geïntegreer met ’n mikronetwerk wat aangedryf word deur konvensionele kragopwekkers en hernubare energiebronne (RES). Die mikronetwerk is aan die netwerk verbind en krag kan verhandel word tussen die hoofnetwerk en die mikronetwerk. Die resultate wat verkry is uit die optimale energiebestuur van die mikronetwerk bevestig weer eens die resultate wat in die hoofnetwerk verkry is en toon dat die integrasie van die aanvraagreaksieprogramme in die energiebestuurprobleem wedersyds voordelig is vir sowel die stelsel as verbruikers en dus die gewenste aanvraagvermindering in die kragstelsel kan teweegbring.

LIST OF ABBREVIATIONS

DR	Demand Response
DED	Dynamic Economic Dispatch
PDED	Pure Dynamic Economic Dispatch
DEED	Dynamic Economic Emission Dispatch
ECDEED	Emission Constrained Dynamic Economic Emission Dispatch
PBDEED	Price Based Dynamic Economic Emission Dispatch
GENCO	Generation Company
SO_2	Sulphur Dioxide
NO_x	Mono-nitrogen oxides
CO	Carbon monoxide
CO_2	Carbon dioxide
TOU	Time of Use
PEM	Price Elasticity Matrices
PBDR	Price Based Demand Response
IBDR	Incentive Based Demand Response
TOU	Time of Use
RTP	Real Time Pricing
CPP	Critical Peak Pricing
EDP	Extreme Day Pricing
ED-CPP	Extreme Day - Critical Peak Pricing
DLC	Direct Load Control
IS	Interruptible Services
EDRP	Emergency Demand Response Programs
CMP	Capacity Market Programs
DB	Demand Bidding/Buyback Programs
AMS	Ancillary Market Services
MPC	Model Predictive Control
GTDR	Game Theory Demand Response

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

The increasing complexity of today's power system and the vast geographical area most power systems span have placed an enormous burden on today's power system planners and operators. Also power systems operators and planners at all times must always satisfy customers load demand and ensure access to uninterrupted power supply. This has birthed the energy management problem of power systems. This problem is basically concerned with the optimal operation and control of the power system. Typically power system operators are either minimizing or maximizing some predetermined objective function (minimizing cost, minimizing emissions, maximizing power system reliability, etc) and determining the optimal commitment and dispatch of thermal generators in the power system considering the load demand constraints and other practical constraints inherent in the power system. One of the most common energy management problems and the most oft researched is the Dynamic Economic Emissions Dispatch (DEED) problem. It's initial variant is termed Static Economic Dispatch (SED) [4]. SED is concerned with minimizing fuel costs and determining the optimal output of thermal generators to satisfy a particular load demand at a specific time instant. The SED later metamorphosed into the Dynamic Economic Dispatch (DED). DED is concerned with determining the optimal output of the committed thermal generators to satisfy demand at a pre-determined scheduling interval with minimal operating costs amongst other constraints. Typically, DED is handled with a division of the total time horizon into smaller time intervals (usually 1 h), solving the SED problem at the smaller time intervals and enforcing ramp rate constraints between consecutive intervals. As general environmental awareness increased, researchers became interested in ways of reducing emission and environmental effects in power systems. Thus, increasing environmental awareness led researchers to consider how to handle emissions [4] and this led to the further evolvement of the DED problem into the DEED problem. The DEED problem seeks to minimize fuel costs and emissions of thermal generators subject to the following constraints: load, ramp rate, maximum and minimum capacity constraints amongst others. This is essentially a mathematical problem with the objectives of minimizing both fuel costs and emissions. This optimization challenge is efficiently handled using the goal attainment method via the transformation of the dual objectives into one objective function [8] or by multi-objective optimization techniques.

Recently the DEED problem has evolved due to the advent of deregulation and liberalization of the power industry. This has expanded the objective of the generator operators from fuel cost and emissions minimization to include profit maximization. This new set up is known as Price Based Dynamic Economic Dispatch (PBDEED). There have been three major research thrusts in the literature concerning DEED/PBDEED. These research thrusts have been pushed by recent advances in the scientific community. The first major research thrust deals with how to solve the resulting DEED/PBDEED problems. This stems from the recent advances in computational solution methods and faster computational processing times. Thus the literature abounds with a host of novel mathematical approaches and meta-heuristic techniques that have been proposed in the literature to handle this problem. The second is the integration of Renewable Energy (RE) sources into the DEED formulations like in [19] and [18]. This research direction stems from the drive by most nations of the world to gradually wean themselves of fossil fired generators and embrace renewable energy based sources. Most of these research works look for ways of handling the intermittent nature of RES whilst simultaneously incorporating it into the DEED problem. Both of these research directions are essentially concerned with introducing optimality at the supply end of the power system and basically seek to ensure that the generators at the supply side always satisfy the load demand at the customer side. They do not seek to curtail the customers load demand. Thus, the third research direction concerns integrating Demand Response (DR) programs into the DEED problem. In this thesis, consideration is given to each of the three research thrusts.

In [44, 30] the definition of demand response is provided thus: "a change 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". Generally, demand response programs are broadly classified into two: Price Based Demand Response (PB-DR) [32] and Incentive Based Demand Response (IB-DR) [33]. In PB-DR, the electricity tariffs vary with time, i.e., different electricity tariffs for various peak times. The aim is to encourage consumers to curtail their energy use to take advantage of favourable prices. Examples of PB-DR include Time of Use Rates (TOU), Real Time Pricing (RTP), Critical Peak Pricing (CPP), Extreme Day Pricing (EDP), and Extreme Day-Critical Peak Pricing (ED-CPP). In IB-DR, incentives are simply offered to consumers to reduce or curtail their electricity use when the power system is stressed. The incentives can be in form of rebates or lower electricity tariffs [34]. It should be noted that unlike PB-DR, consumers can be penalized if their load is not curtailed when the system is stressed. Examples of IB-DR include Direct Load Control (DLC), Interruptible Services (IS), Emergency Demand Response Programs (EDRP), Capacity Market Programs (CMP), Demand Bidding/Buyback Programs (DB) and Ancillary Market Services (AMS). Demand response can be implemented in either regulated and deregulated set-ups. In both set-ups, demand response programs can lead to reduction in harmful emissions and operational costs which brings about environmental and power system benefits [31]. Demand response programs also reduce wholesale market prices [39]. In IB-DR, the incentive is either monetary or is packaged as cheaper electricity tariffs [36] and in order to guarantee effective customer participation, the offered incentive should be attractive in order to spur participation [37]. Unlike the other two research thrusts of DEED that are solely concerned with the supply end of the power system, integrating DR into the DEED problem introduces optimality at the supply and demand side of the power system. To this end, it is this research thrust that is primarily investigated in this thesis. This thesis is concerned with designing optimal practical frameworks that integrate DR programs into the DEED and PBDEED problem. Other research thrusts, are however considered. Whilst integrating DEED and DR, consideration is also given to designing a framework for the integration of RES into a grid connected microgrid and the MPC approach to solving integrated DEED and DR problems is considered.

1.2 RESEARCH OBJECTIVES

The thesis primary intent is to jointly consider DR and DEED and thus introduce optimality at the demand and supply side of today's power system. This is motivated by the belief that true and optimal power systems operations are obtained by a joint and simultaneous consideration of both DR and DEED as opposed to individual considerations. Thus DEED is integrated with both the Price Based DR (PBDR) and Incentive Based DR (IBDR) which are the two types of DR programs. A new variant of DEED which is the PBDEED spurned by the advances in the deregulation of the power industry is also integrated with the IBDR. The resulting model also incorporates practical constraints both from the utility and consumer side. Secondly, in order to to cope with disturbances or modelling uncertainties inherent in mathematical modelling , MPC is applied to solve the developed IBDR integrated with DEED and PBDEED. Finally the last objective is to incorporate an IBDR program into the energy management problem for a grid connected hybrid microgrid. This is necessary because of the intermittent nature of RES.

1.3 RESEARCH CONTRIBUTION

This thesis has a number of contributions to the literature and they are itemized as follows:

- The development of an extended Game Theory Demand Response (GTDR) mathematical model known as IBDR for several customers in more than one scheduling time slot. Furthermore budgetary constraints and maximum customer curtailable power constraints are also built into the GTDR model.
- The combination of the GTDR mathematical model and the DEED mathematical problem leading to the GTDR-DEED model.
- The combination of the GTDR mathematical model and the PBDEED mathematical problem leading to the GTDR-PBDEED model.
- The utilization of MPC on the developed GTDR-DEED and GTDR-PBDEED models.
- The incorporation of IBDR into a grid connected microgrid consisting of solar, wind and conventional energy sources.
- The development of a Time Of Use Demand Response (TOUDR) model which is a PBDR program with three different Price Elasticity Matrices (PEM) for different classes

of customer loads. These PEM are integrated into the DEED problem via the power balance constraint and an addition of a DR cost term into the DEED objective function. Furthermore, a customer scheduling model is introduced which determines the optimal schedule for the three classes of customer loads in light of the utility price and energy levels. Finally, an interactive control strategy is proposed for effective coordination between the utility and the customer side and obtaining mutually acceptable prices and energy levels.

1.4 DETAILED OUTLINE OF STUDY

This thesis is organized as follows:

1.4.1 Chapter One

In this chapter, the thesis is introduced. The chapter details the background and motivation for the thesis topic. Furthermore, the contributions of the thesis and the complete thesis layout is presented.

1.4.2 Chapter Two

This chapter provides an exhaustive literature review on DEED and PBDEED. The chapter also discusses both types of DR programs. A review of the MPC solution methodology and its practical applications in energy systems is also provided. Finally this chapter also considers hybrid microgrids and recent advances in this realm.

1.4.3 Chapter Three

In this Chapter, the GTDR-DEED model is developed and presented. It is also integrated into the DEED problem and solved with practical scenarios.

1.4.4 Chapter Four

In this Chapter, the GTDR-PBDEED model is developed and presented. MPC is utilized to solve both the developed GTDR-DEED and GTDR-PBDEED models.

1.4.5 Chapter Five

The GTDR program is integrated into the energy management problem for a grid connected hybrid microgrid in this chapter.

1.4.6 Chapter Six

In this chapter, the TOUDR program modelled using PEM is presented. It is integrated into the DEED problem and a customer scheduling model is also presented in this chapter. An interactive control framework is proposed for effective coordination between both mathematical models.

1.4.7 Chapter Seven

This chapter provides a conclusion of work done in prior chapters. Furthermore, future research directions are provided.

CHAPTER 2

LITERATURE STUDY

2.1 CHAPTER OVERVIEW

This chapter provides an exhaustive literature review on DEED and PBDEED. The chapter also discusses both types of DR programs. A review of the MPC solution methodology and its practical applications in energy systems is also provided. Finally this chapter also considers hybrid microgrids and recent advances in this realm.

2.2 DYNAMIC ECONOMIC EMISSIONS DISPATCH

The DEED problem is a variant of an earlier optimization problem known as dynamic economic dispatch (DED). The motivation behind DED is to determine the optimal power to be produced from generators over a specific time interval with minimal operational expenses. The thermal generators ought to supply the electric load and not violate some other operational constraints. [45, 46, 28, 47]. A review of dynamic economic dispatch is provided in [4]. The emissions of unsafe and hazardous pollutants like SO_2, NO_x, CO and CO_2 by generators have led to rife outcries for power generating corporations to seek out ways of eliminating or reducing these pollutants [27] as their continued emission is detrimental to humans. A number of approaches have evolved to deal with these pollutions. Prominent approaches include the adoption of pollutant cleaning, fuel switching i.e. using low-emission fuels, substitution of old fuel burners with newer burners and finally the practise of emission dispatching [28]. Emission dispatching has become the approach of choice due to it's minimal capital outlay and execution simplicity [9, 48]. Emission dispatching can be merged into the DED problem using three approaches. The first approach has the minimization of emissions in lieu of fuel costs as it's objective. It is known as pure dynamic emission dispatch (PDED) [1]. An alternative method and by far the most popular has as it's objective: the concurrent minimization of fuel cost and emissions amidst some operational constraints and is known as dynamic economic emission dispatch (DEED) [2, 3]. The final approach minimizes only fuel cost whilst the emissions serve as a constraint and a value which denotes the maximum permissible emissions is defined. This optimization problem has been termed emission constrained dynamic economic dispatch (ECDED)[49].

DEED works by concurrently minimizing fuel costs and gaseous emissions and obtains the optimal generation schedule for a set of committed generating units over a scheduling horizon. Simply put, the aim of DEED is to determine the optimal output of thermal generators under several practical constraints [1]. Some of the often considered constraints include: power balance constraints [2], ramp rate constraints, generator output limit constraints [3], line flow limit constraints, spinning reserve constraints, etc [4]. The problem has received considerable interest by engineers and scientists alike due to increasing environmental consciousness and the need to curtail harmful emissions from thermal generators. In recent years, as many nations of the world have shifted from a regulated power system and embraced deregulation, this has given rise to the development of a new variant of the DEED problem. In this new variant, maximizing profit has replaced the former objective of minimizing cost. This has given birth to the Profit Based Dynamic Economic Emission Dispatch (PBDEED). PBDEED has dual objectives: the minimization of harmful emissions and profit maximization of thermal generators under the same or similar constraints as the DEED problem [5]. The DEED or PBDEED problem is solved depending on if it is in a regulated or deregulated climate.

DEED and DED can be solved using various algorithms [9]. These algorithms can be classed as either conventional i.e. employing mathematical optimization algorithms or can be classed as meta-heuristic i.e. employing artificial intelligence algorithms.

2.2.1 Solving DEED using conventional mathematical optimization algorithms

Prominent instances of the use of mathematical optimization algorithms to solve DEED include [76] where quadratic constrained programming and mixed integer quadratic programming were used, [77] where benders decomposition was used. Other examples include [26] where Mixed Integer Non Linear Programming (MINLP) was used to obtain the optimal dispatch schedule for a CHP plant and in [25] where mixed integer, linear and non-linear programming methods were utilized. Conventional mathematical optimization algorithms have a number of advantages over meta-heuristic algorithms. Firstly, they are often able to guarantee optimal solutions. Secondly, they have short computational processing times. Finally they do not require the explicit definition of domain parameters [4]. They have the disadvantage of being only able to solve convex cost functions and sometimes yield solutions with local optima [8].

2.2.2 Solving DEED using meta-heuristic algorithms

Prominent instances of the use of meta-heuristic algorithms are [78] where artificial physical optimization algorithm was utilized, [79] where artificial bee colony optimization was used, [80] where gravitational search algorithm was utilized, [81] where harmony search algorithm was utilized, [82] where biogeography based optimization was used and [83] where spiral optimization algorithm was utilized. Other examples include Cuckoo Search Algorithm (CSA) [24], Teaching Learning Based Optimization (TLBO)[23], Backtracking Search Algorithm (BSA) [22], Chaotic Self Adaptive Differential Harmony Search (CSADHS) [16], Nondominated Sorting Genetic Algorithm-II (NSGA-II) [17], Hybrid Fire Fly Algorithm (FFA) [18], Harmony Search (HS) [20] amongst others. Their major advantage lies in their capacity to solve concave cost functions. Their disadvantage is the need for explicit definition of domain parameters and extended computational processing times.

2.3 DEMAND RESPONSE

The main purpose behind Demand Side Management is to reduce customer electricity use or alter customer load magnitude and pattern, thereby improving power system stability [42]. This is done either by: "peak clipping, valley filling, load shifting, strategic conservation, and strategic load growth" [43]. These programs have been very successful and have been in widespread use by electric utilities all over the world. In recent years, as the power system has increased in complexity, utilities have embraced Demand Response (DR) programs.

Demand response which is a major DSM strategy is defined as a modification or adjustment in electricity consumption by consumers from their regular consumption levels. This modification can either be due to electricity price changes or to incentives designed to curb consumption at times of power system stress or unreliable power system operation [44, 38]. In monopolistic markets, demand response leads to increased reliability and efficiency of power system operations. It also leads to a decline in emissions of harmful gases and operational expenses. In deregulated markets, all the advantages in monopolistic markets are obtainable. An added advantage of DR schemes in deregulated markets is a fall in the wholesale electricity market price [44, 39]. A cardinal rule adopted in the design of DR schemes by power system operators or ISO's is that benefit to the consumer in the form of reduced tariffs or cash payments should be greater than the consumer's power interruption cost [37]. Ideally the customer also determines the amount of power they are able to willingly curb or curtail [34].

In incentive based DR programs, incentives are simply offered to consumers to reduce or curtail their electricity use when the power system is stressed. The incentives can be in form of rebates or lower electricity tariffs [31, 39]. In price based DR programs there is a time variation of electricity tariffs. As stated before, this thesis is motivated by the desire to introduce optimality in the supply and demand side of the power system. Thus PBDR and IBDR are integrated into DEED and PBDEED. Furthermore Model Predictive Control (MPC) is applied on the developed models (GTDR-DEED and GTDR-PBDEED) as a solution methodology. A review of MPC is provided in the next section.

2.4 MODEL PREDICTIVE CONTROL

Solving the GTDR-DEED and GTDR-PBDEED problem only determines open loop control solutions when viewed from a control systems perspective. The disadvantage of this is that the model cannot compensate for inaccuracies and disturbances arising from modelling uncertainties. This is due to the fact that there is no way for the inaccurate system solutions to be fed back to the system and updated to obtain accurate solutions. Closed-loop systems on the other hand are inherently able to give feedback to the optimization model [5] and update solutions [9]. Due to the superiority of closed-loop systems over open loop systems, MPC which is a prominent closed-loop approach is proposed in this thesis and thus a literature review on MPC is provided. MPC has found wide applications in a number of engineering applications and has recently been used in power system applications like in [10] where MPC was applied to generator maintenance scheduling, [5] and [9] where MPC was applied to economic dispatch problems, [11] where MPC was applied to hybrid PV, wind, diesel and battery systems. [12] presents a detailed overview of the MPC methodology. In view of the successful application of the MPC strategy in power system applications and its ability to handle disturbances and uncertainties, MPC is proposed in this thesis to solve the GTDR-DEED and GTDR-PBDEED mathematical problems. MPC is utilized because in practical applications of GTDR-DEED and GTDR-PBDEED, there might be variations in system parameters like load demand or the price of energy. This can introduce a whole lot of uncertainty or disturbance in the system. MPC overcomes the aforementioned problems. It is envisaged that the proposed MPC approach is able to handle uncertainties and disturbance well and exhibit convergence and robustness which further makes it extremely suitable for real time and practical applications. Open loop systems despite their merits are unable to compensate for inaccuracies and disturbances arising from modelling uncertainties. This is due to the fact that open loop systems have no feed back mechanisms for inaccurate system solutions (in the presence or disturbances and inaccuracies) to be fed back to the system and updated in order to obtain accurate solutions [12]. Closed-loop systems are able to give feedback and update inaccurate solutions [5]. In GTDR-DEED and GTDR-PBDEED, there might be variations in system parameters like load demand or the price of energy, thus MPC is used to solve the GTDR-DEED and GTDR-PBDEED models. The proposed MPC approach is shown to handle uncertainties and disturbance well and exhibit convergence and robustness which further makes it extremely suitable for solving the developed models.

2.5 MICROGRIDS

Microgrids as distinct from a major power grid consists of distributed generation units, storage devices and controllable loads sited close to the customer and spanning a limited physical area [61]. The generation units in micro grids can either be conventional power generators or renewable energy sources. Examples of renewable energy sources are wind power or solar power. Conventional power generators can either be thermal generators or diesel generators. Storage devices in microgrids include batteries, flywheels and pumped storage [61, 63]. Typically modern microgrid systems can either be operated in the "grid connected" or "islanded" mode. In the "grid connected" mode, the microgrid interfaces with the main grid, whilst in the islanded mode, the microgrid is isolated from the main grid when there is a system emergency and is still able to supply local load. Thus microgrids are also able to ensure localized power system operation in the event of a blackout or brownout. Advantages of microgrids include improvement of reliability of electricity supply, sustainability, power quality and lower electricity costs, transmission and distribution line losses. As stated earlier, the generation units in micro grids can either be conventional power generators or renewable energy sources. However, in recent times Renewable Energy Sources (RES) have become preferred for use in microgrids because of their long term environmental and cost benefits over conventional generation sources [67]. They are used either singly or in conjunction with other RES. Recently, the focus of researchers has been on the optimal operation and control of microgrids. This field of research endeavour is commonly referred as the energy management of microgrids and involves minimizing or maximizing some predetermined objective function (minimizing cost, maximizing microgrid reliability, etc) and determining the optimal dispatch (economic dispatch (ED)) and commitment (unit commitment (UC)) of the conventional generators, RES and storage devices. In [64], a model was proposed for a microgrid consisting of a fuel cell, micro-turbine, battery bank, PV and wind energy sources. The model has as it's objective the minimization of the system's fuel cost and determines the optimal power output from conventional and renewable energy sources. In [66], an optimal control strategy for a microgrid containing RES is presented. The microgrid operational state is the "islanded mode" and the objective is to minimize the electricity generation cost and determine the optimal operational schedule of the microgrid considering the stochastic nature of RES. In yet another work [68], the objectives are to maximize financial gain and PV energy consumption in interconnected microgrids which are also grid connected with variable electricity prices. In [75], a microgrid consisting of wind, PV energy sources with battery storage is considered. The objective is to maximize the overall economic benefit of the system and determine optimal output of power sources whilst satisfying load balance constraints. In [70], a microgrid consisting of wind, PV energy sources with batteries is considered. The microgrid is grid connected and investigations are carried out under different grid market policies and Particle Swarm Optimization (PSO) is utilized in solving the obtained mathematical model. In [72], the optimal control strategy for a hybrid microgrid consisting of PV and diesel power source and a battery storage system was proposed. There is a stated objective which is to minimize the diesel generators cost and determine the optimal power output for the power sources under winter and summer conditions. This work was further expanded and improved in [73] with the inclusion of wind power sources and the application of Model Predictive Control (MPC) strategy to handle variations in demand. Another work is [74] where a switched model predictive control strategy for a hybrid PV, diesel and battery power system was proposed. The advantage of the switched MPC over conventional MPC is that it is able to efficiently handle cases when the battery is not permitted to charge and discharge simultaneously. Other works that deal with the energy management of microgrids are [61, 62, 69]. However, the aforementioned works do not incorporate Demand Response (DR) into the optimal energy management problem of microgrids. Failing to include DR into the energy management problem of micirogrids can lead to suboptimal operation of the microgrid. This is because the energy management problem is concerned with the optimal commitment and dispatch of conventional generators, RES and storage devices at the power system's supply side whilst DR programs attempt to provide relief at the power system's demand side [6]. Inclusion of DR programs would make for a better and more reliable microgrid as this would ensure optimal operating conditions at the demand and supply portions of the microgrid [6]. It has been observed that DR programs lead to reduced microgrid operational cost and improved operations. Furthermore the addition of DR programs into the microgrid mix provides some degree of grid flexibility and helps to mitigate the effect of having intermittent RES [7].

A few works have incorporated DR into the energy management problem of microgrids like [6, 7]. While in [7] DR is incorporated into the microgrid and provides reserve capacity, in [6], DR is modelled with detailed residential household appliances consumption information incorporated into a microgrid. The model setup is investigated under a single consumer and under multiple consumers. Both works have as their objective the minimization of the microgrid fuel costs. However, there is still the need to investigate and provide a comprehensive practical framework for incorporating DR into the energy management problem of a microgrid in a way that is beneficial to participating DR customers and does not just seek to minimize microgrid fuel costs. It is imperative that DR programs accurately captures the customers outage cost and factor these costs in the design of the DR programs to be incorporated into the energy management problem of microgrids. This is the primary motivation for incorporating DR programs into the microgrid energy management problem.

In this thesis we incorporate this incentive based DR program into the microgrid energy management problem under the grid connected operational mode. It is important we provide in our model instances for a "grid connected" operational mode where it is imperative for power transfer involving the main grid and the microgrid. The developed model is able to provide grid flexibility and helps to mitigate the effect of having intermittent RES whilst simultaneously using DR to provide relief to the system. The DR model actively incentivises customers to participate in the DR program and ensures that their incentive is greater than the cost of curtailment.

2.6 CHAPTER SUMMARY

In this chapter, a review of the topics considered in this thesis is provided. Thus we introduce and review the topics of DEED, DR, MPC and microgrids. Furthermore, we briefly detail research trends concerning these topics and the research gaps that motivate the models presented in this thesis.

CHAPTER 3

THE DEED PROBLEM WITH GTDR PROGRAMS

3.1 CHAPTER OVERVIEW

In this chapter, a GTDR program is combined with the DEED problem. The combined GTDR-DEED detailed in this chapter has as it's objectives the minimization of fuel costs and emissions. The third objective is the maximization of the benefit to the utility. The combined model presented in this chapter determines the optimal incentive and the optimal customer curtailable power. The developed GTDR model has an intrinsic requirement that the customer incentive should be greater than their cost of curtailment and also has to be financially rewarding for the power utility. To validate the developed mathematical model, two test systems consisting of industrial customers are utilized and exhaustive comparative analyses of the obtained results highlight the usefulness of the model. Results from this chapter have been presented in [8].

3.2 THE DYNAMIC ECONOMIC EMISSION DISPATCH MODEL

As stated earlier, the chief aim of DEED is to minimize fuel costs and harmful emissions and determine the optimal output of available generators over a scheduling horizon. The equations depicting DEED are detailed as follows [5]:

$$min \sum_{t=1}^{T} \sum_{i=1}^{I} C_i(P_{i,t}), \tag{3.1}$$

$$min \sum_{t=1}^{T} \sum_{i=1}^{I} E_i(P_{i,t}), \tag{3.2}$$

with

$$C_i(P_{i,t}) = a_i + b_i P_{i,t} + c_i P_{i,t}^2, \tag{3.3}$$

$$E_i(P_{i,t}) = d_i + e_i P_{i,t} + f_i P_{i,t}^2, \tag{3.4}$$

subject to the following network constraints:

$$\sum_{i=1}^{I} (P_{i,t}) = D_t + loss_t, \tag{3.5}$$

$$P_{i,min} \leq P_{i,t} \leq P_{i,max}, \tag{3.6}$$

$$-DR_i \leq P_{i,t+1} - P_{i,t} \leq UR_i, \tag{3.7}$$

$$loss_t = \sum_{i=1}^{I} \sum_{k=1}^{K} P_{i,t} B_{i,k} P_{k,t}, \tag{3.8}$$

where

$P_{i,t}$ is the power generated from generator i at time t;

C_i is the fuel cost of generator i;

E_i is the emissions cost for generator i;

D_t is the total system demand at time t;

$loss_t$ is the total system losses at time t;

$P_{i,min}$ and $P_{i,max}$ are the minimum and maximum capacity of generator i respectively;

DR_i and UR_i are the maximum ramp down and up rates of generator $i$respectively;

a_i, b_i and c_i are the fuel cost coefficients of generator i respectively;

e_i, f_i and g_i are the emission cost coefficients of generator i respectively;

$B_{i,k}$ is the ikth element of the loss coefficient square matrix of size I;

I and T are the number of generators and the dispatch interval respectively.

Equation (3.3) gives the fuel cost function of the thermal generators. This cost function is typically obtained from "heat run tests" [17]. In these tests, the thermal generator unit is varied through it's normal operating limits and measurements of output power and fuel consumption costs are obtained. The fuel cost function thus give the fuel costs in $/h of the thermal generator unit as a function of its output power. This tests also enables the fuel cost coefficients of individual generator units to be calculated from the measured data. There are number of different fuel cost functions like the linear cost function [28], piecewise linear cost function [29], quadratic cost function [8], valve point effect cost function [17]. However, the quadratic cost is the most prevalent cost function in the literature [4] and is used in this chapter.

Similarly, equation (3.4) gives the emission function for the thermal generator units. The emission functions simply provide a mathematical representation of the relationship between harmful emissions and power produced for a generator. These functions are also obtained through measured tests like the heat run tests [17]. These tests enable the emission coefficients to be calculated. The emission functions gives the total emissions in lb/h of a thermal generator unit as a function of its output power [4]. In this chapter, the quadratic emissions function is used to represent this relationship [8].

The constraints of the mathematical model are detailed as follows:

- The first constraint (3.5) is termed the power balance constraint. This constraint compels the total power generated at time t to equal the sum of the power demand and transmission losses. The transmission losses occur because the power stations are typically sited away from where the power is needed and there are losses in the course of the power being transmitted. The most common and widely accepted method for calculating these losses is by the B-coefficient method which is a method where the power system loss is represented via a quadratic function of the generators output [1] and is given in equation (3.8). As stated before, $B_{i,k}$ is the ikth element of the loss coefficient square matrix B of size I. $P_{i,t}$ and $P_{j,t}$ are the output power of generator i and j respectively. This method has been used in [5] and [9] amongst others.

- Constraint (3.6) is the constraint for generator limits and restricts the amount of generated power to the allowable range for each generator; and

- Constraint (3.7) is the generator ramp rate constraints and restricts the ramp rates for the generators to their allowable ranges.

