8-2013

Optimal Distribution Reconfiguration and Demand Management within Practical Operational Constraints

Benyamin Moradzadeh
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To the Graduate Council:

I am submitting herewith a dissertation written by Benyamin Moradzadeh entitled "Optimal Distribution Reconfiguration and Demand Management within Practical Operational Constraints." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Electrical Engineering.

Kevin Tomsovic, Major Professor

We have read this dissertation and recommend its acceptance:

Fran Li, Husheng Li, Rupy Sawhney

Accepted for the Council:
Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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Optimal Distribution Reconfiguration and Demand Management within Practical Operational Constraints

A Dissertation Presented for

The Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Benyamin Moradzadeh

August 2013

I dedicate this dissertation to my wonderful family.

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Abstract

This dissertation focuses on specific aspects of the technical design and operation of a 'smart' distribution system incorporating new technology in the design process. The main purpose of this dissertation is to propose new algorithms in order to achieve a more reliable and economic distribution system.

First, a general approach based on Mixed Integer Programming (MIP) is proposed to formulate the reconfiguration problem for a radial/weakly meshed distribution network or restoration following a fault. Two objectives considered in this study are to minimize the active power loss, and to minimize the number of switching operations with respect to operational constraints, such as power balance, line flow limits, voltage limit, and radiality of the network. The latter is the most challenging issue in solving the problem by MIP. A novel approach based on Depth-First Search (DFS) algorithm is implemented to avoid cycles and loops in the system. Due to insufficient measurements and high penetration of controllable loads and renewable resources, reconfiguration with deterministic optimization may not lead to an optimal/feasible result. Therefore, two different methods are proposed to solve the reconfiguration problem in presence of load uncertainty.

Second, a new pricing algorithm for residential load participation in demand response program is proposed. The objective is to reduce the cost to the utility company while mitigating the impact on customer satisfaction. This is an iterative approach in which residents and energy supplier exchange information on consumption and price. The prices as well as appliance schedule for the residential customers will be

achieved at the point of convergence. As an important contribution of this work, distribution network constraints such as voltage limits, equipment capacity limits, and phase balance constraints are considered in the pricing algorithm. Similar to the locational marginal price (LMP) at the transmission level, different prices for distribution nodes will be obtained. Primary consideration in the proposed approach, and frequently ignored in the literature, is to avoid overly sophisticated decision-making at the customer level. Most customers will have limited capacity or need for elaborate scheduling where actual energy cost savings will be modest.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Overview

The U.S. electric grid is an enormous and extremely complex system consisting of centralized power plants, transmission lines, and distribution networks. It is capable of carrying over 850 GW of power and continuously balancing supply with fluctuating demand. It does so with remarkable reliability, providing 99.97 percent uptime (when the grid is operational), or about 160 minutes of downtime a year [1, 2]. However, the traditional electric power grid was designed neither with the latest technology nor with the goal of supporting a high-tech economy and enabling low-carbon technologies and energy efficiency and conservation. Several issues regarding the current power systems are addressed in the following:

- Power outages and power quality disruptions cost more than $150 billion annually [3].
- The grid is inefficient at managing peak load.
- The grid does not support robust information flow.
- Very high levels of renewable energy pose challenges for the grid [3].
- The grid has limited support for distributed generation.

- The grid would be strained by high Plug-in Hybrid Electric Vehicles (PHEV) deployments.

Compared to the existing grid, the smart grid promises improvements in reliability, power quality, efficiency, information flow, and improved support for renewable through application of digital technology. Title XIII of the recently signed Energy Independence and Security Act of 2007 [4] includes the following characteristics of a Smart Grid:

- Increase in use of digital control and information technology with real time availability
- Dynamic optimization relating to grid operability
- Inclusion of demand side response (DR)
- Demand side management (DSM) technologies
- Integration of distributed resources including renewables and energy storage
- Deployment of smart metering
- Distribution automation
- Smart appliances and customer devices at the point of end use.

Figure 1.1 illustrates the scope of the Department of Energy (DoE) Grid 2030 vision. A smart grid provides the utility company with actionable information. Utility companies will receive a constant flow of information about their network, their customers, and their options for managing their operations. Therefore, estimating network activity or having to send out physical readers to many locations will not be necessary in future smart gird. Moreover, a smart grid provides support for new applications and components, such as smart appliances, PHEVs, distributed generation, and renewable energy by allowing for better management of their interaction with the grid. In addition to the utility companies, the customers will benefit from the facilities provided by smart grid. For example, customers can be provided with information about their electricity usage patterns and costs. They can use this information to reduce their energy costs and their environmental impact. The above features cannot be achieved without utilizing integrated communications, sensing and measurement, improved interfaces and decision support, advanced control methods, and advanced components such as GPS systems, current limiting conductors, and advanced energy storage.

Figure 1.1: Feature of the future smart grid

The ‘Smart Distribution Grid’ initiative is visualized as a coordinated transition from contemporary legacy distribution systems to an automated, self-healing, and more reliable system. This transition requires a paradigm shift in both design and operations due to the increased use of Demand Side Management (DSM) and Demand

Side Response (DR) programs; and increased penetration of renewable energy resources. Figure 1.2 exhibits the transition from the contemporary distribution system to a future smart distribution grid. Massive deployment of renewable energy systems is expected to occur in electric distribution systems in the near future [4, 5]. New philosophies of redesigning the existing distribution system topology and rapid restoration following system disturbances are imperative to maximize the use of these resources. The distribution system of the future must be designed so that rapid restoration is possible. Rapid distribution restoration can accomplish multiple objectives, including reduction of the classical system average interruption duration and frequency indices, and/or the minimization of unserved energy to loads.

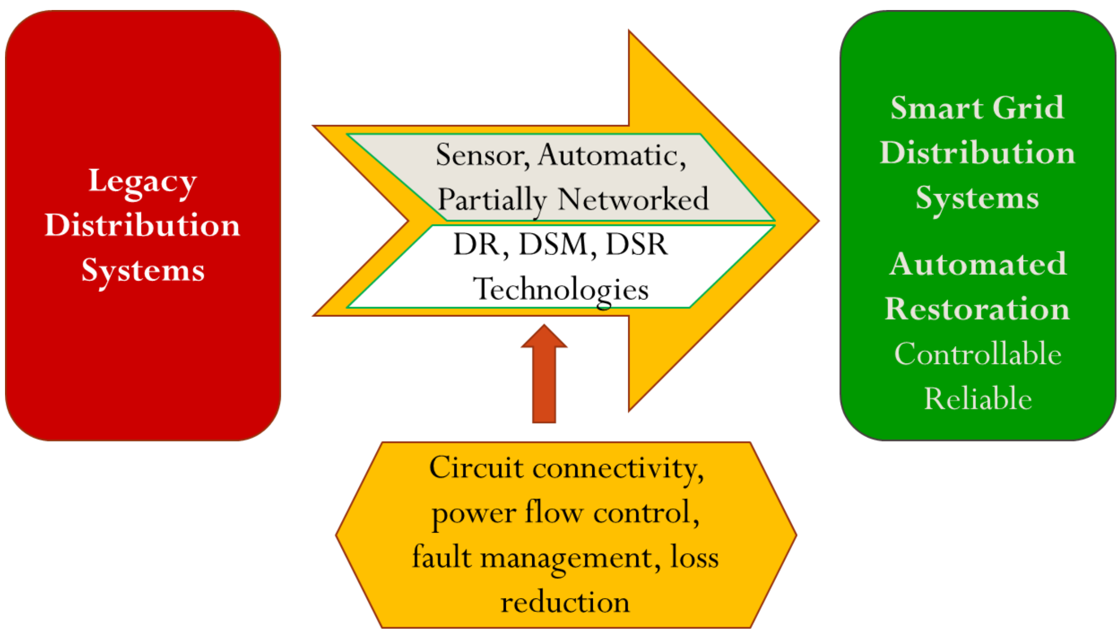


Figure 1.2: Transition to the future smart distribution system

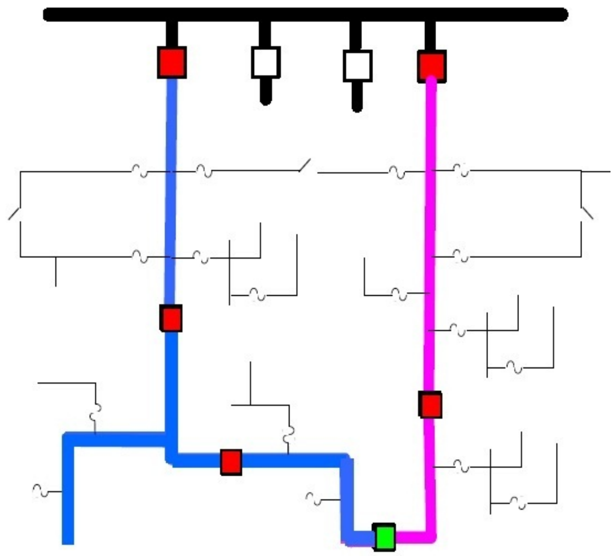
This Ph.D. dissertation concentrates on the application of optimization algorithms to two important features of the future smart distribution systems. The purpose of these approaches is to obtain a more economic and reliable distribution system which benefits both utility companies and customers. First, we address the automated restoration and reconfiguration which is a very important factor in achieving an economic, and reliable distribution system. Then, new approaches for residential demand response management programs are proposed to improve reliability and reduce cost to the utility companies and residential customers.

For distribution system restoration and reconfiguration, a general, fast, and scalable reconfiguration and restoration algorithm is proposed. The purpose of the reconfiguration is to find the optimal configuration of the system to maximize its performance and respond to disturbances quickly. Reconfiguration consists of changing the network configuration by opening/closing feeders and tie switches while the networks remain radial/weakly meshed in operation. Smart gird provides facilities that allow monitoring and control of equipment in distribution substations and out on the feeders. This provides the means to restore service to the customers in a very short period of time. The switch control can be carried out from a control center or by using distributed intelligence or a combination of both. Due to the discrete, non-linear nature of distribution system reconfiguration (DSR) which leads to a large search space, it is challenging to implement DSR for online applications [6]. Another challenge is the uncertainty of the node injections due to lack of sufficient measurements and an increasingly high penetration of controllable loads and renewable resources in distribution systems. These uncertainties should be considered in the reconfiguration problem as the solution from deterministic optimization with nominal values of the node injections may not be optimal/feasible.

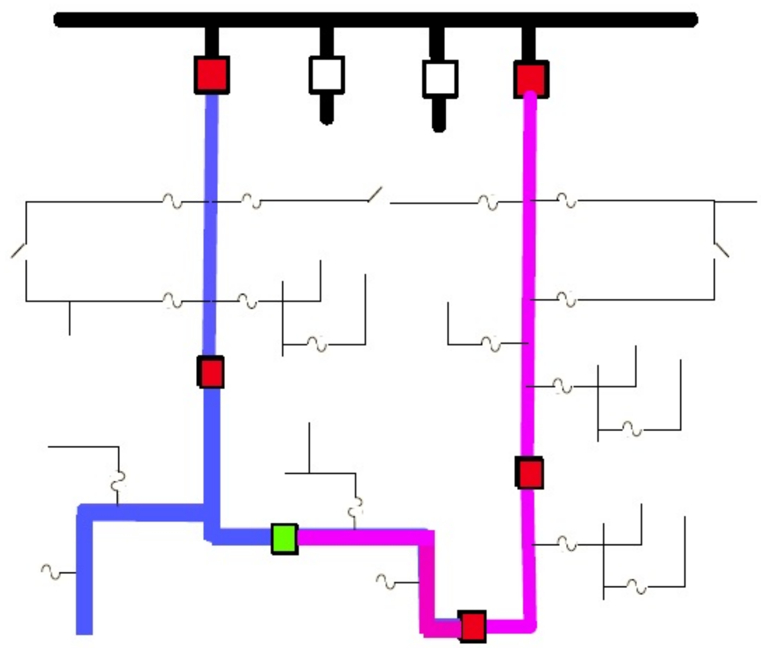
Second, as another important feature of the future smart grid, this dissertation addresses the residential demand response management problem. We propose a decentralized optimization to improve the operation of the distribution system in terms of economy and reliability. The objective of the optimization is to reduce peak load as well as costs to the utility companies and customers while taking customer satisfaction into account. Given the facilities such as two ways communication, measurement units, and smart appliances provided by smart grid, it is possible to develop decentralized residential response management programs which benefit both the grid and customers. As an important contribution of the proposed method, system operational constraints such as equipment capacity limits and voltage limit constraints are considered in the demand response program.

1.2 Distribution System Reconfiguration

Electrical distribution systems must be adequately planned to permit efficient and reliable operation. Although distribution systems may be found as weakly-meshed networked systems in urban areas, the majority of distribution systems operate with a radial topology for technical reasons, such as, facilitating the coordination and protection, and reducing the short-circuit current. Thus, the radiality/weakly meshed constraint is present in almost all of the distribution expansion and operation planning problems. Reconfiguration and restoration after faults are critical features of a reliable distribution grid. Network reconfiguration is the process of altering the topological structures of distribution feeders so that the distribution network operates in a more reliable and economic mode. The distribution automation function of feeder reconfiguration has been addressed for many different objectives such as increasing reliability, maximizing loadability, minimizing losses, minimizing the switching operations, and achieving load balance. Figure 1.3 shows how the switching operations on the tie-line switches can transfer loads between two feeders. Despite its benefits to distribution planning and operation, reconfiguration has not been widely used in industry due to lack of measurement equipment, automatic switchgears, and communication infrastructures. However, technologies such as robust two-way communications, advanced sensors, and state of art controllers, will enable features such automatic distribution reconfiguration and demand response programs.



(a)



(b)

Figure 1.3: Load transfer between nodes. (a) before switching, (b) after switching

This process should be fast enough to improve reliability indices such as a System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI). Figure 1.4 shows that when a permanent fault occurs, customers on "healthy" sections of the feeder may experience a lengthy outage. However, smart gird provides facilities that allow monitoring and control of equipment in distribution substations and out on the feeders. This provides the means to restore service to the customers in a very short period of time. The switch control can be carried out from a control center or by using distributed intelligence or a combination of both.

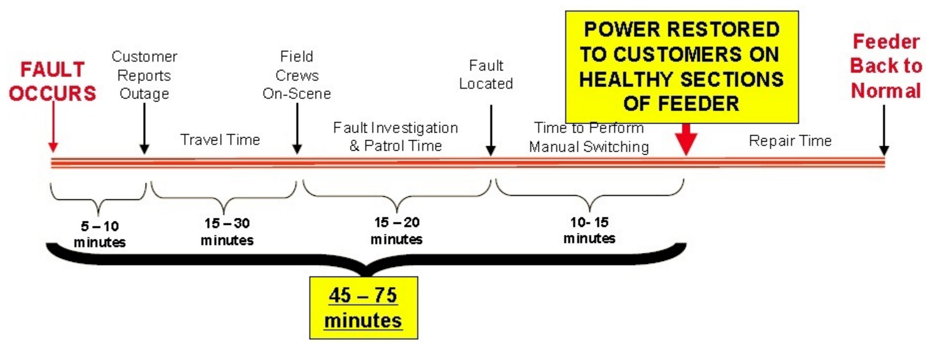


Figure 1.4: Fault location isolation and service restoration

Due to the discrete, non-linear nature of DSR which leads to a huge search space, it is difficult to implement DSR for real-time applications [6]. Moreover, as mentioned before, distribution networks are normally meshed in design but in order to provide proper relay coordination, the operation is nearly always configured radially or weakly-meshed. This makes a MIP-based formulation of DSR even more challenging since the radiality constraint does not lend itself to general analytical expressions. In addition, the number of possible configurations is combinatoric. It is necessary to find a general approach which is fast and accurate enough for real-time applications.

As mentioned before, uncertainty of the nodal injections (loads and renewable resources) is an important factor that should be considered in the reconfiguration process. Performing reconfiguration or restoration without considering these uncertainties may not be feasible and/or optimal for actual node injections. This issue is addressed in this dissertation and efficient algorithms are proposed to obtain robust and optimal reconfiguration.

1.3 Demand Side Management

Demand Response (DR) is an important element in the concept of energy management, and long used as the justification for utility investments. The goal of DR is to reduce demand during periods of peak usage. Utilities have planned to do this in a centralized manner, by sending commands to loads, such as to raise the thermostat set point or disable the air conditioner compressor. A better alternative is to perform DR in a distributed manner, where the endpoints of electricity consumption monitor the status of the grid, and respond appropriately. The utility industry's model for DR is based on extending the Smart Grid to end devices on customer premises to control them directly (centralized control), whereas the information technology (IT) industry model for DR is based on allowing consumers to adjust their consumption of electricity autonomously by continuously tracking conditions (distributed control).

Effective energy management requires consumers to participate in the process of controlling energy usage. Consumers need incentives to participate willingly in a solution for energy management. If consumers are not given the tools that empower them to easily manage energy consumption, confusion and backlash could ensue. This is already being seen in various smart meter deployments where bills have increased, and consumers have initiated class action lawsuits claiming that the smart grid was forced upon them. Simple, easy-to-use products and services that give the consumer choice and control are a must. At the same time, these products and services must interoperate. Market-driven standards provide the best solutions for the consumers; therefore, regulators need to allow innovation through competition among standards and technologies in the house.

Although wholesale market prices vary on hourly-basis and fluctuate between low values at off-peak times and high values at on-peak times, most of the utilities set fixed prices for retail customers. Therefore, the customers' utility bills do not clearly reflect grid issues. While direct load control of end-user loads has existed for decades, price driven response programs are only beginning to be explored at the distribution level. Several pricing models have been proposed, including: Time-of-Use rates (ToU), Critical-Peak Pricing (CPP), Day-Ahead Pricing (DAP), and Real-Time Pricing (RTP). Through reflecting the wholesale market price fluctuation in the end users' bills, the mentioned pricing mechanisms encourage the households to shift their high-load appliances to off-peak hours.