In order to solve the resulting mathematical model with two objective function, it is imperative that both objective functions be converted to one objective function via a weighted factor approach. The resulting objective function (3.9) is still constrained by constraints (3.5)-(3.7):

$$min\left[w\sum_{t=1}^{T}\sum_{i=1}^{I}C_i(P_{i,t})+(1-w)\sum_{t=1}^{T}\sum_{i=1}^{I}E_i(P_{i,t})\right]. \tag{3.9}$$

where w and $1-w$ are two non-negative weighting factors. When converting multi-objective optimization problems into single objective functions, it is required that weighting factors satisfy the following condition [9]:

$$w_1+w_2=1. \tag{3.10}$$

Typically, the choice of weighting factors determines which objective is given preference. If the aim is to solely minimize fuel costs then $w=1$, whilst if it is desired that only emissions be minimized, then $w=0$. In this chapter, since the aim is to simultaneously minimize fuel costs and emissions, equal values are given to the weighting factors [20], [16].

3.3 GAME THEORY BASED DEMAND RESPONSE DESIGN

In [37, 34, 36] the theory of "demand management contracts" which is the underlying foundation of GTDR was given. It is espoused as: "an agreement between utility and customer wherein the customer agrees to willingly shed load and in return receive monetary compensation" [37, 34]. There are 3 cardinal attributes that these contracts must possess and they are given as [38]:

- Efficient customer categorization as customers have varying power needs and thus will be willing to curtail varying amounts of power. This inherently means that customers have different load curtailment costs.
- The expertise to be able to determine the various load curtailment costs for the varying mix of customers [36].
- The incorporation of "customer locational attributes" into contract formulations.

3.3.1 Mathematical Formulations

In order to espouse the basic premise of GTDR [37], only one customer is initially assumed.

$c(\theta, x)$ is given as the customer cost of a customer of type θ who curtails power by x MW. The customer receives payment for curtailing this power and the mathematical function that describes the customer benefit is:

$$V_1(\theta, x, y) = y - c(\theta, x). \tag{3.11}$$

where the financial payment due to the customer is defined as y. Ideally, for the customer to be adequately motivated to participate, $V_1 \geq 0$. The mathematical representation of the benefit to the utility is given by:

$$V_2(\theta, \lambda) = \lambda x - y \tag{3.12}$$

where λ is defined as the cost of not delivering electrical power to a specific customer location. To understand this concept, it is necessary to first comprehend that under some operational conditions especially when the power system is stressed, it might be very expensive or impossible to supply some customer locations with electrical power. Using OPF techniques, it is possible for the power system operator to calculate how much it will cost not to supply power to these customers (load buses). In [37] this value is termed (λ) or the the value of power interruptibility.

The power system operator is interested in maximizing it's benefit:

$$\max_{x,y}[\lambda x - y] \tag{3.13}$$

- θ: "customer type", normalized in $[0, 1]$.
- x: amount or magnitude of electrical power to be curbed by the customer.
- $c(\theta, x)$: the financial implication of curbing x kW by the "customer type" θ.
- λ: "value of power interruptibility".

3.3.1.1 Customer Cost Function

As hitherto posited, $c(\theta, x)$ is the cost of customer type θ due to his curtailment of x MW. A quadratic cost function given in [37] is used to represent this cost and is denoted as:

$$c(\theta, x) = K_1 x^2 + K_2 x - K_2 x\theta. \tag{3.14}$$

where K_1 and K_2 are the customer cost function coefficients. θ is the customer type [36] and is used to classify the various customers based on the amount of load they are curtailing. θ is normalized in the interval $0 \leq \theta \leq 1$, therefore $\theta = 1$ is the "most willing" customer and $\theta = 0$ is the "least willing".

A synopsis of the pre-requisite mathematical conditions for the customer cost function is detailed below:

- quadratic form $c(\theta, x) = K_1 x^2 + K_2 x - K_2 x\theta$.
- $K_2 x\theta$ categorizes different customers based on their type θ
- An increase in θ leads to a corresponding decrease in marginal cost, thus the customer with the smallest marginal cost is the most willing customer ($\theta = 1$) and is the customer with the highest customer marginal benefit. Similarly, the customer with the greatest marginal cost is the least willing customer ($\theta = 0$) and is the customer with the lowest customer marginal benefit.
- $\partial c/\partial x = 2K_1 x + K_2 - K_2\theta$
- The customer marginal cost must always be positive.
- The customer cost function must be convex i.e. increasing marginal cost.
- When no power is curbed, there should be no cost incurred. ($c(\theta, 0) = 0$).

It is now possible to extend the formulations hitherto developed to multiple customers [37]:

Let y_j represent the incentive given to customer j. The benefit accruing to the customer is therefore given by:

$$u_j = y_j - (K_1 x^2 + K_2 x - K_2 x\theta), forj = 1, \ldots, J, \tag{3.15}$$

The benefit to the utility is given as:

$$u_o = \sum_{j=1}^{J} \lambda_j x_j - y_j \tag{3.16}$$

The utility seeks to maximize it's benefit given as:

$$max_{x,y} \sum_{j=1}^{J} [\lambda_j x_j - y_j] \tag{3.17}$$

s.t.

$$y_j - (K_1 x_j^2 + K_2 x_j - K_2 x_j \theta_j) \geq 0, forj = 1, \ldots, J, \tag{3.18}$$

$$\begin{array}{c} y_j - (K_1 x_j^2 + K_2 x_j - K_2 x_j \theta_j) \geq y_{j-1} - (K_1 x_{j-1}^2 + K_2 x_{j-1} - K_2 x_{j-1} \theta_{j-1}), \\ forj = 2, \ldots, J, \end{array} . \tag{3.19}$$

There are two variables in the mathematical model hitherto detailed. They are the power curtailed (x MW) and the incentive paid ($ y). The constraints for the mathematical model are explained thus: Constraint (3.18) is known as the "Individual rationality constraint". It's role is to constrain the customer benefit to surpass zero. Constraint (3.19) is termed the "Incentive compatibility constraint". It's role is to make sure that the amount of compensation received by customers is commensurate with the amount of load they curtailed.

The demand response model hitherto described (equations (3.17)-(3.19)) is expanded over multiple time periods (24 hours) and is combined with DEED. Furthermore the two demand response model constraints (individual rationality and incentive compatibility constraints) are implemented over a 24 hour scheduling interval. Additional constraints relating to the utility's daily budget and the customers maximum curtailable power are also included into the developed model. The final GTDR model is detailed below:

$$max_{x,y} \sum_{t=1}^{T} \sum_{j=1}^{J} [\lambda_{j,t} x_{j,t} - y_{j,t}] \tag{3.20}$$

s.t.

$$\sum_{t=1}^{T}[y_{j,t} - (K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j)] \geq 0, for j = 1, \ldots, J, \tag{3.21}$$

$$\begin{gathered} \textstyle\sum_{t=1}^{T}[y_{j,t} - (K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j)] \geq \\ \textstyle\sum_{t=1}^{T}[y_{j-1,t} - (K_{1,j-1}x_{j-1,t}^2 + K_{2,j-1}x_{j-1,t} - K_{2,j-1}x_{j-1,t}\theta_{j-1})] \; . \\ for j = 2, \ldots, J, \end{gathered} \tag{3.22}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{J} y_{j,t} \leq UB \tag{3.23}$$

$$\sum_{t=1}^{T} x_{j,t} \leq CM_j \tag{3.24}$$

where UB is the utility's total budget and CM_j is customer j daily limit of curtailable power. The explanation for the constraints are given below:

The role of constraint (3.21) is to make sure that the customer's total incentive is greater than the total curtailment cost.

The role of constraint (3.22) is to make sure that there is a corresponding increase in customer monetary benefit as the amount of curtailed power increases.

The role of constraint (3.23) is to make sure that the utility daily total program expenditure is lower than or equal to it's daily budgeted amount.

The role of constraint (3.24) is to make sure that the amount of load shed by each customer is less than the customers maximum allowable curtailable power.

3.4 COMBINED DEED AND GAME THEORY BASED MATHEMATICAL MODEL

The final GTDR-DEED model including all the formulated constraints is given below:

$$min \left[w_1[\sum_{t=1}^{T}\sum_{i=1}^{I} C_i(P_{i,t})] + w_2[\sum_{t=1}^{T}\sum_{i=1}^{I} E_i(P_{i,t})] - w_3[\sum_{t=1}^{T}\sum_{j=1}^{J}[\lambda_{j,t}x_{j,t} - y_{j,t}]] \right]. \tag{3.25}$$

subject to the following network constraints:

$$\sum_{i=1}^{I} P_{i,t} = D_t - \sum_{j=1}^{J} x_{j,t}, \tag{3.26}$$

$$P_{i,min} \leq P_{i,t} \leq P_{i,max}, \tag{3.27}$$

$$-DR_i \leq P_{i,t+1} - P_{i,t} \leq UR_i, \tag{3.28}$$

$$y_j - (K_1 x_j^2 + K_2 x_j - K_2 x_j \theta_j) \geq 0, for j = 1, \ldots, J, \tag{3.29}$$

$$\begin{array}{c} y_j - (K_1 x_j^2 + K_2 x_j - K_2 x_j \theta_j) \geq y_{j-1} - (K_1 x_{j-1}^2 + K_2 x_{j-1} - K_2 x_{j-1} \theta_{j-1}), \\ for j = 2, \ldots, J, \end{array} . \tag{3.30}$$

$$\sum_{t=1}^{T} \sum_{j=1}^{J} y_{j,t} \leq UB \tag{3.31}$$

$$\sum_{t=1}^{T} x_{j,t} \leq CM_j \tag{3.32}$$

where w_1,w_2 and w_3 are the weights and the prerequisite mathematical stipulation for the weights is:

$$w_1 + w_2 + w_3 = 1 \tag{3.33}$$

The mathematical model detailed above seeks to optimally obtain the following variables: $x_{j,t}$,$y_{j,t}$ and $P_{i,t}$.

3.5 NUMERICAL SIMULATIONS, OBTAINED RESULTS AND DISCUSSIONS

The parameters used to verify the developed mathematical model given by equations (3.25)-(3.33) are given in this section. This is followed by a presentation of the results and a discussion of the same results.

3.5.1 Customer Side Data

To solve the optimization problem, it is necessary to state the assumptions utilized. We begin by assuming that the utility knows the maximum amount of power every customer is willing to curtail (CM_j). This customer maximum curtailable power is closely linked with and the determining factor of customer willingness θ. The range of θ is the interval $0 \leq \theta \leq 1$, therefore the customer willing to curb the least amount of power (lowest CM_j= Customer 1) will have $\theta = 0$ and the customer willing to curb the greatest amount of power (highest CM_j=Customer 5) will have $\theta = 1$. Other customers will adopt values of CM_j based on the amount of power they want to curb within the interval 0 and 1. Simply put, this enables the ranking of the customers in terms of their voluntary ability to curb electrical power. Another customer information that is known to the utility is their outage cost function coefficients (($K_{1,j}$) and ($K_{2,j}$)). The values of λ or "locational attribute" or "value of power interruptibility" are given as the Locational Marginal Prices (LMP) [39]. In effect, these values give the monetary cost of NOT delivering power to a specific location or customer [36]. To obtain λ hourly values, LMP from the Pennsylvania-New Jersey-Maryland (PJM) Market [40] is used. The optimization model determines the optimal customer power curbed ($x_{j,t}$), optimal customer incentive ($y_{j,t}$) and optimal generated power ($P_{i,t}$).

To validate the developed mathematical models (equations (3.25)-(3.33)), two test power system scenarios are used. Scenario one is made up of 6 thermal generators at the supply side and 5 willing aggregated customers at the demand side. Scenario two is made up of 10 thermal generators at the supply side and 7 willing aggregated customers at the demand side. Scenario two is essentially a bigger test system as the load demand, utility budget, number of generators and number of customers exceeds that of scenario one. For all simulations performed with both scenarios, all three objectives are given equal consideration. Thus all three objectives have equal weights ($w_1 = w_2 = w_3 = \frac{1}{3}$) and are converted into a single objective function.

3.5.2 Six Generator Units and Five Customers

The fuel cost coefficients and the emission cost coefficients are obtained from [5] and shown in Table 3.1. Figure 3.1 presents the total initial hourly demand, with one mid-day peak

Table 3.1: Data of the six unit system.

i	a_i	b_i	c_i	e_i	f_i	g_i	$P_{i,min}$	$P_{i,max}$	DR_i	UR_i
1	240	7	0.007	13.8593	0.32767	0.00419	100	500	120	80
2	200	10	0.0095	13.8593	0.32767	0.00419	50	200	90	50
3	220	8.5	0.009	40.2669	-0.54551	0.00683	80	300	100	65
4	200	11	0.009	40.2669	-0.54551	0.00683	50	150	90	50
5	220	10.5	0.008	42.8955	-0.51116	0.00461	50	200	90	50
6	190	12	0.0075	42.8955	-0.51116	0.00461	50	150	90	50

Table 3.2: Customer cost function coefficients, customer type and daily customer energy limit (scenario 1).

j	$K_{1,j}$	$K_{2,j}$	θ_j	$CM_j(MWh)$
1	1.847	11.64	0	200
2	1.378	11.63	0.1734	280
3	1.079	11.32	0.4828	410
4	0.9124	11.5	0.7208	500
5	0.8794	11.21	1	700

which is consistent with industrial customers, Figure 3.2 gives the hourly values of power interruptibility ($\lambda_{j,t}$) obtained from the PJM Market on the 30th of April 2014 and Table 3.2 gives the cost function coefficients, customer type and daily customer power limit. It is further assumed that the utility has a daily budget of \$ 50 000. The transmission loss formula coefficients for the six unit test system are given by equation (3.34).

$$B = 10^{-4} \times \begin{bmatrix} 0.420 & 0.051 & 0.045 & 0.057 & 0.078 & 0.066 \\ 0.051 & 0.180 & 0.039 & 0.048 & 0.045 & 0.060 \\ 0.045 & 0.039 & 0.195 & 0.051 & 0.072 & 0.057 \\ 0.057 & 0.048 & 0.051 & 0.213 & 0.090 & 0.075 \\ 0.078 & 0.045 & 0.072 & 0.090 & 0.207 & 0.096 \\ 0.066 & 0.060 & 0.057 & 0.075 & 0.096 & 0.255 \end{bmatrix} perMW \tag{3.34}$$

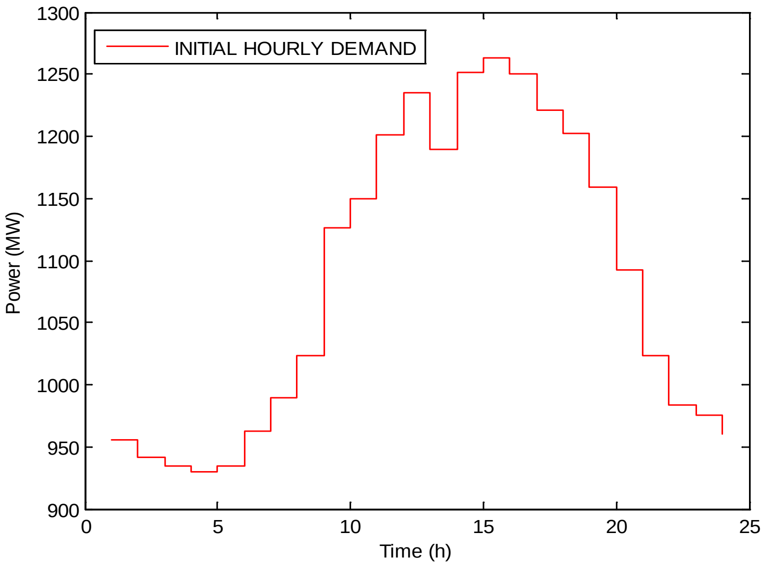

Figure 3.1: Total Initial Hourly Demand (Scenario 1).

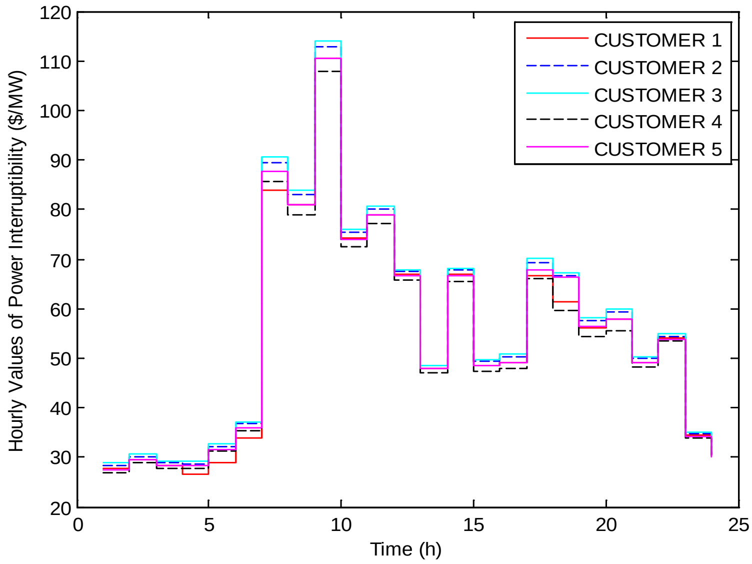

Figure 3.2: Hourly Values of Power Interruptibility for different customers (Scenario 1).

3.5.3 Ten Generator Units and Seven Customers

The fuel cost coefficients and the emission cost coefficients are obtained from [9] and shown in Table 3.3. Figure 3.3 presents the total initial hourly demand. Figure 3.4 gives the hourly values of power interruptibility obtained from the PJM Market on the 1st of May 2014 and Table 3.4 gives the cost

Table 3.3: Data of the ten unit system.

i	a_i	b_i	c_i	e_i	f_i	g_i	$P_{i,min}$	$P_{i,max}$	DR_i	UR_i
1	958.2	21.6	0.00043	360.0012	-3.9864	0.04702	150	470	80	80
2	1313.6	21.05	0.00063	350.0056	-3.9524	0.04652	135	460	80	80
3	604.97	20.81	0.00039	330.0056	-3.9023	0.04652	73	340	80	80
4	471.6	23.9	0.0007	330.0056	-3.9023	0.04652	60	300	50	50
5	480.29	21.62	0.00079	13.8593	0.3277	0.0042	73	243	50	50
6	601.75	17.87	0.00056	13.8593	0.3277	0.0042	57	160	50	50
7	502.7	16.51	0.00211	40.2669	-0.5455	0.0068	20	130	30	30
8	639.4	23.23	0.0048	40.2669	-0.5455	0.0068	47	120	30	30
9	455.6	19.58	0.10908	42.8955	-0.5112	0.0046	20	80	30	30
10	692.4	22.54	0.00951	42.8955	-0.5112	0.0046	55	55	30	30

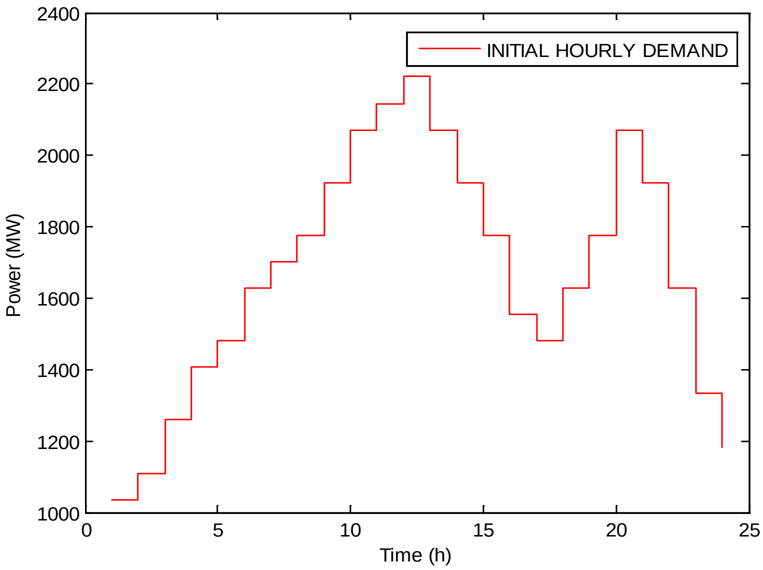

Figure 3.3: Total Initial Hourly Demand (Scenario 2).

function coefficients, customer type and daily customer power limit. It is further assumed that the utility has a daily budget of \$ 100 000. The transmission loss formula coefficients for the ten unit test system are given by equation (1) and it is shown in the appendix.

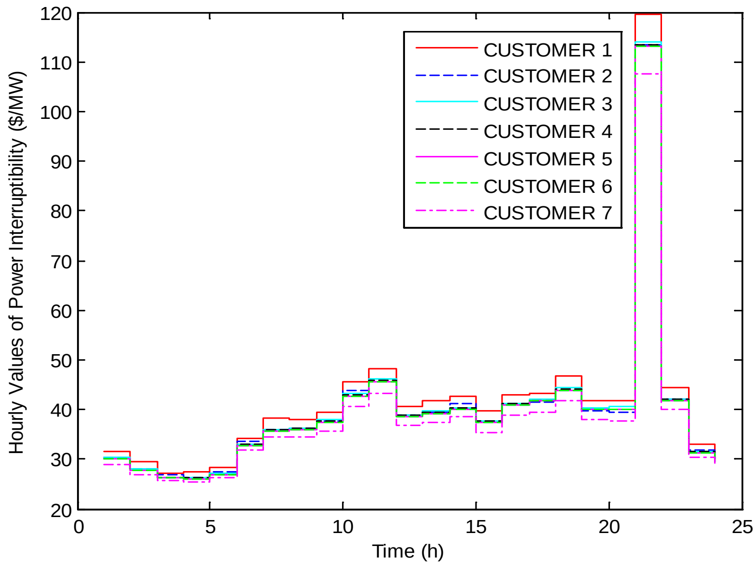

Figure 3.4: Hourly Values of Power Interruptibility for different customers (Scenario 2).

Table 3.4: Customer cost function coefficients, customer type and daily customer energy limit (scenario 2).

j	$K_{1,j}$	$K_{2,j}$	θ_j	$CM_j(MWh)$
1	1.847	11.64	0	180
2	1.378	11.63	0.14	230
3	1.079	11.32	0.26	310
4	0.9124	11.5	0.37	390
5	0.8794	11.21	0.55	440
6	1.378	11.63	0.84	530
7	1.5231	11.5	1	600

3.5.4 Solution Methodology and Results

To solve the developed mathematical model, the CONOPT solver is deployed on the Advanced Interactive Multidimensional Modelling System (AIMMS) [41]. For Scenario 1, Figure 3.5 shows the total load demand profile before and after demand response, Figure 3.6 shows the optimal power curtailed and optimal determined incentive for all the five customers. Figure 3.7 - Figure 3.12 shows the optimal power generated for all generators under normal DEED and after the DR program schedule has been implemented. Table 3.5 presents the final parameters from the combined DR-DEED program for the case of scenario 1. For Scenario 2, Figure 3.13 shows the total load demand profile before and after

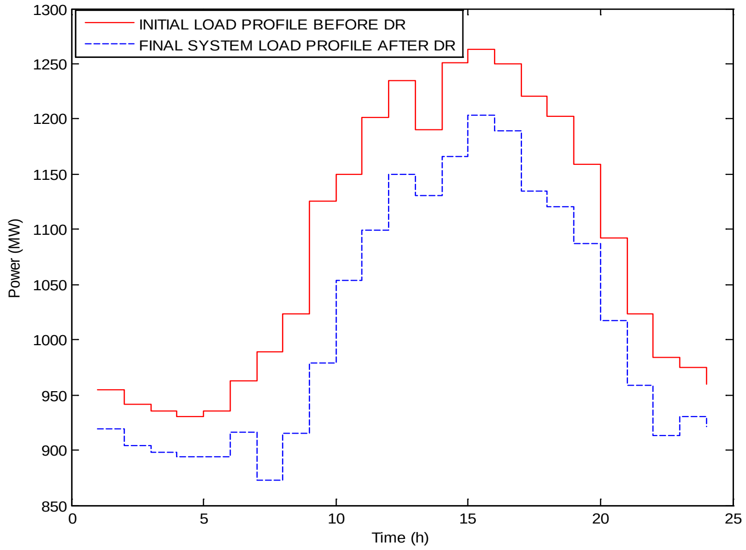

Figure 3.5: Total Load Profile Before and After Demand Response (Scenario 1).

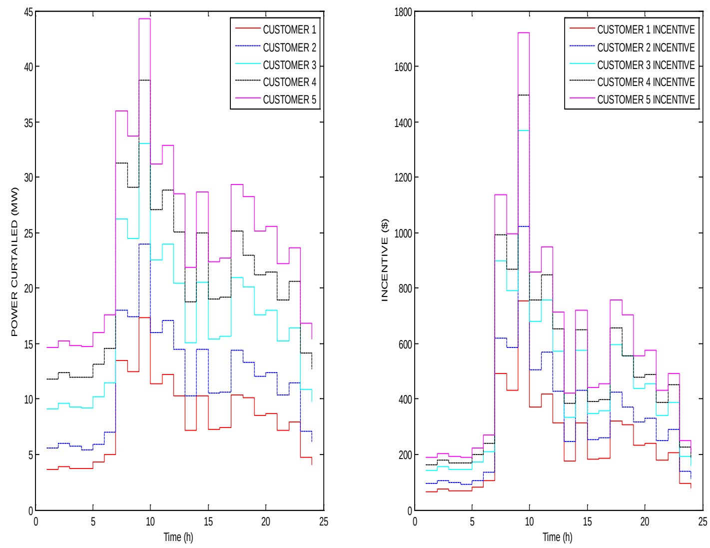

Figure 3.6: Optimal Power Curtailed and Optimal Incentive for All Customers (Scenario 1).

demand response, Figure 3.14 shows the optimal power curtailed and optimal determined incentive for all the seven customers. Table 3.6 presents the final parameters from the combined DR-DEED program for scenario 2.

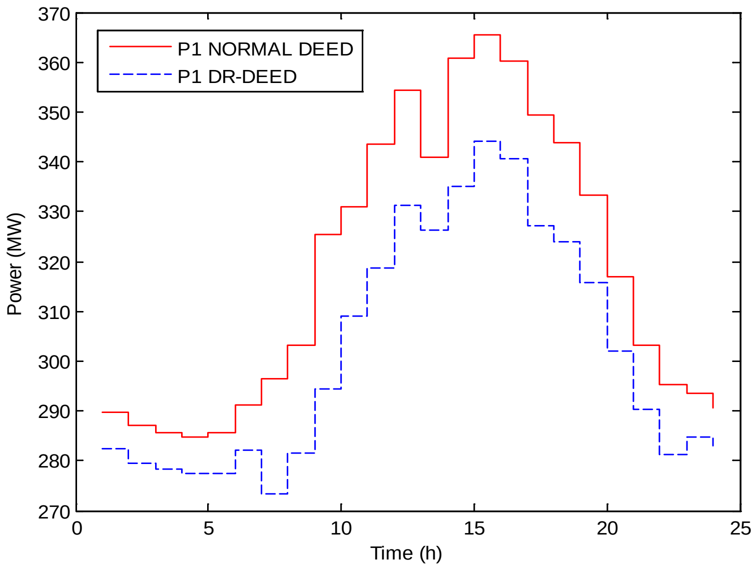

Figure 3.7: Generation output of unit 1 for scenario 1.

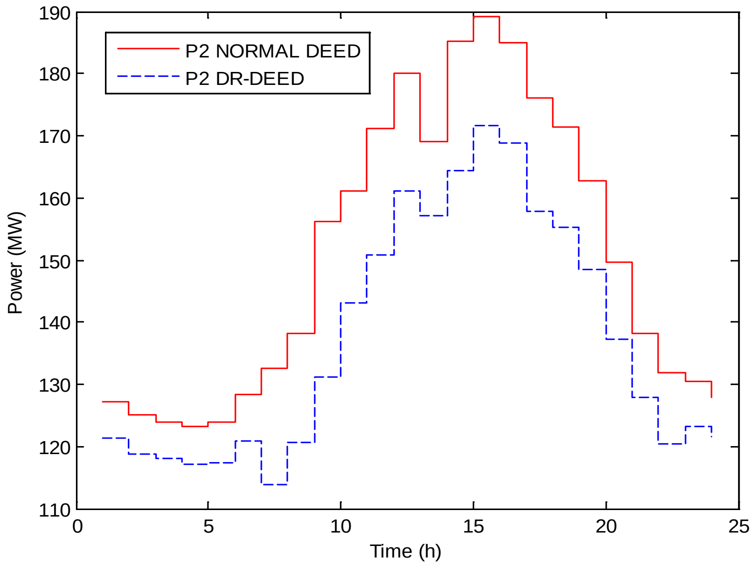

Figure 3.8: Generation output of unit 2 for scenario 1.