One of the challenges in the future distribution grid will be high utilization of PHEVs. Because of this, there will be a considerable potential for congestion in distribution systems. Congestion can happen in distribution lines and cables or in the form of overload in transformers. In order to avoid secondary transformer overload in distribution laterals, the utility company can encourage the customers to shift and/or reduce their loads. This concept is shown in Figure 1.5 where customers shift their loads to avoid congestion in a distribution network. Current advancements in computing and communication areas make it possible to design transactive demand response programs at the residential level. Implementing RTP in transactive markets requires distributed controllers and a centralized auction to create an interactive system which can limit demand at key times on a distribution system and decrease congestion [7].

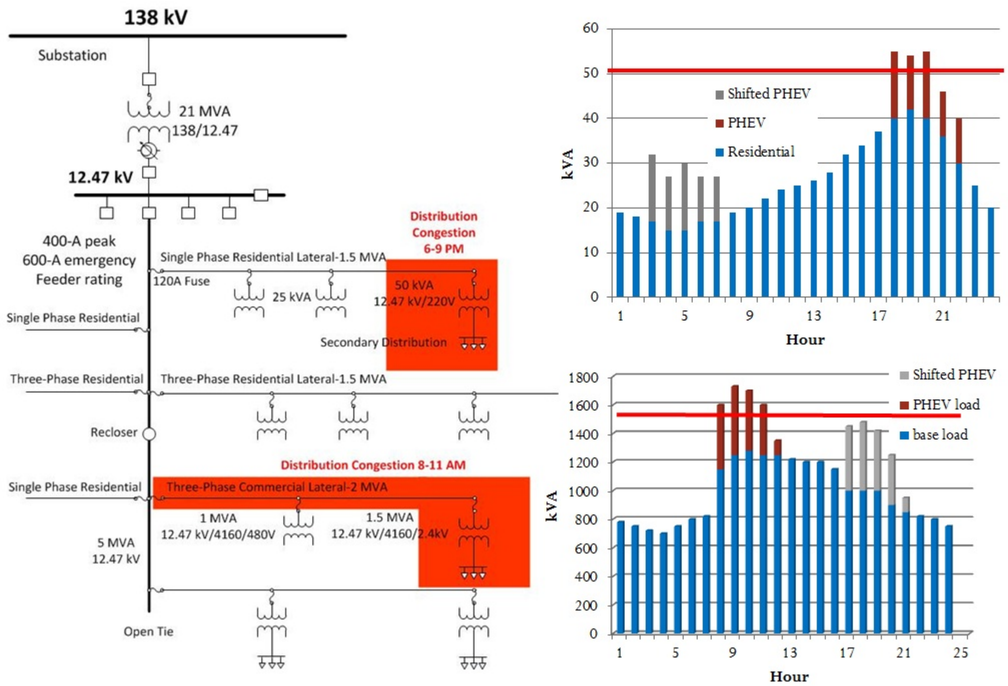


Figure 1.5: Potential distribution congestion

As shown in Figure 1.6, demand side management programs can be done for three different categories of loads: industrial loads, commercial loads, and residential lodes. In all the mentioned categories, customers respond to the time-varying prices. Compared to industrial and commercial loads, it is very hard to accurately forecast hourly energy consumption in the houses. As exhibited in Figure 1.7, currently the ISO/RTO operator has visibility into transmission substations, and may have visibility into large subtransmission substations where large commercial and industrial customer demand response (DR) programs are located, but generally does not have visibility into the distribution network where most of the small commercial and the main residential DR takes place. Other entities, such as utility distribution companies (UDCs), load-serving entities (LSEs), electricity service providers (ESPs), and curtailment service providers (CSPs) interact directly with consumers on the one hand and the ISO/RTO operator on the other hand. They play an important role in bundling the DR from their subscribed customers into products used in the ISO/RTO markets [8].

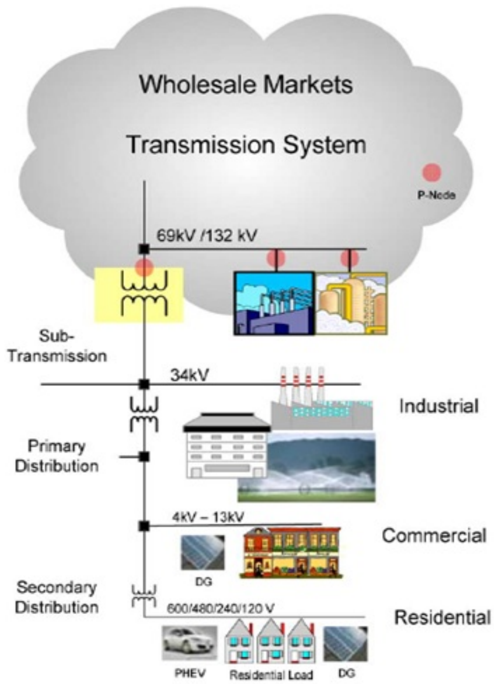


Figure 1.6: Different types of distribution system loads

Why DR is important at resident level? According to [9], around74% of the nation's electricity consumption occurs in buildings. Reducing demand requires the awareness of energy consumers on careful consumption patterns as well as constructing more energy efficient buildings. Considering the large portion of the residential load, it is of prime importance to provide incentives for the residential customers to participate in DSM and DR programs. Smart grid will provide facilities

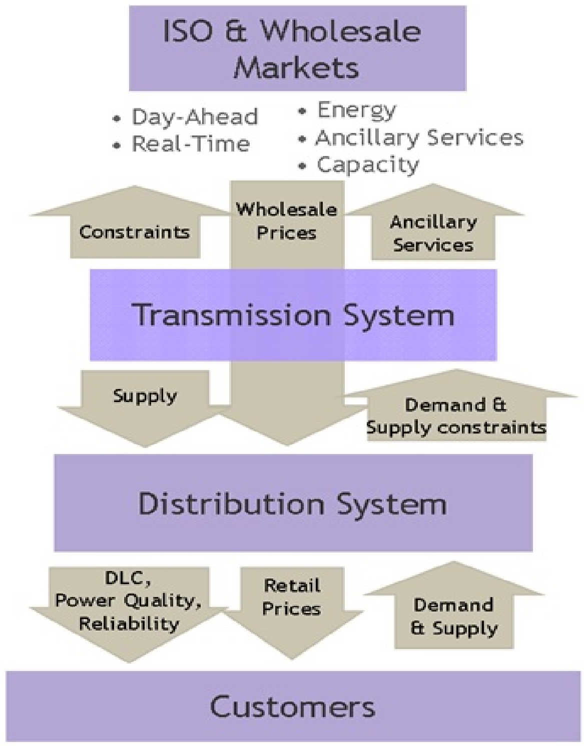


Figure 1.7: ISO and demand response in distribution level

such as Advanced Metering Infrastructures (AMI) and Home Area Networks (HAN) to enable decentralized demand response programs for the residential loads.

AMI: While in the past smart metering was a high point in technology, it has now moved under the umbrella of smart grid technologies. It serves to provide data to the operator on consumption patterns and helps in a two-way information flow between the utility and customers. While the utility can see the consumption pattern, the customer can know the energy pricing data and its effects on energy bills [9].

HAN: Home area networks are a part of the next generation solutions that smart grid technologies will offer. It includes remotely monitored and controlled thermostatic control, energy storage schemes, Plug-in Hybrid Electric Vehicles (PHEV) and roof top solar panels. These elements together become a whole system on their own that need to be controlled and operated from within a home. With integration of these devices in a large scale, it provides the local system operator with an effective energy storage system [9].

A schematic of HAN system which controls the energy consumption of different devices is shown in Figure 1.8. Figure 1.9 demonstrates the interaction between HANs and utility company through AMI.

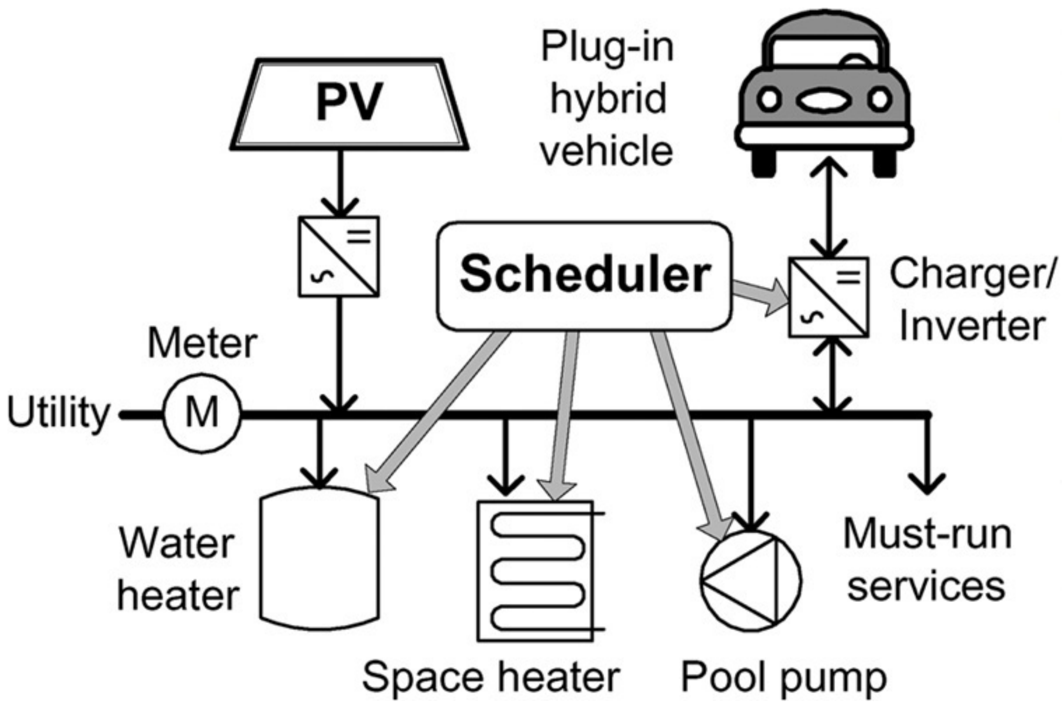


Figure 1.8: HAN schedules the residential appliances

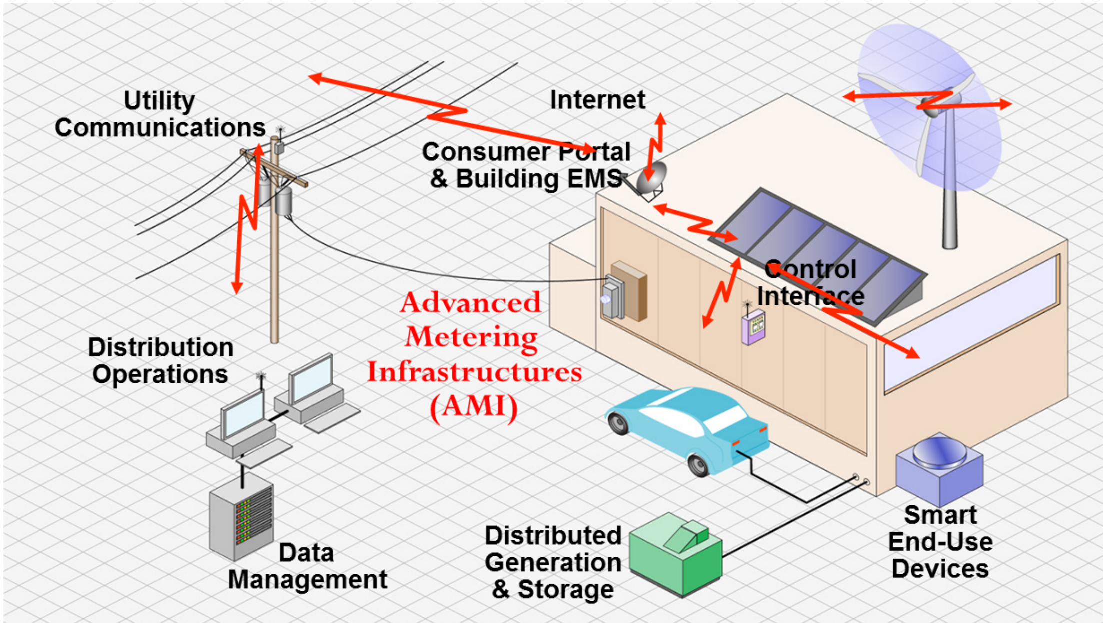


Figure 1.9: Communication between HANs and Utility company through AMI

1.4 Summary of Contributions

The contribution of this work is summarized as follows:

1.4.1 Distribution restoration/reconfiguration

- **A general approach based on MIP.**

A MIP-based reconfiguration/restoration is proposed. The MIP formulation is fast and scalable and can be easily implemented for practical sized distribution systems. Many of the proposed approaches in the literature rely on heuristic search or population based approaches to solve the reconfiguration problem. Nevertheless, solutions based on heuristic methods suffer from a number of shortcomings. Two objective functions considered in this work are minimizing the active power loss and minimizing the switching operations to restore the system after a fault. A comparison on the performance of Mixed Integer Linear Programming (MILP) and Mixed Integer Quadratic Programming (MIQP) in solving the problem is provided.

- **A radiality constraint formulation suitable for MIP.**

As mentioned before, the most challenging part in MIP-based formulation of DSR is to come up with a mathematical expression of the radiality constraint. In this work, possible radial configurations are identified based on Depth First Search (DFS) method that allows radial and weakly-meshed constraints to be easily expressed. The cycle detection approach is performed in off-line and before optimization. This makes the MIP-based DSR very fast and suitable for real-time applications. In addition, the proposed formulation can easily handle weakly-meshed networks.

- **The effect of Community Energy Storage (CES) systems on reconfiguration.**

It is shown that CES charging/discharging impacts the optimal configuration through changing line flows and voltage levels. Discharging of the storage units can mitigate the congestion on the lines and consequently the reconfiguration.

- **DSR with load uncertainty**

Due to insufficient measurements and high utilization of controllable loads in distribution systems, deterministic reconfiguration may not be optimal/feasible. We propose two different approaches to manage uncertainties associated with load measurements/forecast. The first method is based on fuzzy MIP (FMIP) that considers load uncertainties as intervals and models membership functions for objective function and constraints. The second approach, on the other hand, is based on stochastic MIP (SMIP) which assumes Gaussian probability distribution function (PDF) for an estimated load. It is shown that the proposed methods lead to robust results which are feasible for different loading conditions.

1.4.2 Residential demand response management

- **A decentralized residential response management approach.**

This problem minimizes the cost to the utility company as well as customer dissatisfaction. A decentralized optimization is developed based on dual decomposition and subgradient method. This is an iterative approach in which the utility company and residential customers exchange a small amount of information on price and hourly energy consumption. Prices as well as appliance scheduling for every house is obtained within a small number of iterations.

- **Simplified decision-making at the customer level.**

The proposed residential response management program avoids burdening customers with sophisticated calculations on energy consumption. The energy management in a house will be performed by the HAN. The HAN communicates with the utility company through AMI to receive the price and schedules based on this information exchange.

- **Detailed models of the residential loads.**

Detailed models of residential appliances, such as, PHEV, air conditioner, washer/dryer, and water heater, are developed and employed in the optimization. Various utility functions based on the device models are considered.

- **Complete distribution system constraints.**

As one of the most important contributions of the work, network constraints, such as line flow limits, phase balance, transformer capacity, and voltage limits are considered in the pricing algorithm. It is shown how these constraints affect the price and residential load scheduling. For example, customers on a lateral with overloaded secondary distribution transformer are charged higher prices because of their high energy usage. This encourages the customers to reduce their load and system stress. This reduction is based on the utility functions considered for different appliances.

- **Demand response with uncertainty in residential load.**

One of the important challenges in residential demand response is due to the highly random behavior of the residential customers. Similar to the energy market in transmission level, a two stage pricing is proposed. In the day-ahead pricing, the nodal prices and appliance schedules are obtained through the decentralized optimization. An algorithm based on chance constraint optimization is developed to consider the uncertainty of the residential demand in day-ahead. In real-time, on the other hand, prices are calculated based on the actual loads.

Chapter 2

Background

This chapter includes two sections. In the first section, an overview on the previous works on distribution system restoration/reconfiguration and residential demand response management is provided. Then, different optimization techniques will be briefly discussed in the second section.

2.1 Literature Review

2.1.1 Distribution System Reconfiguration

If exact optimization techniques are employed, the radiality constraints must be explicitly represented in the mathematical modeling. This is not the case, however, when heuristic or meta-heuristic techniques are used, where the radiality constraints are controlled implicitly.

The distribution automation function of feeder reconfiguration has been addressed for many different objectives, including: minimizing the number of switching operations [10], minimizing losses: [11–26], increasing reliability [27,28], and achieving load balance [29].

A Mixed Integer Linear Programming (MILP)-based approach for minimizing loss and number of switching operations is addressed in [10].

In [13], the reconfiguration problem is formulated as a minimum cost network flow problem and solved using a modified linear programming. The modifications in the Simplex algorithm are introduced mainly to maintain a radial network configuration while enforcing the line flow capacity limits. Although this approach is useful for loss reduction, it is not able to deal with other objectives, such as, minimizing the number of switching operations. Moreover, it only gives sub-optimal solution. In [14], the same approach has been extended to the case of distribution networks with embedded generation.

In [15], the authors present a methodology to integrate Mixed Integer Programming (MIP)-based reconfiguration with optimal power flow (OPF) using a Benders decomposition approach. However, the radiality constraint doesn't hold except for a few specific initial configurations and cannot guarantee radiality.

In [16], a network topology-based approach is used to formulate the reconfiguration problem for loss reduction. A strategy based on the loop incidence matrix, A, is used to avoid loops during the reconfiguration procedure. If the determinant of A is equal to 1 or -1, then the system is radial. Otherwise, if the determinant of A is equal to zero, this means that either the system is not radial or a group of loads is disconnected from service. In [17], a genetic algorithm approach is compared with a MILP model in which all bus voltage magnitudes are assumed to be 1 p.u. in the evaluation of the losses and the radiality constraint is enforced by using a heuristic based on the comparison between the node-to-substation path resistance and the resistance of the shortest path to the substation for that node. Such a heuristic needs to be revised in the presence of embedded generators. The authors of [18] used an evolutionary algorithm; References [19] and [20] used two specialized genetic algorithms. All proposals implicitly consider the radial operation constraint. In [18], the radial operation constraint is assured using graph theory, while that in [19] and [20] is controlled inside genetic operators.

The problem of finding the state of switching devices (open or closed) in primary distribution networks to minimize the total loss is addressed in [21]. A best-first search procedure is devised to guide the switch opening procedure. Initially, all switches are set to the “closed” state so that the network operates in meshed mode. Then, a candidate switch is selected for opening. The criterion for selecting a switch is precisely the least increase in total loss that the switch opening would cause. [21] suggests that it “would be highly desirable if the radiality constraint could be expressed in analytical form.” If this is possible, the radiality constraints could be incorporated in a mathematical model and solved by using a precise optimization technique.

Heuristic based reconfiguration of electric distribution networks for resistive line loss reduction is discussed in [22]. Here also, the solution procedure starts by closing all of the network switches, which are opened one after another so as to establish the optimum flow pattern in the networks using many approximations. The objective of reconfiguration in [23] is to reduce loss and balance the loads. A branch exchange strategy is used to guarantee the radiality of the system. The difference between each heuristic algorithm is the sensitivity analysis used to decide which branch should be removed/opened at each step. Thus, the radial operation constraint of the system is imposed implicitly by the heuristic algorithms and not explicitly in the model.

An alternative mathematical model that allows the solution of the reconfiguration problem using commercial software is presented in [17]. In this model, the radiality of the system is represented by algebraic relations using so-called path-based connectivity modeling. The authors of this study explicitly recognize that it is very difficult to find a mathematical model for the reconfiguration problem and solve it with a conventional technique like the branch-to-node algorithm.

The traditional distribution analysis requires exact information of component parameters. However, due to the uncertainties associated with insufficient measurements and high penetration of controllable loads and renewable resources distribution reconfiguration with deterministic optimization may not lead to an optimal/feasible result. Reference [24] proposes a reliability-oriented reconfiguration (ROR) method that deals with uncertainties. The ROR method uses interval analysis to quantify the impact of uncertain data and to maximize the possibility of reliability improvement and/or loss reduction. Fuzzy programming and stochastic programming are two popular methods to deal with uncertainties in distribution system optimization problems.

The fuzzy approach has been proven to be very suitable for the modeling of uncertainty in load estimation and restoration problems [25]. In this approach, the uncertainty of a load value is modeled through a range of possible load values and the corresponding possibilities of appearing of these values. In this way, it is necessary to analyze all possible supply restoration scenarios and to economically quantify all possible outcomes in order to obtain the best restoration scenario. A procedure for supply restoration in distribution networks based on fuzzy risk management is proposed in [25]. The method models uncertainty in recognizing consumer loads by describing them with fuzzy numbers.

Reference [26] proposes a stochastic capacitor placement for distribution systems using probabilistic models of loads and wind generation. In this work, using probabilistic models of load and wind generation, a stochastic capacitor planning formulation is proposed. The proposed formulation minimizes the total cost of newly located and sized capacitors and the annual energy loss in a DS while considering limits on load bus voltages.

2.1.2 Residential Demand Response Management

Available DR technologies are mainly categorized into the following: Direct Load Control (DLC) strategies [27, 28] where a controller centrally interrupts the jobs of participating appliances mostly in case of emergencies and to curtail high peak load; Dynamic Pricing programs [29], which includes several rates and tariffs to manage the demand for electricity in a decentralized manner, e.g., Time of Use (TOU), Critical Peak Pricing (CPP), Real Time Pricing (RTP) and Day Ahead Pricing (DAP) rates; Demand bidding programs [30], where a market participant directly makes an offer to the wholesale market (or the retailer) for reducing electricity during peak times on the next day.

Reference [31] distinguishes between the following:

a) Incentive-Based DR:

- Direct load control (DLC): utility or grid operator gets free access to customer processes.
- Interruptible/curtailable rates: customers get special contract with limited sheds.
- Emergency demand response programs: voluntary response to emergency signals.
- Capacity market programs: customers guarantee to pitch in when the grid is in need.
- Demand bidding programs: customers can bid for curtailing at attractive prices

b) Time-Based Rates DR:

- Time-of-use rates: a static price schedule is applied.
- Critical peak pricing: a less predetermined variant of TOU.
- Real-time pricing (RTP): wholesale market prices are forwarded to end customers.

RTP may be the most efficient way of managing electricity demand in the future but it faces the challenging problem of what these price signals should be to avoid causing physical and market instabilities while reflecting the true conditions of the market at the same time. In fact, it has been shown that RTP are likely to cause more volatility or even instabilities when customers respond to this new information and form a new feedback loop in the power system control model [32–34].

As observed in [35], since all the residences are given the same dynamic price, current HAN that individually operated by each residence will simultaneously schedule the load to the low-price period, and, consequently, a new "rebound" peak is created to the grid.

There exists extensive literature on demand response [36–43]. In [36], the formulation of an appliance commitment problem for a residential customer is described using an electrical water heater load as an example. The thermal dynamics of heating and coasting of the water heater load is modeled by physical models; random hot water consumption is modeled with statistical methods.

In [37] and [38] residential response management is performed only on selected types of appliances. In [38], the authors extend the study to electricity usage of different appliances in a typical household and propose a method for customers to schedule their available distributed energy resources to maximize net benefits in a day-ahead market. Still, the paper fails to reflect the energy provider's interests. As mentioned before, if every household tends to shift its load to off-peak times, the energy provider will face a new on-peak period. In other words, it shifts in time rather than limits the peak.

In [39–41], researchers include both energy provider and customer benefits. The authors in [39] consider a power network where end customers choose their daily schedules of household appliances/loads by playing games among themselves and the utility company tries to adopt adequate pricing tariffs that differentiate the energy usage in time and level to make the Nash equilibrium minimize the energy costs. Customer satisfaction is not explicitly represented in the problem formulation. In [40] and [41] a decentralized optimization based on dual decomposition and subgradient multipliers is used to maximize social welfare. Although customer satisfaction is considered, these efforts fail to model different loads in the customer utility functions. In [43], a message-passing approach is suggested to develop a decentralized optimization of the residential energy management. The decentralized optimization is developed based on alternating direction method of multipliers.

One of the most important issues in residential response management is due to uncertainty of customer's energy consumption behavior and hourly electricity price. For example, utilities usually provide some estimated day-ahead prices as a guideline for the consumers. However, many random factors such as different consumers' reactions to real-time prices and the intermittency of renewable energy sources generally lead to prediction noise that should not be ignored. References [44–48] propose methods to predict prices. The households schedule their appliances considering the uncertainties in prices.

In [47], price uncertainty is modeled through robust optimization techniques. The model materializes into a simple linear programming algorithm to adjust the hourly load level of a given consumer in response to hourly electricity prices. The objective of the model is to maximize the utility of the consumer subject to a minimum daily energy-consumption level, maximum and minimum hourly load levels, and ramping limits on such load levels.

Reference [48] argues that any residential load control strategy in real-time electricity pricing environments requires price prediction capabilities. By applying a simple weighted average price prediction filter to the actual hourly-based price values used by the Illinois Power Company from January 2007 to December 2009, the authors obtain the optimal choices of the coefficients for each day of the week to be used by the price predictor filter.

In [49] an input-output hidden Markov model is proposed for analyzing and forecasting electricity spot prices. In [50] a Markov Decision Process (MDP) is proposed to find decision thresholds for both non-interruptible and interruptible loads under a deadline constraint. Numerical results suggest that incorporating the statistical knowledge into the scheduling policies can result in significant savings, especially for short tasks. It is demonstrated with real price data from Commonwealth Edison that scheduling with mismatched modeling and online parameter estimation can still provide significant economic advantages to consumers.

In [51] the electricity price is modeled as a Markov chain with unknown transition probabilities. This model features implicit estimation of the impact of future electricity prices and current control operation on long-term profits. The Q-learning algorithm is then used to adapt the control operation to the hourly available price in order to maximize the profit for the electric vehicle owner during the whole parking time.

Reference [52] discusses the modeling of uncertainties in aggregated thermostatically controlled loads using a state queuing (SQ) model. The cycling times of thermostatically controlled appliances (TCAs) vary with the TCA types and sizes, as well as the ambient temperatures.

Reference [53] develops an online learning application that implicitly estimates the impact of future energy prices and of consumer decisions on long term costs and schedules residential device usage. The algorithm models both energy prices and residential device usage as Markov, but does not assume knowledge of the structure or transition probabilities of these Markov chains. The paper focuses on energy consumption at one house and doesn't consider the utility company and grid issues.

Reference [54] suggests a coordinated home energy management system (HEMS) architecture where the distributed residential units cooperate with each other to achieve real-time power balancing. The economic benefits for the retailer and incentives for the customers to participate in the proposed coordinated HEMS program are given. The coordinated HEMS design problem is formulated as a dynamic programming (DP) and use approximate DP approaches to efficiently handle the design problem. A distributed implementation algorithm based on convex optimization based dual decomposition technique is also presented. The focus is on the deferrable appliances, such as Plug-in (Hybrid) Electric Vehicles (PHEV), in view of their higher impact on the grid stability. Certainty equivalent Control Theory is used to deal with the uncertainty in customer energy consumption.

Reference [55] extends the work in [40] to include the effect from load uncertainty. The optimal prices are derived under load uncertainty and show how it influences power consumption and generating capacity. Different models are used to formulate demand uncertainty.

Authors in [56] develop a model that integrates two period electricity markets, uncertainty in renewable generation, and real-time dynamic demand response. A load-serving entity decides its day-ahead procurement to optimize expected social welfare a day before energy delivery. At delivery time when renewable generation is realized, it sets prices to manage demand and purchase additional power on the real-time market, if necessary, to balance supply and demand.

In [57], a game theoretic algorithm is suggested to coordinate the operation of demand-side resources via pricing in order to tackle the intermittency and fluctuations in wind power generation.

Reference [58] proposes distributed algorithms for control and coordination of loads and distributed energy resources (DERs) in distribution networks. These algorithms are relevant for load curtailment control in demand response programs, and also for coordination of DERs for provision of ancillary services. Both the distributed load-curtailment and DER coordination problems can be cast as distributed resource allocation problems with constraints on resource capacity.

2.2 Constrained Optimization

Constrained optimization problems are problems for which a function $f(x)$ is to be minimized or maximized subject to constraints $\Phi(x)$. Here $f : R^n \rightarrow R$ is called the objective function and $\Phi(x)$ is a Boolean-valued formula. In Mathematics the constraints $\Phi(x)$ can be an arbitrary Boolean combination of equations $g(x) = 0$, weak inequalities $g(x) \geq 0$, strict inequalities $g(x) > 0$, and $x \epsilon \mathbb{Z}$ statements. The following notation will be used.

$$\max\ f(x) \quad s.t. \quad \Phi(x) \tag{2.1}$$

Global Optimization: A point $u \epsilon R^n$ is said to be a global minimum of f subject to constraints Φ if u satisfies the constraints and for any point v that satisfies the constraints, $f(u) \leq f(v)$.

Local Optimization: A point $u \epsilon R^n$ is said to be a global minimum of f subject to constraints Φ if u satisfies the constraints and for some $r > 0$, if v satisfies $|v - u| < r \Lambda \Phi(v)$, then $f(u) \leq f(v)$.

2.2.1 Classic Optimization Methods

The methods used to solve local and global optimization problems depend on specific problem types. Optimization problems can be categorized according to several criteria. Depending on the type of functions involved there are linear and nonlinear (polynomial, algebraic, transcendental, ...) optimization problems. If the constraints involve $x \epsilon \mathbb{Z}$, we have integer and mixed integer-real optimization problems.

Linear Programming

Lnear programming is a technique to minimize/maximize a linear objective function, subject to linear equality and linear inequality constraints. Its feasible region is a convex polyhedron, which is a set defined as the intersection of finitely many half spaces, each of which is defined by a linear inequality. A closed convex polytope may be regarded as the set of solutions to the system of linear inequalities known as constraints. A linear programming algorithm finds a point in the polyhedron where this function has the smallest (or largest) value if such point exists. Linear programs can be expressed in canonical form:

$$\begin{gathered} \max\ c^T x \\ s.t \\ Ax \leq b \\ x \geq 0 \end{gathered} \tag{2.2}$$

where x represents the vector of variables (to be determined), c and b are vectors of (known) coefficients, and A is a (known) matrix of coefficients. x is an $n \times 1$ vector; b is an $m \times 1$ vector; and A is an $m \times n$ matirx. Interior Point and Simplex, and Revised Simplex are the most common methods used to solve a linear programming problem.

The simplex and revised simplex algorithms solve a linear programming problem by moving along the edges of the polytope defined by the constraints, from vertices to vertices with successively smaller values of the objective function, until the minimum is reached. Interior point algorithms for linear programming, loosely speaking, iterates from the interior of the polytope defined by the constraints. They get closer to the solution very quickly, but unlike the simplex/revised simplex algorithms, do not find the solution exactly.

Quadratic programming

A linearly constrained optimization problem with a quadratic objective function is called a quadratic program (QP). The general quadratic program can be written as:

$$\begin{aligned} &\min \; c^T x + \frac{1}{2} x^T Q x \\ &s.t. \\ &Ax \leq b \\ &x \geq 0 \end{aligned} \tag{2.3}$$

When the objective function $f(x)$ is strictly convex for all feasible points the problem has a unique local minimum which is also the global minimum. A sufficient condition to guarantee strictly convexity is for Q to be positive definite.

Mixed Integer Programming

A mixed-integer program is the minimization or maximization of a linear function subject to linear constraints. More explicitly, a mixed-integer program with n variables and m constraints has the form:

$$\begin{gathered} \max \; c^T x \\ s.t. \\ Ax \leq b \\ l \leq x \leq u \\ x_j \; integer \; for \; all \; j \; in \; D \; which \; is \; a \; subset \; of \; \{1...n\} \end{gathered} \tag{2.4}$$

If all the variables can be rational (the set D is empty), this is a linear programming problem, which can be solved in polynomial time. However, when some or all of the variables must be integer, corresponding to pure integer and mixed integer programming respectively, the problem becomes NP-complete (formally intractable).

There are three major algorithms to solve integer programming problems: Branch and Bound, Branch and Cut, Branch and Price.

Branch and Bound: The most widely used method for solving integer programs is branch and bound. Subproblems are created by restricting the range of the integer variables. For binary variables, there are only two possible restrictions: setting the variable to 0, or setting the variable to 1. More generally, a variable with lower bound l and upper bound u will be divided into two problems with ranges l to q and $q+1$ to u respectively. Lower bounds are provided by the linear-programming relaxation to the problem: keep the objective function and all constraints, but relax the restrictions to derive a linear program. If the optimal solution to a relaxed problem is (coincidentally) integral, it is an optimal solution to the subproblem, and the value can be used to terminate searches of subproblems whose lower bound is higher [59].

Branch and Cut: For branch and cut, the lower bound is again provided by the linear-programming (LP) relaxation of the integer program. The optimal solution to this linear program is at a corner of the polytope which represents the feasible region (the set of all variable settings which satisfy the constraints). If the optimal solution to the LP is not integral, this algorithm searches for a constraint which is violated by this solution, but is not violated by any optimal integer solutions. This constraint is called a cutting plane. When this constraint is added to the LP, the old optimal solution is no longer valid, and so the new optimal will be different, potentially providing a better lower bound. Cutting planes are iteratively until either an integral solution is found or it becomes impossible or too expensive to find another cutting plane. In the latter case, a tradional branch operation is performed and the search for cutting planes continues on the subproblems [59].

Branch and Price: This is essentially branch and bound combined with column generation. This method is used to solve integer programs where there are too many variables to represent the problem explicitly. Thus only the active set of variables are maintained and columns are generated as needed during the solution of the linear program. Column generation techniques are problem specific and can interact with branching decisions [59].

Decentralized Optimization

The decentralized optimization is developed based on dual decomposition method. Dual decomposition method is used for dynamic optimization on large-scale network in which distributed agents pass relatively small messages [60].