3.5.5 Discussion of Results

Considering scenario 1, from Figure 3.5 it is observed that the combined DR-DEED model brings about a reduction in the load profile. As shown in Figure 3.6, each customer contributes to the eventual power reduction shown in Figure 3.5. Another observation as shown in Figure 3.6 is that the

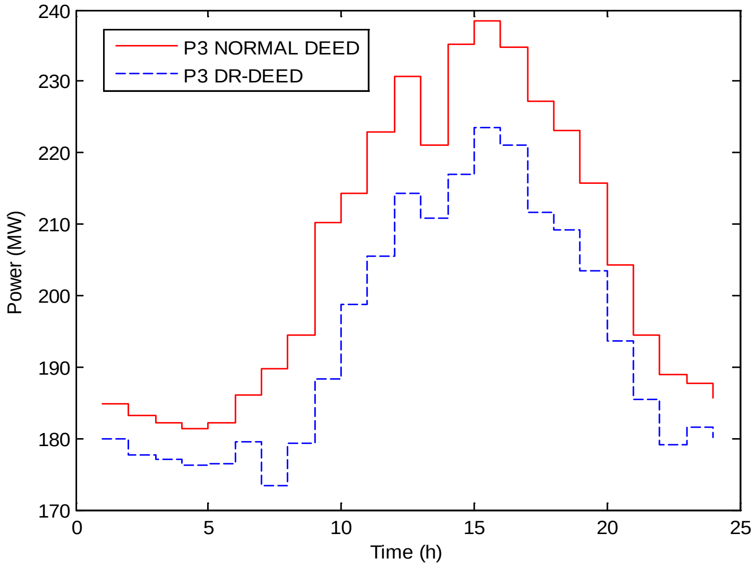

Figure 3.9: Generation output of unit 3 for scenario 1.

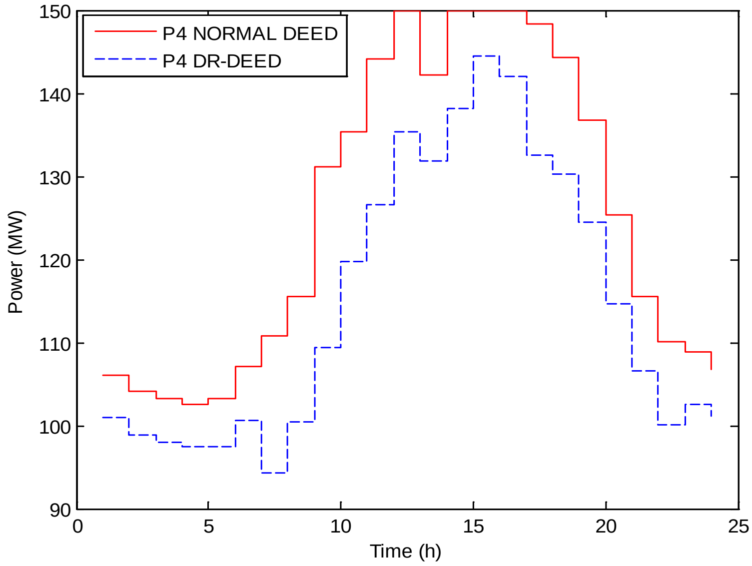

Figure 3.10: Generation output of unit 4 for scenario 1.

incentive received by customers increases as the customer willingness increases. Thus the most willing customer (with CM_j of 700 MW and θ_j of 1) has a higher incentive than the least willing customer (with CM_j of 200 MW and θ_j of 0). Figure 3.7 - Figure 3.12 simply show that the generators actually reduce power output in light of the demand reduction by willing customers. This shows that demand response programs especially in the form of incentive payments are useful in altering customer load

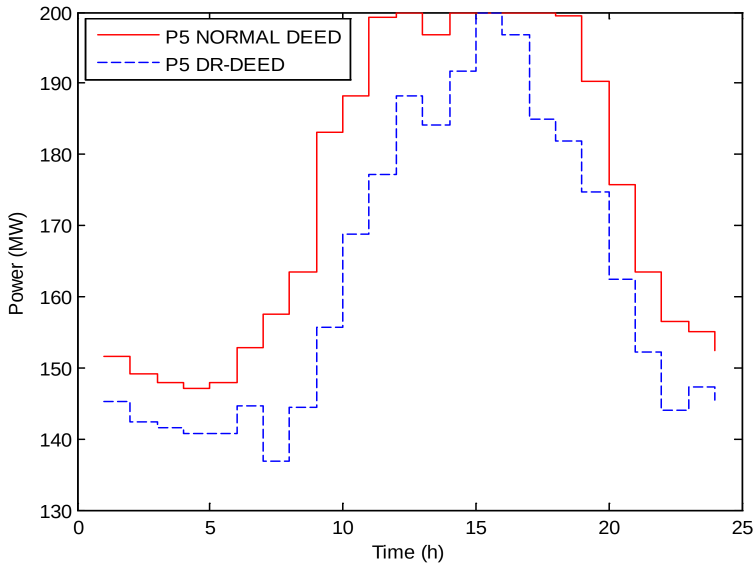

Figure 3.11: Generation output of unit 5 for scenario 1.

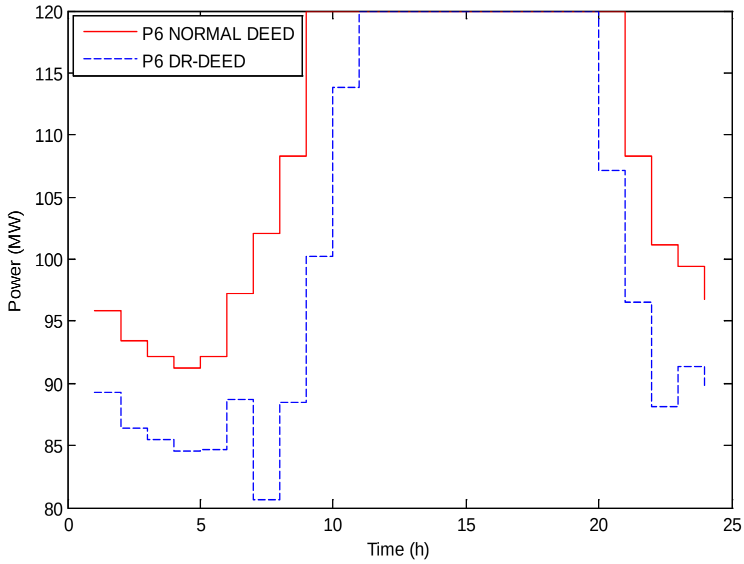

Figure 3.12: Generation output of unit 6 for scenario 1.

patterns and total system demand. This reduction of the customers load patterns in turn reduces the probability of events like blackouts and brown outs thus improving the reliability or security of the power system. Table 3.5 details the total power saved and total incentive received by each customer over a 24 hour period. As can be seen from Table 3.5, the higher the customer willingness, the greater the power curtailed and incentive received. Obtained results from scenario 2 which consists of more

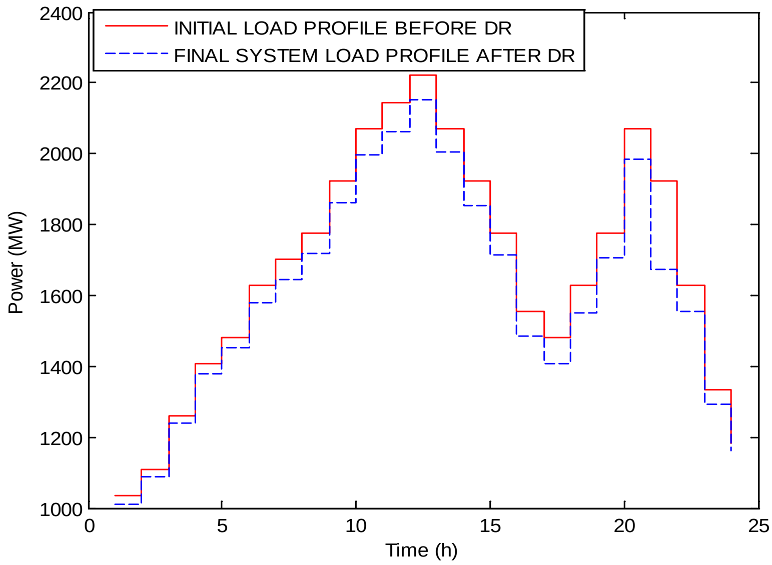

Figure 3.13: Total Load Profile Before and After Demand Response (Scenario 2).

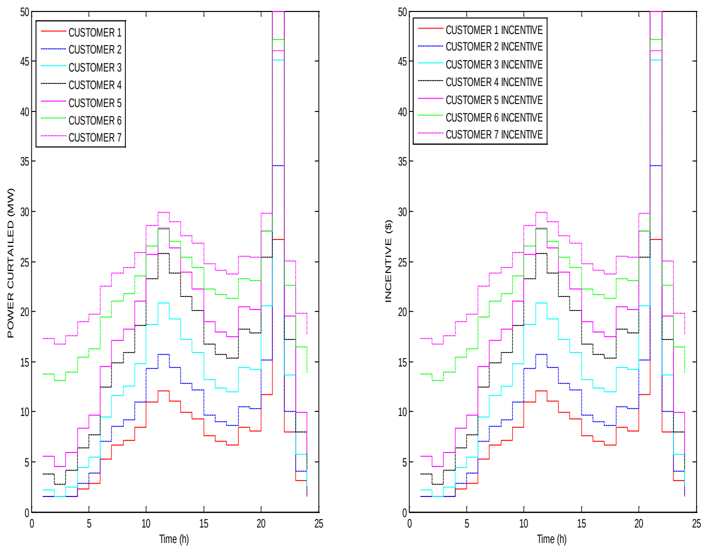

Figure 3.14: Optimal Power Curtailed and Optimal Incentive For All Customers (Scenario 2).

generators and customers than scenario 1, corroborate the conclusions drawn from scenario 1. The combined DR-DEED formulation reduces total demand over a 24 hour period by 2670.57 MW (see Figure 3.13 and Figure 3.14) and an inspection of the incentive received by each customer (see Figure 3.14 and Table 3.6) shows that the customers are compensated commensurate with the level of load they are actually willing to curb (i.e. customer willingness). Furthermore, there is also a reduction in power generated by the generators due to the curtailed customer demand. The optimal customer power curtailed ($x_{j,t}$), optimal incentive paid to customers ($y_{j,t}$) and power generated from all generators ($P_{i,t}$) (the three variables obtained by the mathematical model) for both scenario 1 and scenario 2 are given in the appendix. (Table 1 - Table 6). In the simulations done, it is assumed that the utility gives equal preference to the three objectives and gives equal weights to the three objectives, thus $w_1 = w_2 = w_3 = \frac{1}{3}$. It has however become vital in optimization with more than a single objective function, to validate the effect of augmented ranking of objectives over another on obtained solutions. We therefore present an analysis of optimization results using the base case when the utility gives equal preference to each objective ($w_1 = w_2 = w_3 = \frac{1}{3}$), when the utility chooses to minimize cost alone ($w_1 = 1, w_2 = w_3 = 0$), when the utility chooses to minimize emissions alone ($w_2 = 1, w_1 = w_3 = 0$) and when the utility chooses to maximize its DR benefit alone ($w_3 = 0, w_1 = w_2 = 0$). The four parameters evaluated are the total generator costs (\$), total emissions (lb), total generator power (MW) and total power losses (MW). Table 3.7 gives the various weight cases and Table 3.8 and Table 3.9 give the various results for Scenario 1 and 2 respectively. They show that the best results are obtained when DR and DEED are considered jointly. Considering DR alone i.e. maximizing only the utility benefit (C4), produces suboptimal results. C2 always gives the lowest cost, but gives the highest emissions and the highest losses. C3 gives the lowest emissions but doesn't give the lowest cost. Depending on the most pressing objective of the utility, the model can be adjusted accordingly. However analyses of the results show that the results are best with cases BC and C3. To provide a comparison of the DR-DEED with normal DEED we vary the weights for DEED with both the six bus and ten bus systems (Scenario 1 and 2 respectively). Tables 3.10 and 3.11 give the total generator costs (\$), total emissions (lb), total generator power (MW) and total power losses (MW) for DEED in both example scenarios. It is observed that as w increases, the costs decreases and the emission and losses increases. This means that as the weighting factor is increased (the importance of minimizing emissions is decreased, while the importance of minimizing costs increases), emissions and losses actually increase and costs decrease. This is expected and consistent with results obtained from the literature [9], [5]. To see the benefits of DR-DEED over conventional DEED we compare the Table 3.8 (DR-DEED) and Table 3.10 (normal DEED) for Scenario 1 and Table 3.9 (DR-DEED) and Table 3.11 (normal DEED) for Scenario 2. When the objective is to solely minimize cost (C2 in Table 3.8 and w=1 in Table 3.10), DR-DEED gives lower cost, emissions, losses and generated power. When the objective is to solely minimize emissions (C3 in Table 3.9 and w=0 in Table 3.11), again DR-DEED give lower costs, emissions, losses and generated power. It can be rightly concluded, that integrating both DR and DEED formulations together with their interdependent constraints gave better results than considering either DR or DEED independently.

Table 3.5: Final Results from the combined DR-DEED program (scenario 1).

	Total Power Saved (MW)	Total Incentive Received ($)
Customer 1	195.18	5775.42
Customer 2	276.01	7791.49
Customer 3	405.23	10774.40
Customer 4	495.07	11995.48
Customer 5	581.53	13663.22
Utility	**1953.02**	**50000.00**

Table 3.6: Final results from the combined DR-DEED program (scenario 2).

	Total Power Saved (MW)	Total Incentive Received ($)
Customer 1	180.00	5849.30
Customer 2	230.00	6901.25
Customer 3	310.00	8992.28
Customer 4	390.00	10762.01
Customer 5	440.00	11338.26
Customer 6	530.00	18720.82
Customer 7	590.57	23448.62
Utility	**2670.57**	**86012.54**

Table 3.7: Various weighting factor values.

	w_1	w_1	w_3
Base Case (BC)	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
Case 2 (C2)	1	0	0
Case 3 (C3)	0	1	0
Case 4 (C4)	0	0	1

3.6 CHAPTER SUMMARY

This chapter presents a modification of the DEED formulation with a game theory based DR program. The three objectives in the optimization problem are to minimize the fuel and emissions costs and maximize the utility DR benefit subject to the conventional DEED constraints and some extra constraints. The model determines the optimal generator output from the available generators and

Table 3.8: Optimal DR- DEED results with various weighting factor values (Test System 1).

	COST (DR-DEED)($)	EMISSIONS (DR-DEED) (lb)	POWER GENERATED (DR-DEED)(MW)	LOSS (DR-DEED) (MW)
BC	**291898.16**	**24474.04**	**24266.59**	**265.61**
C2	288430.67	31426.55	24205.79	308.20
C3	299397.36	21106.33	24176.39	231.01
C4	300815.08	21473.48	24291.10	234.85

Table 3.9: Optimal DR- DEED results with various weighting factor values (Test System 2).

	COST (DR-DEED)($)	EMISSIONS (DR-DEED) (lb)	POWER GENERATED (DR-DEED)(MW)	LOSS (DR-DEED) (MW)
BC	**989439.22**	**192743.96**	**38574.55**	**1137.11**
C2	968899.75	356332.96	38682.66	1254.66
C3	994464.46	183068.82	38548.88	1120.88
C4	1006653.84	210026.09	39125.16	1190.38

Table 3.10: Optimal DEED results with various weighting factor values (Test System 1).

	COST (DEED)($)	EMISSIONS (DEED) (lb)	POWER GENERATED (DEED)(MW)	LOSS (DEED) (MW)
$w = 0$	322786.57	25639.31	26233.14	279.14
$w = 0.5$	**317046.37**	**28029.95**	**26262.74**	**308.74**
$w = 1$	315021.43	35096.95	26308.30	354.30

Table 3.11: Optimal DEED results with various weighting factor values (Test System 2).

	COST (DEED)($)	EMISSIONS (DEED) (lb)	POWER GENERATED (DEED)(MW)	LOSS (DEED) (MW)
$w = 0$	1057670.13	248103.17	41438.53	1330.53
$w = 0.5$	**1052722.84**	**249936.27**	**41440.51**	**1332.51**
$w = 1$	1035411.67	380595.81	41540.71	1432.71

the game theory demand response program helps the utility determine the optimal customer load to curtail and the optimal incentive to be paid to customers who agree to curtail their load. The game theory model used in developing the DR model also included extra practical constraints like maximum power targets and total budget. Furthermore the individual rationality constraint and the incentive compatibility constraint were modified and optimized over a day instead of just an hour. From obtained results, it can be observed that the DR-DEED program helps to reduce total demand over a 24 hour period by 1953.02 MW in the first scenario and reduces the total demand by 2670.57 MW in the second scenario. Results obtained from the model also show that willing customers can provide a cost efficient way to reduce demand in the power system.

CHAPTER 4

GTDR-DEED AND GTDR-PBDEED USING AN MPC APPROACH

4.1 CHAPTER OVERVIEW

In this chapter, a Game Theory Demand Response (GTDR) program is combined with the Dynamic Economic Emission Dispatch (DEED) and the Price Based Dynamic Economic Emission Dispatch (PBDEED) mathematical models. Both mathematical problems are multi-objective optimization problems with the dual objectives of minimizing costs and emissions in the case of the DEED and minimizing emissions and maximizing profits as in the case of PBDEED. The GTDR program is an incentive based demand response program and provides incentives for willing customers who agree to curtail their demand. The programs are structured to ensure that the incentive paid to customers exceeds or equals their cost of curtailment. This gives rise to a GTDR-DEED problem which minimizes fuel and emissions costs and determines the optimal incentive and load curtailment for customers and a GTDR-PBDEED problem which minimizes emissions, maximizes profits and determines the optimal incentive and load curtailment for customers. A Model Predictive Control (MPC) approach is deployed to solve both proposed mathematical models and the obtained results show that the closed-loop controller is superior to the open loop controller as it shows better robustness against uncertainties and disturbances. Results from this chapter have been presented in [13].

4.2 DEED AND PBDEED MODEL FORMULATIONS

4.2.1 The Dynamic Economic Emission Dispatch Model

The DEED problem is concerned with minimizing the fuel costs and emission of thermal generators and determining their optimal power output. The mathematical formulation is presented below [5]:

$$min \sum_{t=1}^{T} \sum_{i=1}^{I} C_i(P_{i,t}), \tag{4.1}$$

$$min \sum_{t=1}^{T} \sum_{i=1}^{I} E_i(P_{i,t}), \tag{4.2}$$

with

$$C_i(P_{i,t}) = a_i + b_i P_{i,t} + c_i P_{i,t}^2, \tag{4.3}$$

$$E_i(P_{i,t}) = d_i + e_i P_{i,t} + f_i P_{i,t}^2, \tag{4.4}$$

subject to the following network constraints:

$$\sum_{i=1}^{I} (P_{i,t}) = D_t + loss_t, \tag{4.5}$$

$$P_{i,min} \leq P_{i,t} \leq P_{i,max}, \tag{4.6}$$

$$-DR_i \leq P_{i,t+1} - P_{i,t} \leq UR_i, \tag{4.7}$$

where

$$loss_t = \sum_{i=1}^{I} \sum_{k=1}^{K} P_{i,t} B_{i,k} P_{k,t}, \tag{4.8}$$

$P_{i,t}$ is the power generated from generator i at time t;

C_i is the fuel cost of generator i;

E_i is the emissions for generator i;

D_t is the total system demand at time t;

$loss_t$ is the total system losses at time t;

$P_{i,min}$ and $P_{i,max}$ are the minimum and maximum capacity of generator i respectively;

DR_i and UR_i are the maximum ramp down and up rates of generator i respectively;

a_i, b_i and c_i are the fuel cost coefficients of generator i respectively;

e_i, f_i and g_i are the emission coefficients of generator i respectively;

$B_{i,k}$ is the ikth element of the loss coefficient square matrix of size I;

I and T are the number of generators and the dispatch interval respectively.

The following is a brief description of the constraints:

- The first constraint (4.5) is termed the power balance constraint. This constraint compels the total power generated at time t to equal the sum of the power demand and transmission losses.
- Constraint (4.6) is the constraint for generator limits and restricts the amount of generated power to the allowable range for each generator; and
- Constraint (4.7) is the generator ramp rate constraints and restricts the ramp rates for the generators to their allowable ranges.

For the sake of simplicity, the fuel cost and emission cost ((4.3) and (4.4)) are both assumed to be quadratic functions of the generators active power output [8]. Furthermore other transmission and distribution line constraints are ignored. In order to solve the resulting mathematical model with two objective function, it is imperative that both objective functions be converted to one objective function via a weighted factor approach and the objective function is still constrained by the same constraints (4.5)-(4.7).

$$min\left[w\sum_{t=1}^{T}\sum_{i=1}^{I}C_i(P_{i,t})+(1-w)\sum_{t=1}^{T}\sum_{i=1}^{I}E_i(P_{i,t})\right]. \tag{4.9}$$

4.2.2 Profit Based Dynamic Economic Emission Dispatch Model

In a deregulated market environment, the objective is to maximize profit and minimize emissions. Let us assume that the forecast energy price at time t is given by EP_t, the revenue is given by $\sum_{t=1}^{T}\sum_{i=1}^{I}EP_t * P_{i,t}$ [5] and the cost by $\sum_{t=1}^{T}\sum_{i=1}^{I}C_i(P_{i,t})$. Thus, the profit is given by:

$$\sum_{t=1}^{T}\sum_{i=1}^{I}EP_t * P_{i,t}-\sum_{t=1}^{T}\sum_{i=1}^{I}C_i(P_{i,t}), \tag{4.10}$$

The final optimization problem is given by:

$$max\sum_{t=1}^{T}\sum_{i=1}^{I}EP_t * P_{i,t}-\sum_{t=1}^{T}\sum_{i=1}^{I}C_i(P_{i,t}), \tag{4.11}$$

$$min\sum_{t=1}^{T}\sum_{i=1}^{I}E_i(P_{i,t}), \tag{4.12}$$

with

$$C_i(P_{i,t})=a_i+b_iP_{i,t}+c_iP_{i,t}^2, \tag{4.13}$$

$$E_i(P_{i,t})=d_i+e_iP_{i,t}+f_iP_{i,t}^2, \tag{4.14}$$

subject to the following network constraints:

$$\sum_{i=1}^{I}(P_{i,t}) \leq D_t + loss_t, \tag{4.15}$$

$$P_{i,min} \leq P_{i,t} \leq P_{i,max}, \tag{4.16}$$

$$-DR_i \leq P_{i,t+1} - P_{i,t} \leq UR_i. \tag{4.17}$$

It is observed that the constraints for both DEED and PBDEED are quite similar, the only difference being the power balance constraint. For the DEED model, it is imperative that generated power should match the load demand, while in PBDEED, generated power can be less than the total demand as the aim is to maximize total profit. Again, it is instructive to mention that just like in the DEED formulations, the fuel cost and emissions are both assumed to be quadratic functions of the generators active power output and other transmission and distribution line constraints are ignored. The multi-objective optimization can be transformed into a single objective function using a weighting factor w subject to the same constraints (4.15)-(4.17):

$$min\left[w\left[\sum_{t=1}^{T}\sum_{i=1}^{I}C_i(P_{i,t}) - EP_t * P_{i,t}\right] + (1-w)\sum_{t=1}^{T}\sum_{i=1}^{I}E_i(P_{i,t})\right]. \tag{4.18}$$

4.3 GAME THEORY BASED DEMAND RESPONSE FORMULATIONS

The objective of the Game Theory Demand Response (GTDR) formulations is to maximize the utility benefit [8]:

$$max_{x,y}\sum_{t=1}^{T}\sum_{j=1}^{J}[\lambda_{j,t}x_{j,t} - y_{j,t}] \tag{4.19}$$

s.t.

$$\sum_{t=1}^{T}\left[y_{j,t} - (K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j)\right] \geq 0,\ for\ j = 1,\ldots,J, \tag{4.20}$$

$$\begin{gathered}\textstyle\sum_{t=1}^{T}\left[y_{j,t} - (K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j)\right] \geq \\ \textstyle\sum_{t=1}^{T}\left[y_{j-1,t} - (K_{1,j-1}x_{j-1,t}^2 + K_{2,j-1}x_{j-1,t} - K_{2,j-1}x_{j-1,t}\theta_{j-1})\right]\ , \\ for\ j = 2,\ldots,J,\end{gathered} \tag{4.21}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{J}y_{j,t} \leq UB, \tag{4.22}$$

$$\sum_{t=1}^{T} x_{j,t} \leq CM_j, \tag{4.23}$$

The customer outage cost function is assumed to be quadratic and is given by:

$$(K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j). \tag{4.24}$$

where $K_{1,j}$ and $K_{2,j}$ are the cost function coefficients of customer j;
$x_{j,t}$ is the amount of power curtailed by a customer j at time t;
$y_{j,t}$ is the incentive of a participating customer j at time t;
UB is the utility's total budget;
CM_j is the daily limit of interruptible energy for customer j;
J and T are the total number of customers and the total time interval respectively;
$\lambda_{j,t}$ is the "value of power interruptibility" of participating customer j at time t. This parameter gives the cost of the electric utility not delivering electric power to a particular location on the grid. $\lambda_{j,t}$ can be calculated from optimal power flow routines (OPF);
θ_j is the "customer type" [36]. θ is normalized in the interval $0 \leq \theta \leq 1$ and categorizes the different kinds of customers based on their willingness or readiness to shed power, with $\theta = 0$ being the least willing and $\theta = 1$ the most willing customer.
The following is a concise description of the constraints:
Constraint (4.20) is known as the "Individual rationality constraint". It's role is to constrain the customer benefit to surpass zero.
Constraint (4.21) is termed the "Incentive compatibility constraint". It's role is to make sure that the amount of compensation received by customers is commensurate with the amount of load they curtailed.
The role of constraint (4.22) is to make sure that the utility daily total program expenditure is lower than or equal to it's daily budgeted amount.
The role of constraint (4.23) is to make sure that the amount of load shed by each customer is less than the customers maximum allowable curtailable power.
In the next section, the combined DEED/PBDEED and game theory based demand response models are detailed.

4.4 MATHEMATICAL MODEL OF DEED/PBDEED COMBINED WITH GAME THEORY BASED DEMAND RESPONSE FORMULATIONS

4.4.1 The GTDR-DEED Model

The weighted single objective GTDR-DEED mathematical formulation is:

$$\begin{gathered} min\ w_1 \left[\sum_{t=1}^{T}\sum_{i=1}^{I} C_i(P_{i,t})\right] + w_2 \left[\sum_{t=1}^{T}\sum_{i=1}^{I} E_i(P_{i,t})\right] \\ +w_3 \left[\sum_{t=1}^{T}\sum_{j=1}^{J} [y_{j,t} - \lambda_{j,t} x_{j,t}]\right] \end{gathered} \tag{4.25}$$

subject to the following network constraints:

$$\sum_{i=1}^{I} P_{i,t} = D_t + loss_t - \sum_{j=1}^{J} x_{j,t}, \tag{4.26}$$

$$P_{i,min} \leq P_{i,t} \leq P_{i,max}, \tag{4.27}$$

$$-DR_i \leq P_{i,t+1} - P_{i,t} \leq UR_i, \tag{4.28}$$

$$\sum_{t=1}^{T}[y_{j,t} - (K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j)] \geq 0,\ for\ j = 1, \ldots, J, \tag{4.29}$$

$$\begin{gathered} \sum_{t=1}^{T}[y_{j,t} - (K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j)] \geq \\ \sum_{t=1}^{T}[y_{j-1,t} - (K_{1,j-1}x_{j-1,t}^2 + K_{2,j-1}x_{j-1,t} - K_{2,j-1}x_{j-1,t}\theta_{j-1})]\ , \\ for\ j = 2, \ldots, J, \end{gathered} \tag{4.30}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{J} y_{j,t} \leq UB, \tag{4.31}$$

$$\sum_{t=1}^{T} x_{j,t} \leq CM_j, \tag{4.32}$$

$$loss_t = \sum_{i=1}^{I}\sum_{k=1}^{K} P_{i,t}B_{i,k}P_{k,t}, \tag{4.33}$$

where w_1,w_2 and w_3 are the weights and the following condition is required to be satisfied when choosing weights:

$$w_1 + w_2 + w_3 = 1. \tag{4.34}$$

The variables to be determined by the optimization model are $x_{j,t}$,$y_{j,t}$ and $P_{i,t}$.