Dual Decomposition: Consider the following convex equality constrained optimization problem:

$$\begin{gathered} \min\ f(x) \\ s.t. \\ Ax = b \end{gathered} \tag{2.5}$$

The Lagrangian L is defined as:

$$L\left(x, y\right) = f(x) + y^T\left(Ax - b\right) \tag{2.6}$$

The corresponding Lagrange dual function $g(y)$ is the infimum with respect to the primal variable x:

$$g(y) = \inf_x\ L(x, y) \tag{2.7}$$

The Lagrange dual problem is the maximization of the Lagrange dual function $(max\, g(y))$ and the optimal x can be obtained through the following equation:

$$x^* = \min_x L(x, y^*) \tag{2.8}$$

We solve the Lagrange dual problem (2.8) with the subgradient method. The subgradient method is a generalization of the gradient descent method to non-differentiable functions, using the iterations:

$$y^{k+1} = y^k + \alpha^k \nabla g(y^k) \tag{2.9}$$

where k is the iteration index, α is the step size, and $\nabla g(y^k)$ is a subgradient to g. According to (2.5):

$$\nabla g(y^k) = A\tilde{x} - b \tag{2.10}$$

where $\tilde{x} = \min_x L(x, y^k)$.

x and y are updated in each iteration according to dual ascent method:

$$x^{k+1} := \min_x L(x, y^k) \tag{2.11}$$

$$y^{k+1} := y^k + \alpha^k (Ax^{k+1} - b) \tag{2.12}$$

Now, suppose f is separable

$$f(x) = f1(x_1) + \ + f_N(x_N),\ x = (x_1, ..., x_N) \tag{2.13}$$

Then L is seperable in $x:\ L(x, y) = L_1(x_1, y) + \cdots + L_N(x_N, y) - y^T b$,

$$L_i(x_i, y) = f_i(x_i) + y^T A_i x_i \tag{2.14}$$

Therefore, x-minimization in the dual ascent splits into N separate minimizations:

$$x_i^{k+1} := \min_{x_i} L_i(x_i, y^k) \tag{2.15}$$

which can be carried out in parallel. Using the dual decomposition theory, the problem is solved in a distributed manner. Then, x and y are updated in each iteration k as follows:

- scatter dual variable,y^k, to the agents.
- update x_i in parallel according to (2.15)
- update y^k:

$$y^{k+1} := y^k + \alpha^k (\sum A x^{k+1} - b) \tag{2.16}$$

This process converges when $\sum A x^{k+1}$ gets close to b. This means that the dual variable, y, doesn't get updated anymore.

2.2.2 Heuristic Methods

Heuristic optimization methods are essentially computational and therefore they have been naturally introduced following the development of electronic computing devices. First contributions go back to authors in [61] and [62] who developed procedures to solve the traveling salesman problem, but the most significant advances in the domain have been made in the late 1980s and 1990s when the main techniques have been introduced.

Optimization heuristics, which are sometimes also labeled approximation methods, are generally divided into two broad classes, constructive methods also called greedy algorithms and local search methods. Local search uses only information about the solutions in the neighborhood of a current solution and is thus very similar to hill climbing where the choice of a neighbor solution locally maximizes a criterion. The classical local search method for minimizing a given objective function $f(x)$ can be formalized as presented in Algorithm 1.

Algorithm 1: Pseudo-code for the classical local search procedure.

1. Generate initial solution
2. While stopping criteria not met
    3. Select $x^n \epsilon N(x^c)$ (neighbor to current solution)
    4. If $f(x^n) < f(x^c)$ then $x^c = x^n$
5. End

Hill-climbing uses information about the gradient for the selection of a neighbor x^n in statement 3 whereas local search algorithms choose the neighbors according to some random mechanism. This mechanism as well as the criteria for acceptance in statement 4, which are specific for a particular heuristic, define the way the algorithm walks through the solution space. The stopping criteria often consists in a given number of iterations.

Local search methods are generally divided into trajectory methods which work on a single solution and population based methods (some of them are also called evolutionary algorithms by some authors), where a whole set of solutions is updated simultaneously. In the first class, we find threshold methods and tabu search whereas the second class consists of genetic algorithms, differential evolution methods and ant colonies. All these local search methods have particular rules for either or both, the choice of a neighbor and the rules for acceptance of a solution. All the methods, except for tabu search, allow uphill moves, i.e. accept solutions which are worse than the previous one, in order to escape local minima.

2.2.3 Optimization Under Uncertainty

A large number of problems in power systems require that decisions be made in the presence of uncertainty. Examples of uncertainty are uncertainty in demand, generation from renewable resources, and uncertainties associated from measurements. A key difficulty in optimization under uncertainty is in dealing with an uncertainty space that is huge and frequently leads to very large-scale optimization models. Decision-making under uncertainty is often further complicated by the presence of integer decision variables to model logical and other discrete decisions in a multi-period or multi-stage setting. In this section, we briefly review theory and methodology that have been developed to cope with the complexity of optimization problems under uncertainty.

Stochastic Programing

Under the standard two-stage stochastic programming paradigm, the decision variables of an optimization problem under uncertainty are partitioned into two sets [63]. The first stage variables are those that have to be decided before the actual realization of the uncertain parameters. Subsequently, once the random events have presented themselves, further design or operational policy improvements can be made by selecting, at a certain cost, the values of the second-stage, or recourse, variables. Traditionally, the second-stage variables are interpreted as corrective measures or recourse against any infeasibilities arising due to a particular realization of uncertainty. However, the second-stage problem may also be an operational-level decision problem following a first-stage plan and the uncertainty realization. Due to uncertainty, the second-stage cost is a random variable. The objective is to choose the first-stage variables in a way that the sum of the first-stage costs and the expected value of the random second-stage costs is minimized. The concept of recourse has been applied to linear, integer, and non-linear programming [63].

A standard formulation of the two-stage stochastic linear program is:

$$\begin{gathered} \min\, c^t x + E_{\omega \epsilon \Omega}[Q(x,\omega)] \\ s.t. \\ x \epsilon X \end{gathered} \tag{2.17}$$

with

$$
\begin{gathered}
Q(x,\omega) = min\, f(\omega)^t y \\
s.t. \\
D(\omega)y \geq h(\omega) + T(\omega)x, \quad y\epsilon Y
\end{gathered}
\tag{2.18}
$$

where $X \subseteq \Re^{n1}$ and $Y \subseteq \Re^{n2}$ are polyhedral sets. Here, $c\epsilon\Re^{n1}$, ω is a random variable from a probability space $(\Omega, \mathcal{F}, P)$ with $\Omega \subseteq \Re^k$, $f : \Omega \rightarrow \Re^{n_2}$, $h : \Omega \rightarrow \Re^{m_2}$, $D : \Omega \rightarrow \Re^{m_2 \times n_2}$, $D : \Omega \rightarrow \Re^{m_2 \times n_1}$. Problem (2.17) with variables x constitute the first stage which needs to be decided prior to the realization of the uncertain parameters $\omega\epsilon\Omega$. Problem (2.18) with variables y constitute the second stage. Under the assumption of discrete distributions of the uncertain parameters, the problem can be equivalently formulated as a large-scale linear program which can be solved using standard linear programming technology.

Probabilistic programming

The recourse-based approach to stochastic programming requires the decision-maker to assign a cost to recourse activities that are taken to ensure feasibility of the second-stage problem. In essence, the philosophy of this approach is that infeasibilities in the second stage are allowed at a certain penalty. The approach thus focuses on the minimization of expected recourse costs. In the probabilistic or chance-constraint approach, the focus is on the reliability of the system, i.e., the system's ability to meet feasibility in an uncertain environment. This reliability is expressed as a minimum requirement on the probability of satisfying constraints [64]. Consider the classical linear programming model:

$$\begin{aligned} &\max\ c^t x \\ &s.t. \\ &Ax \geq b, \quad x \geq 0 \end{aligned} \tag{2.19}$$

where c and x are n-vectors, b is an m-vector, and A is an $m \times n$ matrix. Assume that there is uncertainty regarding the constraint matrix A and the right-hand side vector b, and that the system is required to satisfy the corresponding constraint with a probability $p \epsilon (0,1)$. Then, the probabilistic linear program corresponding to the classical (deterministic) linear program can be stated as follows:

$$\begin{aligned} &\max\ c^t x \\ &s.t. \\ &P(a^t x \geq b) \geq p, \quad x \geq 0 \end{aligned} \tag{2.20}$$

Consider the case when $m = 1$, i.e., the case of a single constraint $P(a^t x \geq b) \geq p$. Further, assume that the vector a is deterministic while the right-hand side b is a random variable with cumulative distribution F. Let β be such that $F(\beta) = p$. Then, the constraint $P(a^t x \geq b) \geq p$ can be written as $F(a^t x) \geq p$ or $a^t x \geq \beta$. In this simple case, the probabilistic program is equivalent to a standard linear program.

Fuzzy mathematical programming

Similar to stochastic programming, fuzzy programming also addresses optimization problems under uncertainty. A principal difference between the stochastic and fuzzy optimization approaches is in the way uncertainty is modeled. In the stochastic programming case, uncertainty is modeled through discrete or continuous probability functions. On the other hand, fuzzy programming considers random parameters as fuzzy numbers and constraints are treated as fuzzy sets. Some constraint violation is allowed and the degree of satisfaction of a constraint is defined as the membership function of the constraint [65]. Consider the following fuzzy optimization:

$$\begin{aligned} &\max \widetilde{c}^t x \\ &s.t. \\ &\widetilde{A}x \leq \widetilde{b}, \ \ x \geq 0 \end{aligned} \tag{2.21}$$

where $\widetilde{c}$, $\widetilde{A}$, and $\widetilde{b}$ represent fuzzy intervals for parameters c, A, and b, respectively. Let a_{ij} and Δa_{ij}, respectively, represent the center and spread of the fuzzy number $\widetilde{a}_{ij}$. Similarly, let c_j and Δc_jdenote the center and spread of the fuzzy number $\widetilde{c}_{ij}$. Now, consider the following membership functions:

$$u_i(x) = \begin{cases} 1, & if\, A_i x \leq b_i \\ 1 - \frac{A_i x - b_i}{\Delta A_i x + \Delta b_i}, & if\, b_i < A_i x < b_i + \Delta A_i x + \Delta b_i \\ 0, & otherwise \end{cases} \tag{2.22}$$

and

$$u_0(x) = \begin{cases} 1, & if\, b_0 \leq c^t x \\ 1 - \frac{b_0 - c^t x}{\Delta b_0 + \Delta c^t x}, & if\, b_0 - \Delta b_0 - \Delta c^t x < cx < b_0 \\ 0, & otherwise \end{cases} \tag{2.23}$$

where $[b_0 - \Delta b_0, b_0]$ denotes the aspiration range for the objective. Then, the Bellman–Zadeh decision-making criterion leads to the following equivalent of the possibilistic program after the introduction of a new variable λ:

$$
\begin{gathered}
max\,\lambda \\
s.t. \\
c^t x + \Delta c^t x(1-\lambda) \geq b_0 - \Delta b_0(1-\lambda) \\
Ax - \Delta Ax(1-\lambda) \leq b + \Delta b(1-\lambda) \\
x \geq 0,\ \ 0 \leq \lambda \leq 1
\end{gathered}
\tag{2.24}
$$

Chapter 3

Distribution System Restoration/Reconfiguration

In this chapter, the motivation, contribution and detailed formulation of distribution system reconfiguration is provided.

3.1 Motivation and Contribution

From the literature review in the last chapter, it seems clear that the explicit representation of the radiality constraints is an issue that has not yet been appropriately solved. Therefore, many of the proposed approaches have used heuristic search or population based approaches to solve the problem. Nevertheless, solutions based on heuristic methods suffer from a number of shortcomings. If formulating the radiality/weakly-meshed constraint is possible, then the restoration/reconfiguration and distribution system expansion problems can be solved using integer programming techniques. In this dissertation, a general approach taking advantage of practical operating constraints is introduced. The main contribution is to offer a general approach based on MIP to formulate reconfiguration for radial or weakly meshed distribution systems. Employing the proposed method, many different objectives can be formulated easily. The study also investigates the effect of Community Energy Storage Systems (CES) [66] discharge on reconfiguration solution. Performance of MIP on two objectives is investigated: 1- minimizing the loss; and 2- minimizing the number of switching operations, which is important for fault location and isolation, fault repair and system restoration. Two different formulations are proposed for each objective function. The first formulation is a linear formulation of reconfiguration problem while the second one includes quadratic objective function and constraint set. A Depth-first strategy is used to formulate the radiality constraint for the MIP. This is a very general approach that can be applied to any given system and objective function. None of the researches in the literature have heretofore reported formulating the radiality constraint for MIP. As an important feature, the proposed approach offers very fast reconfiguration and restoration of distribution systems. Another challenge in DSR is uncertainties associated with loads and renewable resources. This problem is caused by insufficient measurements and high penetration of controllable loads and renewable resources. Therefore, DSR with deterministic optimization may not lead to an optimal/feasible result. We need to come up with a method which gives us an optimal solution for different loading conditions. In other words, we need to make a compromise between optimality and feasibility. In this dissertation, two different methods based on fuzzy MIP (FMIP) and stochastic MIP (SMIP) are proposed to solve reconfiguration problem in presence of load uncertainty. Performances of the proposed approaches are compared by implementing them on two test systems. It is shown that the solutions obtained by FMIP, SMIP are robust enough to deal with different loading conditions. If we are certain about the probability distribution function of the load forecast/measurement error, SMIP may lead to a more optimal solution. However, problem with SMIP is the computational intensity which makes it inappropriate for real-time applications. Specially, if we want to achieve more accurate results, we need to increase the number of scenarios in our stochastic approach which makes it more computational intense and slow. On the other hand, it will be shown that FMIP is very fast and appropriate for real-time applications. Membership functions for fuzzy optimization are modeled based on the radial structure of the distribution system to give feasible and optimal results. In general, if we want to perform reconfiguration in real-time, it will be more practical to use FMIP. In the following, first the deterministic MIP-based DSR is presented and then robust DSR based on FMIP and SMIP will be discussed.

3.2 Deterministic MIP-Based DSR

In this case, nominal values of the loads are considered as the deterministic values and uncertainty is neglected. Two methods based on Mixed Integer Linear Programming (MILP) and Mix Integer Quadratic Programming (MIQP) are introduced. It is shown that compared to MIQP, the MILP-based DSR leads to a faster but sub-optimal solution.

3.2.1 MILP-Based DSR

The status of a switch is a binary variable and the other variables, such as CES units power output, and line flows are modeled as continuous real numbers. The DSR optimization problems considered in this study are given as the minimization of active power loss and minimization of the total number of switching operations subject to a set of constraints including power balance, thermal limits of the lines, CES units' constraints, and radiality of the system. It will be shown that CES output power can change the configuration of the network by changing line flows. Specifically:

- Objective: Loss minimization

$$\min \sum_{i=1}^{n_i} r_i \left(u_i + v_i\right) \tag{3.1}$$

- Objective: Minimizing switching actions

$$\min \sum_{i \epsilon NO} x_i - \sum_{i \epsilon NC} x_i + \sum_{i=1}^{n_i} r_i \left(u_i + v_i\right) \tag{3.2}$$

Subject to:

- Power balance and line flow limit constraints

$$A^T(u-v) = P - P_b \tag{3.3}$$

$$u_i + v_i \leq x_i.P_i^{f,max} \tag{3.4}$$

$$x_i \epsilon \{0,1\}$$

$$u_i, v_i \geq 0$$

- Radiality constraint

$$\sum_{i=1}^{N_j} x_i \leq N_j - 1 \tag{3.5}$$

- CES Constraint

$$-(1-SC_i^b)C_i^b \leq P_i^b t \leq C_i^b SC_i^b - d_i^b \tag{3.6}$$

$$P_{ch,max}^b \leq P_i^b \leq P_{dc,max}^b \tag{3.7}$$

where n_i is number of the lines, $u_i - v_i = P_i^f$, $u_i + v_i = \left|P_i^f\right|$, and P_i^f is active power flow on the i^{th} line. $u_i$and v_i are non-negative variables which cannot both be non-zero simultaneously. r_i is the resistance of the corresponding branch. A is the reduced node incidence matrix of the system. x_i is the swith status, $x_i = 0$ and $x_i = 1$ represent an open switch and closed switch, respectively. P is the vector of node injection active power. $P_i^{f,max}$ is the maximum active power flow limit on the i^{th} line. NO and NC are normally open (tie-line) and normally close switches, respectively. N_j is the number of switches in loop j (described in more detail in the next sections). P_b is the active power output of the CES units. SC_i^b and C_i^b are state of charge (SoC) and capacity (kWh) of the battery storage unit i, respectively. d_i^b is the depth of discharge of unit i. $P_{ch,max}^b$ and $P_{dc,max}^b$ are maximum charge and discharge rates of the battery storage units, respectively.

The first objective function penalizes high flows through branches with higher resistance while the second objective, in case of faults, searches for minimum number of switching actions to isolate the fault and remove overload condition in such a way that the minimum-loss topology is obtained. As results show, the optimization utilizes CES units to locally supply loads to reduce power flow on the lines and consequently to reduce loss. Implementing CES unit may also lead to change in the result of reconfiguration through changing the line flows and voltages on the nodes.

Power balance and line flow limit constraints are expressed in (3.3) and (3.4), respectively. Note that line losses are not considered in power balance equations as they are usually negligible compared to loads. Radiality of the system is guaranteed by enforcing (3.5). (3.6) states that the output energy of a CES unit should be smaller than the current available energy in the battery. Constraint (3.7) assures shallow discharge of units to prolong battery life.

3.2.2 MIQP-Based DSR

In addition to the active power, reactive power is also taken into account in this formulation. The optimization problem is formulated as follows:

- Objective: Loss minimization

$$\min \sum_{i=1}^{n_i} r_i \left(\left(P_i^f \right)^2 + \left(Q_i^f \right)^2 \right) + \sum_{i=1}^{n_b} P_b^2 \tag{3.8}$$

- Objective: Minimizing switching actions

$$\min \sum_{i \epsilon NO} x_i - \sum_{i \epsilon NC} x_i + \sum_{i=1}^{n_i} r_i \left(\left(P_i^f \right)^2 + \left(Q_i^f \right)^2 \right) + \sum_{i=1}^{n_b} P_b^2 \tag{3.9}$$

Subject to:

- Power flow constraints

$$A^T P_f = P - P_b \tag{3.10}$$

$$A^T Q_f = Q - Q_b \tag{3.11}$$

- Line thermal limit constraint

$$|I_i| \leq x_i I_i^{max} \tag{3.12}$$

$$x_i \epsilon \{0, 1\}$$

- Voltage constraint

$$V_{i,min} \leq |V_i| \leq V_{i,max} \tag{3.13}$$

- Radiality constraint

$$\sum_{i=1}^{N_j} x_i \leq N_j - 1 \tag{3.14}$$

- Battery constraint

$$-(1 - SC_i^b)C_i^b \leq P_i^b t \leq C_i^b SC_i^b - d_i^b \tag{3.15}$$

$$-P_{ch,max}^b \leq P_i^b \leq P_{dc,max}^b \tag{3.16}$$

$$PF > PF_{min} \tag{3.17}$$

P_i^f and Q_i^f are active and reactive power flow on the i^{th} line and P and Q are active and reactive power load vectors. A is the reduced node incidence matrix of the system.

P_b and Q_b are active and reactive power output of a battery unit. I_i^{max} is the thermal limit of line i. V_i is the voltage magnitude on node i. PF and PF_{min} are the power factor and minimum acceptable power factor of the battery storage unit.

The first term in the objective function (3.8) penalizes high flows through branches with higher resistance while the second term captures the damaging effect of fast charging and discharging of the battery units. Constraints (3.10)-(3.11) are the power balance equations. The thermal limit constraint of distribution lines and cables is guaranteed by (3.12). Radiality of the reconfigured system is preserved by utilizing (3.14).

Voltage limit constraint is considered by (3.13). A linear formulation of the voltage constraint based on the deviation of the voltage on a node from substation voltage is used in this study. The voltage difference between two nodes in a distribution system can be approximated by [17]:

$$V_i^2 - V_j^2 \simeq 2(r_j p_j + x_j q_j) \tag{3.18}$$

where r_j and x_j are resistance and reactance of line j, respectively. p_j and q_j are active and reactive power flows on line j. Therefore, the quadratic voltage drop through a path α_k^i reaching bus i from substation s is approximated by:

$$V_s^2 - V_i^2 \simeq 2\sum_{j\epsilon\alpha_k^i}(r_j p_j + x_j q_j) \tag{3.19}$$

The voltage deviation on a node with respect to the substation should not violate a certain limit, ΔV_{max}:

$$V_s - V_i \leq \Delta V_{max} \tag{3.20}$$

Combining (3.19) and (3.20), the quadratic voltgae drop is formulated as follows:

$$V_s^2 - V_i^2 \leq \delta_{max} \tag{3.21}$$

where $\delta_{max} = \Delta V_{max}(2V_s - \Delta V_{max})$. Therefore the bus voltage drop limitation for each candidate path, α_k^i, leading to bus i can be incorporated to the problem as follows:

$$2\sum_{j\epsilon\alpha_k^i}(r_j p_j + x_j q_j) \leq \delta'_{max} \tag{3.22}$$

where $\delta'_{max} = \delta_{max} + M(N_\alpha - \sum_{j\epsilon\alpha_k^i} X_j)$. The term $M(N_\alpha - \sum_{j\epsilon\alpha_k^i} X_j)$ is added to prevent (3.22) from being binding for any inactive path corresponding to bus i. M is a large positive number and N_α is the number of switches in path α_k^i.

3.2.3 Radiality Constraints

In order to maintain the radiality of the system, the number of closed lines in each loop needs to be less than the total number of lines making the loop as proscribed by (3.5). In other words, there should be at least one open branch in each potential loop. A DFS-based approach is employed here to detect all the cycles assuming that all switches are closed. Note if there are some acceptable loops in a weakly meshed system, they can simply be removed from (3.5).

DFS is a general technique for traversing a graph. DFS always expands one of the nodes at the deepest level of the tree. Only when the search hits a dead end (a non-goal node with no expansion) does the search backtrack and expand nodes at shallower levels [67]. In this study, DFS is specialized to find all possible loops (cycles) in a given graph. Let's define a path in a given graph as a sequence of vertices such that from each of its vertices there is an edge to the next vertex in the sequence.

Therefore, a cycle is a closed path with no repeated vertices other than the starting and ending vertices. To illustrate, consider vertex A in Figure 3.1(a). All vertices are labeled initially as unexplored vertices or nodes. There are three options to continue: $A \rightarrow B$, $A \rightarrow D$, and $A \rightarrow E$. For choosing the next vertex, the right vertex has priority. Hence, DFS picks $A \rightarrow B$ and vertex B is labeled as visited node (Figure 3.1(b)). $B \rightarrow C$ is the only edge that the DFS can take from B and the vertex C is labeled as a visited vertex. Therefore, there are two visited nodes and two discovery edges so far. When DFS gets to C, it can choose either $C \rightarrow D$ or $C \rightarrow E$. DFS chooses the right edge, $C \rightarrow D$, and visits vertex D (Figure 3.1(d)). For vertex D, there is only one option $D \rightarrow A$. Since the vertex A is the starting vertex, a cycle is detected (Figure 3.1(e)). Search then returns to the last visited vertex, which is D. As there is no option to traverse, it labels the vertex D as an unexplored vertex and moves to C. For vertex C, the edge $C \rightarrow D$ has already been explored and therefore the next left edge, C→E, is taken and the vertex E is labeled as visited (Figure 3.1(f)). Then only one option $E \rightarrow A$ should be chosen and another cycle is detected (Figure 3.1(g)). Search now returns to E and the vertex E is labeled as unexplored vertex and DFS gets back to the last visited vertex, which is C again. For the last visited vertices C and B, there is also no more unexplored edge remaining and therefore they are labeled as unexplored vertices. The DFS returns to the starting vertex A. Two unexplored edges $A \rightarrow D$ and $A \rightarrow E$ are left. The next right edge $A \rightarrow D$ is chosen (Figure 3.1(h)) and the above process should be repeated to detect other cycles starting from vertex A. After detecting all the cycles starting from vertex A, the vertex and its connected edges are removed from the graph and the above process should be repeated for the next arbitrary vertex. The above process should be stopped when the number of vertices of the graph is less than three. After finding all the cycles, if there are two identical cycles, one of them should be removed.

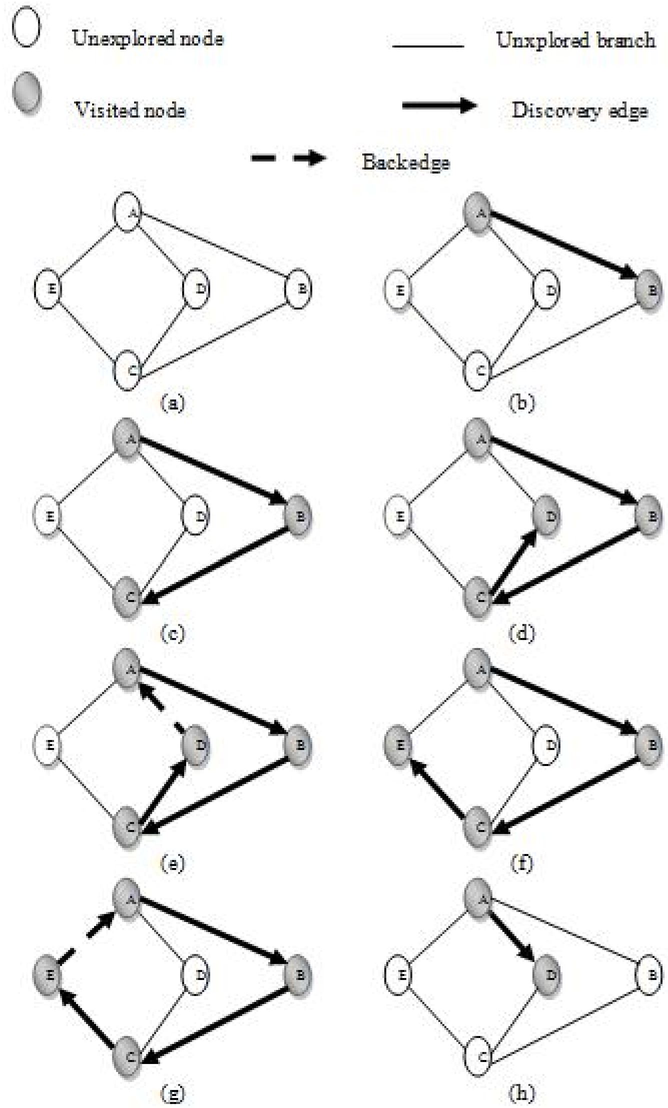


Figure 3.1: DFS-based approach on a simple example

3.3 Reconfiguration with Load Uncertainty

As mentioned before, due to insufficient measurements and/or high utilization of demand response programs and renewable resources in the distribution system, the deterministic optimization may not be optimal/feasible.

In this dissertation, two different approaches are proposed to formulate the reconfiguration problem with uncertain load data. The first approach is based on FMIP in which the constraints and the objective function are converted to fuzzy relations. This means that the constraints are allowed to violate with some degrees which are determined by their membership functions. In the second approach, the reconfiguration problem is formulated as a stochastic optimization problem based on load probability distribution functions (PDF). In this section, the effect of load uncertainty on loss minimization DSR is studied. These methods can be implemented for other objectives with some modifications.

3.3.1 FMIP-Based DSR

It is assumed that the load forecast on a node is an interval number:

$$\begin{aligned} P_l \epsilon [P - \triangle P, P + \triangle P] \\ Q_l \epsilon [Q - \triangle Q, Q + \triangle Q] \end{aligned} \tag{3.23}$$

where P and Q represent the nominal (forecasted) load on the bus and ΔP and ΔQ are the maximum variation of active and reactive power load. In order to convert the deterministic optimization problem (3.8) into a fuzzy optimization, the power balance constraint (3.10)-(3.11), line flow limits (3.12), and voltage limits (3.22) constraints can be expressed as fuzzy relations. Different membership functions are considered for the above constraints which are described in the following.

Active/reactive power balance constraints

The optimum configuration should be able to tolerate severe loading scenarios. Because of the radial structure of distribution system if load on every node increases, the line flows increase and there will be a higher possibility of violation in line flow and voltage limit constraints. The membership function considered for fuzzy active power balance constraints is depicted in Figure 3.2. A constant power factor is considered for loads on every bus. The membership function indicates that it is more desirable if the power balance equations are satisfied for maximum loading cases. This will give more conservative solution compared to the deterministic optimization where power balance equations should be satisfied for nominal loads.

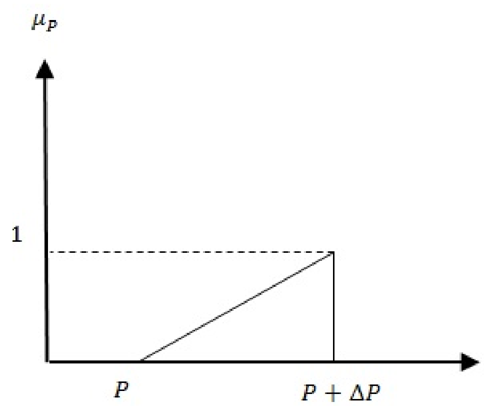


Figure 3.2: Membership function of the active power balance constraint

Line thermal limit constraint

Line flows can also be modeled by a soft constraint. The membership function considered for the line flow limit constraint is shown in Figure 3.3. The membership function μ_I indicates that configuration of the system becomes less acceptable as the power flows on the lines increases above the maximum thermal limit of the lines.

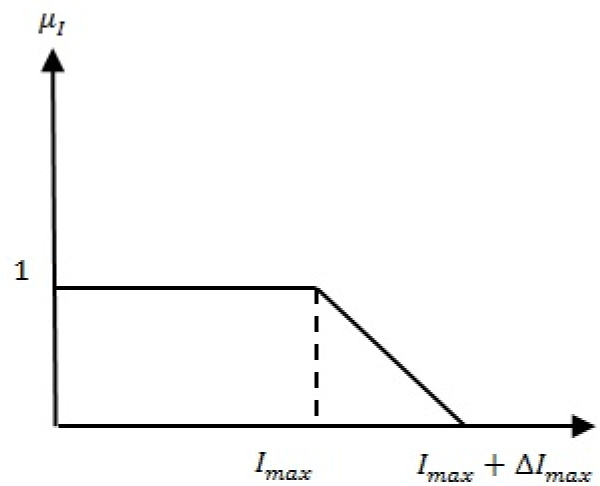


Figure 3.3: Membership function of line thermal limit constraint

Voltage limit constraint

Voltage limit constraint (3.22) is also converted to a soft constraint to account for load uncertainty. The membership function for voltage constraint is similar to the one assigned for line thermal limit. This means that (3.22) is allowed to violate to some degree $\Delta\delta'_{max}$.

Based on the symmetric approach, the objective function, should be essentially smaller than or equal to some aspiration level, Z_0, for each objective.

$$\widetilde{Z} \widetilde{\leq} Z_0 \tag{3.24}$$

The membership function of (3.24) can be modeled by Figure 3.4. The aspiration level represents the ideal system configuration with minimum loss and optimal battery discharge. A configuration becomes less acceptable as the system loss increases above the ideal value as indicated by the reduced membership in Figure 3.4. One good candidate for Z_0 is the result of the optimization problem (3.8) with nominal load values.

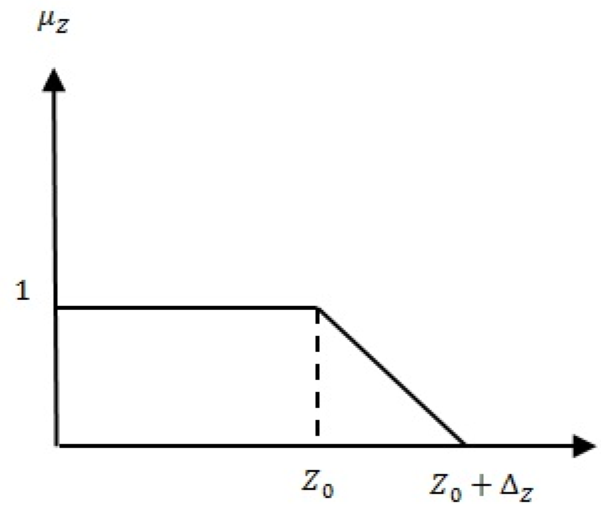


Figure 3.4: Membership function of the objective function

Since the constraints and objective function are represented by membership functions, min-max method can be used to solve the optimization problem. In this approach the objective function and constraints are treated symmetrically. Mathematically,

$$\lambda^* = \max\ \min(\mu_Z, \mu_P, \mu_I, \mu_V) \tag{3.25}$$

Consequently, the following equivalent parametric model can be used:

$$\begin{aligned} &\max\ \lambda \\ &s.t. \\ &\mu_Z \geq \lambda \\ &\mu_P \geq \lambda \\ &\mu_V \geq \lambda \\ &\mu_I \geq \lambda \\ &(3.14) - (3.17) \\ &0 \leq \lambda \leq 1,\ x\epsilon\{0,1\} \end{aligned} \tag{3.26}$$

The problem thus becomes maximizing a scaler value λ such that the membership values of all constraints should be greater than or equal to this λ.

3.3.2 SMIP-Based DSR

In order to find a solution, which takes account of the stochastic characteristic of load, stochastic optimization is introduced to solve the problem of DSR. It is assumed that the forecasted load has a Guassian probability distribution function (PDF) with mean value $\widetilde{P_{di}}$ and standard deviation σ. At the i^{th} bus of a distribution system, the PDF is shown in Figure 3.5 and can be defined as follows:

$$\rho d_i = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(P_{di} - \widetilde{P_{di}})}{2\sigma^2}} \tag{3.27}$$

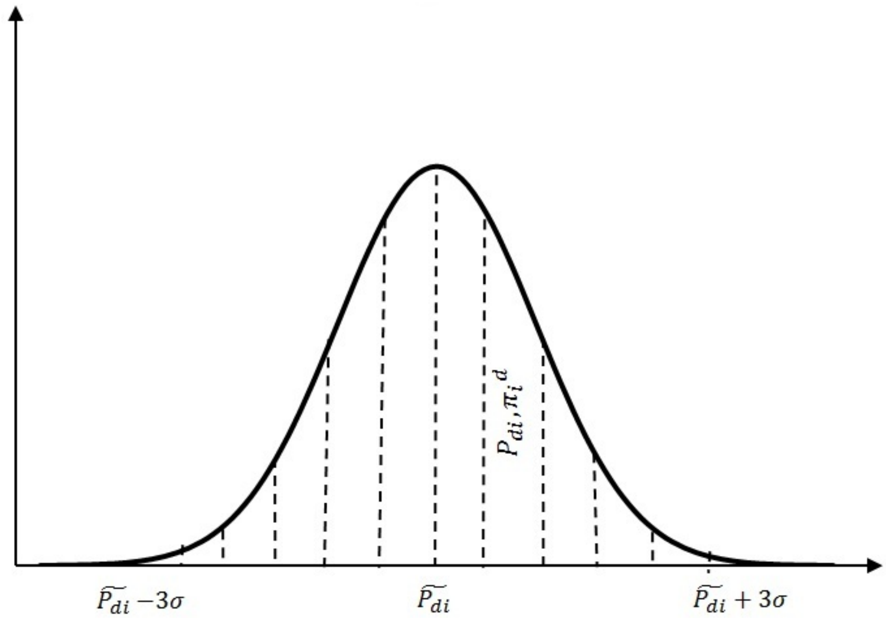


Figure 3.5: Probability density function of the Load

σ is assumed to be the same at all buses (this will significanty reduces the computational intensity). Taking an interval of $\widetilde{P_{di}} \pm 3.5\sigma$, it is split into n_d segments of equal widths. The d^{th} segment has an area (or probability) π_i^d and average power value that equals P_{di}. As we have chosen σ to be same at all the buses, π_i^d at the i^{th} bus equals π_j^d at the j^{th} bus and in general equals π^d. This allows for a probabilistic load model that has n_d pairs of values with the d^{th} pair having a load and its corresponding probability that equals (π_i^d, π^d).