4.4.2 The GTDR-PBDEED Model

For the GTDR-PBDEED, we assume that the utility or the Independent System Operator (ISO) wants to maximize its profit and benefit and minimize emissions as it is operating in a deregulated environment. This can be given as:

$$\begin{gathered} min\ w_1 \left[\sum_{t=1}^{T}\sum_{i=1}^{I}\left[C_i(P_{i,t}) - EP_t * P_{i,t}\right] + \sum_{t=1}^{T}\sum_{j=1}^{J}\left[y_{j,t} - \lambda_{j,t}x_{j,t}\right]\right] \\ +w_2\sum_{t=1}^{T}\sum_{i=1}^{I}E_i(P_{i,t}) \end{gathered} \tag{4.35}$$

subject to the following network constraints:

$$\sum_{i=1}^{I} P_{i,t} \leq D_t + loss_t - \sum_{j=1}^{J} x_{j,t}, \tag{4.36}$$

$$P_{i,min} \leq P_{i,t} \leq P_{i,max}, \tag{4.37}$$

$$-DR_i \leq P_{i,t+1} - P_{i,t} \leq UR_i, \tag{4.38}$$

$$\sum_{t=1}^{T}[y_{j,t} - (K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j)] \geq 0, for\ j = 1, \dots, J, \tag{4.39}$$

$$\begin{gathered} \sum_{t=1}^{T} y_{j,t} - (K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j) \geq \\ \sum_{t=1}^{T}\left[y_{j-1,t} - (K_{1,j-1}x_{j-1,t}^2 + K_{2,j-1}x_{j-1,t} - K_{2,j-1}x_{j-1,t}\theta_{j-1})\right], \\ for\ j = 2, \dots, J, \end{gathered} \tag{4.40}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{J} y_{j,t} \leq UB, \tag{4.41}$$

$$\sum_{t=1}^{T} x_{j,t} \leq CM_j, \tag{4.42}$$

$$loss_t = \sum_{i=1}^{I}\sum_{k=1}^{K} P_{i,t}B_{i,k}P_{k,t}, \tag{4.43}$$

where w_1 and w_2 are the weights and the following condition is required to be satisfied when choosing weights:

$$w_1 + w_2 = 1. \tag{4.44}$$

The variables to be determined by the optimization model are $x_{j,t}$,$y_{j,t}$ and $P_{i,t}$.

4.4.3 Model Predictive Control Strategy

The open loop GTDR-DEED model and GTDR-PBDEED model are defined over the time interval T with optimization variables $x_{1,t}$, $y_{1,t}$, $P_{1,t}$,...., $x_{1,T}$, $y_{1,T}$, $P_{1,T}$ ($i = 1, 2, ..., I$ and $j = 1, 2, ..., J$). Optimizing the identical mathematical model over a different horizon ($v+1$,$v+T$), the optimization variables is given as $x_{1,v+1}$, $y_{1,v+1}$, $P_{1,v+1}$, ..., $x_{1,v+T}$, $y_{1,v+T}$, $P_{1,v+T}$.

Therefore the closed-loop (MPC) GTDR-DEED problem is given below:

$$\begin{aligned} min\ w_1 \left[\sum_{t=v+1}^{T}\sum_{i=1}^{I} C_i(P_{i,t})\right] + w_2\left[\sum_{t=v+1}^{T}\sum_{i=1}^{I} E_i(P_{i,t})\right] \\ +w_3\left[\sum_{t=v+1}^{T}\sum_{j=1}^{J}[y_{j,t} - \lambda_{j,t}x_{j,t}]\right], \end{aligned} \tag{4.45}$$

where v is termed the "MPC switching interval". Both the open loop and close loop models have equivalent constraints and at each closed loop iteration, the constraints are simply updated. Obtained results from the model are utilized in the initial sample interval $(v+1, v+2)$ and this result serves as the input in the second sample interval $(v+2, v+3)$. This provides a closed feed back scheme. A full description of the MPC algorithm is provided in [12]. Similarly, the closed-loop (MPC) GTDR-PBDEED problem is given as:

$$\begin{aligned} min\ w_1 \left[\sum_{t=v+1}^{T}\sum_{i=1}^{I}[C_i(P_{i,t}) - EP_t * P_{i,t}] + \sum_{t=v+1}^{T}\sum_{j=1}^{J}[y_{j,t} - \lambda_{j,t}x_{j,t}]\right] \\ +w_2\left[\sum_{t=v+1}^{T}\sum_{i=1}^{I} E_i(P_{i,t})\right]. \end{aligned} \tag{4.46}$$

4.5 NUMERICAL SIMULATIONS, OBTAINED RESULTS AND DISCUSSIONS

To verify the proposed GTDR-DEED and GTDR-PBDEED mathematical formulations, a case study of six generator units and five industrial customers is used [8]. The data for the generator units has also been used in [5] and was originally obtained from [27]. Table 4.1 shows the fuel cost coefficients and the emission coefficients [5]. The system consists of six thermal units, twenty six buses, and forty six transmission lines [27]. The maximum load demand is 1263 MW. Table 4.2 gives the initial hourly demand [27], which has one mid-day peak synonymous with industrial customers. Table 4.3 gives the hourly values of power interruptibility ($\lambda_{j,t}$) obtained from the Pennsylvania-New Jersey-Maryland (PJM) Market [40] LMP prices on the 30th of April 2014. For PBDEED, the energy price (EP_t) is assumed to be the highest LMP price. Table 4.4 details the cost function coefficients, customer type and daily customer energy limit [8]. The assumption is that the utility knows the customers daily limit of interruptible energy (CM_j) which it then uses to rank the customers in order of increasing willingness to curb electric power. Furthermore, the utility knows the outage cost function coefficients

Table 4.1: Data of the six unit system.

i	a_i	b_i	c_i	e_i	f_i	g_i	$P_{i,min}$	$P_{i,max}$	DR_i	UR_i
1	240	7	0.007	13.8593	0.32767	0.00419	100	500	120	80
2	200	10	0.0095	13.8593	0.32767	0.00419	50	200	90	50
3	220	8.5	0.009	40.2669	-0.54551	0.00683	80	300	100	65
4	200	11	0.009	40.2669	-0.54551	0.00683	50	150	90	50
5	220	10.5	0.008	42.8955	-0.51116	0.00461	50	200	90	50
6	190	12	0.0075	42.8955	-0.51116	0.00461	50	150	90	50

of participating customers ($K_{1,j}$ and $K_{2,j}$). The customer cost function coefficients, customer type and daily energy limit were originally obtained and modified from [36] which contains practical data from a US case study. The transmission loss formula coefficients for the six unit test system [27] are given by equation (4.47) and the utility daily budget (UB) is \$ 50 000. The decision variables for both GTDR-DEED and GTDR-PBDEED are the optimal customer power to be curtailed ($x_{j,t}$), optimal incentive to be paid to customers ($y_{j,t}$) and power generated from all generators ($P_{i,t}$). The entire dispatch period is 24 h ($T = 24$) and the sampling period is 1 h as has always been used in the literature [27] and also in [4] and [8]. The Advanced Interactive Multidimensional Modelling System (AIMMS) [41] is utilized to build and solve both GTDR-DEED and GTDR-PBDEED models using the CONOPT solver.

$$B = 10^{-4} \times \begin{bmatrix} 0.420 & 0.051 & 0.045 & 0.057 & 0.078 & 0.066 \\ 0.051 & 0.180 & 0.039 & 0.048 & 0.045 & 0.060 \\ 0.045 & 0.039 & 0.195 & 0.051 & 0.072 & 0.057 \\ 0.057 & 0.048 & 0.051 & 0.213 & 0.090 & 0.075 \\ 0.078 & 0.045 & 0.072 & 0.090 & 0.207 & 0.096 \\ 0.066 & 0.060 & 0.057 & 0.075 & 0.096 & 0.255 \end{bmatrix} perMW \tag{4.47}$$

4.5.1 Simulation Results Without Disturbance

The MPC strategy is implemented on both the GTDR-DEED and the GTDR-PBDEED problem. As stated before, for multi-objective problems in order to solve the problem with minimal computational complexity, it is often necessary to use the goal attainment method or weighted sum approach and convert the objectives into a single objective [5]. Thus, for GTDR-DEED, $w_1 = w_2 = w_3 = \frac{1}{3}$ while for GTDR-PBDEED, $w_1 = w_2 = 0.5$. The values for the weights are chosen so that equal preference is given to all the objectives and in both cases, the sum of the weights equals 1. Figure 4.1 and Figure 4.2 show the results obtained from the MPC implementations on GTDR-DEED and the GTDR-PBDEED

Table 4.2: Total Initial Hourly Demand

Time(h)	Total Demand (MW)
1	955
2	942
3	935
4	930
5	935
6	963
7	989
8	1023
9	1126
10	1150
11	1201
12	1235
13	1190
14	1251
15	1263
16	1250
17	1221
18	1202
19	1159
20	1092
21	1023
22	984
23	975
24	960

respectively. Each figure shows the optimal power generated from all generators, the total demand profile, optimal power curtailed by the customers and the optimal customer incentive. For comparison purposes, we also show obtained results of the GTDR-DEED and GTDR-PBDEED with open loop control in Figure 4.3 and Figure 4.4 respectively. A careful comparison of the figures shows that both open loop and closed-loop control yield similar results. Table 4.5 provides a numerical results comparison between both approaches. From the results it shows that the closed-loop returns better results than the open loop approach. This is because comparing GTDR-DEED under both the open loop and closed-loop approaches, it becomes easily discernible from the results that the closed-loop approach returns lower fuel costs ($ 290554.50 to the open loop's $ 291898.16). The closed-loop approach again returns lower emissions (24332.84 lb to open loop's 24474.04 lb). Even though both

Table 4.3: Hourly Values of Power Interruptibility.

$\lambda_{j,t}$ (\$)					
	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$
$t = 1$	27.61	28.30	28.79	26.93	27.60
$t = 2$	29.41	30.07	30.53	28.79	29.44
$t = 3$	28.24	28.87	29.28	27.66	28.32
$t = 4$	26.69	28.76	29.14	27.74	28.24
$t = 5$	29.01	32.24	32.64	31.20	31.66
$t = 6$	33.96	36.67	37.15	35.38	35.99
$t = 7$	83.97	89.46	90.65	85.71	87.70
$t = 8$	81.10	82.88	83.79	79.06	81.06
$t = 9$	110.60	112.93	114.11	107.72	110.44
$t = 10$	74.12	75.43	76.09	72.40	73.95
$t = 11$	78.95	80.19	80.65	77.29	78.93
$t = 12$	66.85	67.55	67.76	65.75	66.67
$t = 13$	47.98	48.58	48.63	47.10	47.93
$t = 14$	66.82	67.74	68.07	65.55	66.74
$t = 15$	48.50	49.35	49.69	47.41	48.47
$t = 16$	49.21	50.28	50.87	47.94	49.19
$t = 17$	66.65	69.36	70.29	66.05	67.71
$t = 18$	61.49	66.57	67.19	59.69	66.24
$t = 19$	56.19	57.67	58.25	54.48	56.53
$t = 20$	57.92	59.38	59.98	55.58	57.98
$t = 21$	49.16	49.86	50.36	48.31	48.96
$t = 22$	54.00	54.38	54.84	53.46	53.63
$t = 23$	34.37	34.67	34.96	33.98	34.21
$t = 24$	30.30	30.71	31.00	29.89	30.20

approaches yield the same amount of customer incentive (\$50000), the closed-loop approach to GTDR-DEED yields better energy curtailment (1957.38 MWh to open loop's 1953.02 MWh) and also lower energy loss (264 MWh to open loop's 266 MWh). Going further to compare GTDR-PBDEED under the closed-loop approach and the open loop approach, from Table 4.5 we see that the closed-loop approach again yields lower total fuel costs, emissions, energy generated and energy losses. The closed-loop approach also yields a higher total customer incentive (\$ 32228.39 to the open loop's \$ 31954.89) and higher total profits (\$ 1119751.99 to the open loop's \$ 1095533.01). Furthermore results from the closed-loop approach converge to that of the open loop solution both under GTDR-DEED and GTDR-PBDEED as evidenced by Figure 4.5 and Figure 4.6 respectively, thereby demonstrating

Table 4.4: Customer Cost Function Coefficients, Customer Type and Daily Customer Energy Limit.

j	$K_{1,j}$	$K_{2,j}$	θ_j	$CM_j(MWh)$
1	1.847	11.64	0	200
2	1.378	11.63	0.1734	280
3	1.079	11.32	0.4828	410
4	0.9124	11.5	0.7208	500
5	0.8794	11.21	1	700

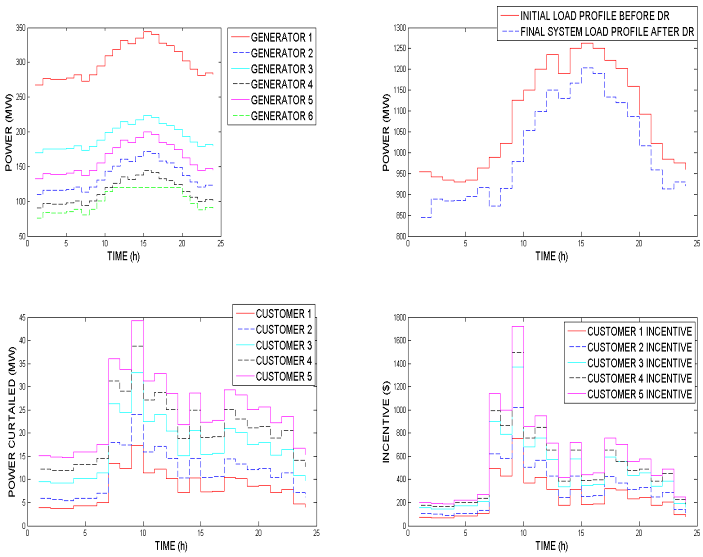

Figure 4.1: GTDR-DEED closed-loop results with no disturbance.

the convergence ability of the MPC algorithm.

4.5.2 Simulation Results With Disturbance

To test the robustness of the MPC algorithm against uncertainties and disturbance, we assume that for GTDR-DEED and GTDR-PBDEED the demand randomly increases between 3.5% to 10% of the initial demand. Also the energy price is similarly randomly varied between -5% to 5% of the initial energy price. Similarly for GTDR-DEED, $w_1 = w_2 = w_3 = \frac{1}{3}$ while for GTDR-PBDEED, $w_1 = w_2 = 0.5$. Figure 4.7 and Figure 4.8 shows the results obtained for GTDR-DEED and GTDR-PBDEED respectively. For comparison purposes we also show results for GTDR-DEED and GTDR-PBDEED under open loop control (See Figure 4.9 and Figure 4.10 respectively. Table 4.6 shows a

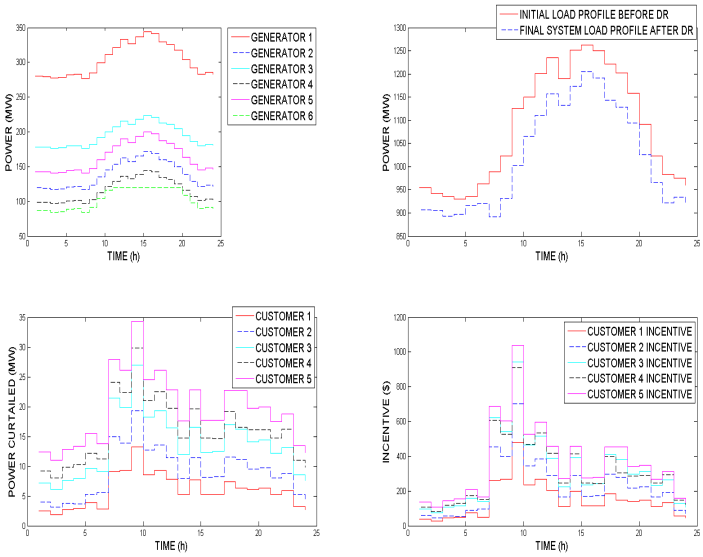

Figure 4.2: GTDR-PBDEED closed-loop results with no disturbance.

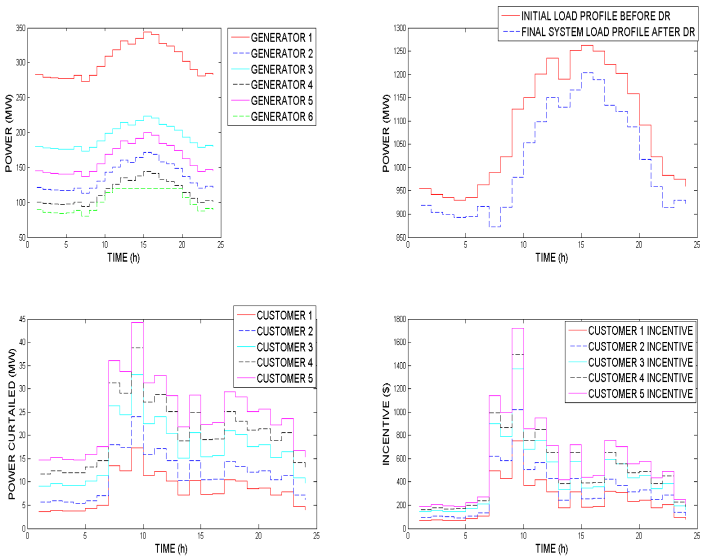

Figure 4.3: GTDR-DEED open loop results with no disturbance.

numerical comparison between both open loop and closed-loop control. It shows that the closed-loop approach yields better results and handles disturbances and uncertainties in a manner superior to the conventional open loop approach. This is because comparing GTDR-PBDEED under both approaches, it is seen from Table 4.6 that the closed-loop approach returns lower fuel costs ($ 316258.72 to the open loop's $ 318937.26). The closed-loop approach again returns lower emissions (27865.93 lb to

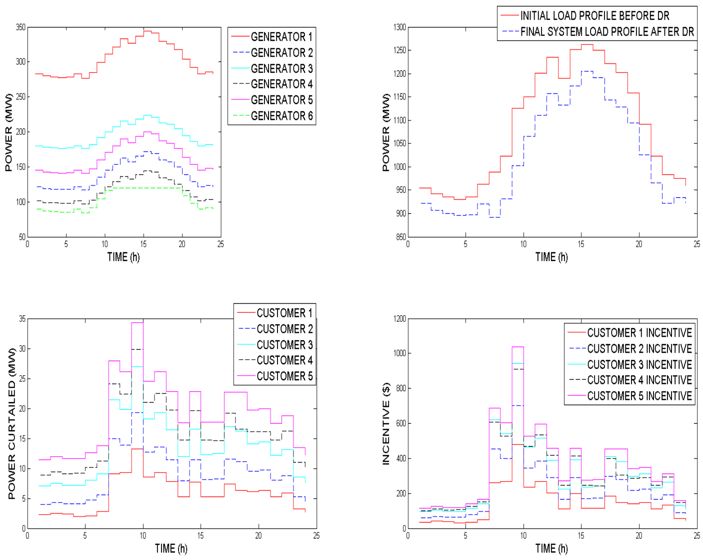

Figure 4.4: GTDR-PBDEED open loop results with no disturbance.

Table 4.5: Solutions from both open loop and closed-loop without disturbance.

	Open Loop		Closed-Loop	
	GTDR DEED	GTDR PBDEED	GTDR DEED	GTDR PBDEED
Total Fuel Cost ($)	291898.16	294006.12	290554.50	293964.84
Total Emissions (lb)	24474.04	24739.27	24332.84	24734.78
Total Customer Incentive ($)	50000	31954.89	50000	32228.39
Total Customer Energy Curtailed (MWh)	1953.02	1518.68	1957.38	1530.03
Total Energy Generated (MWh)	24266.59	24435.32	24156.62	24431.98
Total Energy Loss (MWh)	266	269	264	268.94
Total Profit ($)		1095533.01		1119751.99

open loop's 28204.86 lb). Again, the closed-loop approach to GTDR-DEED yields better energy curtailment (1508.77 MWh to open loop's 1504.47 MWh) and also lower energy loss (307.11 MWh to open loop's 311.41 MWh). Finally, the closed-loop approach also yields a higher total customer incentive ($ 35889.02 to the open loop's $ 31533.21) and higher total profits ($ 1214384.57 to the open loop's $ 1208383.41) Comparing GTDR-DEED under the closed-loop approach and the open loop approach, from Table 4.6 we see that the closed-loop approach again yields lower total fuel costs, emissions, energy generated and energy losses. Both approaches yield the same amount of customer incentive ($50000). Figure 4.11 and Figure 4.12 shows the performance of the open loop controller and the closed-loop controller with disturbance.

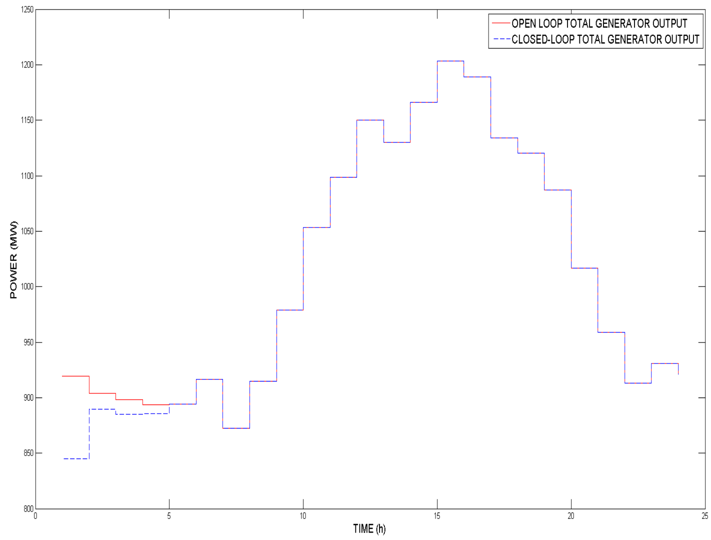

Figure 4.5: The convergence of the closed-loop solutions to that of the open loop solutions for GTDR-DEED.

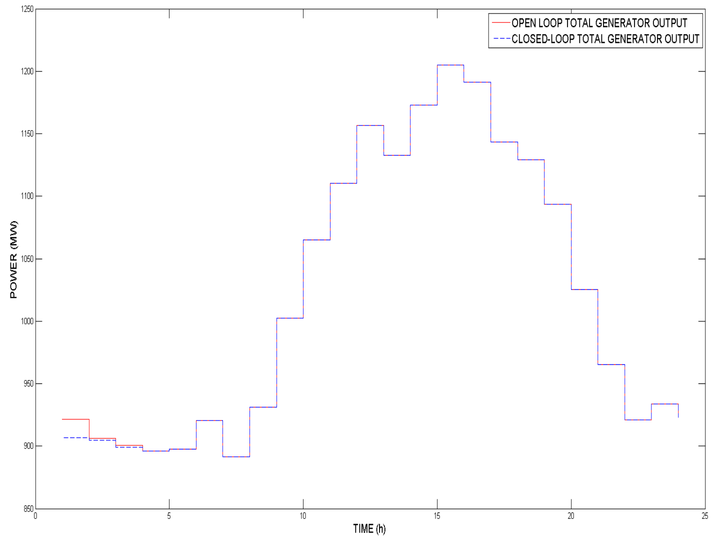

Figure 4.6: The convergence of the closed-loop solutions to that of the open loop solutions for GTDR-PBDEED.

4.5.3 Discussion of Results

The results obtained can be discussed along two lines. Results from GTDR-DEED and GTDR-PBDEED will be discussed and analysed. Also discussions can be done comparing results obtained

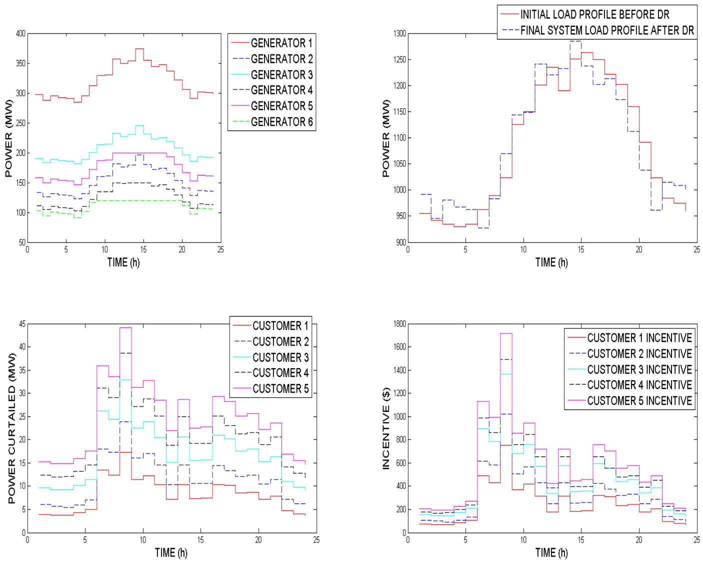

Figure 4.7: GTDR-DEED closed-loop results with disturbance.

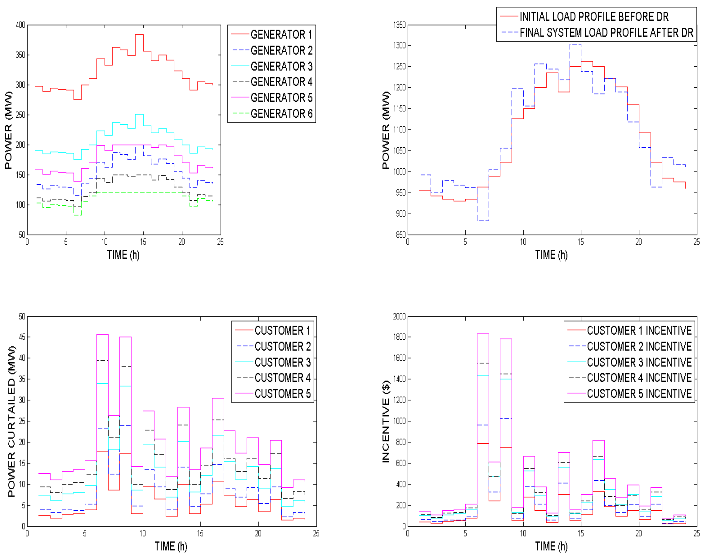

Figure 4.8: GTDR-PBDEED closed-loop results with disturbance.

under open loop and closed-loop control strategies. The discussion would focus on the following economic and power system parameters: Total Fuel Cost ($), Total Emissions (lb), Total Customer Incentive ($), Total Customer Energy Curtailed (MWh), Total Energy Generated (MWh), Total Energy Loss (MWh) and Total Profit ($). In simulations done, we gives equal preference to all the objectives and thus give them equal weights (see equations 4.34 and 4.44). We ignore investigating the

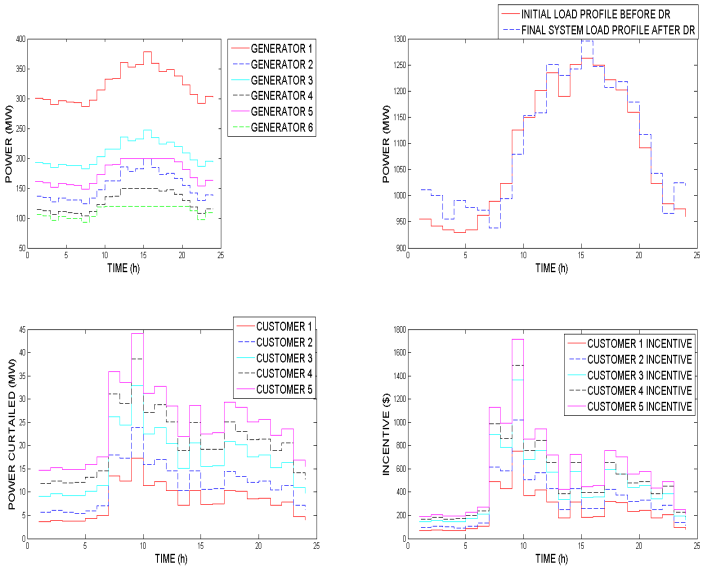

Figure 4.9: GTDR-DEED open loop results with disturbance.

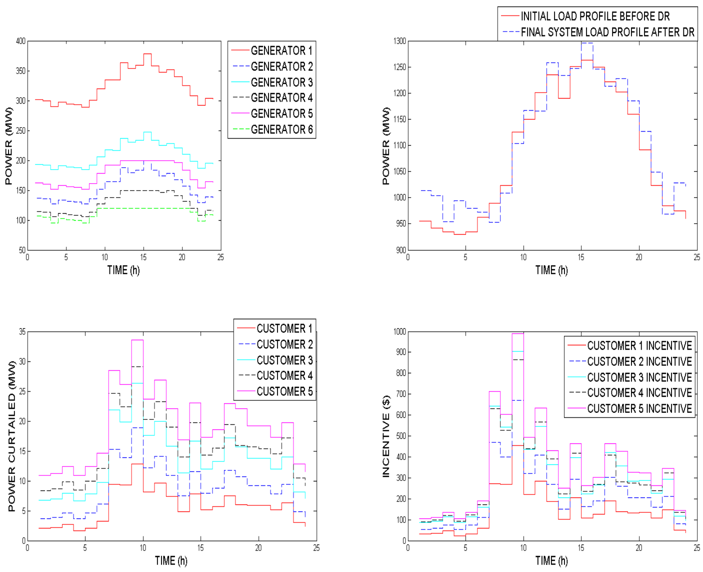

Figure 4.10: GTDR-PBDEED open loop results with disturbance.

effect of varying the weights (and hence the objectives) as this and the effect of using a larger power system has been done in [8]. As stated earlier, GTDR-PBDEED is for a deregulated environment, whilst GTDR-DEED is for a regulated environment. From the obtained results in Table 4.5 and Table 4.6, the GTDR-PBDEED saves less power than GTDR-DEED, therefore more power is generated by GTDR-PBDEED under both open and closed-loop strategies. This means that the emission, cost

Table 4.6: Solutions from both open loop and closed-loop with disturbance.

	Open Loop		Closed-Loop	
	GTDR DEED	GTDR PBDEED	GTDR DEED	GTDR PBDEED
Total Fuel Cost ($)	317149.16	318937.26	314454.33	316258.72
Total Emissions (lb)	27943.02	28204.86	27546.48	27865.93
Total Customer Incentive ($)	50000	31533.21	50000	35889.02
Total Customer Energy Curtailed (MWh)	1954.18	1504.47	1954.05	1508.77
Total Energy Generated (MWh)	26273.87	26415.30	26060.27	26200.99
Total Energy Loss (MWh)	308.28	311.41	303.56	307.11
Total Profit ($)		1208383.41		1214384.57

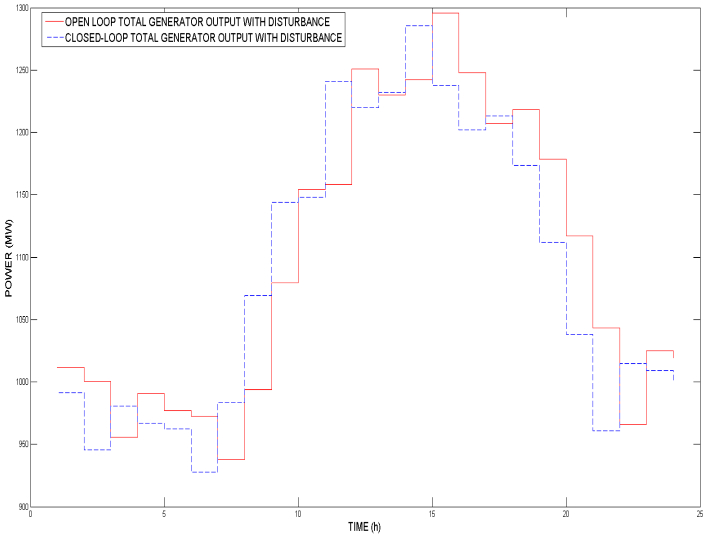

Figure 4.11: Total generator output of GTDR-DEED using both open loop and closed-loop control with disturbance.

and losses of GTDR-PBDEED are greater than those of GTDR-DEED. It can also be seen from both tables, that because the utility/ISO in GTDR-PBDEED wants to maximize profit, the total incentive paid to customers never equals the maximum utility budget, unlike in GTDR-DEED where the maximum utility budget is always reached as maximizing profit is not an objective in this case. In a nutshell, the results show that DR has benefits to the power system either under a regulated or deregulated environment. The results also show the superiority of MPC over conventional open loop approach. MPC returns better results than open loop with and without disturbance. Furthermore the convergence ability of the MPC algorithm to the open loop solution is also shown. Looking at Figures

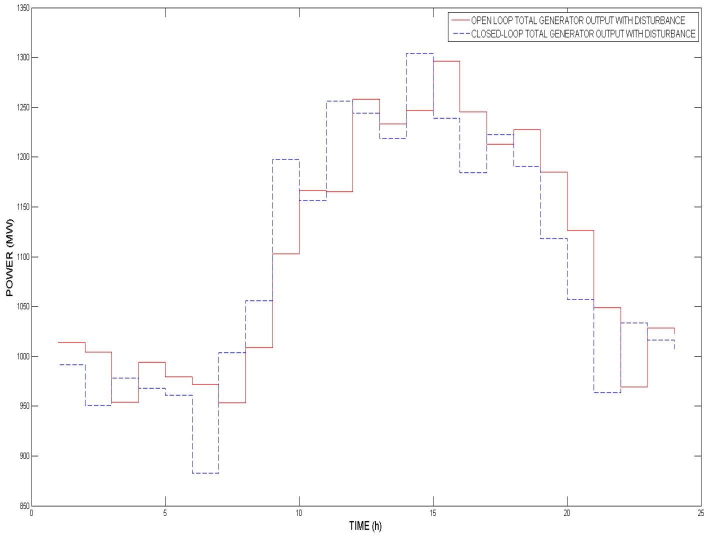

Figure 4.12: Total generator output of GTDR-PBDEED using both open loop and closed-loop control with disturbance.

4.5 and 4.6 it shows convergence between both closed and open loop solutions. This happens in the fifth hour for the GTDR-DEED and in the fourth hour for the GTDR-PBDEED case. Both cases demonstrate the convergence capability of the MPC algorithm. This means that the MPC approach can be used and restarted at any time instant and would still converge which guarantees optimality at all times which is very important in practical purposes. Again considering Figures 4.11 and 4.12, they show that the total generator output of the closed-loop strategy is in the neighbourhood of the open loop solutions for GTDR-DEED and GTDR-PBDEED respectively. Table 4.6 shows that the closed-loop approach handles disturbance better and gives better economic and power system parameters. Comparing Table 4.6 with Table 4.5, it shows that disturbances actually make for a more inefficient and expensive system. This is because with disturbances under both open loop and closed-loop control schemes and for both GTDR-DEED and GTDR-PBDEED, the disturbed system actually returns higher fuel costs, emissions, losses and energy generated (see Table 4.5). However the closed-loop controller still presents better results than the open loop controller. It is necessary to provide a comparative analysis of obtained results with similar prior works in the literature [8]. The work in [8] is essentially a GTDR-DEED "open loop controller without disturbance" problem and the results are in the second column in Table 4.5. Comparing results with the closed-loop controller (fourth column in Table 4.5), as has been shown before it is seen that the closed-loop approach returns lower fuel costs ($ 290554.50 to the open loop's $ 291898.16), lower emissions (24332.84 lb to open loop's 24474.04 lb) and lower energy loss (264 MWh to open loop's 266 MWh) whilst the closed-loop approach to GTDR-DEED yields better energy curtailment (1957.38 MWh to open loop's 1953.02

MWh).

4.6 CHAPTER SUMMARY

In this chapter, a game theory based demand response program (GTDR) is integrated into both the DEED and PBDEED problems. The resultant GTDR-DEED model has the minimization of fuel costs, emissions and maximization of utility benefit as its objectives and the GTDR-PBDEED has the maximization of profit and utility benefit and the minimization of emissions as its objectives. Both models determine the optimal generator output, customer power curtailed and customer incentives. MPC technique (a closed-loop technique) has been applied in solving both the GTDR-DEED and GTDR-PBDEED models. Furthermore a comparison was provided between the performances of the open loop model with that of the closed-loop model. Obtained results indicate that the closed-loop model of GTDR-DEED and GTDR-PBDEED generally yields better results using the defined solution parameters than its open loop counterpart. Also the closed-loop model showed convergence and better handling of uncertainty and disturbances in system parameters.

CHAPTER 5

INCORPORATING GTDR INTO A GRID CONNECTED HYBRID MICROGRID

5.1 CHAPTER OVERVIEW

In this chapter, the economic dispatch of a microgrid with renewable energy sources and having demand response is presented. The microgrid is principally powered by conventional distributed generation generators and supplemented with stochastic renewable energy sources coupled with demand response. The grid connected operational modes is considered in this chapter and the optimal dispatch strategy is obtained by minimizing the generators cost and demand response cost whilst simultaneously satisfying the load demand constraints amongst other constraints. The developed mathematical model is tested on a case study under both operational modes and obtained results show the effectiveness of the developed model. Results from this chapter have been published in [15]

5.2 MATHEMATICAL MODEL OF MICROGRID

The microgrid used in this thesis, consists of conventional generators and RES at the supply side and demand response formulations at the customer side. The RES consists of a PV system and a wind energy system. The energy produced from a PV generator S_t in an hour is given as [73]

$$S_t = n_{pv} A_c Ipv_t, \tag{5.1}$$

where n_{pv} is the efficiency of the solar PV generator/array, Ipv_t (kW h/m^2) is the solar irradiation incident on the solar PV array per hour, A_c is the PV array's area and S_t is energy produced from from the solar generator on a hourly basis. The hourly output of a wind generator is highly dependent on the wind speed and the wind speed is given as [73]:

$$vhub_t = vref_t \left(\frac{hhub}{href}\right)^{\beta}, \tag{5.2}$$

where $vhub_t$ is the wind speed per hour at the required elevation $hhub$, $vref_t$ is the wind speed per hour at the reference elevation $href$ and β is defined as the power law exponent ranging from $\frac{1}{7}$ to $\frac{1}{4}$. For the purpose of this thesis, $\frac{1}{7}$ is used. To mathematically correlate the hourly wind speed to power generated, the following mathematical notation is used [73]:

$$W_t = 0.5 n_w \rho_{air} C_p A V^3, \tag{5.3}$$

where V is the wind velocity at hub height, ρ_{air} is the air density, C_p is the power coefficient of the wind turbine, depending the chosen design, A is the area of the wind turbine rotor swept area, n_w the efficiency of the wind generator and W_t is the wind generator energy output per hour.

The mathematical models for the microgrid at the supply side and the demand response model at the demand side are presented in the following subsections.

5.2.1 Grid-Connected Microgrid

One of the major advantages of a grid connected microgrid is that it is possible for power to be traded with the main grid. In this thesis, we assume that a trading scheme exists whereby power can either be sold to the main grid. This trading scheme exists to cater for the intermittent nature of RES. Thus if W_t is the forecast (maximum) wind power obtainable from the wind generator while S_t is the forecast (maximum) solar power obtainable from the solar generator, we define Pw_t as the power generated by the wind generator and Ps_t as the power generated by the solar generator in the microgrid at time t. If the microgrid's supply cannot meet its demand, then power has to be purchased from the main grid, and if the microgrid's supply exceeds its demand, then the excess power can be sold to the main grid. We thus denote Pr_t as the transferable power between the microgrid and the main grid at time t.

If an assumption is made that Locational Marginal Prices (LMP's) [40, 39] are used to purchase power between the main and micro grid from a specific interface bus (given as γ_t), then the total transaction cost for trading transferable power is $C_r(Pr_t)$ and is given as :

$$C_r(Pr_t) = \left\{ \begin{array}{cc} \gamma_t \times Pr_t & Pr_t > 0 \\ 0 & Pr_t = 0 \\ -\gamma_t \times Pr_t & Pr_t < 0 \end{array} \right\}. \tag{5.4}$$

The objective function in the grid connected mode is thus to minimize the fuel cost of the conventional generators and the transaction costs of the transferable power and is given as:

$$min \sum_{t=1}^{T} \sum_{i=1}^{I} C_i(P_{i,t}) + \sum_{t=1}^{T} C_r(Pr_t). \tag{5.5}$$

s.t.

$$\sum_{i=1}^{I} P_{i,t} + Pw_t + Ps_t + Pr_t = D_t, \tag{5.6}$$

$$P_{i,min} \leq P_{i,t} \leq P_{i,max}, \tag{5.7}$$

$$0 \leq Pw_t \leq W_t, \tag{5.8}$$

$$0 \leq Ps_t \leq S_t, \tag{5.9}$$

$$-Pr_{max} \leq Pr_t \leq Pr_{max}, \tag{5.10}$$

$$-DR_i \leq P_{i,t+1} - P_{i,t} \leq UR_i, \tag{5.11}$$

where Pr_t is the transferable power between the main grid and the microgrid at time t;
$C_r(Pr_t)$ is the transaction cost for trading transferable power at time t;
W_t is the forecast (maximum) wind power obtainable from the wind generator while S_t is the forecast (maximum) solar power obtainable from the solar generator.
$P_{i,t}$ is the power generated from conventional generator i at time t;
Pw_t is the power generated from the wind generator at time t;
Ps_t is the power generated from the solar generator at time t;
C_i is the fuel cost of conventional generator i;
D_t is the total system demand at time t;
$P_{i,min}$ and $P_{i,max}$ are the minimum and maximum capacity of generator i respectively;
Pr_{max} is the maximum power that can be transferred between the main grid and microgrid;
DR_i and UR_i are the maximum ramp down and up rates of conventional generator i respectively;
a_i and b_i are the fuel cost coefficients of conventional generator i respectively;
I and T are the number of conventional generators and the dispatch interval respectively.

The following is a brief description of the constraints:

- The first constraint (5.6) is the power balance constraint and ensures that at any time t, the total power generated from the conventional, wind and solar generators and the power transferred from the main grid equals the total demand.
- The second constraint is the generation limits constraint for the conventional generators (5.7) and ensures that the generator limits are not exceeded; and
- The third and fourth constraints are the generation limits constraint for the renewable generators ((5.8) and (5.9)). They ensure that the optimal values for the wind and solar generators are less than or equal to the forecast or maximum values; and
- The fifth constraint (5.10) is the limit for the transferable power between the main grid and microgrid. This is dictated by the physical characteristics of the transmission facilities between the main grid and microgrid; and
- The final constraint (5.11) is the conventional generator ramp rate limits constraints and ensures that the generator ramp rate limits are not violated.

For the sake of simplicity, the conventional generator fuel cost (5.12) is assumed to be a quadratic functions of the generators active power output and is given as [72]:

$$C_i(P_{i,t}) = a_i P_{i,t}^2 + b_i P_{i,t}, \tag{5.12}$$

5.2.2 Demand Response Model

The Demand Response (DR) model used in this thesis is an incentive based DR program utilizing concepts from Game Theory. Thus it is termed a Game Theory Demand Response Program (GTDR). For a full description of the modified GTDR model, the reader is referred to Chapter 3. As stated earlier, it has been structured in such a way that is beneficial to participating DR customers. Towards this end, is is extremely essential that the customers curtailment cost be accurately captured and factored into the design of the DR program. The customer outage cost function is assumed to be quadratic and is given by:

$$(K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j). \tag{5.13}$$

where $K_{1,j}$ and $K_{2,j}$ are the cost function coefficients of customer j;
$x_{j,t}$ is the amount of power curtailed by a customer j at time t;
$y_{j,t}$ is the incentive of a participating customer j at time t;
θ_j is the "customer type" [8, 36]. θ is normalized in the interval $0 \leq \theta \leq 1$ and categorizes the different kinds of customers based on their willingness or readiness to shed power, with $\theta = 0$ being the least willing and $\theta = 1$ the most willing customer.

The objective of the Game Theory Demand Response (GTDR) formulations is to maximize the microgrid operator's DR benefit:

$$max_{x,y} \sum_{t=1}^{T} \sum_{j=1}^{J} [\lambda_{j,t} x_{j,t} - y_{j,t}] \tag{5.14}$$

s.t.

$$\sum_{t=1}^{T} \left[y_{j,t} - (K_{1,j} x_{j,t}^2 + K_{2,j} x_{j,t} - K_{2,t} x_{j,t} \theta_j) \right] \geq 0, \; for \; j = 1, \ldots, J, \tag{5.15}$$

$$\begin{gathered} \textstyle\sum_{t=1}^{T} \left[y_{j,t} - (K_{1,j} x_{j,t}^2 + K_{2,j} x_{j,t} - K_{2,t} x_{j,t} \theta_j) \right] \geq \\ \textstyle\sum_{t=1}^{T} \left[y_{j-1,t} - (K_{1,j-1} x_{j-1,t}^2 + K_{2,j-1} x_{j-1,t} - K_{2,j-1} x_{j-1,t} \theta_{j-1}) \right] \;, \\ for \; j = 2, \ldots, J, \end{gathered} \tag{5.16}$$

$$\sum_{t=1}^{T} \sum_{j=1}^{J} y_{j,t} \leq UB, \tag{5.17}$$

$$\sum_{t=1}^{T} x_{j,t} \leq CM_j, \tag{5.18}$$

where $\lambda_{j,t}$ is the "value of power interruptibility" of participating customer j at time t. This parameter gives the cost of not delivering electric power to a particular location on the microgrid. $\lambda_{j,t}$ can be calculated from optimal power flow routines (OPF);
UB is the microgrid operator's total budget;
CM_j is the daily limit of interruptible energy for customer j;
J and T are the total number of customers and the total time interval respectively;
The following is a concise description of the constraints:
Constraint (5.15) is known as the "Individual rationality constraint". It's role is to constrain the customer benefit to surpass zero.
Constraint (5.16) is termed the "Incentive compatibility constraint". It's role is to make sure that the amount of compensation received by customers is commensurate with the amount of load they

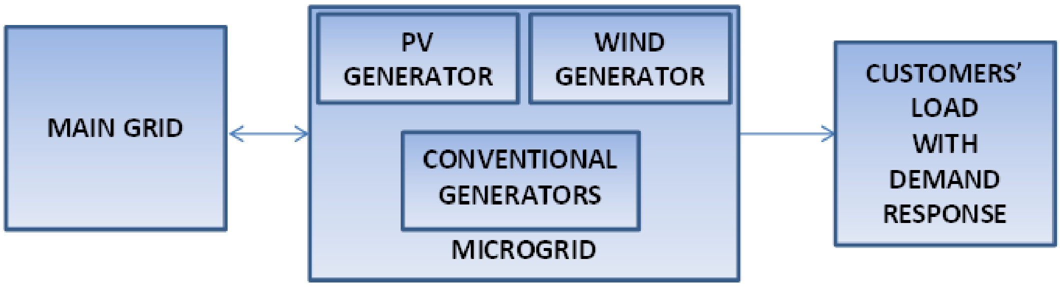

Figure 5.1: System set-up of a grid connected microgrid with a demand response model.

curtailed.

The role of constraint (5.17) is to make sure that the utility daily total program expenditure is lower than or equal to it's daily budgeted amount.

The role of constraint (5.18) is to make sure that the amount of load shed by each customer is less than the customers maximum allowable curtailable power.

5.2.3 Combined Microgrid and Demand Response Model

5.2.3.1 Grid-connected Microgrid with Demand Response Model

For the grid connected microgrid with a demand response model, there are two objective functions. One objective function seeks to minimize the fuel cost of conventional generators and the transaction cost for trading transferable power. The second objective function seeks to maximize the grid operator's DR benefit.

The mathematical formulation is presented below:

$$min\ w\left[\sum_{t=1}^{T}\sum_{i=1}^{I} C_i(P_{i,t}) + \sum_{t=1}^{T} C_r(Pr_t)\right] + (1-w)\left[\sum_{t=1}^{T}\sum_{j=1}^{J}[y_{j,t} - \lambda_{j,t}x_{j,t}]\right]. \tag{5.19}$$

subject to the following network constraints:

$$\sum_{i=1}^{I} P_{i,t} + Pw_t + Ps_t + Pr_t = D_t - \sum_{j=1}^{J} x_{j,t}, \tag{5.20}$$

$$P_{i,min} \leq P_{i,t} \leq P_{i,max}, \tag{5.21}$$

$$0 \leq Pw_t \leq W_t, \tag{5.22}$$

$$0 \leq Ps_t \leq S_t, \tag{5.23}$$

$$-Pr_{max} \leq Pr_t \leq Pr_{max}, \tag{5.24}$$

$$-DR_i \leq P_{i,t+1} - P_{i,t} \leq UR_i, \tag{5.25}$$

$$\sum_{t=1}^{T}[y_{j,t} - (K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j)] \geq 0,\ for\ j = 1, \ldots, J, \tag{5.26}$$

$$\begin{gathered} \textstyle\sum_{t=1}^{T}[y_{j,t} - (K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j)] \geq \\ \textstyle\sum_{t=1}^{T}[y_{j-1,t} - (K_{1,j-1}x_{j-1,t}^2 + K_{2,j-1}x_{j-1,t} - K_{2,j-1}x_{j-1,t}\theta_{j-1})]\ , \\ for\ j = 2, \ldots, J, \end{gathered} \tag{5.27}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{J} y_{j,t} \leq UB, \tag{5.28}$$

$$\sum_{t=1}^{T} x_{j,t} \leq CM_j, \tag{5.29}$$

where w and $1 - w$ are the objective function weights and the following condition is required to be satisfied when choosing weights:

$$w + (1 - w) = 1. \tag{5.30}$$

The variables to be determined by the optimization model are $x_{j,t}$,$y_{j,t}$, Pw_t, Ps_t, Pr_t and $P_{i,t}$.

5.3 SIMULATION RESULTS AND DISCUSSIONS

To verify the proposed microgrid energy management with demand response mathematical formulations, a case study consisting of three conventional (diesel) generator units, one wind generator, one solar generator and three customers is used. A scheduling interval of 24 hours is considered, however for the solar generator a scheduling interval of 8 hours (8 AM - 6 PM) is considered. The decision variables are $x_{j,t}$, $y_{j,t}$, Pw_t, Ps_t, Pr_t and $P_{i,t}$. Table 5.1 shows the conventional generator parameters.

Table 5.1: Data of the three-unit system.

i	a_i	b_i	$P_{i,min}$	$P_{i,max}$	DR_i	UR_i
1	0.06	0.5	0	4	3	3
2	0.03	0.25	0	6	5	5
3	0.04	0.3	0	9	8	8

Table 5.2 gives the initial hourly microgrid demand and the hourly values of power interruptibility ($\lambda_{j,t}$). The wind and solar generators have power ratings of between 0 - 11 kW and 0 - 15 kW respectively and the maximum power that can be transferred between the main grid and microgrid is given as 4 kW. For this microgrid it is initially assumed that all three customers have equal values of power interruptibility. Table 5.4 details the cost function coefficients, customer type and daily customer power limit. The assumption is that the microgrid operator knows the customers daily limit of interruptible energy (CM_j) which it then uses to rank the customers in order of increasing willingness to curb electric power. In other words, CM_j aids the microgrid operator in determining θ_j. Also, the microgrid operator knows the outage cost function coefficients of participating customers ($K_{1,j}$ and $K_{2,j}$) and the microgrid operator's daily budget (UB) is \$ 500. Values for W_t and S_t are adapted from [73] and shown in Table 5.3.

The Advanced Interactive Multidimensional Modelling System (AIMMS) [41] is utilized to build and solve the resulting mathematical models using the CONOPT solver.

5.3.1 Grid-Connected Mode

In the simulations for the grid connected microgrid (equations (5.19)-(5.30)), $w = 0.5$. Figure 5.2 shows the optimal output power from the three conventional generators, Figure 5.3 shows the optimal transferred power between the main grid and micro grid. Figure 5.4 shows the optimal customer power curtailed and incentive received for curtailment by each microgrid consumer. The complete model results detailing the optimal power generated by conventional generators, optimal power generated by wind and solar generators, optimal power transferred between the main grid and microgrid, optimal power curtailed by the customers and optimal incentive by the customers is shown in Tables 7, 8, 9 and 10 in the Appendix. Table 5.5 gives the total daily energy curtailed and incentive received by each of the customers.

Table 5.2: Total initial hourly demand and λ values

Time(h)	D_t (kW)	$\lambda_{j,t}$ ($)
1	31.83	1.57
2	31.40	1.40
3	31.17	2.20
4	31.00	3.76
5	31.17	4.50
6	32.10	4.70
7	32.97	5.04
8	34.10	5.35
9	37.53	6.70
10	38.33	6.16
11	40.03	6.38
12	41.17	6.82
13	39.67	7.30
14	41.70	7.80
15	42.10	8.50
16	41.67	7.10
17	40.70	6.80
18	40.07	6.30
19	38.63	5.80
20	36.40	4.20
21	34.10	3.80
22	32.80	3.01
23	32.50	2.53
24	32.00	1.42

5.3.2 Discussion of Results

A close look at results obtained from the simulations provides interesting underlying perspectives on the operational mode of the microgrid. It is observed that the conventional generators in the microgrid cannot satisfy demand alone. This now makes it imperative that the microgrid deploys the DR program and transacts with the main grid. From Figure 5.3 we see that when Pr_t is negative, power is being sold to the main grid whilst if it is positive, power is being bought from the main grid. Thus from the figure, it is observed that power is bought in the early hours of the morning and late at night when the renewable energy sources are not producing at their maximum. When the renewable energy sources are fully on stream, there is power available to sell to the main grid especially when the

Table 5.3: Forecast power from the wind and solar generators

Time(h)	W_t (kW)	S_t (kW)
1	7.56	0
2	7.50	0
3	8.25	0
4	8.48	0
5	8.48	0
6	9.42	0
7	9.82	0
8	10.35	7.99
9	10.88	10.56
10	11.01	13.61
11	10.94	14.97
12	10.68	15
13	10.42	14.78
14	10.15	14.59
15	9.67	13.56
16	8.98	11.83
17	8.37	10.17
18	7.61	7.66
19	6.70	0
20	5.72	0
21	7.21	0
22	7.75	0
23	7.88	0
24	7.69	0

Table 5.4: Customer cost function coefficients, customer type and daily customer curtailable energy limit

j	$K_{1,j}$	$K_{2,j}$	θ_j	CM_j
1	1.079	1.32	0	30
2	1.378	1.63	0.45	35
3	1.847	1.64	0.9	40

solar generator comes on stream. Due to the fact that power from the conventional generators costs less than power transferred from the main grid, the conventional generators have to produce close to their maximum output (see Figure5.2).

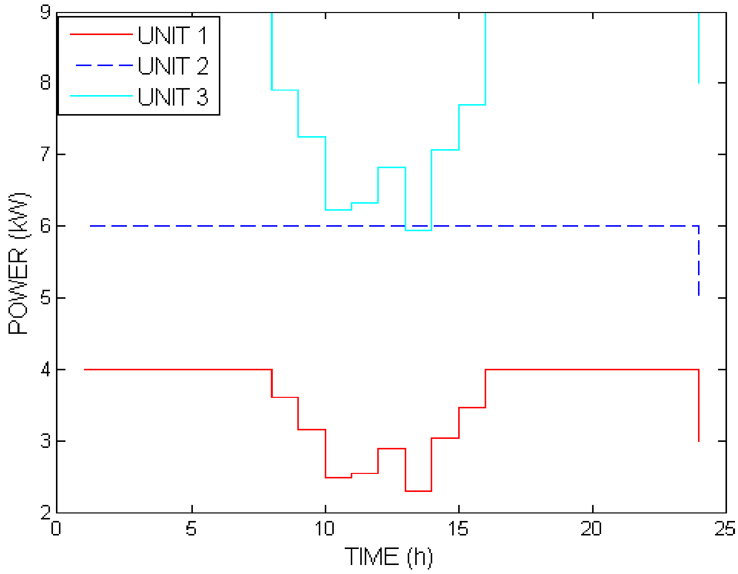

Figure 5.2: Optimal power from conventional generators

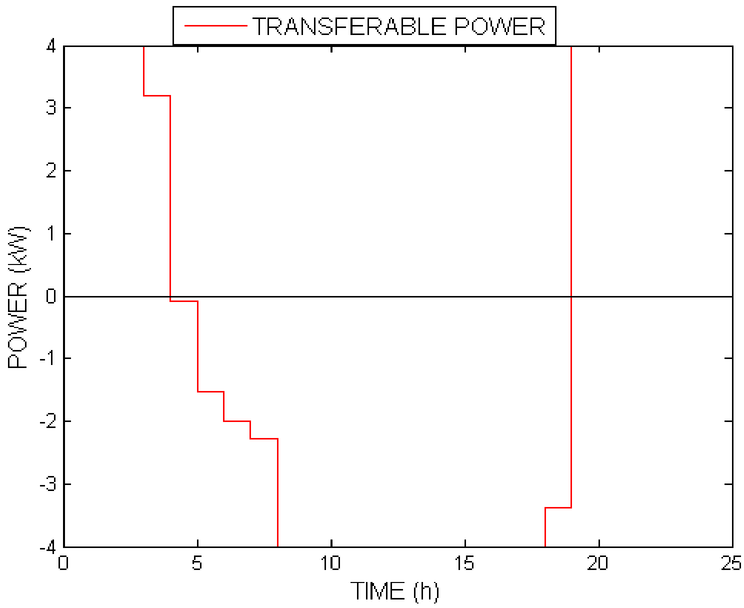

Figure 5.3: Optimal power transferred between main grid and microgrid

Figure 5.4 shows the power curtailed and incentive received by each customer. Table 5.5 shed more light on these results as they show that the customers receive incentive payments in line with the amount of load they curtail (i.e. customer willingness). Thus, Customer 3 has a greater incentive than Customers 1 and 2, as Customer 3 curtails the greatest amount of energy and is thus the most willing customer. Customer 1 curtails the least amount of energy and thus receives the least amount

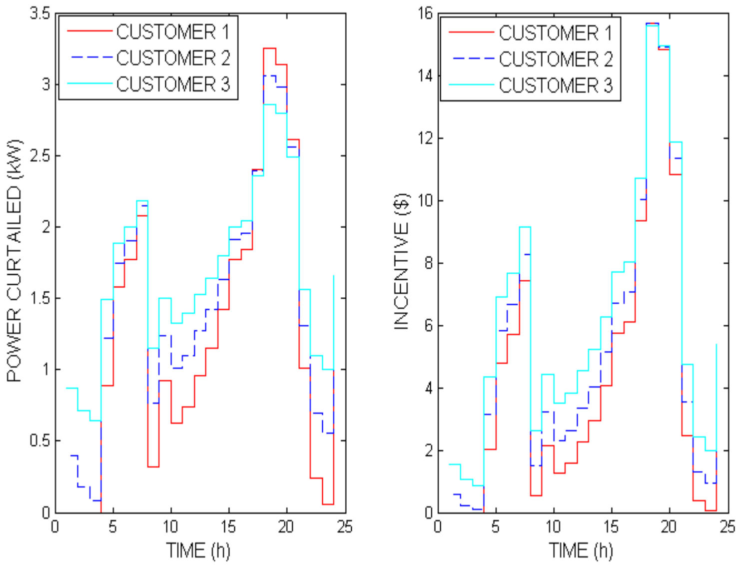

Figure 5.4: Customer power curtailed and incentive paid

Table 5.5: Total energy curtailed and customer incentive received

j	Total energy curtailed (kWh)	Total incentive ($)
1	30	103.27
2	35	122.66
3	40	145.32

of incentive. This show that the "incentive compatibility constraint" is not violated.