We also assume a constant power factor (PF) for all the loads:

$$\widetilde{Q_{di}} = PF.\widetilde{P_{di}} \tag{3.28}$$

Specifically, the problem of DSR is formulated as a two-stage SMIP model. The first stage involves solving a radiality-constrained DSR in the base case without load uncertainty and the second stage addresses the scenarios where load uncertainties occur. In the model, decisions made in the first stage are status of switches and battery discharges. Decisions made in the second stage include active/reactive power flow on the lines and voltages on the buses. Decisions on status of switches and battery discharge are only made in the first stage and does not change across scenarios. The active/reactive power flow on the lines and voltages on the buses are determined for each scenario in order to minimize the active power loss.

Mathematically, the two-stage SMIP model is formulated as:

$$\min \quad \sum_{\omega=1}^{N_\omega} \pi_\omega \left[\sum_{i=1}^{n_i} R_i \left(\left(P_{i\omega}^{f} \right)^2 + \left(Q_{i\omega}^{f} \right)^2 \right) + \sum_{i=1}^{n_b} P_b^2 \right] \tag{3.29}$$

Subject to:

- Power flow constraints

$$A^T P_{f\omega} = P_\omega - P_b \tag{3.30}$$

$$A^T Q_{f\omega} = Q_\omega - Q_b \tag{3.31}$$

- Line thermal limit constraint

$$|I_{i\omega}| \leq x_i I_i^{max} \tag{3.32}$$

$$x_i \epsilon \{0, 1\}$$

- Voltage constraint

$$V_{min} \leq |V_{i\omega}| \leq V_{max} \tag{3.33}$$

- Radiality consttraint

$$\sum_{i=1}^{N_j} x_i \leq N_j - 1 \tag{3.34}$$

- Battery onstraint

$$-(1 - SC_i^b)C_i^b \leq P_i^b t \leq C_i^b SC_i^b - d_i^b \tag{3.35}$$

$$-P_{ch,max}^b \leq P_i^b \leq P_{dc,max}^b \tag{3.36}$$

$$PF > PF_{min} \tag{3.37}$$

where ω is an index of load scenarios and symbols with subscript ω represent corresponding values under load scenario ω. π_ω is the probability of scenario ω. The objective function is the expected penalty of high flows through branches with higher resistance as well as fast discharging of the battery units. Constraints (3.30)-(3.31) are the power balance equations of all scenarios. The thermal limit constraint of distribution lines and cables is guaranteed by (3.32). Voltage limit constraint is considered by (3.33).

An appropriate scenario set is critical to the SMIP model. Generally with more scenarios, the uncertainty model of load will be more precise. Nevertheless, computational requirements for solving scenario-based optimization models depend on the number of scenarios. For this reason, an effective scenario reduction method is essential for solving large scale system. The reduction technique is a scenario-based approximation with a smaller number of scenarios and a reasonably good approximation of the original system. We determine a subset of scenarios and a probability measure based on this subset that is the closest to the initial probability distribution in terms of probability metrics. Efficient algorithms based on backward and fast forward methods are developed that determine optimal reduced measures [68].

3.4 Simulation Results

This section presents and discusses results from the application of the methodology to two electrical systems. The first system includes one main source, 33 buses, 32 NC switch branches, and five NO switch lines. The second system, on the other hand, consists of three sources, 83 buses and 96 branches.

The simulations are performed on a 2.66 GHz, 4 GB RAM PC. The software tools used to solve the MIP problems are MATLAB 2011b and ILOG CPLEX 12.2 under the 64 bit operation system. Two different electrical systems are studied to show the effectiveness of the proposed approaches.

3.4.1 Single-source, 32-bus system

The first electrical system is a 37-branch test system used by Baran and Wu [23]. It is assumed that all the branches have either NC or NO switches. The system is depicted in Figure 3.6. Five CES units are located on buses 9, 17, 18, 22, and 30. The batteries capacity, maximum discharge rate, and power factor are 75 kW, 25 kW, and 0.9, respectively. Before starting the optimization, the cycle detection approach is performed on the adjacency matrix of the system graph assuming that all the switches are closed, which identifies 26 cycles. The branches making different cycles are then identified and according to (3.14), the number of closed branches in each loop should be less than the total number of branches creating the loop. Table 3.1 shows the sequence of visited vertices starting from vertex 2 obtained by the DFS-based strategy as an example. Then, according to (3.5) number of closed branches in each loop should be less than the total number of branches creating the loop. Note that the process is performed only once and before the optimization.

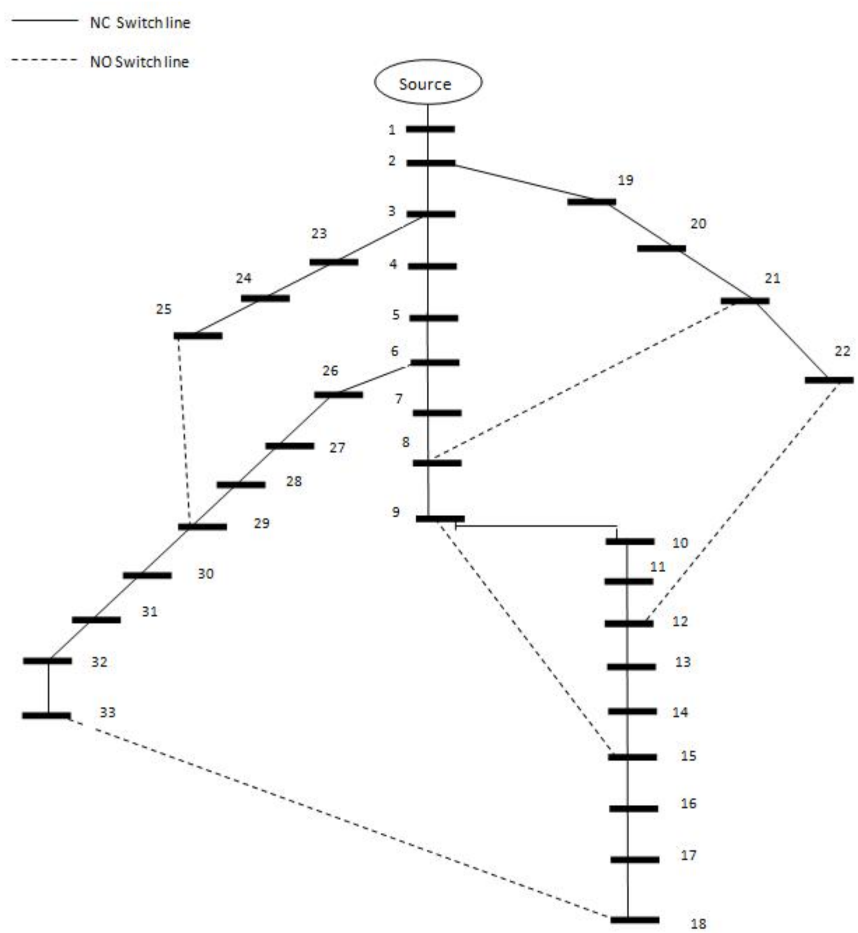


Figure 3.6: 32-bus test system

Table 3.1: Sequence of visited nodes in each cycle starting from node 2

Loop	Vertex
1	2,3,4,5,6,7,8,9,10,11,12,22, 21,20,19,2
2	2,3,4,5,6,7,8,9,15,14,13,12,22, 21,20,19,2
3	2,3,4,5,6,7,8,21,20,19,2
4	2,3,4,5,6,26,27,28,29,30,31,32, 33,18,17,16,15,9,8,21,20,19,2
5	2,3,4,5,6,26,27,28,29,30,31,32, 33,18,17,16,15,9,10,11,12,22, 21,20,19,2
6	2,3,4,5,6,26,27,28,29,30,31,32,33, 18,17,16,15,14,13,12,11,10, 9,8,21,20,19,2
7	2,3,4,5,6,26,27,28,29,30,31,32,33, 18,17,16,15, 14,13,12,22,21,20,19,2
8	2,3,23,24,25,29,28,27,26,6,7, 8,9,10,11,12, 22,21,20, 19,2
9	2,3,23,24,25,29,28,27,26,6,7, 8,9,15,14,13,12, 22,21,20,19,2
10	2,3,23,24,25,29,28,27,26,6,7, 8,21,20,19,2
11	2,3,23,24,25,29,30,31,32,33, 18,17,16,15,9,8, 21,20,19,2
12	2,3,23,24,25,29,30,31,32,33,18,17, 16,15,9,10, 11,12,22,21,20,19,2
13	2,3,23,24,25,29,30,31,32,33, 18,17,16,15,14,13, 12,11,10, 9,8,21,20,19,2
14	2,3,23,24,25,29,30,31,32,33,18, 17,16,15,14,13, 12,22,21,20,19,2

Deterministic Optimization

In this section deterministic MIP-based DR is presented for two objectives. The first optimization problem minimizes the active power loss while the second optimization minimizes the total number of switching operations to restore a system after faults.

Loss Minimization

The objective is to find the optimum topology of the system with minimum active power loss. Table 3.2 compares the results obtaind by MILP and MIQP. Batteries' discharge estimated by MIP is exhibited in Table 3.3. According to Table 3.2, MIQP leads to better results. However, the speed of MILP is much higher. Even though MILP doesn't give the optimal solution, i.e. the minimum loss, it reduces the loss significantly. Therefore, it may be beneficial to use MILP when a large system is being studied. Voltage profile of the system after reconfiguration is demonstrated in Figure 3.7.

Table 3.2: Reconfiguration result for loss minimization-first system

Parameter	MILP	MIQP
Optimal solutionopen switches	8-21,10-11,13-14, 16-17, 28-29	7-8,9-10, 14-15, 25-29, 32-33
kW loss- new configuration, without CES	161.58	139.55
kW loss- new configuration, with CES	149.77	131.42
kW loss- Original system	202.5	
Minimum voltage- new configuration, without CES (pu)	0.927	0.938
Minimum voltage- new configuration, with CES (pu)	0.93	0.94
Minimum voltage- original system (pu)	0.913	
Processing time (s)	0.028	0.5

Table 3.3: Battery output power estimated by MIP-first system

Bus	kW
9	15.63
17	11.53
18	19.28
22	19.66
30	23.89

Minimizing the Switching Operations

In this optimization problem we are interested in restoring the system after a fault with minimum number of switching operations. We also would like to study the impact of battery units on the reconfiguration result. Let's assume that branches 9-10 and 27-28 are out of service because of faults. Three different cases are studied here: 1- there is no CES unit in the system; and line 12-22 has a high flow limit. 2- there is no CES unit in the system; and line 12-22 has a small flow limit. 3- there are CES units in the system; and line 12-22 has a small flow limit. When fault occurs and lines 9-10 and 27-28 are taken out, two tie-lines should be closed to supply the demand. The MIP prefers to close tie-lines 10-12 and 25-29 as these are the closest NO switches to the faulted areas (Case 1). In Case 2, however, because of the low

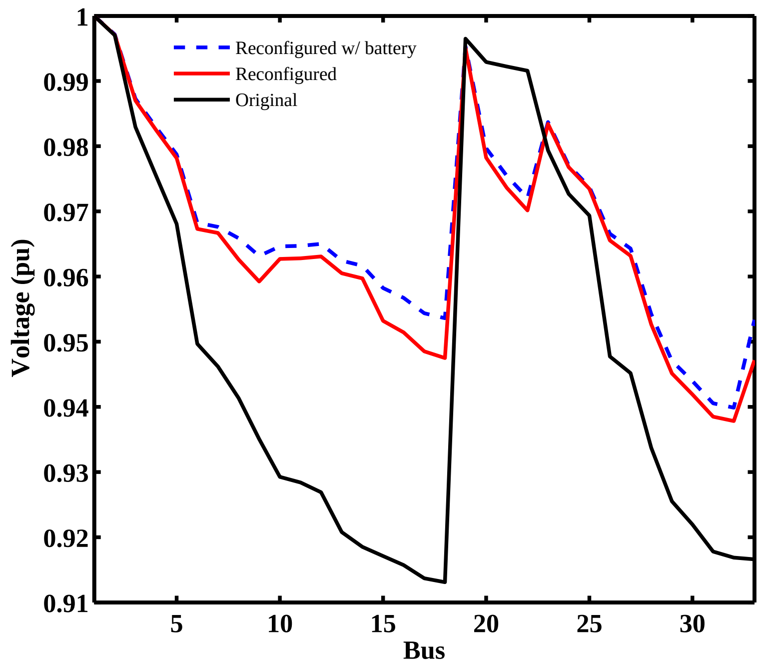


Figure 3.7: Voltage profile of the 32-bus system

line flow limit of line 12-22, the next closest tie-line, which is line 9-15 is closed and this leads to more active power loss (Case 2). In the third case, since storage units locally supply some parts of loads, the overload condition on line 12-22 is removed. This allows tie-line 12-22 to close and configuration of the system is the same as Case 1. Table 3.4 exhibit the results obtained by MIP.

Table 3.4: Reconfiguration results obtained by MIQP

Parameter	Case 1	Case 2	Case 3
Optimal solution- open switches	8-21, 9-10, 9-15, 18-33,27-28	8-21, 9-10, 12-22, 18-33,27-28	8-21, 9-10, 9-15, 18-33,27-28
kW loss	143.3	161.64	135.36
Minimum voltage (pu)	0.935	0.933	0.94
Processing time (s)	0.03	0.033	0.13

DSR with load uncertainty

The FMIP and SMIP approaches are now applied to solve the reconfiguration problem in the presence of load uncertainty. The nominal loads are considered as deterministic. For FMIP, it is assumed that the load belongs to the range $[P - \Delta P, P + \Delta P]$ where P is the load nominal value and ΔP is assumed to be 21% of the nominal load as an example for large uncertainty. A constant power factor is considered for the loads on every node. As mentioned in section II-B, a distribution system operator may allow line thermal limit and voltage constraints to be violated to some degrees determined by a membership function (3.3). Two cases for FMIP-based reconfiguration are considered here. In the first case, which is called FMIP with soft constraints (SC FMIP), the operational constraints (3.12) and (3.22) are allowed to violate up to 10% of their maximum limit. The second case, HC FMIP, on the other hand, considers hard operational constraints which does not allow for any constraint violations. Obviously, HC FMIP may lead to a higher loss configuration as it allows for less flexibility in the line flow and voltage limit constraints.

For the SMIP reconfiguration, the forecasted load is modeled as a Gaussian probability distribution function with nominal load as the mean value and standard deviation, σ, of 6%. The load can change in the range of $P \pm 3.5\sigma$. Monte Carlo simulation is used to generate 5000 load scenarios. Then, the number of the scenarios is reduced to 200 using the scenario reduction technique.

Table 3.5 and Table 3.6 show the reconfiguration result obtained by FMIP and SMIP. The system loss for the nominal load is also shown in Table 3.5. As obsereved in Table 3.5, both FMIP and SMIP lead to configurations with higher losses compared to the deterministic case. The reason is that the mentioned approaches lead to conservative solutions which are feasible for different loading conditions. In order to compare the performance of FMIP and SMIP, the solutions are examined for 5000 scenarios to see what percentage of the load scenarios lead to constraint violation. The computation time for deterministic, FMIP, and SMIP reconfiguration is also shown in Table 3.7. As observed in Table 3.7, HC FMIP and SMIP are very close in terms of robustness but HC FMIP is much faster (HC FMIP leads to a slightly more conservative solution with more power extraction from battery units). It is worth noting that because of the radial structure of the distribution system, higher loads on the nodes cause higher flows on the lines. Therefore, there will be higher possibility that the line flow limits and voltage limit constraints are violated. This feature is considered in membership function shown in Table 3.2 and that is the reason that FMIP leads to a robust and optimal result.