In simulations performed, it is assumed that the grid operator places equal preference to the two objective functions ($w = 0.5$). This is known as the Base Case. However it is crucial in multi-objective optimization problems to analyse and view the impact of giving varied preference weights to objectives and how they influence the microgrid solutions. Thus (w is varied from 0 to 1). When ($w = 1$), it means that the objective is to minimize fuel cost /transaction cost with no attention paid to the grid operator DR benefit. When ($w = 0$), it means the objective is to maximize the grid operator DR benefit and ignore the minimization of the fuel cost/ transaction cost. Results of this experiment is presented in Table 5.6. The analysis is done by collecting six parameters from the model. The parameters collected are the total conventional power cost (i.e. the total cost of power from the conventional generators), total transferred power transaction cost (i.e. the total cost of power transferred between the main grid and microgrid), total customer incentive (i.e. daily total monetary amount received by the customers as incentive for shedding power), total customer energy curtailed (i.e. total energy all customers curtailed over a 24 hour period), total conventional energy generated (i.e. total energy generated by the conventional generators) and total transferred energy (i.e. total energy transferred between the main grid and the microgrid). The results of the simulations are shown in Table 5.6 and show the trade off's between the two objectives. The results show that lower costs are achieved in the microgrid when the grid operator's DR benefit is maximized at the expense of minimizing fuel/transaction costs.

To further investigate the robustness of our model, we perform sensitivity analysis of the model to the values of power interruptibility ($\lambda_{j,t}$). It is initially assumed that in the microgrid, all three customers have equal $\lambda_{j,t}$, however we investigate the effect of varying $\lambda_{j,t}$ on obtained results. We assume that Customer 1 has a $\lambda_{j,t}$ that is 90% of it's initial $\lambda_{j,t}$, while Customer 3 has a $\lambda_{j,t}$ that is 110% of their initial $\lambda_{j,t}$. Figure 5.5 shows the different values of power interruptibility for each customer. From Table 5.7 we see this effect on the results on of the microgrid and especially on the customers. We observe that a clear link between λ and the customer is shown as the customer who had a λ decrease, also had a reduction in incentive for the same amount of power curtailed, the customer with the same λ had essentially the same incentive whilst the customer with λ increase had an increase in incentive. It is worth noting that the incentive compatibility constraint from game theory still holds and is not violated.

Finally we investigate the effect of CM_j on the grid connected microgrid model. In the default case C3 in Table 5.8, the total daily energy curtailed by all three customers is 105 kWh. We vary the total value from between 95 kWh to 115 kWh and check the sensitivity of the microgrid via our obtained solutions to CM_j. From Table 5.9 we see very clearly the effect. As the load customers agree to curtail increases, the conventional energy generated by conventional generators reduces and thus the cost reduces. Again as more energy is curtailed by the customers, the incentive increases. This is perfectly rational and expected. Furthermore as the energy curtailed by customers increases, there is an increase in the energy to be transferred between the main grid and the microgird (see Figure 5.6). This also leads to a corresponding increase in the total transferred power transaction cost. A breakdown of this transferred power in Table 5.10 shows that as CM_j increases the power bought from the main grid reduces while there is an increase in the power sold by the microgrid to the main grid. Thus it follows that if we want to be able to sell more power to the microgrid (reduce the instances of Pr_t having positive values in Figure 5.3 and Figure 5.6) we have to curtail more power. This insight is very important especially in instances where the price for selling power to the main grid differs from the buying price.

5.4 CHAPTER SUMMARY

In this chapter, the energy management problem for a microgrid incorporating a demand response program was investigated. The demand response program is a game theory based demand response

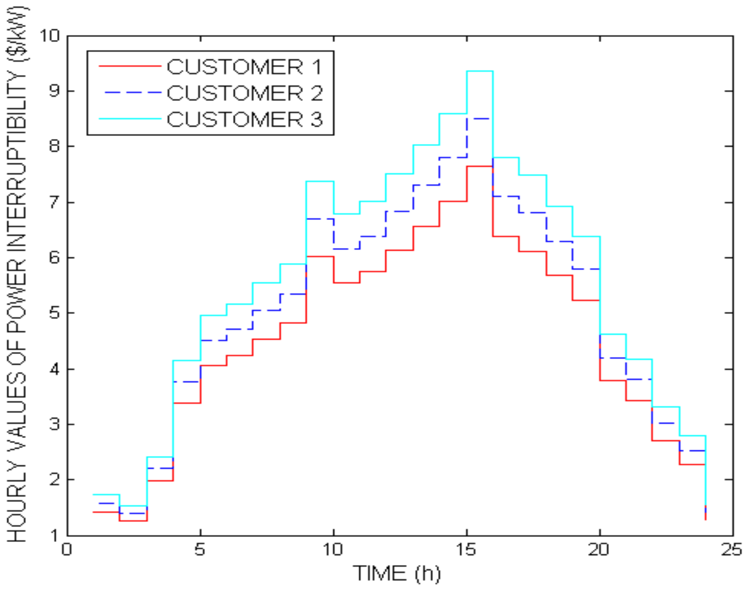

Figure 5.5: Varying values of power interruptibility.

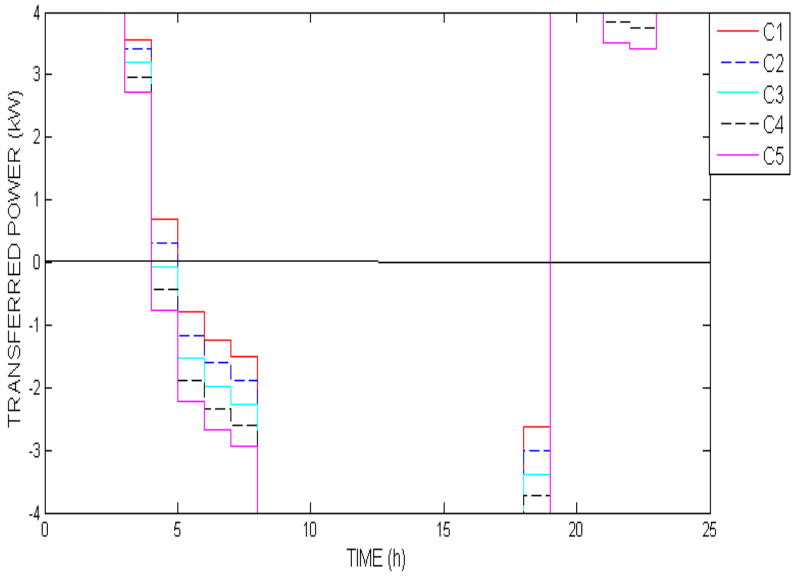

Figure 5.6: Effect of varying CM_j on Pr_t

program (GTDR) and the grid connected operational mode for a microgrid is investigated. The objective is to minimize the fuel cost of conventional generators and the transaction cost for trading transferable power and at the same time maximize the grid operator DR's benefit. The optimization model has a scheduling interval of 24 hours and determines the optimal customer power curtailed, optimal customer incentive, optimal power generation schedule for the conventional generators and

Table 5.6: Investigating the effect of w on the grid connected microgrid.

	$w = 0$	$w = 0.1$	$w = 0.2$	$w = 0.3$	$w = 0.4$
Total Conventional Power Cost ($)	237	240	241	244	246
Total Transferred Power Transaction Cost ($)	417	383	381	393	407
Total Customer Incentive ($)	340	349	360	361	363
Total Customer Energy Curtailed (kWh)	101	103	105	105	105
Total Conventional Energy Generated (kWh)	411	416	417	420	423
Total Transferred Energy (kWh)	83.5	76.9	76.2	78.2	80.8
			w=0.5		
Total Conventional Power Cost ($)			**250**		
Total Transferred Power Transaction Cost ($)			**427**		
Total Customer Incentive ($)			**371**		
Total Customer Energy Curtailed (kWh)			**105**		
Total Conventional Energy Generated (kWh)			**428**		
Total Transferred Energy (kWh)			**84.5**		
	$w = 0.6$	$w = 0.7$	$w = 0.8$	$w = 0.9$	$w = 1.0$
Total Conventional Power Cost ($)	256	264	270	270	270
Total Transferred Power Transaction Cost ($)	443	436	454	450	450
Total Customer Incentive ($)	391	433	500	500	500
Total Customer Energy Curtailed (kWh)	105	105	105	105	105
Total Conventional Energy Generated (kWh)	434	443	450	450	450
Total Transferred Energy (kWh)	87.9	86.9	89.9	88.9	88.9

Table 5.7: Total customer energy curtailed and incentive paid for grid connected microgrid with varying lambda.

j	Total Energy Curtailed (kWh)	Total Incentive ($)
1	30	102.42
2	35	122.49
3	40	146.92

optimal power to be transferred between the main grid and microgrid. The Advanced Interactive Multidimensional Modelling System (AIMMS) is used to solve the developed model, and obtained results indicate that incorporating DR programs into the energy management of microgrid problem is helpful and introduces optimality at both the supply and demand side of the microgrid. Sensitivity analysis of obtained results to the weighting factor, value of power interruptibility and total value of customer power curtailed was performed to validate the robustness of obtained solutions.

Table 5.8: Varying CM_j.

j	C1 (kWh)	C2 (kWh)	C3 (kWh)	C4 (kWh)	C5 (kWh)
1	27.5	28.75	**30**	31.25	32.5
2	32.5	33.75	**35**	36.25	37.5
3	35	37.5	**40**	42.5	45
Total	95	100	**105**	110	115

Table 5.9: Effect of Varying CM_j on the Grid Connected Microgrid.

	C1	C2	C3	C4	C5
Total Conventional Power Cost ($)	255	252	**250**	248	246
Total Transferred Power Transaction Cost ($)	414	420	**427**	433	438
Total Customer Incentive ($)	320	345	**371**	399	428
Total Customer Energy Curtailed (kWh)	95	100	**105**	110	115
Total Conventional Energy Generated (kWh)	434	431	**428**	425	423
Total Transferred Energy (kWh)	82.4	83.4	**84.4**	85.1	85.5

Table 5.10: Breakdown of the effect of varying CM_j on the power transferred between main grid and microgrid

	C1	C2	C3	C4	C5
Total Energy Bought from Main Grid (kWh)	36.25	35.72	**35.19**	34.55	33.66
Total Energy Sold to the Main Grid (kWh)	-46.13	-47.67	**-49.18**	-50.57	-51.83

CHAPTER 6

THE DEED PROBLEM WITH A TIME OF USE DR PROGRAM

6.1 CHAPTER OVERVIEW

In this chapter, a Time of Use Demand Response (TOUDR) program is incorporated into the multi-objective dynamic economic emission dispatch (DEED) optimization problem. The resulting optimization problem is termed TOUDR-DEED. The DR program has been developed using the customers' Price Elasticity Matrices (PEM), which models the customer behaviour under different conditions. An interactive control strategy between utility and consumers is proposed for the combined TOUDR-DEED model which determines the optimal power to be generated by minimizing fuel, emissions and DR costs and also the optimal price. The customer in light of the utility's optimal price minimizes its electricity cost and optimally schedules power consumption. Obtained results indicate that voluntary DR programs are mutually beneficial to utility and consumers alike and can bring about desired demand reduction in the power system. Results from this chapter have been published in [14].

6.2 DYNAMIC ECONOMIC EMISSIONS DISPATCH

The mathematical representation is presented below [5]:

$$min \sum_{i=1}^{T} \sum_{k=1}^{N_g} C_k(P_{k,i}), \tag{6.1}$$

$$min \sum_{i=1}^{T} \sum_{k=1}^{N_g} E_k(P_{k,i}), \tag{6.2}$$

with

$$C_k(P_{k,i}) = a_k + b_k P_{k,i} + c_k P_{k,i}^2, \tag{6.3}$$

$$E_k(P_{k,i}) = d_k + e_k P_{k,i} + f_k P_{k,i}^2, \tag{6.4}$$

subject to the following network constraints:

$$\sum_{k=1}^{N_g} (P_{k,i}) = D_i + loss_i, \tag{6.5}$$

$$P_{k,min} \leq P_{k,i} \leq P_{k,max}, \tag{6.6}$$

$$-DR_k \leq P_{k,i+1} - P_{k,i} \leq UR_k, \tag{6.7}$$

$$loss_i = \sum_{k=1}^{N_g} \sum_{j=1}^{N_g} P_{k,i} B_{j,k} P_{j,i}, \tag{6.8}$$

where

$P_{k,i}$ is the power generated from generator k at time i;

C_k is the fuel cost of generator k;

E_k is the emissions cost for generator k;

D_i is the total system demand at time i;

$loss_i$ is the total system losses at time i;

$P_{k,min}$ and $P_{k,max}$ are the minimum and maximum capacity of generator k respectively;

DR_k and UR_k are the maximum ramp down and up rates of generator $k$respectively;

a_k, b_k and c_k are the fuel cost coefficients of generator k respectively;

e_k, f_k and g_k are the emission cost coefficients of generator k respectively;

$B_{j,k}$ is the jk th element of the loss coefficient square matrix of size N_g;

N_g and T are the number of generators and the dispatch interval respectively.

The following is a brief description of the constraints:

- The first constraint (6.5) is termed the power balance constraint. This constraint compels the total power generated at time t to equal the sum of the power demand and transmission losses.
- Constraint (6.6) is the constraint for generator limits and restricts the amount of generated power to the allowable range for each generator; and
- Constraint (6.7) is the generator ramp rate constraints and restricts the ramp rates for the generators to their allowable ranges.

The multi-objective optimization can be transformed into a single objective function using a weighting factor w subject to the same constraints (6.5)-(6.7).

$$min\left[w\sum_{i=1}^{T}\sum_{k=1}^{N_g}C_k(P_{k,i})+(1-w)\sum_{i=1}^{T}\sum_{k=1}^{N_g}E_k(P_{k,i})\right]. \tag{6.9}$$

6.3 PRICE BASED DR PROGRAMS

As stated before, in price based DR programs there is a time variation of electricity tariffs. The price based DR program used in this chapter is the TOUDR program. For this kind of program, the price of elasticity is calculated for peak, off-peak and standard times based on the energy cost in each time period. The aim is to encourage consumers to curtail their energy use to take advantage of favourable prices [50]-[51].

6.3.1 Price Elasticity Matrices

Elasticity is a yard stick used to measure the sensitivity of consumer reactions to price. Ideally, if the price of specific goods or services increases, then the demand for that service decreases. Therefore, an elasticity coefficient is simply a measure to indicate the change in demand of a commodity stemming from a change in price of that commodity. Mathematically, elasticity can be represented as:

$$E=\frac{\triangle d/d_0}{\triangle p/p_0}, \tag{6.10}$$

$$E=\frac{\triangle dp_0}{\triangle pd_0}, \tag{6.11}$$

where $\triangle d$ is the change in demand, $\triangle p$ change in price, d_0 is the initial demand and p_0 initial price [55]. It is necessary to mention that the above elasticities are known as self elasticities. Another variant of elasticity is the cross elasticity. Cross elasticities measure the change in demand of a specific commodity, stemming from a change in the price of another different commodity. From a power systems perspective, if a price increase in off-peak hours causes demand in these off-peak hours to decrease, then we measure with self elasticity. When a price increase in off-peak hours leads to an increase in demand in peak hours, then we utilize cross elasticity. As a rule, self elasticities are negative and cross elasticities are positive. The mathematical representation of cross elasticities is given below:

$$E(i,j)=\frac{\triangle d_i/d_{0i}}{\triangle p_j/p_{0j}}, \tag{6.12}$$

$$E(i,j)=\frac{\triangle d_i\times p_{0j}}{\triangle p_j\times d_{0i}}, \tag{6.13}$$

where i and j indicate two different time periods such as peak and off-peak, d_{0i} denotes the initial demand at time instant i, p_{0j} is the initial price at time instant j. $\triangle p_j$ is the change in price at time

j and $\triangle d_i$ is the change in demand at time i. For a power system, if all the elasticities are to be measured over a specific interval (i.e. a 24 hour period), then there is the need for an elasticity matrix, in which the diagonal represent the self elasticities and the off-diagonal elements represent the cross elasticities.

$$\begin{bmatrix} E(1,1) & E(1,2) & ... & ... & E(1,24) \\ E(2,1) & E(2,2) & ... & ... & E(2,24) \\ ... & ... & E(i,j) & ... & ... \\ ... & ... & ... & ... & ... \\ E(24,1) & E(24,2) & ... & ... & E(24,24) \end{bmatrix}. \tag{6.14}$$

The load economic profile for Price Based DR programs is given below [56]:
Let $B(d_i)$ be the total customer benefit in time i from the use of d_i kWh of electrical energy and let p_i be the electricity price during hour i, therefore
Customers profit

$$S_i = B(d_i) - p_i d_i, \tag{6.15}$$

To maximize customers' profit, $\frac{\partial S_i}{\partial d_i}$ should be equal to zero, therefore

$$\frac{\partial Bd(i)}{\partial d_i} = p_i, \tag{6.16}$$

The most common benefit function is the quadratic benefit function defined as [56]:

$$B(d_i) = B(d_{0i}) + p_{0i}(d_i - d_{0i}) \left[1 + \frac{d_i - d_{0i}}{2E(i,i)d_{0i}}\right], \tag{6.17}$$

where

d_{0i} is the initial demand at time i, $i = 1, 2, \ldots, 24$;

p_{0i} is the initial demand at time i, $i = 1, 2, \ldots, 24$;

$E(i,i)$ is the self elasticity;

$B(d_{0i})$ is the benefit at d_{0i};

$$\frac{\partial Bd(i)}{\partial d_i} = p_{0i} \left[1 + \frac{d_i - d_{0i}}{E(i,i)d_{0i}}\right], \tag{6.18}$$

Equating (6.16) and (6.18) we obtain that:

$$d_i = d_{0i} \left[1 + \frac{E(i,i)[p_i - p_{0i}]}{p_{0i}}\right], \tag{6.19}$$

Similarly for the multi period elastic loads, it is assumed that demand rescheduling occurs. Thus, the demand at time i is a function of prices at times i=$1, 2, \ldots, T$. In this thesis we assume $T = 24$ and the cross elasticity in (6.12) is reproduced below:

$$E(i,j) = \frac{\triangle d_i/d_{0i}}{\triangle p_j/p_{0j}}, \tag{6.20}$$

Working with the linearity assumption that $\frac{\triangle d_i}{\triangle p_j}$ is constant for $i, j = 1, 2, 3, \ldots, 24$, the following relationship is obtained between price and demand:

$$d_i = d_{0i} \left[1 + \frac{\sum_{j=1}^{24} E(i,j)[p_j - p_{0j}]}{p_{0j}} \right], \tag{6.21}$$

Combining the single period (6.19) and multi period (6.21) we obtain:

$$d_i = d_{0i} \left[1 + \frac{E(i,i)[p_i - p_{0i}]}{p_{0i}} + \frac{\sum_{j=1}^{24} E(i,j)[p_j - p_{0j}]}{p_{0j}} \right]. \tag{6.22}$$

6.4 COMBINED INTERACTIVE DEMAND RESPONSE - DYNAMIC ECONOMIC EMISSIONS ECONOMIC DISPATCH (DR-DEED)

The DR target loads fall into three different classes [53],[55]. The load classes are: inflexible loads, flexible loads and night-time loads. For instance the inflexible loads are the customer loads that must be switched on. Customers would not curtail these loads to participate in demand response programs as they impact heavily on the benefit of customers. For residential customers, examples of these kinds of loads are cookers, stoves, refrigerators and heating systems. Depending on the industry, some loads are also inflexible for industrial customers like industrial motors for some critical processes. The other loads are loads that customers are willing to curtail. However, customers have varying load responses to price increases hence different degrees of flexibility. Flexible loads are loads that customers are completely flexible about. They can readily adjust these loads to price variations. Examples of such kinds of loads for residential customers are vacuum cleaners, dishwashers and water purifiers/boilers. Industrial examples of this kind of load are industrial pumps. Finally night-time loads are loads that the customer can schedule to hours with the lowest electricity prices, e.g. late in the night and very early hours of the morning. Examples of such kinds of loads for residential customers are washing machines, electric hot water heaters and tumble dryers. For industrial customers, these can include furnaces. It is assumed that there is a mix of these classes of loads in the power system with the total power system load, a summation of the three different classes. It is further assumed that the utility has an estimate of each class of load and each load class has a different price elasticity matrix (PEM). The PEM's are obtained through a historical analysis of customers' demand response to increases or decreases (deviations) in the price of electricity. Each load class has a different PEM, i.e. a 24×24 square matrix. The difference between the PEM of each load class is the position of the non-zero elements in the matrix. Equations (6.23), (6.24) and (6.25) show sample PEM structure for inflexible, flexible and night-time loads respectively.

$$E_{inflexible} = \begin{bmatrix} E(1,1) & E(1,2) & 0 & 0 & 0 & 0 & 0 \\ E(2,1) & E(2,2) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & E(3,3) & E(3,j) & 0 & 0 & 0 \\ 0 & 0 & E(i,3) & E(i,j) & E(i,22) & 0 & 0 \\ 0 & 0 & 0 & E(22,j) & E(22,22) & 0 & 0 \\ 0 & 0 & 0 & 0 & E(23,22) & E(23,23) & E(23,24) \\ 0 & 0 & 0 & 0 & 0 & E(24,23) & E(24,24) \end{bmatrix}, \quad (6.23)$$

$$E_{flexible} = \begin{bmatrix} E(1,1) & 0 & 0 & 0 & 0 & 0 & 0 \\ E(2,1) & E(2,2) & 0 & 0 & 0 & 0 & 0 \\ E(3,1) & E(3,2) & E(3,3) & 0 & 0 & 0 & 0 \\ E(4,1) & E(4,2) & E(4,3) & E(4,j) & 0 & 0 & 0 \\ E(5,1) & E(5,2) & E(5,3) & E(5,j) & 0 & 0 & 0 \\ 0 & E(6,2) & E(6,3) & E(6,j) & 0 & 0 & 0 \\ 0 & 0 & E(7,3) & E(7,j) & 0 & 0 & 0 \\ 0 & 0 & 0 & E(8,j) & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & E(19,22) & E(19,23) & 0 \\ 0 & 0 & 0 & 0 & E(20,22) & E(20,23) & E(20,24) \\ 0 & 0 & 0 & 0 & E(21,22) & E(21,23) & E(21,24) \\ 0 & 0 & 0 & 0 & E(22,22) & E(22,23) & E(22,24) \\ 0 & 0 & 0 & 0 & 0 & E(23,23) & E(23,24) \\ 0 & 0 & 0 & 0 & 0 & 0 & E(24,24) \end{bmatrix}, \quad (6.24)$$

$$E_{night-time} = \begin{bmatrix} E(1,1) & E(1,2) & ... & E(1,j) & ... & E(1,23) & E(1,24) \\ E(2,1) & E(2,2) & ... & E(2,j) & ... & E(2,23) & E(2,24) \\ 0 & 0 & E(3,3) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & E(i,j) & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & E(22,22) & 0 & 0 \\ E(1,23) & E(2,23) & ... & E(i,23) & ... & E(23,23) & E(23,24) \\ E(1,24) & E(2,24) & ... & E(i,24) & ... & E(23,24) & E(24,24)) \end{bmatrix}. \quad (6.25)$$

Since there are three types of load classes m;$m = 1, 2, 3$, the total system load is a summation of the three load classes. We define d_{0i}^m as the initial estimated participating load of class m at time i. The total initial system load d_{0i}=$\sum_{m=1}^{3} d_{0i}^m$ and d_i^m is defined as the responding or participating load of class m at time i. The total final system load d_i=$\sum_{m=1}^{3} d_i^m$. The cost of the voluntary DR program to the utility at time i can therefore be defined as:

$$COSTDR_i = p_{0i}d_{0i} - p_i d_i \tag{6.26}$$

Thus, the weighted single objective DR-DEED mathematical formulation from the utility perspective can be gives as shown in equation (6.27):

$$min\left[w\left[\sum_{i=1}^{T}\sum_{k=1}^{N_g}C_k(P_{k,i}) + \sum_{i=1}^{T}COSTDR_i\right] + (1-w)\sum_{i=1}^{T}\sum_{k=1}^{N_g}E_k(P_{k,i})\right]. \tag{6.27}$$

subject to the following network constraints:

$$\sum_{k=1}^{N_g}(P_{k,i}) = D_i + loss_i, \tag{6.28}$$

$$P_{k,min} \leq P_{k,i} \leq P_{k,max}, \tag{6.29}$$

$$-DR_k \leq P_{k,i+1} - P_{k,i} \leq UR_k, \tag{6.30}$$

where

$$d_i^m = d_{0i}^m\left[1 + \frac{E_m(i,i)[p_i - p_{0i}]}{p_{0i}} + \frac{\sum_{j=1}^{24}E_m(i,j)[p_j - p_{0j}]}{p_{0j}}\right]. \tag{6.31}$$

An interactive control strategy is used in this research. The reason behind an interactive control strategy is to obtain a final optimal price and energy levels satisfactory to both the utility and customers. Thus, the utility initially determines the optimal price (p_i) and suggested energy level (d_i) using (equations (6.27)-(6.31)). The customers respond by scheduling their appliances and loads in light of the provided utility price. The responding customers' energy levels are sent back to the utility and the utility revises the PEM's using equation (6.13). The utility again determines the price in light of the responding customers' energy levels and revised PEM's. This process is repeated until convergence is achieved. Figure 6.1 shows the complete flow chart for the proposed interactive control strategy. The intention of this interactive design of the DR program is to seek an optimal price signals and a desired level of market participation of the DR program.

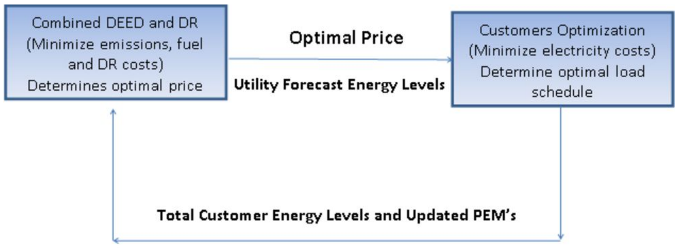

Figure 6.1: Flowchart of the Interactive TOUDR-DEED Program.

6.4.1 Customer Side Objective Function and Constraints

The participating customer first needs to classify his loads into the three available loads classes: flexible, inflexible and night-time loads. The customer's optimization model has an objective function that minimizes the electricity bill/costs of all three kinds of loads. In the model formulation given below, i represents time slot and a represents the loads of the industrial customer. The decision variable is binary V_{ia} which is either 1 or 0 and represents if the load a is switched on or off in time slot i. The consumers are assumed to be acting rationally and seek to minimize electricity costs of all loads, devices, machines or appliances. We assume a scheduling interval of one hour, thus in one day there will be 24 time slots. The objective function and constraints are represented mathematically below:

$$min \sum_{i=1}^{24} \sum_{a=1}^{A} B_a V_{ia} p_i, \tag{6.32}$$

subject to :

$$\sum_{S_a}^{E_a} V_{ia} = Z_a, \tag{6.33}$$

$$\sum_{a=1}^{A} B_a V_{ia} \leq EL_i, \tag{6.34}$$

where

B_a is the energy consumption of load a in each time slot (MWh) respectively;

V_{ia} is the decision variables either 1 or 0 and states if the load a is switched on or off in time slot i;

p_i is utility defined price/tariff for each time slot in South African Rands ZAR/kWh;

Z_a is the total number of time slots required for loads a to complete its task;

EL_i is the total energy level of the participating customer at the last round;

S_a is the start time slot for load a;

E_a is the end time slot for loads a;

A is the maximum number of load a, the industrial customer wants to schedule.

The following is a brief explanation of the constraints:

- Constraint (6.33) ensures that there are sufficient time slots for a load, device or machine to complete its tasks. This is also the constraint that handles the flexibility of the appliance/load. For instance, let us assume two time slots are required for an appliance to complete a task, i.e., Z_a= 2. If the customer is flexible about the appliance, i.e., the appliance must not run at specific time slots, the difference between the start time slot and end time slot would be greater than Z_a. If the customer is however inflexible about the appliance, the difference between start time slot S_a and end time slot E_a would be exactly Z_a. For night-time loads, both start time slot S_a and end time slot E_a would be either in the early hours of the morning or late at night.

- The final constraint (6.34) ensures that the customer's new energy level does not exceed the energy levels of the last round. For the initial optimization it is the maximal estimated energy level for that customer. This ensures that there is actually relief in the power system.

6.5 NUMERICAL SIMULATIONS, OBTAINED RESULTS AND DISCUSSIONS

In this section, we present the parameters and results of the combined interactive DR-DEED optimization model both at the utility side and at the customer side. The proposed mathematical optimization models are tested on two example test systems. The first example test system is a six unit test system and the second is a ten unit test system. In both numerical simulations, the default weighting factor $w = 0.5$.

Table 6.1: Data of the Six-Unit System.

i	a_i	b_i	c_i	e_i	f_i	g_i	$P_{i,min}$	$P_{i,max}$	DR_i	UR_i
1	240	7	0.007	13.8593	0.32767	0.00419	100	500	120	80
2	200	10	0.0095	13.8593	0.32767	0.00419	50	200	90	50
3	220	8.5	0.009	40.2669	-0.54551	0.00683	80	300	100	65
4	200	11	0.009	40.2669	-0.54551	0.00683	50	150	90	50
5	220	10.5	0.008	42.8955	-0.51116	0.00461	50	200	90	50
6	190	12	0.0075	42.8955	-0.51116	0.00461	50	150	90	50

6.5.1 Test System 1

Test system 1 consists of six unit generators at the supply side and two aggregated industrial customers at the customer side. At the utility side, the goal is to obtain the optimal price p_i and forecast demand d_i while at the customer side, the major aim is to obtain the optimal customer schedule in view of the utility determined optimal price and forecast demand.

6.5.1.1 Utility Side Optimization

The fuel cost coefficients and the emission cost coefficients modified are obtained from [5] and shown in Table 6.1. The initial electricity tariff values are obtained from Eskom's (the South African utility) Tariff book [54] and shown in Table 6.2. The total initial demand is also shown in Table 6.2. The TOU periods are assumed to be off-peak (23:00-04:00) hours, standard (05:00-06:00, 11:00-17:00 and 21:00-22:00) hours and peak (07:00-10:00 and 18:00-20:00) hours [54]. The assumed TOU elasticity values obtained from [53] are given in Table 6.3. The transmission loss formula coefficients for the six unit test system are given by equation (6.35).

$$B = 10^{-4} \times \begin{bmatrix} 0.420 & 0.051 & 0.045 & 0.057 & 0.078 & 0.066 \\ 0.051 & 0.180 & 0.039 & 0.048 & 0.045 & 0.060 \\ 0.045 & 0.039 & 0.195 & 0.051 & 0.072 & 0.057 \\ 0.057 & 0.048 & 0.051 & 0.213 & 0.090 & 0.075 \\ 0.078 & 0.045 & 0.072 & 0.090 & 0.207 & 0.096 \\ 0.066 & 0.060 & 0.057 & 0.075 & 0.096 & 0.255 \end{bmatrix} per MW \tag{6.35}$$

Table 6.2: Initial TOU Prices and Total Demand.

Time(h)	TOU Prices (R/kWh)	Total Demand (MW)
1	0.2595	963
2	0.2595	948
3	0.2595	942
4	0.2595	935
5	0.4669	955
6	0.4669	963
7	0.7021	1263
8	0.7021	1380
9	0.7021	1360
10	0.7021	1210
11	0.4669	1165
12	0.4669	1143
13	0.4669	1110
14	0.4669	1117
15	0.4669	1170
16	0.4669	1150
17	0.4669	1221
18	0.7021	1420
19	0.7021	1490
20	0.7021	1450
21	0.4669	1238
22	0.4669	1159
23	0.2595	975
24	0.2595	960

Table 6.3: TOU Self and Cross Elasticity.

One	Peak	Off-peak	Standard
Peak	-0.1	0.016	0.012
Off-Peak	0.016	-0.1	0.01
Standard	0.012	0.01	-0.1

6.5.1.2 Customer Side Optimization

Most logical customers are always on the lookout for ways or measures to use energy efficiently and do so at minimal cost [57],[58]. In this research, the goal of the customer is to minimizes

Table 6.4: Load Data for First Customer.

	B_a	S_a	E_a	Z_a
Flexible				
LOAD 1	5	1	24	12
LOAD 2	4	1	24	12
Inflexible				
LOAD 3	15	1	24	24
LOAD 4	10	1	24	24
Night-time				
LOAD 5	5	1 and 21	6 and 24	5
LOAD 6	1.5	1 and 21	6 and 24	4

Table 6.5: Load Data for Second Customer.

	B_a	S_a	E_a	Z_a
Flexible				
LOAD 1	15.7	1	24	12
LOAD 2	5.3	1	24	12
LOAD 3	14	1	20	11
Inflexible				
LOAD 4	15	1	24	24
Night-time				
LOAD 5	5	1 and 21	6 and 24	5
LOAD 6	5	1 and 21	6 and 24	4

their electricity bill/costs and optimally schedule their appliance and hence their energy plan in light of the provided utility price. To verify the mathematical formulations for the customer side (equations (6.32-6.34)), two aggregated industrial customers are assumed. Both aggregated industrial customers consist of 20 and 15 identical sub-customers respectively and there is a regulator which can schedule these loads. The underlying principles can easily be extended to residential or other kinds of customers. The customer just has to identify the loads that can be grouped under flexible, night-time and inflexible. For the sake of simplicity, it is further assumed that the customer classification does not change and each customer has six loads. Table 6.4 and Table 6.5 show the load data for the two industrial sub-customers.

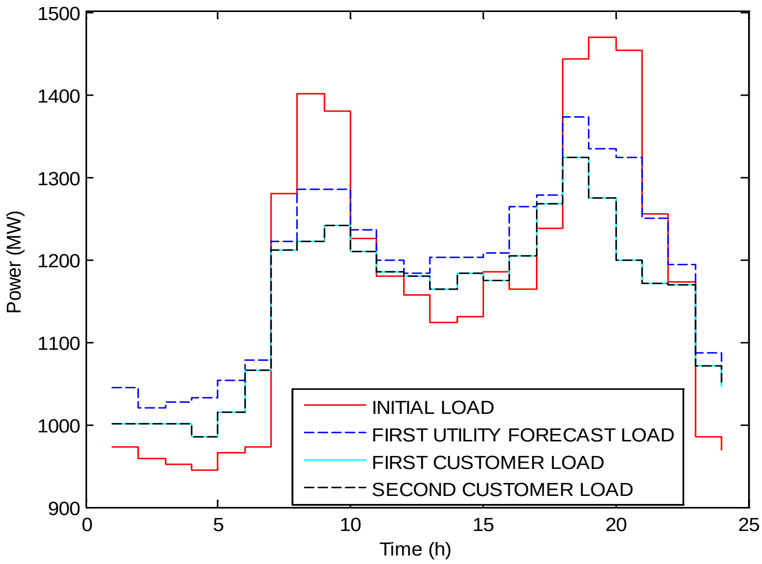

Figure 6.2: Load profiles at different stages of interactive control for test system 1.

6.5.1.3 Solution Methodology and Results

Both optimization models are built and solved using the Advanced Interactive Multidimensional Modelling System (AIMMS) [41]. After the first utility optimization (6.27-6.31)) and the corresponding customer side optimization, (equations (6.32)-(6.34)) the customers return their energy consumption to the utility. The utility revises the PEM's and again performs optimization. This interactive control process continues until convergence is reached. In this research, after the third round of interactive control, convergence was achieved. Figure 6.2 shows the load profiles at different stages of the interactive control process, Figure 6.3 shows the utility determined price at different stages of the interactive control process, Figure 6.4 shows the initial system load and the final optimal converged load and finally Figure 6.5 shows the initial price and the final utility price.

Figure 6.6 - Figure 6.11 shows the optimal power generated for all generators under initial system load (normal DEED) and final optimal converged load (TOUDR-DEED).

The final optimal scheduling solution is shown in Table 6.6 and Table 6.7 for customers in the first and second groups respectively.

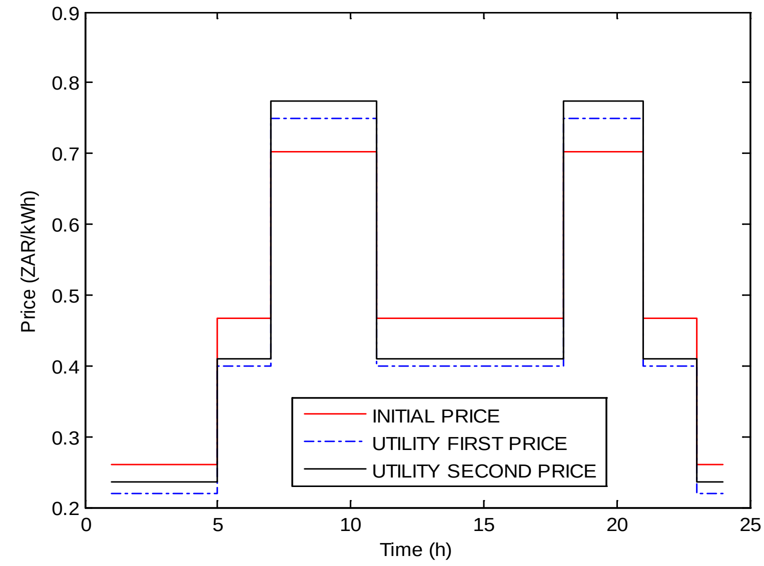

Figure 6.3: Utility determined price at different stages of interactive control for test system 1.

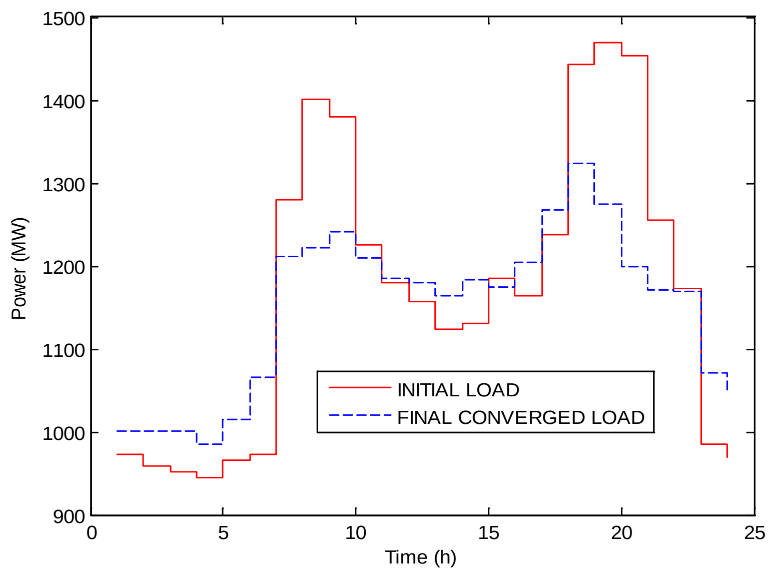

Figure 6.4: Initial Load and Final Converged Load for test system 1.

6.5.2 Test System 2

Test system 2 consists of ten unit generators at the supply side and two aggregated industrial customers at the customer side. Similar to the first example test system, we verify the

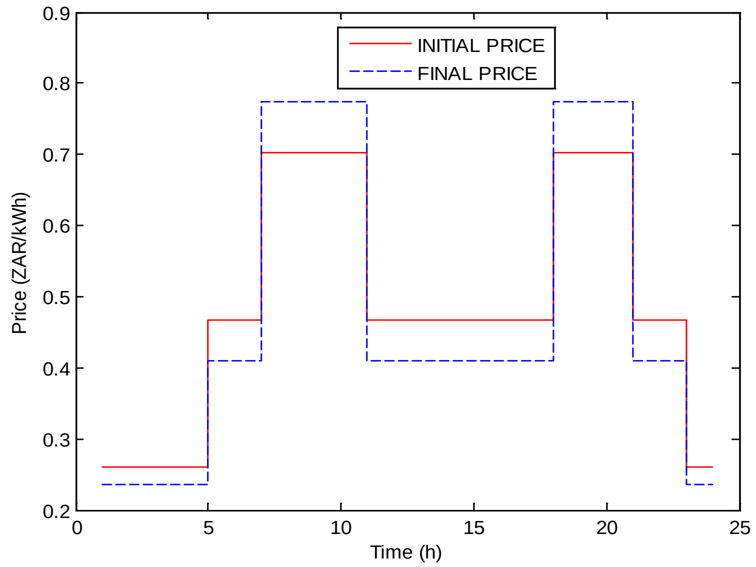

Figure 6.5: Initial Price and Final Price for test system 1.

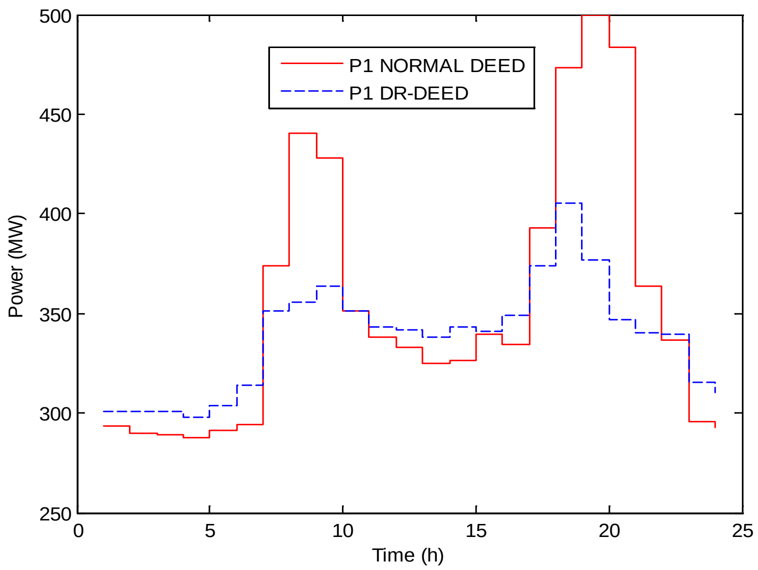

Figure 6.6: Generation output of unit 1 for test system 1.

mathematical formulations at both the utility and the customer side.

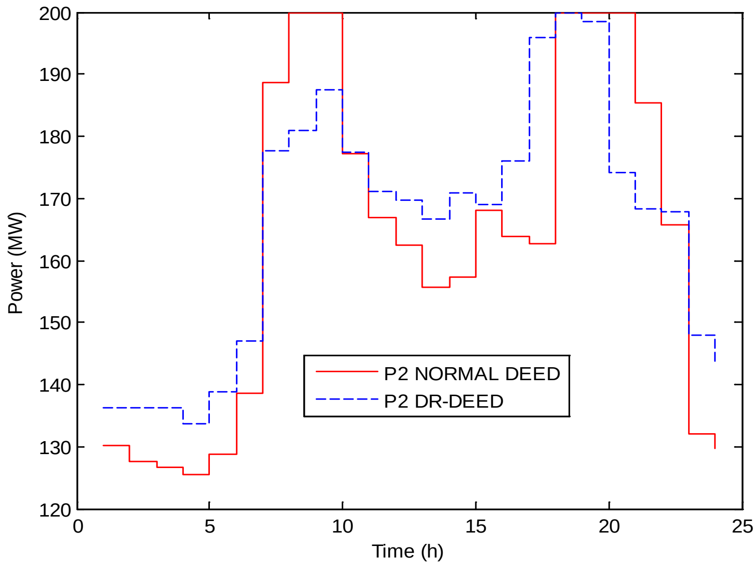

Figure 6.7: Generation output of unit 2 for test system 1.

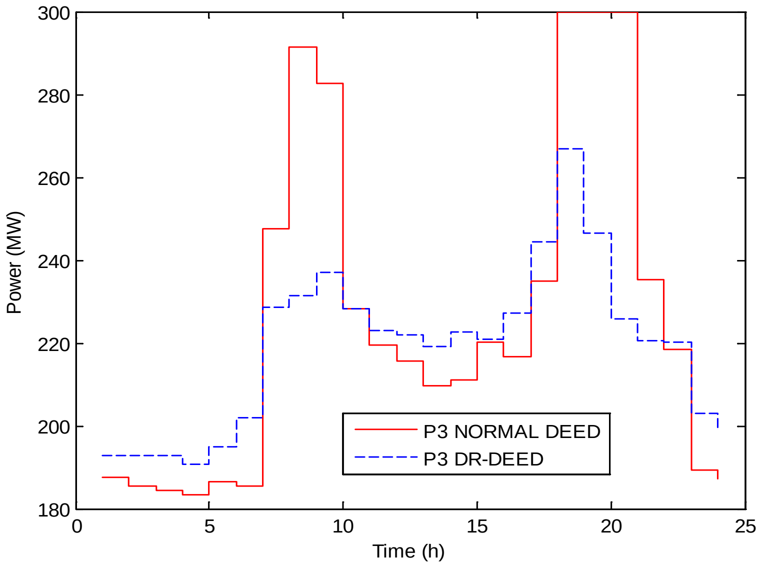

Figure 6.8: Generation output of unit 3 for test system 1.

6.5.2.1 Utility Side Optimization

The fuel cost coefficients and the emission cost coefficients modified are obtained from [9] and shown in Table 6.8. The initial electricity tariff values are similarly obtained from Eskom's (the South African utility) Tariff book [54] and shown in Table 6.9. The total initial demand

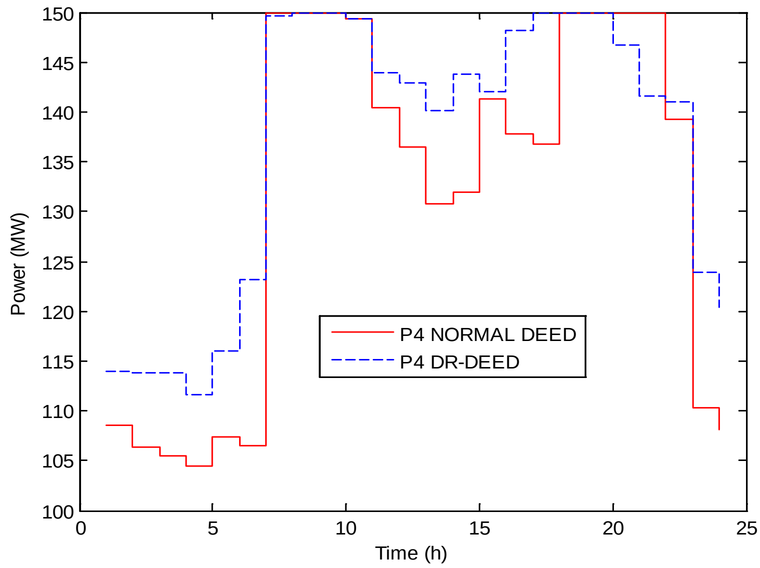

Figure 6.9: Generation output of unit 4 for test system 1.

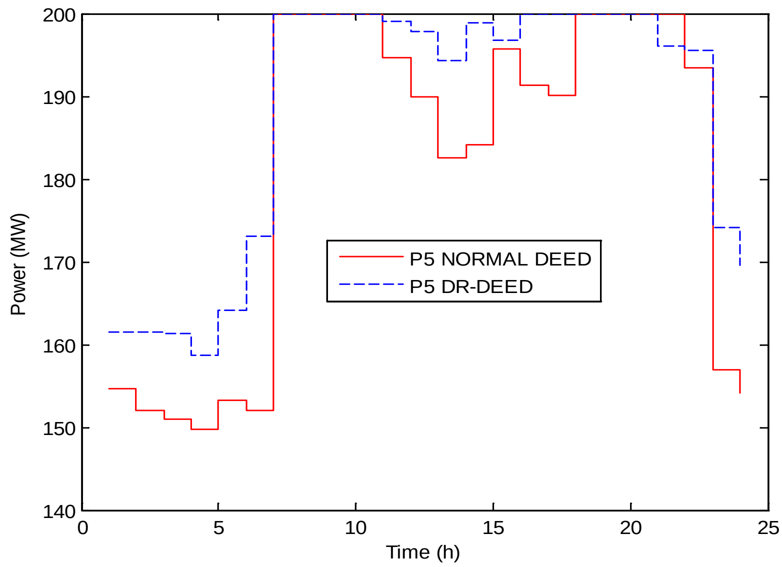

Figure 6.10: Generation output of unit 5 for test system 1.

is also shown in Table 6.9. The TOU periods and elasticity values are as assumed in the first example test system given in Table 6.3. The transmission loss formula coefficients for the ten unit test system are given by equation (1) and it is shown in the appendix.

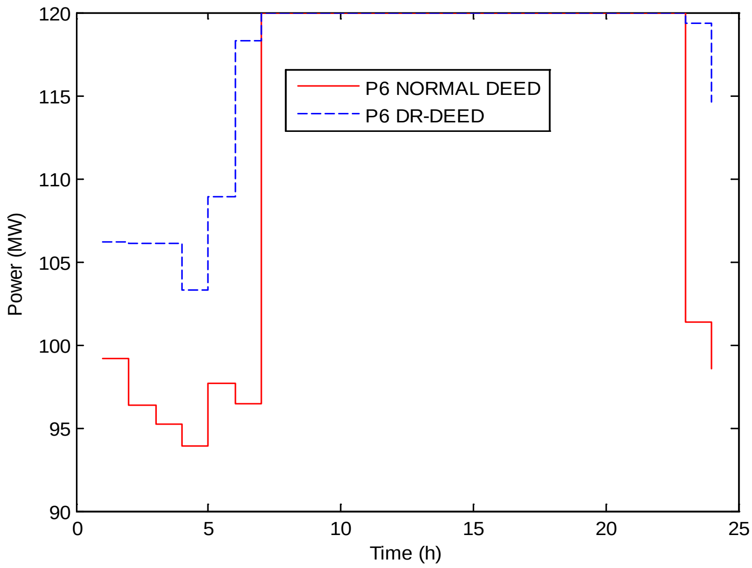

Figure 6.11: Generation output of unit 6 for test system 1.

Table 6.6: Optimal Load Scheduling Model Solution for Customer 1 (Test System 1).

LOADS	TIME SLOTS
LOAD 1	7-11,13-14,16,18-21
LOAD 2	7-11,14,16-20,22
LOAD 3	1-24
LOAD 4	1-24
LOAD 5	5-6,21-23
LOAD 6	1-3,22

Table 6.7: Optimal Load Scheduling Model Solution for Customer 2 (Test System 1).

LOADS	TIME SLOTS
LOAD 1	1-4,11-15,17,23-24
LOAD 2	6-10,13,16,18-22
LOAD 3	7-10,12,15-20
LOAD 4	1-24
LOAD 5	5-6,21-22,24
LOAD 6	5-6,21-22

6.5.2.2 Customer Side Optimization

To verify the mathematical formulations for the customer side, (equations (6.32)-(6.34)) two aggregated industrial consumers are assumed. The load data for both aggregated customer

Table 6.8: Data of the Ten-Unit System.

i	a_i	b_i	c_i	e_i	f_i	g_i	$P_{i,min}$	$P_{i,max}$	DR_i	UR_i
1	958.2	21.6	0.00043	360.0012	-3.9864	0.04702	150	470	80	80
2	1313.6	21.05	0.00063	350.0056	-3.9524	0.04652	135	460	80	80
3	604.97	20.81	0.00039	330.0056	-3.9023	0.04652	73	340	80	80
4	471.6	23.9	0.0007	330.0056	-3.9023	0.04652	60	300	50	50
5	480.29	21.62	0.00079	13.8593	0.3277	0.0042	73	243	50	50
6	601.75	17.87	0.00056	13.8593	0.3277	0.0042	57	160	50	50
7	502.7	16.51	0.00211	40.2669	-0.5455	0.0068	20	130	30	30
8	639.4	23.23	0.0048	40.2669	-0.5455	0.0068	47	120	30	30
9	455.6	19.58	0.10908	42.8955	-0.5112	0.0046	20	80	30	30
10	692.4	22.54	0.00951	42.8955	-0.5112	0.0046	55	55	30	30

groups in similar to the one given in Table 6.4 and Table 6.5, the only difference is in the number of customers within each aggregated group. It is assumed that both aggregated industrial customer groups consist of 30 and 20 identical customers respectively and there is a regulator that can schedule these loads.

6.5.2.3 Solution Methodology and Results

The solution methodology employed is similar to the first example test system. AIMMS is again used to solve both optimization problems. In this research, after the third round of interactive control, convergence was achieved. Figure 6.12 shows the initial system load and the final optimal converged load, Figure 6.13 shows the initial price and the final utility price, Figure 6.14 and Figure 6.15 shows the optimal power generated for generators 1 and 2 under initial system load (normal DEED) and optimal converged load (DR-DEED) respectively. The final customer optimal scheduling solution is shown in Table 6.10 and Table 6.11 for customers in the first and second groups respectively.

(6.27-6.31))

6.5.3 Discussion of Results

In summary, a concise and sequential description of the steps followed in this research is described below:

Table 6.9: Initial TOU Prices and Total Demand.

Time(h)	TOU Prices (R/kWh)	Total Demand (MW)
1	0.2595	1036
2	0.2595	1110
3	0.2595	1258
4	0.2595	1406
5	0.4669	1480
6	0.4669	1628
7	0.7021	2072
8	0.7021	2146
9	0.7021	2220
10	0.7021	2072
11	0.4669	1924
12	0.4669	1776
13	0.4669	1702
14	0.4669	1628
15	0.4669	1480
16	0.4669	1554
17	0.4669	1776
18	0.7021	1924
19	0.7021	2072
20	0.7021	1924
21	0.4669	1628
22	0.4669	1628
23	0.2595	1332
24	0.2595	1184

Table 6.10: Optimal Load Scheduling Model Solution for Customer 1 (Test System 2).

LOADS	TIME SLOTS
LOAD 1	7-10,12-16,18-20
LOAD 2	7-8,10-18,20
LOAD 3	1-24
LOAD 4	1-24
LOAD 5	1,3,5,21,24
LOAD 6	1-2,4,21

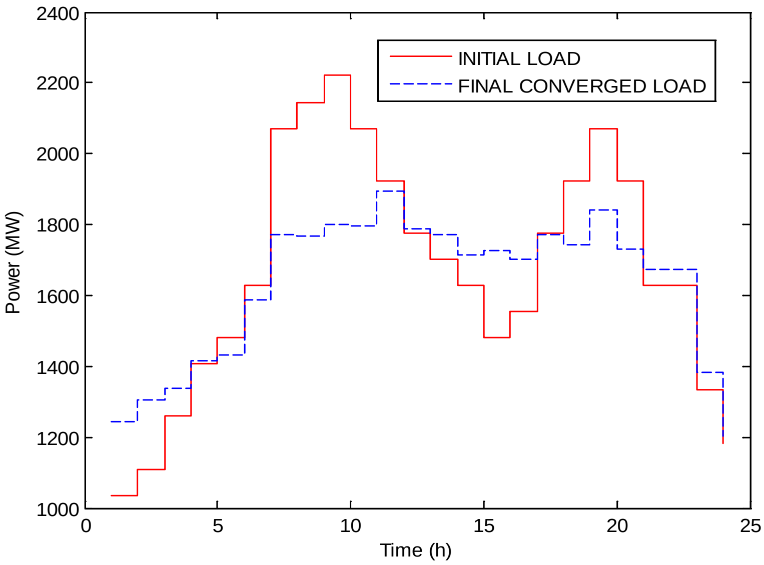

Figure 6.12: Initial Load and Final Converged Load for test system 2.

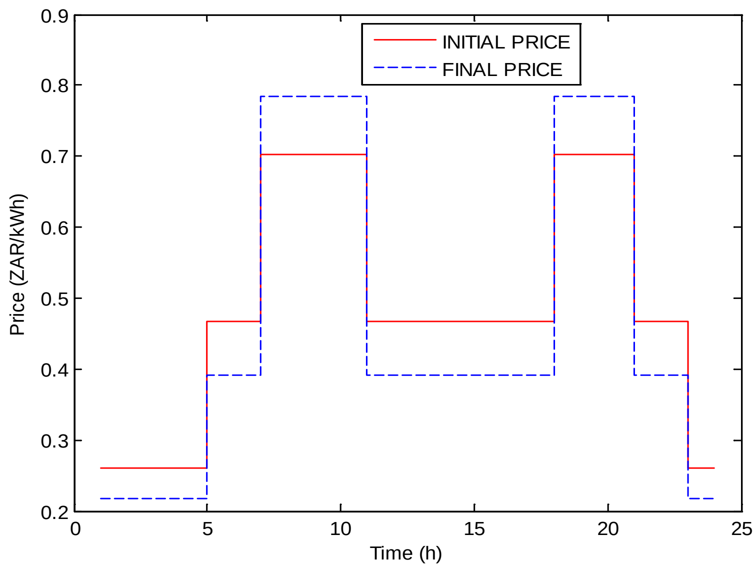

Figure 6.13: Initial Price and Final Price for test system 2.

- Step 1: Obtain initial load profile and initial pricing scheme (initial load in Figure 6.2 and initial price in Figure 6.3 respectively).