Table 3.5: Reconfiguration with load uncertanty-first system

	SC FMIP	HC FMIP	SMIP
Optimal solution- open switches	7-8,11-12,14-15, 18-33,25-29	7-8,11-12,14-15, 17-18,25-29	7-8,11-12,14-15, 17-18,25-29
loss (nominal load)	134.47	138.30	138.94

Table 3.6: Battery discharge with load uncertainty-first system

	SC FMIP	HC FMIP	SMIP
Bus	kW	kW	kW
9	18.71	16.99	15.02
17	12.69	12.18	10.76
18	22.56	19.87	17.54
22	22.96	25	24.84
30	24.87	25	22.90

Table 3.7: Comparison of the approaches-first system

	Deterministic	SC FMIP	HC FMIP	SMIP
Infeasible scenarios (%)	54	20.2	4.49	4.52
Computation time (s)	0.5	1.32		49

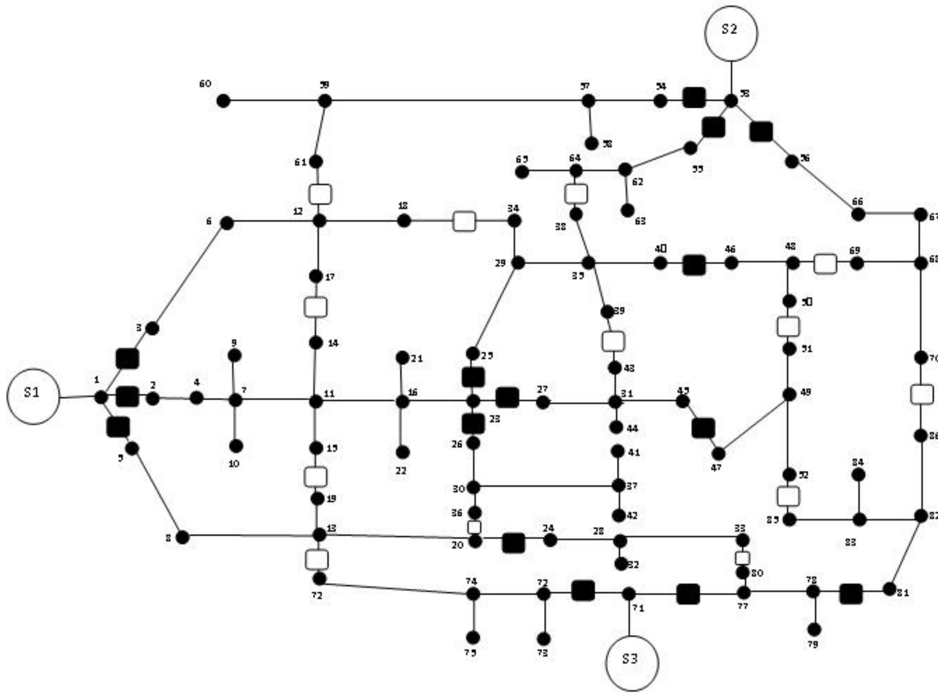


Figure 3.8: 86-bus test system

3.4.2 Multiple source, 86-bus System

The distribution system shown in Figure 3.8 contains 86 load buses, three supply buses, and 96 branches [21]. 68 branches are assumed to be non-switch branches and only 28 branches are equipped with switches. From those 28 switch branches, 13 lines are NO (tie-line) switch branches and the remaining switch lines are NC switch branches. The system has 9 battery storage units with 150 kWh capacity and 100 kW maximuim charge/discharge rate. Since the system has a very good power factor, i.e. reactive power load is negligible compared to active power load; the reactive power term can be eliminated from the equations with a very good approximation. First, similar to the last section, the DFS-based cycle detection approach is employed to detect possible loops/cycles. Running the loop finder routine, 1949 loops are detected in 25.28 seconds. It is worth noting that even though the cycle detection approach is not fast, it does not cause any problem as it is done in off-line and before the optimization.

Deterministic Reconfiguration

Loss Minimization

Table 3.8 and Table 3.9 compare the results obtained by MILP and MIQP. Since no penalty for battery discharge is considered in MILP, all the batteries can discharge up to 100kW. Similar to the previous section, it can be seen that MIQP gives a better result compared to MILP. In addition, it is observed that MIQP leads to a fast reconfiguration as the quadratic constraints are removed from formulation. Voltage profile of the system after optimization is shown in Figure 3.9.

Table 3.8: Reconfiguration result for loss minimization

Parameter	MILP	MIQP
Optimal solution- open switches	1-5,12-61,14-17, 15-19,18-34,20-24, 23-25,23-26,39-43,40-46, 50-51,52-85,70-86	12-61,13-76,14-17,15-19, 18-34,20-24,20-36, 23-25,39-43,48-69, 50-51,52-85,70-86
kW loss- configuration, without CES	1775.1	1691.6
kW loss- new configuration, with CES	1715	1630.9
kW loss- original system	2070.7	
Minimum voltage, new configuration, without CES (pu)	0.9	0.9
Minimum voltage- new configuration, with CES (pu)	0.9	0.91
Minimum voltage original system (pu)	0.844	
Processing time (s)	0.2	0.27

Table 3.9: Battery active power estimated by mip-second system

	MILP	MIQP
Bus	kW	kW
23	100	100
28	100	100
51	100	100
52	100	100
63	100	100
70	100	53.45
76	100	44.83
81	100	13.32
87	100	100

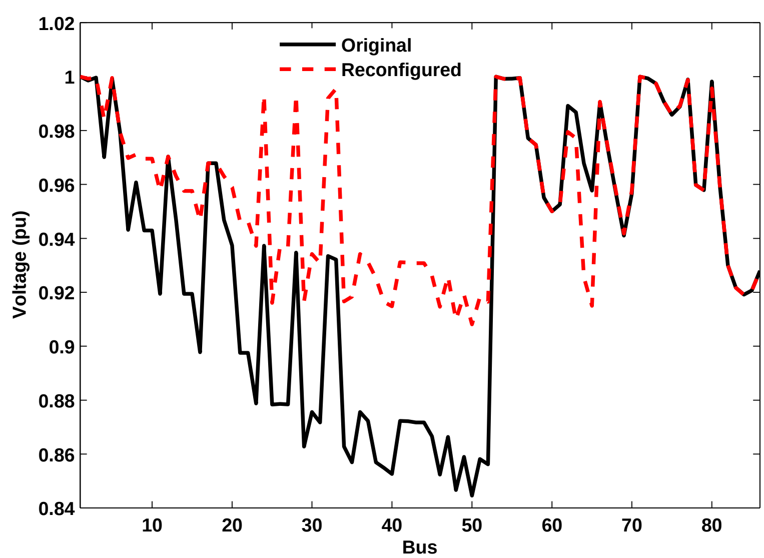


Figure 3.9: Voltage profile of the 86-bus system

Minimizing the Switching Operations

Performance of the proposed approach for minimizing switching actions is investigated for the case in which faults occur on branches 40-46 and 20-24. Three different cases are considered here: 1- There is no CES unit in the system, and line 48-69 has a high flow limit. 2- There is no CES unit in the system, and line 48-69 has a low flow limit. 3- There are CES units in the system, and line 48-69 has a low flow limit.

When lines 20-24 and 40-46 are taken out from system due to a fault, switching actions need to take place in order to avoid customer interruption. MIP prefers to close tie-lines 33-80 and 48-69 which are close to the faulted area and therefore lead to minimum loss configuration (Case1). If line 48-69 has a low flow limit, the optimization searches for the best alternative (Case 2). In Case 3, due to utilization of storage units, the flow on line 48-69 is reduced. Therefore, the configuration of the system will be the same as Case 1. Table 3.10 exhibits the results obtained by MIP.

Table 3.10: Reconfiguration results obtained by MILP and MIQP

Parameter	Case 1	Case 2	Case 3
Optimal solution- open switches	12-61,13-76,14-17, 15-19,18-34, 20-24,20-36,38-64, 39-43,40-46, 50-51,52-85,70-86	12-61,13-76,14-17, 15-19,18-34, 20-24,20-36,38-64, 39-43,40-46, 48-69,52-85,70-86	12-61,13-76,14-17, 15-19,18-34, 20-24,20-36,38-64, 39-43,40-46, 50-51,52-85,70-86
kW loss	1800	2048	1720
Minimum voltage (pu)	0.89	0.83	0.90
Processing time (s)	0.05	0.05	0.05

DSR with load uncertainty

In this case, the same assumptions for the last example are made. Table 3.11 and Table 3.12 show the reconfiguration result obtained by FMIP and SMIP. The system loss for the nominal load is also shown in Table 3.11. As observed in Table 3.11, HC FMIP and SMIP give the same configuration with some differences in battery discharges. The results are tested for 10,000 load scenarios. As observed in Table 3.13, HC FMIP and SMIP have similar level of robustness (HC FMIP gives a slightly more robust solution with more power extraction from batteries). Given the fact that HC FMIP is much faster than SMIP, it is recommended to use this approach for real-time applications.

Table 3.11: Reconfiguration with load uncertanty-second system

Parameter	SC FMIP	HC FMIP	SMIP
Optimal solution- open switches	12-61,13-76,14-17, 15-19,20-24,23-25, 23-26,38-64,39-43,40-46, 50-51,52-85,70-86	12-61,13-76,14-17, 15-19,18-34,20-24, 23-26,23-27,38-64,40-46, 50-51,52-85,70-86	12-61,13-76,14-17, 15-19,18-34,20-24, 23-26,23-27,38-64,40-46, 50-51,52-85,70-86
loss (nominal load)	1662.6	1811.8	1818.8

Table 3.12: Battery active power estimated by smip-second system

	SC FMIP	HC FMIP	SMIP
Bus	kW	kW	kW
23	77.98	100	100
28	100	100	100
51	94.73	100	100
52	94.92	100	100
63	100	100	100
70	43.68	35.57	32.01
76	44.60	49.62	44.86
81	79.00	100	13.28
87	95.78	100	100

Table 3.13: Comparison of the approaches-second system

	Deterministic	SC FMIP	HC FMIP	SMIP
Infeasible scenarios (%)	35.6	12.7	3.3	3.34
Computation time (s)	1.3	2.64		650

3.5 Review

This chapter proposes MIP-based reconfiguration for radial and weakly-meshed distribution systems. A general approach based on DFS is proposed to formulate radiality constraint for MIP. Simulation results show that MILP is much faster than MIQP. However, it gives a sub-optimal solution as it formulates a linear function for the loss. MIQP, on the other hand, includes voltage limit constraint and exact formulation for line thermal limit. This chapter also shows the impact of CES units on the reconfiguration result. The concept is shown by contribution of CES units in removing overload conditions from distribution lines.

In addition to the deterministic optimization, DSR with uncertain load data is formulated based on fuzzy and stochastic programming optimizations. The results show that both FMIP and SMIP lead to robust optimal solutions which are feasible for different load scenarios. It is also shown that FMIP is much faster than SMIP and thus more appropriate for real-time applications.

Chapter 4

RTP-Based Residential Response Management

4.1 Motivation and Contribution

In this chapter, a pricing mechanism based on social welfare maximization is proposed for residential customers. The proposed method is an iterative approach in which residents and energy supplier (utility distribution company) exchange information on consumption and price. Local agents in the houses, HAN, interact with the energy provider's agent to arrive at a real time price, which reflects the aggregated load on the substation. Different customers and appliances have different disutility functions based on the detailed model of the load. Every residence or service point has an agent that seeks to minimize the utility bill as well as customer dissatisfaction. HANs consider scheduling of the appliances such as plug-in hybrid electric vehicle (PHEV), heating, ventilation, and air conditioning (HVAC), water heater, washer, and so on. As a consideration of the proposed approach, and frequently ignored in the literature, is to avoid overly sophisticated decision-making at the customer level. Most customers will have limited capacity or need for elaborate scheduling where actual energy cost savings will be modest. The distribution company sends a price signal, which reflects the aggregated energy consumption and network loading of the consumers to the agents. The agents plan for energy consumption of the home appliances based on the received information.

The challenge in this problem is to converge to a solution across the numerous customers while ensuring the utility distribution system satisfies operational and reliability constraints. According to the literature review section, much of the literature in this area fails to account for these network constraints. The effect of distribution system constraints such as transformer capacity, line flow limits, voltage limit, and phase balance are shown and discussed. Similar to the transmission system, nodal price is proposed for the laterals on a feeder. In other words, there is not a unique price for all the laterals feeding from the same substation. When the decision converges to a solution, the real-time prices as well as the home appliance energy consumptions are determined.

4.2 System Model

Consider a set of households/customers that are served by a single utility company. The utility company participates in wholesale market to purchase electricity from generation companies and then sells it to the customers in the retail market. Each residence has a smart meter that communicates with various devices at the residence. The smart meters communicate with the utility company through AMI. This concept is exhibited in Figure 4.1.

The utility company can determine a cost function based on the day-ahead Locational Marginal Price (LMP) and the aggregated load on the substation. In this work, a quadratic cost function is considered to reflect the cost to the utility

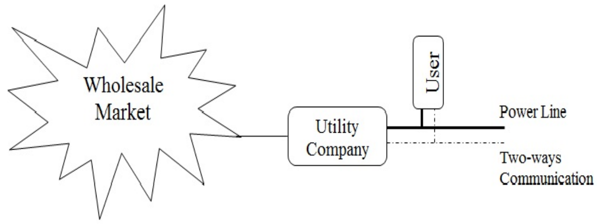


Figure 4.1: Electricity market relationship to residential customers

company. Note that any convex cost function can be easily considered in the proposed formulation.

The distribution company sends a price signal, which reflects the aggregated energy consumption and the distribution network constraints. The resident agents schedule energy consumption of the home appliances based on the received information. In response, they send the aggregated planned energy consumption of every house to the utility agent. This process repeats until the schedule convergences. The challenge in this problem is to converge to a solution across the numerous customers while ensuring the utility distribution system satisfies operational and reliability constraints. In this section, the detailed models of the cost functions considered for the utility company and the end users are explained.

4.2.1 Utility

A typical representative section of a residential feeder, including part of the substation is shown in Figure 4.2 [69]. The utility company tends to minimize its cost while ensuring that the distribution system operational constraints are satisfied. The cost function can be expressed as a convex function based on the aggregated residential load supplied by the utility:

$$C^t = \sum_{i=1}^{N_l} a(P_i^t)^2 + bP_i^t + c \tag{4.1}$$

where C^t is the cost of providing energy at time t; P_i^t is the aggregated load on lateral i at time t; N_l is the number of laterals; and a, b, and c are constants. Figure 4.3 exhibits the cost function used by BC Hydro company and the approximated function that is used in this work [70].

In order to improve system reliability and reducing customer disturbances, the utility company needs to make sure that the network operational constraints such as equipment capacity, line flow limits, and voltage level are not violated. In addition to the mentioned constraints, current and voltage imbalance are the most severe power quality problems in low voltage (LV) distribution networks [71]. An increase in the voltage imbalance can result in overheating and de-rating of all induction motor types of loads and also the distribution transformers [72, 73]. Voltage imbalance can also cause network problems such as mal-operation of protection relays and voltage regulation equipment, and generation of non-characteristic harmonics from power electronic loads. As shown in Figure 4.2, residential loads are mostly single-phase. Therefore, the electric utilities usually try to distribute the residential loads equally among the three phases of distribution feeders [72]. However, phase balancing of a 3-phase residential feeder will be very challenging due to the random nature of residential loads. Besides, the magnitude of neutral current of the residential feeders will be very stochastic and may cause random tripping of feeders due to neutral current constraint. Therefore, it is very important for the utility company to mitigate the phase imbalance problem.

In this dissertation, equipment capacity, line flow limits, and phase balance are considered as the grid operational constraints. The optimization problem