- Step 2: The utility performs DR-DEED optimization using (equations (6.27-6.31)) and obtains the utility forecast load and price (first utility forecast load in Figure 6.2 and

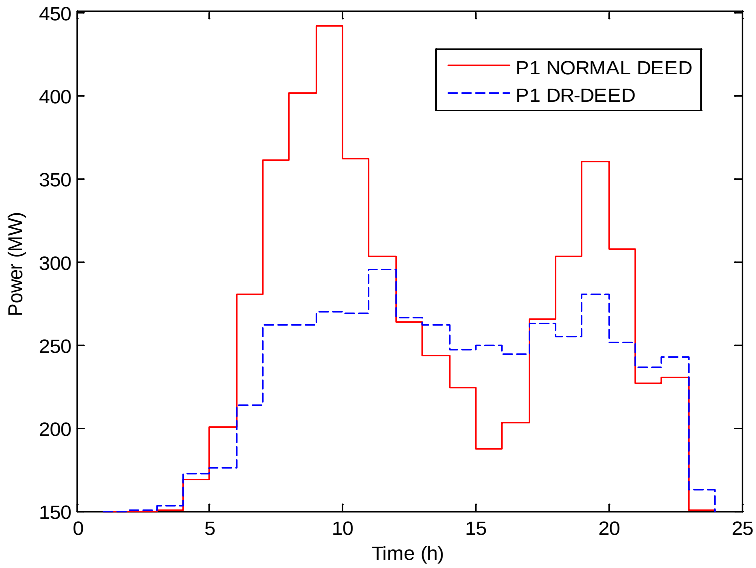

Figure 6.14: Generation output of unit 1 for test system 2.

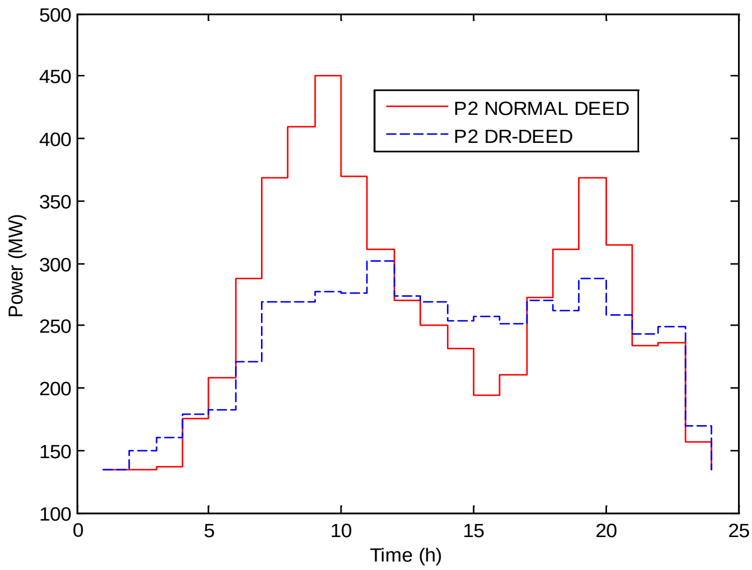

Figure 6.15: Generation output of unit 2 for test system 2.

utility first price in Figure 6.3 respectively).

- Step 3: In light of the utility's given price the customers schedules their loads using (equations (6.32-6.34)) and returns the information back to the utility (first customer load in Figure 6.2).

Table 6.11: Optimal load scheduling model solution for customer 2 (Test System 2).

LOADS	TIME SLOTS
LOAD 1	4,6,9,11-13,16-17,19,21-23
LOAD 2	3,7-8,10-15,18,20,22
LOAD 3	7-11,14-15,17-20
LOAD 4	1-24
LOAD 5	2,5-6,21-22
LOAD 6	2,5-6, 22

- Step 4: The utility revises the PEM using equation (6.13) and again performs DR-DEED optimization using (equations (6.27-6.31)) and obtains the utility price (utility second price in Figure 6.3).

- Step 5: The customers again schedule their loads using (equations (6.32-6.34)) in light of the new price and returns the information back to the utility (second customer load in Figure 6.2).

This interactive scheme continues until convergence is reached. In test system 1, this happens when the second customer load equals the first customer load (see second customer load and first customer load in Figure 6.2. In this context, we define convergence as when the utility's given price does not cause a change in the customers prior load schedule, thus obtaining an electricity price and demand mutually acceptable to the utility and customers whilst simultaneously reducing energy levels.

The TOUDR program helps to reduce power system congestion especially around peak times. It also shifts the load to the off peak and standard periods. Most of the generators produce more in off peak/standard periods in order to reduce power production in peak periods. From the numerical simulations at the customer side, the model returns the optimal time slots to use the devices/ appliances. The flexibility of the appliances are dictated by the peculiar needs of the customer and these determine the constraints of the mathematical model. The advantage of the interactive control strategy is the information flow is uni-directional and energy levels are obtained that provide power system relief and are acceptable to the utility and consumers. The model can easily be extended to accommodate a wider variety of consumers. Tables 6.12 and 6.13 give the optimal cost, emissions and loss for DEED and TOUDR-DEED for both

Table 6.12: Optimal results with various weighting factor values (Test System 1).

	COST (DEED) ($)	EMISSIONS (DEED) (lb)	LOSS (DEED) (MW)	COST (DR-DEED) ()($)	EMISSIONS (DR-DEED) (lb)	LOSS (DR-DEED) (MW)
$w = 0$	342946	30995	339	341581.09	29281.75	317.62
$w = 0.1$	342348	31034	342	340878.08	29331.20	321.74
$w = 0.2$	341503	31200	345	340245.37	29463.34	326.01
$w = 0.3$	340673	31501	349	339449.65	29766.07	331.12
$w = 0.4$	339927	31950	354	338657.95	30249.68	337.59
$w = 0.5$	**339105**	**32696**	**360**	**337873.11**	**30992.79**	**345.02**
$w = 0.6$	338450	33612	366	337123.86	32055.84	353.44
$w = 0.7$	337935	34751	373	336525.81	33411.16	362.62
$w = 0.8$	337613	36033	381	336136.54	34970.12	372.33
$w = 0.9$	337502	37236	389	335980.10	36580.42	382.12
$w = 1.0$	337541	38475	397	336021.41	38078.87	391.45

example test systems. From both tables, the impact of DR on cost, emission and losses can be clearly seen. DR brings a reduction in total demand and hence this brings about a corresponding decrease in costs, emissions and losses. Both tables also show the variation of cost, emission and losses when weighting factor w ranges from 0 to 1. This analysis has become vital in optimization with more than a single objective function in order to validate the effect of augmented ranking of objectives over another on obtained solutions. In this case, it is observed that as w increases, the cost decreases and the emission and losses increases. This means that as the weighting factor is increased (the importance of minimizing emissions is decreased, while the importance of minimizing costs increases), emissions and losses actually increase and costs decrease.

6.6 CHAPTER SUMMARY

In this chapter, a modification of the DEED formulation with price based DR programs is presented. The objective in the optimization problem is to minimize the fuel, emissions and DR costs subject to the conventional DEED constraints and some extra constraints. Investigations with different price elasticity matrices were assumed and the TOU tariffs were used as the initial prices, giving rise to a TOU based DR-DEED problem formulation. As an interactive control strategy is used, two customer mathematical models are presented where

Table 6.13: Optimal results with various weighting factor values (Test System 2).

	COST (DEED) ($)	EMISSIONS (DEED) (lb)	LOSS (DEED) (MW)	COST (DR-DEED) ()($)	EMISSIONS (DR-DEED) (lb)	LOSS (DR-DEED) (MW)
$w = 0$	1054224	248251	1322	1032488	201833.38	1208.98
$w = 0.1$	1053155	248335	1322	1032317.21	201849.93	1209.34
$w = 0.2$	1051556	248616	1322	1031558.71	201990.82	1209.81
$w = 0.3$	1051049	248799	1322	1031149.41	202145.70	1210.29
$w = 0.4$	1050295	249232	1323	1030376.40	202601.31	1210.98
$w = 0.5$	**1049419**	**249992**	**1324**	**1028962.79**	**203827.13**	**1212.25**
$w = 0.6$	1047376	252671	1326	1025657.35	208270.98	1215.23
$w = 0.7$	1043923	259564	1330	1020300.86	218584.69	1221.68
$w = 0.8$	1039460	274423	1343	1015861.03	233260.72	1233.86
$w = 0.9$	1034599	308177	1374	1010121.27	273874.56	1271.85
$w = 1.0$	1032513	378260	1424	1006570.04	385080.80	1353.53

the customer classifies their loads into flexible, inflexible and night-time loads and optimizes their demand in light of the utility suggested demand and final price. The customer schedules their load in order to minimize their electricity consumption and hence their electricity costs. Obtained simulation results indicate that DR programs reduce the total load curve and peak demand.

CHAPTER 7

CONCLUSION

7.1 CHAPTER OVERVIEW

This chapter concludes the thesis and provides probable future directions for more research.

7.2 CONCLUSIONS

In this thesis, various DR programs are integrated into the DEED and it's variant PBDEED. This thesis was motivated primarily by the fact that joint and simultaneous consideration of both programs will yield better solutions than individual considerations of either DEED and DR. Most complex systems or networks have been shown to operate better when considered as a whole instead of in parts. Thus, this thesis begun by introducing the research and it's motivation and proceeded with a literature review of the topics under consideration. It was stated in the literature review that there are three major research trends concerning DEED. The first research focus is the integration of DR programs into DEED/PBDEED problems. The second trend is concerned with solution methodologies. The literature is replete with instances of novel solution methods for solving DEED problems. The third research thrust deals with the dispatch of RES in a power grid. These RES are known to be intermittent in nature. These three research trends are considered to some degree in this thesis. Thus in this thesis various models of DEED/PBDEED integrated with DR is presented. The GTDR-DEED, GTDR-PBDEED and TOUDR-DEED models are developed and empirically tested with practical system set-ups. Also the MPC solution approach is considered and applied on a GTDR-DEED and GTDR-PBDEED problem. Again two RES (solar and wind) are considered when they are powering a grid connected microgrid that also has a GTDR program. Results from all the mathematical validations are very encouraging and show the suitability and practicability of the developed mathematical frameworks.

In Chapter 3, the DEED formulation was with a game theory based DR program (GTDR-DEED). The model developed from game theory also included extra practical constraints like maximum power targets and total budget. In addition, two constraints: individual rationality constraint and the incentive compatibility constraint were modified and optimized over a day instead of just an hour. Results showed that the DR-DEED program reduce total demand over a 24 hour period by 1953.02 MW in the first scenario and reduces the total demand by 2670.57 MW in the second scenario.

In Chapter 4, (GTDR) was integrated into both the DEED and PBDEED problems. The GTDR-DEED model is for a regulated environment, whilst the GTDR-PBDEED is for a de-regulated environment which is price dependent. For both models MPC was utilized. MPC was chosen for it's ability to handle uncertainty and disturbance in the model parameters. Obtained results indicate that indeed MPC is superior to the open loop approach and moreover the closed loop solutions converge to the open loop solutions.

In Chapter 5, a grid connected micorgrid powered by RES and conventional generators with a GTDR program was considered. The proposed model is able to buy power from the grid in the event of power shortage and sell to the grid when there is excess power. Also the GTDR program reduces demand on the microgrid. A sensitivity analysis of obtained results to some model parameters was also performed.

Finally in Chapter 6, the DEED formulation is integrated with a TOUDR program. Various price elasticity matrices were used representing the different types of customer load classification and an interactive control strategy was utilized in other to get mutually acceptable electricity load demand and price.

All the aforementioned models presented in this thesis, shows the advantages of having DR programs in a power system, either in the main grid or in a microgrid. DR programs when integrated with DEED/PBDEED curtail demand thereby bringing relief to the power system. They also provide for reduced costs and emissions at the supply side of the power spectrum. Taken together, joint consideration of DEED and DR should be adopted by utilities and her customers in the management of today's power system.

7.3 RECOMMENDATIONS AND FUTURE WORK

There are a number of possible future research extensions of this thesis. They are briefly listed below:

- The incorporation of penalties via a penalty function for customers who refuse to curtail their load and those who curtail their load but not the hitherto agreed amount.

- The design of a DR scheme for power systems powered by Combined Heat and Power (CHP) generators. This DR scheme should be incentive based and will give incentives to customers curtailing their heat consumption.

- The incorporation of the unit commitment problem into the GTDR-DEED, GTDR-PBDEED and TOUDR-DEED problems.

- A stochastic model able to handle more uncertainty like when the customers cost function coefficients are unknown.

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$$B = 10^{-5} \times \begin{bmatrix} 4.9 & 1.4 & 1.5 & 1.5 & 1.6 & 1.7 & 1.7 & 1.8 & 1.9 & 2.0 \\ 1.4 & 4.5 & 1.6 & 1.6 & 1.7 & 1.5 & 1.5 & 1.6 & 1.8 & 1.8 \\ 1.5 & 1.6 & 3.9 & 1.0 & 1.2 & 1.2 & 1.4 & 1.4 & 1.6 & 1.6 \\ 1.5 & 1.6 & 1.0 & 4.0 & 1.4 & 1.0 & 1.1 & 1.2 & 1.4 & 1.5 \\ 1.6 & 1.7 & 1.2 & 1.4 & 3.5 & 1.1 & 1.3 & 1.3 & 1.5 & 1.6 \\ 1.7 & 1.5 & 1.2 & 1.0 & 1.1 & 3.6 & 1.3 & 1.2 & 1.4 & 1.5 \\ 1.7 & 1.5 & 1.4 & 1.1 & 1.3 & 1.2 & 3.8 & 1.6 & 1.6 & 1.8 \\ 1.8 & 1.6 & 1.4 & 1.2 & 1.3 & 1.2 & 1.6 & 4.0 & 1.5 & 1.6 \\ 1.9 & 1.8 & 1.6 & 1.4 & 1.5 & 1.4 & 1.6 & 1.5 & 4.2 & 1.9 \\ 2.0 & 1.8 & 1.6 & 1.5 & 1.6 & 1.5 & 1.8 & 1.6 & 1.9 & 4.4 \end{bmatrix} perMW \tag{1}$$

Table 1: Optimal customer power curtailed ($x_{j,t}$) (scenario 1).

$x_{j,t}$	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$t=1$	3.64	5.61	9.1	11.76	14.67
$t=2$	3.93	5.99	9.58	12.36	15.25
$t=3$	3.74	5.73	9.24	11.97	14.8
$t=4$	3.72	5.38	9.2	11.99	14.75
$t=5$	4.29	5.9	10.18	13.14	15.96
$t=6$	5.02	7.01	11.46	14.57	17.55
$t=7$	13.49	18	26.27	31.27	35.98
$t=8$	12.43	17.41	24.47	29.12	33.67
$t=9$	17.31	23.97	33.02	38.76	44.25
$t=10$	11.36	16	22.55	27.1	31.22
$t=11$	12.22	17.11	23.95	28.8	32.87
$t=12$	10.25	14.51	20.46	25.05	28.51
$t=13$	7.14	10.32	15.09	18.8	21.86
$t=14$	10.27	14.52	20.54	25.01	28.65
$t=15$	7.3	10.52	15.42	19.04	22.37
$t=16$	7.4	10.66	15.66	19.19	22.75
$t=17$	10.4	14.44	20.95	25.12	29.36
$t=18$	10.15	13.29	20.14	22.98	28.26
$t=19$	8.52	12.08	17.59	21.18	25.11
$t=20$	8.71	12.39	17.98	21.45	25.6
$t=21$	7.18	10.4	15.23	18.94	22.18
$t=22$	7.92	11.43	16.44	20.59	23.66
$t=23$	4.73	7.11	10.91	14.12	16.82
$t=24$	4.07	6.21	9.78	12.75	15.44

Table 2: Optimal customer incentive ($y_{j,t}$) (scenario 1).

$y_{j,t}$	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$t=1$	66.77	97.38	142.73	163.93	189.25
$t=2$	74.23	107.15	155.22	178.97	204.42
$t=3$	69.36	100.37	146.19	169.21	192.72
$t=4$	68.97	91.72	145.25	169.64	191.29
$t=5$	83.85	104.57	171.44	199.84	224.04
$t=6$	104.85	135.13	208.72	240.43	270.9
$t=7$	493.22	619.34	898.62	992.56	1138.2
$t=8$	430.06	584.81	789.42	867.07	996.98
$t=9$	755	1022.53	1369.56	1495.06	1721.79
$t=10$	370.73	506.67	680.55	757.22	857.15
$t=11$	417.86	568.09	758.94	849.43	950.14
$t=12$	313.12	429.42	571.7	653.06	714.9
$t=13$	177.38	246	334.09	383.01	420.35
$t=14$	314.36	430.13	575.72	651.2	721.88
$t=15$	183.3	253.79	346.86	391.88	439.96
$t=16$	187.43	259.17	356.34	397.59	455.04
$t=17$	320.93	426.3	596.22	656.51	757.93
$t=18$	308.29	371.06	555.8	555.61	702.35
$t=19$	233.26	317.23	436.7	477.43	554.32
$t=20$	241.4	330.81	454.14	488.53	576.21
$t=21$	178.82	249.18	339.32	388.05	432.79
$t=22$	207.89	289.72	387.94	452.73	492.38
$t=23$	96.45	138.15	192.33	227.32	248.68
$t=24$	77.88	112.79	160.6	189.18	209.53

Table 3: Optimal power generated by generators ($P_{i,t}$) (scenario 1).

$P_{i,t}$	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$
$t=1$	282.56	121.4	179.94	100.98	145.23	89.29
$t=2$	279.47	118.87	177.75	98.79	142.48	86.43
$t=3$	278.38	117.98	176.99	98.02	141.52	85.43
$t=4$	277.46	117.22	176.34	97.37	140.7	84.58
$t=5$	277.58	117.32	176.42	97.45	140.8	84.68
$t=6$	282	120.93	179.54	100.58	144.72	88.76
$t=7$	273.23	113.77	173.35	94.38	136.95	80.67
$t=8$	281.69	120.68	179.33	100.36	144.45	88.49
$t=9$	294.38	131.06	188.3	109.33	155.72	100.21
$t=10$	309.17	143.14	198.75	119.79	168.84	113.88
$t=11$	318.67	150.91	205.47	126.5	177.27	120
$t=12$	331.14	161.1	214.28	135.31	188.33	120
$t=13$	326.31	157.15	210.86	131.9	184.04	120
$t=14$	335.06	164.3	217.05	138.09	191.81	120
$t=15$	344.1	171.7	223.44	144.48	199.84	120
$t=16$	340.62	168.85	220.98	142.01	196.74	120
$t=17$	327.29	157.95	211.56	132.59	184.91	120
$t=18$	323.92	155.2	209.18	130.21	181.93	120
$t=19$	315.81	148.57	203.44	124.48	174.73	120
$t=20$	301.91	137.2	193.61	114.65	162.39	107.16
$t=21$	290.42	127.81	185.49	106.53	152.19	96.55
$t=22$	281.3	120.36	179.05	100.09	144.11	88.13
$t=23$	284.8	123.23	181.53	102.56	147.21	91.36
$t=24$	282.88	121.65	180.16	101.2	145.5	89.58

Table 4: Optimal customer power curtailed ($x_{j,t}$) (scenario 2).

$x_{j,t}$	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$	$j=6$	$j=7$
$t=1$	1.5	1.5	2.17	3.78	5.57	13.73	17.27
$t=2$	1.5	1.5	1.5	2.75	4.52	13.06	16.71
$t=3$	1.5	1.56	2.47	4.18	5.96	13.98	17.62
$t=4$	2.28	2.87	4.39	6.4	8.31	15.48	18.95
$t=5$	2.88	3.83	5.45	7.68	9.62	16.31	19.73
$t=6$	5.24	7.04	9.49	12.47	14.54	19.46	22.49
$t=7$	6.71	8.49	11.6	14.88	17.09	21.08	23.8
$t=8$	7.17	9.18	12.51	15.94	18.21	21.79	24.37
$t=9$	8.47	10.92	14.8	18.62	20.99	23.57	25.91
$t=10$	10.93	14.31	18.69	23.31	25.69	26.57	28.57
$t=11$	12.08	15.76	20.84	25.8	28.28	28.22	29.93
$t=12$	11.07	14.44	19.22	23.88	26.39	27.01	28.99
$t=13$	9.97	12.85	17.21	21.49	23.89	25.42	27.57
$t=14$	9.29	12.17	15.91	20.07	22.27	24.38	26.78
$t=15$	7.61	9.64	13.2	16.75	18.99	22.29	24.73
$t=16$	7.07	8.96	12.37	15.76	17.99	21.65	24.09
$t=17$	6.71	8.65	11.99	15.3	17.51	21.35	23.78
$t=18$	8.42	10.51	14.43	18.2	20.51	23.26	25.5
$t=19$	8.09	10.34	14.18	17.9	20.22	23.08	25.4
$t=20$	11.74	15.19	20.55	25.38	28.05	28.07	29.76
$t=21$	27.22	34.54	45.11	50	50	47.12	46.04
$t=22$	7.95	10.04	13.62	17.22	19.52	22.63	25.04
$t=23$	3.12	4.03	5.75	7.98	9.92	16.51	19.8
$t=24$	1.5	1.69	2.56	4.24	5.95	13.97	17.75

Table 5: Optimal customer incentive ($y_{j,t}$) (scenario 2).

$y_{j,t}$	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$	$j = 7$
$t = 1$	21.62	18.1	23.3	40.42	55.41	285.29	454.27
$t = 2$	21.62	18.1	14.99	26.86	40.81	259.35	425.32
$t = 3$	21.62	19	27.21	46.21	61.27	295.16	472.92
$t = 4$	36.09	40.13	57.57	83.66	102.73	359	547.06
$t = 5$	48.88	58.43	77.66	109.56	129.86	396.98	592.75
$t = 6$	111.57	138.68	176.58	232.12	259.41	557.81	770.4
$t = 7$	161.1	184.38	242.2	309.93	342.92	651.42	862.98
$t = 8$	178.27	207.84	273.79	347.38	383.38	695.02	904.22
$t = 9$	231.19	273.69	360.14	451.39	493.33	809.33	1022.21
$t = 10$	348.09	425.15	533.69	664.71	710.2	1022.34	1242.93
$t = 11$	409.99	500.05	643.01	794.31	846.14	1150.16	1364.1
$t = 12$	354.95	431.9	559.84	693.52	745.32	1055.71	1280.48
$t = 13$	299.89	355.93	463.54	577.08	622.43	937.72	1157.52
$t = 14$	267.63	325.7	406.25	512.89	548.39	864.74	1092.48
$t = 15$	195.45	224.39	298.55	377.24	413	726.37	931.21
$t = 16$	174.58	200.23	268.74	340.85	375.22	686.3	883.64
$t = 17$	161.08	189.48	255.49	324.57	358.01	667.79	861.27
$t = 18$	228.89	257.5	345.74	433.97	473.3	788.89	990.38
$t = 19$	215.09	250.88	335.72	422.07	461.44	776.72	982.72
$t = 20$	391.43	469.64	627.97	771.5	833.36	1138.29	1348.83
$t = 21$	1685.36	1989.37	2573.84	2643.25	2450.73	3147.16	3229.11
$t = 22$	209.08	239.3	314.07	395.41	433.74	748.06	955.03
$t = 23$	54.23	62.58	83.91	115.92	136.68	406.2	596.89
$t = 24$	21.62	20.78	28.48	47.19	61.18	295.01	479.98

Table 6: Optimal power generated by generators ($P_{i,t}$) (scenario 2).

$P_{i,t}$	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$	$i=8$	$i=9$	$i=10$
$t=1$	150	135	73	60	165.66	160	130	60	20	55
$t=2$	150	135	76.17	60	211.46	160	130	90	21.92	55
$t=3$	150	135	119.16	85.66	243	160	130	120	39.66	55
$t=4$	155.62	162.08	164.93	131.13	243	160	130	120	58.55	55
$t=5$	171.55	178.11	181.05	147.14	243	160	130	120	65.2	55
$t=6$	200.8	207.55	210.64	176.54	243	160	130	120	77.41	55
$t=7$	216.29	223.14	226.3	192.1	243	160	130	120	80	55
$t=8$	234.44	241.4	244.66	210.33	243	160	130	120	80	55
$t=9$	270.1	277.29	280.73	246.17	243	160	130	120	80	55
$t=10$	303.12	310.52	314.13	279.35	243	160	130	120	80	55
$t=11$	319.59	327.1	330.79	295.9	243	160	130	120	80	55
$t=12$	358.7	366.46	340	300	243	160	130	120	80	55
$t=13$	305.72	313.14	316.77	281.97	243	160	130	120	80	55
$t=14$	268.07	275.25	278.68	244.13	243	160	130	120	80	55
$t=15$	234.12	241.08	244.34	207.01	243	160	130	120	80	55
$t=16$	178.39	184.99	187.96	157.01	243	160	130	120	68.05	55
$t=17$	162.11	168.61	171.5	137.65	243	160	130	120	61.26	55
$t=18$	193.61	200.32	203.36	169.31	243	160	130	120	74.41	55
$t=19$	230.27	237.21	240.45	212.13	243	160	130	120	80	55
$t=20$	305.3	312.46	315.88	262.13	243	160	130	120	80	55
$t=21$	225.3	232.46	235.88	212.13	243	160	130	120	59.34	55
$t=22$	197.21	203.94	207	162.13	243	160	130	120	75.91	55
$t=23$	150	136.54	139.26	112.13	243	160	130	120	47.96	55
$t=24$	150	135	88.67	62.13	243	160	130	109.28	27.08	55

Table 7: Optimal power produced by conventional generators and transfer power between the microgrid and main grid

	$P_{j,t}$ (kW)			Pr_t (kW)
	$i=1$	$i=2$	$i=3$	
$t=1$	4	6	9	4
$t=2$	4	6	9	4
$t=3$	4	6	9	3.19
$t=4$	4	6	9	-0.08
$t=5$	4	6	9	-1.54
$t=6$	4	6	9	-1.99
$t=7$	4	6	9	-2.27
$t=8$	3.60	6	7.90	-4
$t=9$	3.16	6	7.25	-4
$t=10$	2.49	6	6.23	-4
$t=11$	2.55	6	6.33	-4
$t=12$	2.89	6	6.83	-4
$t=13$	2.30	6	5.95	-4
$t=14$	3.04	6	7.06	-4
$t=15$	3.47	6	7.71	-4
$t=16$	4	6	9	-4
$t=17$	4	6	9	-4
$t=18$	4	6	9	-3.38
$t=19$	4	6	9	4
$t=20$	4	6	9	4
$t=21$	4	6	9	4
$t=22$	4	6	9	4
$t=23$	4	6	9	4
$t=24$	3	5	8	4

Table 8: Optimal power from the wind and solar generators

Time(h)	Pw_t (kW)	Ps_t (kW)
1	7.56	0
2	7.50	0
3	8.25	0
4	8.48	0
5	8.48	0
6	9.42	0
7	9.82	0
8	10.35	7.99
9	10.88	10.56
10	11.01	13.61
11	10.94	14.97
12	10.68	15
13	10.42	14.78
14	10.15	14.59
15	9.67	13.56
16	8.98	11.83
17	8.37	10.17
18	7.61	7.66
19	6.70	0
20	5.72	0
21	7.21	0
22	7.75	0
23	7.88	0
24	7.69	0

Table 9: Optimal power curtailed by the customers

	$x_{j,t}$ (kW)		
$t = 1$	0.00	0.40	0.87
$t = 2$	0.00	0.18	0.71
$t = 3$	0.00	0.08	0.64
$t = 4$	0.89	1.22	1.49
$t = 5$	1.58	1.75	1.89
$t = 6$	1.77	1.90	2.00
$t = 7$	2.08	2.15	2.18
$t = 8$	0.32	0.77	1.15
$t = 9$	0.92	1.24	1.50
$t = 10$	0.63	1.01	1.33
$t = 11$	0.74	1.10	1.40
$t = 12$	0.96	1.27	1.53
$t = 13$	1.15	1.42	1.64
$t = 14$	1.42	1.63	1.80
$t = 15$	1.77	1.91	2.00
$t = 16$	1.84	1.96	2.04
$t = 17$	2.40	2.39	2.36
$t = 18$	3.25	3.06	2.86
$t = 19$	3.14	2.98	2.80
$t = 20$	2.61	2.56	2.49
$t = 21$	1.01	1.31	1.56
$t = 22$	0.24	0.70	1.10
$t = 23$	0.06	0.56	1.00
$t = 24$	1.19	1.45	1.66

Table 10: Optimal incentive received by customers

	$y_{j,t}$ (\$)		
	$j=1$	$j=2$	$j=3$
$t=1$	0.00	0.57	1.56
$t=2$	0.00	0.21	1.06
$t=3$	0.00	0.09	0.87
$t=4$	2.04	3.13	4.33
$t=5$	4.78	5.81	6.89
$t=6$	5.69	6.67	7.68
$t=7$	7.42	8.27	9.13
$t=8$	0.53	1.50	2.64
$t=9$	2.13	3.22	4.42
$t=10$	1.27	2.32	3.51
$t=11$	1.57	2.64	3.83
$t=12$	2.27	3.36	4.55
$t=13$	2.95	4.04	5.22
$t=14$	4.07	5.13	6.26
$t=15$	5.73	6.71	7.72
$t=16$	6.10	7.05	8.03
$t=17$	9.36	10.04	10.71
$t=18$	15.67	15.65	15.60
$t=19$	14.82	14.90	14.95
$t=20$	10.83	11.36	11.87
$t=21$	2.45	3.54	4.73
$t=22$	0.37	1.31	2.43
$t=23$	0.08	0.93	2.00
$t=24$	3.12	4.21	5.37