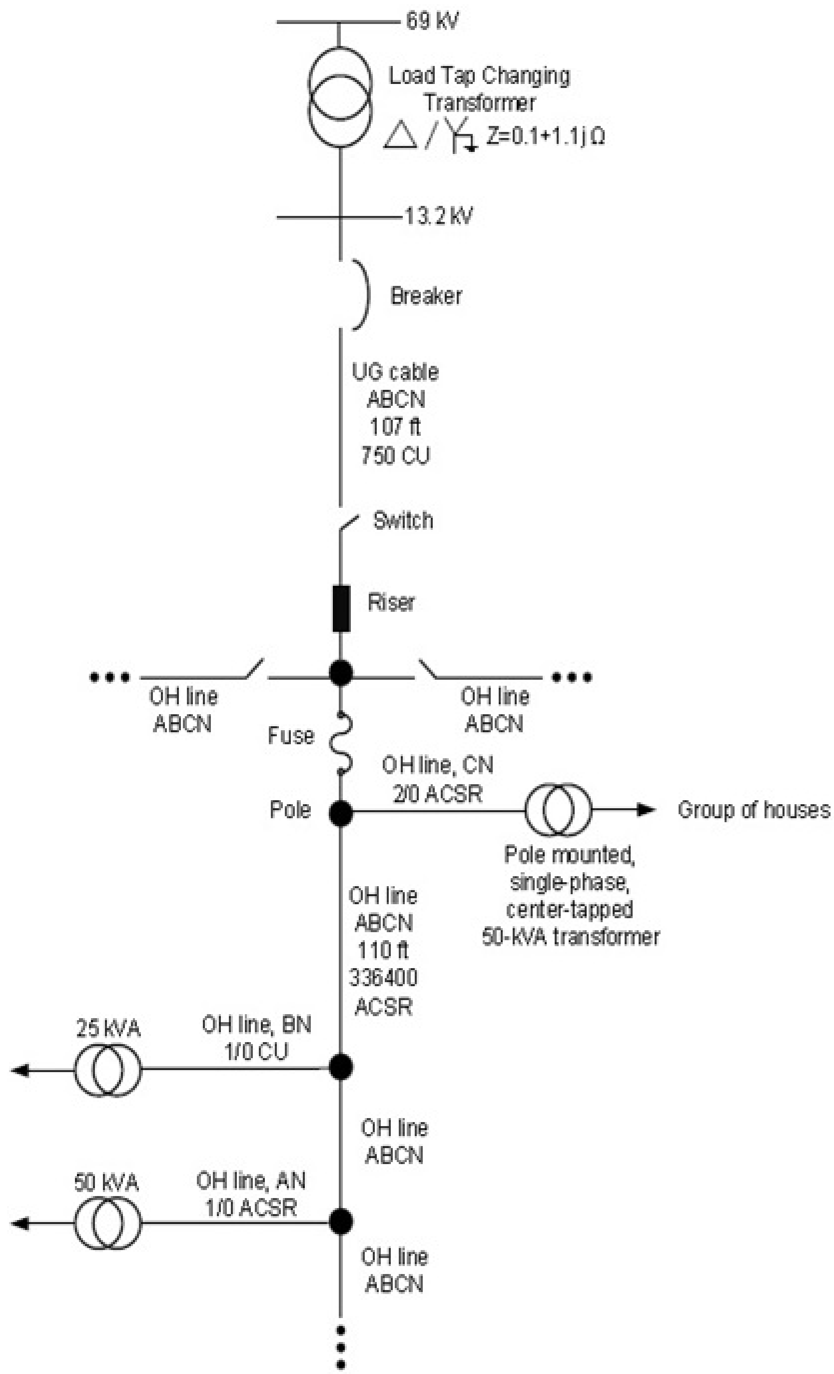


Figure 4.2: A small section of a residential feeder

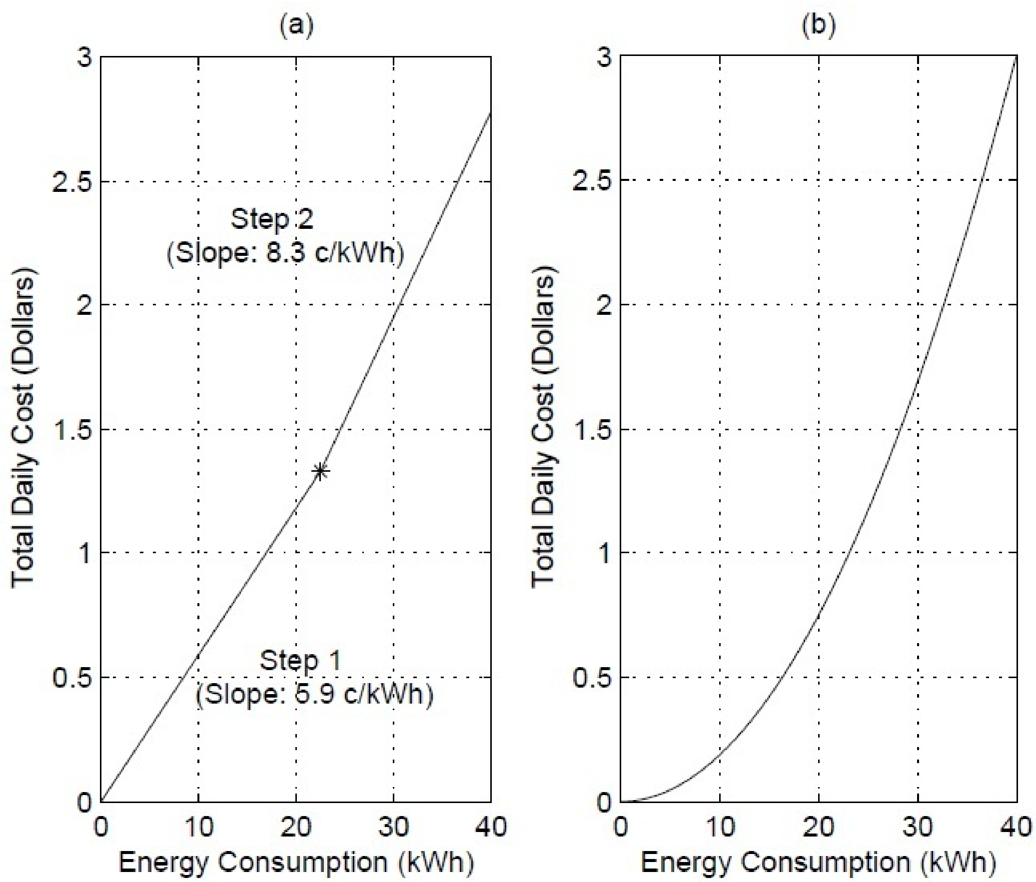


Figure 4.3: Two sample increasing and convex cost function: (a) model used by BC Hydro (b) and estimated cost function

(4.2) minimizes the cost to the utility company subject to the distribution system constraints.

$$\min \sum_{t=1}^{T} C^t \tag{4.2}$$

$s.t$

$$\left| \sum_{i=1}^{N_a} P_{i,a}^t - \sum_{i=1}^{N_b} P_{i,b}^t \right| \leq \gamma \tag{4.3}$$

$$\left| \sum_{i=1}^{N_a} P_{i,a}^t - \sum_{i=1}^{N_c} P_{i,c}^t \right| \leq \gamma \tag{4.4}$$

$$\left| \sum_{i=1}^{N_b} P_{i,b}^t - \sum_{i=1}^{N_c} P_{i,c}^t \right| \leq \gamma \tag{4.5}$$

$$AP_l^t = P_i^t, \forall i \tag{4.6}$$

$$0 \leq P_i^t \leq P_i^{max} \tag{4.7}$$

$$0 \leq P_l^t \leq P_l^{max} \tag{4.8}$$

where N_a, N_b, and N_c are number of An, Bn, and Cn phase laterals, respectively. $P_{i,a}^t$, $P_{i,b}^t$, and $P_{i,c}^t$ are residential loads on phases a, b, and c, respectively.γ is the maximum level of acceptable phase imbalance. A is the node-incidence matrix; and P_l^t and P_i^t are vectors of line flows and loads on the buses at time t, respectively.

Equations (4.3) and (4.4) state that the phase imbalance should stay in a standard range set by the utility company (γ). For example, the utility company can set γ based on over-capacity of unbalanced transformer (OCUT) index used in [71]. It is worth mentioning that the formulation can easily include 3-phase and 2-phase laterals as well. (4.6) expresses active power balance on every node (for the sake of simplicity the active power loss on the line is not considered). Equations (4.7) and (4.8) formulate the line flow limit and secondary distribution transformer capacity limit, respectively.

4.2.2 Residential Customers

In every household, HAN schedules the appliances to minimize the utility bill while mitigating the impact on the user's comfort. The loads within the residence can be categorized based on whether they can be scheduled to later times. These will be labeled schedulable and non-schedulable loads. For instance, lighting and computer usage are generally non-schedulable loads; while washing machines, heating and air conditioning systems are considered as schedulable loads. Obviously, the agents can only manage schedulable loads. Note some loads can be reduced, such as, lighting, for periods of time at the cost of convenience and would normally be done at times of extreme shortage. For simplicity, these are not modeled here. In this study, residential loads are divided into five classes. In the following section, the detailed model of a smart home is presented.

Class 1

This class includes non-schedulable appliances such as refrigerator-freezer, electric stove, lighting, TV, computer, etc. As mentioned before, one of the important features of the pricing algorithm is to avoid burdening the customers. Since it will be very inconvenient for the customers to forecast their usage of this class of appliances, it is assumed that the HANs will estimates the energy consumption of this class based on statistic data and parameters such as number of people in the house, day of the week, and season. This information can be estimated based on the customer behavior during the last couple of days. Note that the information can also be entered by the customers if they want to. Because of the inaccurate prediction of the energy usage of class 1 appliances, a normal distribution function is used to model uncertainty of the forecast. Normal distribution function has been widely used in load forecasting in power systems [74]. Suppose that E_1^t is the estimated energy consumption of class 1 appliances in a house. Then, the actual energy consumption of non-schedulable loads is obtained by:

$$\widetilde{E_1^t} = E_1^t + \delta,\ \delta = \aleph(0, \sigma_1^2) \tag{4.9}$$

where $\widetilde{E_1^t}$ is the actual load and δ is the forecast error with zero mean and variance σ^2.

Class 2

This class contains devices which have a prescribed energy requirement, E, that has to be completed over T time slots, starting from time t_1. An example is charging of a PHEV, where the user may specify the time for charging to start and required completion time. For example, a PHEV sedan for a 40-mile daily driving range needs $E = 16kWh$ in the battery [75]. The PHEV utility function considered in this dissertation is as follows:

$$U(q) = \alpha_{EV} \left(E - q^{end}\right)^2 \tag{4.10}$$

where q^{end} is the total energy given to the battery by the end of charging period, and α_{EV} is the weighting factor determined based on customer preference. The charge level at each time slot is given by:

$$q(\tau) = q^{init} + \sum_{t=t_1}^{\tau} p_b(t).t \tag{4.11}$$

$$p_b^{min} < p_b^t < p_b^{max}$$

where p_b^t is the charging rate at time t. p_b^{min} and p_b^{min} are minimum and maximum charging rates, respectively.

Class 3

This class includes thermal loads such as HVAC, water heater, and cooled water reservoir, with temperature profile θ , which must be kept within minimum and maximum temperature limits, $\theta_{min}$and θ_{max}. The temperature of the heat store evolves according to:

$$\theta(t) = \theta(t-1) + \alpha(\theta^{amb}(t) - \theta(t-1)) + \beta E^t \tag{4.12}$$

$$\theta_{min} \leq \theta(t) \leq \theta_{max}$$

$$0 \leq E^t \leq E_{max}$$

where $\theta^{amb}(t)$ is the ambient temperature profile; E^t is the energy consumption of the thermal load at time t; and α and β are parameters that specify the thermal characteristics of the appliance and the environment where it operates. This formulation models the fact that the current temperature depends on the current power draw as well as the temperature in the previous time-slot.

The utility function is developed based on the deviation of the temperature from customer setting as follows:

$$U(q) = \alpha_{AC} \left(\theta(t) - \theta^{set}\right)^2 \tag{4.13}$$

where α_{AC} is the determined based on how customer cares about the temperature. This class includes thermal loads such as HVAC, water heater, and cooled water reservoir, with temperature profile θ , which must be kept within minimum and maximum temperature limits, θ_{min} and θ_{max}. The temperature of the heat store evolves according to:

$$\theta(t) = \theta(t-1) + \alpha(\theta^{amb}(t) - \theta(t-1)) + \beta E^t \tag{4.14}$$

where $\theta^{amb}(t)$ is the ambient temperature profile; E^t is the energy consumption of the thermal load at time t; and α and β are parameters that specify the

thermal characteristics of the appliance and the environment where it operates. This formulation models the fact that the current temperature depends on the current power draw as well as the temperature in the previous time-slot [76, 77].

The utility function is developed based on the deviation of the temperature from customer setting as follows:

$$\alpha_{ac}\left(\theta(t) - \theta^{set}\right)^2 \tag{4.15}$$

$$\theta_{min} \leq \theta(t) \leq \theta_{max}$$

where α_{ac} is the determined based on how customer cares about the temperature.

Class 4

This class of appliances includes deferrable loads. These loads must consume a minimum amount of power over a given interval of time, which is characterized by the constraint $\sum_{t\epsilon\tau} p_l(t) \geq E$, where E is the minimum total consumption for a certain period of time. In some cases, such as dishwasher and cloth washer/dryer, the load can only be turned on or off in each time period. These appliances consume more or less fixed power while they are on. The primary interest of customers is that the work is done by a certain time. Therefore, based on the electricity price and the resident's comfort, the HAN decides when to turn the device on.

Class 5

This class of appliance inculdes battery storage units which can be used to maximize the utilization of the renewable energy resources such as rooftop solar panels. The utility function of a battery is considered as follows:

$$U(q) = \alpha_1(P_b^t)^2 + \alpha_2 P_b^t P_b^{t+1} \tag{4.16}$$

where α_1 and $\alpha_2$are positive constants and P_b^t is the battery output power at time t. The first term captures the damaging effect of fast charging and discharging; the second term penalizes charging/discharging cycles. The charge/discharge constraints are formulated as follows:

$$-(1 - SC_b^{t-1})C_b \leq P_b^t.t \leq (SC_b^{t-1} - D_b)C_b \tag{4.17}$$

$$-P_{ch,max} \leq P_b^t \leq P_{dc,max}^b \tag{4.18}$$

where SC_b is the state of the charge of the battery, D_b is the minimum acceptable energy in the battery, and C_b is the capacity of the batter. in order to preserve battery's life, (6) guarantees shallow discharge.

4.3 Pricing Mechanism

We are looking for a decentralized demand response management in which HANs at the residence communicate with the utility company through AMI. HANs receive the prices for the next 24 hours from the utility company and schedule residential appliances based on the hourly prices and customers' utility functions. Then, the day-ahead prices are updated based on the energy usage of the residents and network operational constraints. As mentioned earlier, even though uncertainty of the demand is considered in the day-ahead optimization, due to the highly unpredictable behavior of the customers day-ahead prices do not exactly reflect the actual residential loads. Therefore, the prices need to be updated in real-time. This dissertation offers a two-stage pricing approach to encourage residential customers to participate in the DR management program. In the first stage, day-ahead prices are calculated based on social welfare maximization. The second stage determines the real-time prices based on the actual residential loads.

4.3.1 Day-ahead pricing

From a social fairness point of view, it is desirable to minimize the cost to the energy provider while mitigating the impact on the user's comfort. The social welfare maximization is mathematically formulated as follows:

$$\min \sum_{t=1}^{T} \left(\sum_{i=1}^{N_l} C(P_i^t) + \sum_{i=1}^{N_l} \sum_{j=1}^{N_i} \sum_{k=1}^{N_j} D_{k,j,i}^t \right) \tag{4.19}$$

$s.t$

$$\sum_{j=1}^{N_i} \sum_{k=1}^{N_j} E_{k,j}^t \leq P_i^t, \forall i \tag{4.20}$$

$$(4.3) - (3.4) \tag{4.21}$$

$$class(2) - (4)\, constraints \tag{4.22}$$

where P_i^t is the aggregated load on node i; and $D_{k,j,i}^t$ is the disutility (discomfort) function corresponding to the k^{th} appliance in j^{th} house which is located on node i. $E_{k,j}^t$ is the energy cosumption of k^{th} appliance in j^{th} house. Constraint (4.20) guaranties the supply-demand balance on every node. Constraint (4.21) includes the network operational constraints (4.3)-(3.4). (4.22) includes constraints corresponding to different classes of residential loads explained in the last session.

When load uncertainty exists due to the stochastic behavior of the residential customers, the optimization problem (4.19) can turn into minimization of the expected value of the objective function (stochastic optimization model). In order to avoid sophisticated algorithms at the residence, we only consider the uncertainty associated with the class 1 appliances in the day-ahead. The uncertainty of the other load types will be addressed in real-time price adjustment program. Since no utility function is considered for class 1 appliances, the uncertaity only affects constraint (4.20). Different uncertainty models can be considered. In this dissertation, a normal distribution function is used to model uncertainty of the demand forecast for class 1 appliances. The energy provider guarantees to supply the residential demand. In other words, the probability of power shortage should be very small. Mathematically,

$$Pr\left(\sum_{j=1}^{N_i}\widetilde{E_{k,j}^t} - P_i^t \geq \eta\right) \leq \varepsilon, \forall i \tag{4.23}$$

where η is a specified threshold indicating the amount of supply shortage and ε is a small positive value [38]. It is assumed that δ is an independent variable for different houses. Therefore, the aggregated δ over N_i houses will be calculated as follows:

$$\delta_{agg} = \sum_{j=1}^{N_i}\delta_j \sim \aleph\left(0, \sum_j \sigma_j^2\right) \tag{4.24}$$

Therefore, (4.23) turns into:

$$Pr\left(\sum_{j=1}^{N_i} E_{k,j}^t + \delta_{agg} - P_i^t \geq \eta\right) \leq \varepsilon, \forall i \tag{4.25}$$

$$\sum_{j=1}^{N_i} E_{k,j}^t \leq P_i^t + \eta - \left(\sqrt{\sum_j \sigma_j^2}\right) Q^{-1}(\varepsilon) \tag{4.26}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty exp(-\frac{u^2}{2})du$. In addition to the forecasted demand, every HANs needs to report its δ to the utility company. Despite the fact that the centralized optimization problem (4.19) seems easy to solve, the communication overhead requirements create concerns. Moreover, customers generally want to preserve their privacy and may wish to withhold detailed information on energy consumption to the utility company. Therefore, a decentralized optimization method seems both preferable and more practical to implement. This can be done through deployment of Advanced Metering Infrastructures (AMI) and HANs.

A global solution can be efficiently found for a convex optimization problem. However, when the network is not convex, even finding a feasible solution becomes difficult. The optimization problem (4.19) is convex, except for class 4 residential loads which are on/off devices. We simply relax the integer constraints (on/off) and convert the integer programming optimization problem into linear programming. An approximate solution can be obtained by rounding the solutions of the relaxed problem into the nearest integers.

The convex problem (4.19) has a separable structure. Therefore, it can be solved in a decentralized way through dual decomposition and sub-gradient method. Keeping the rest of the constraints implicit, the Lagrangian function for (4.19) is given by:

$$L\left(\{\lambda_i^t\},\{E_{k,j}^t\},\{P_i\}\right)=\sum_{t=1}^{T}\sum_{i=1}^{N_l}C(P_i^t)+\sum_{t=1}^{T}\sum_{i,j,k}D_{k,j,i}^t+\sum_{t=1}^{T}\sum_{i=1}^{N_l}\left(\lambda_i^t B_i^t\right)$$

$$\min\ L\left(\{\lambda_i^t\},\{E_{k,j}^t\},\{P_i\}\right) \tag{4.27}$$

where $B_i^t=\sum_{j,k}E_{j,k}^t\,(l)-P_i^t\,(l)-\eta+\left(\sqrt{\sum_j\sigma_j^2}\right)Q^{-1}(\varepsilon)$. λ_i^t denotes the Lagrange multiplier corresponding to constraint (4.20). The Lagrangian minimization (4.27), is easily seen to be decomposed to optimizations at the utility level and residents. Specifically, the dual decomposition method consists of the following iterations, indexed by $\ell=1,2,...$ and initialized with arbitrary $\lambda_i^t\geq 0$, and β_i as the step size.

$$\min \left(\sum_{i=1}^{N_l} C(P_i^t) - \sum_{i=1}^{N_l} \lambda_i^t(l) P_i^t(l) \right), \ \forall i \tag{4.28}$$

$s.t$

$$(4.3) - (3.4) \tag{4.29}$$

$$\min \left(D_{k,j}^t(l) + \lambda_i^t E_{j,k}^t(l) \right), \ \forall i \tag{4.30}$$

$s.t$

$$class(2) - class(4)\, constraints \tag{4.31}$$

The Lagrangian multiplier for each node is updated according to:

$$\lambda_i^t\left(l+1\right) = \max\left[\lambda_i^t\left(l\right) + \beta_i B_i^t, 0\right], \forall i$$

The Lagrangian multipliers are considered as the nodal prices. This is a similar concept to LMP in transmission system. Through setting the nodal prices, the utility company can involve the customers in mitigating violations in network operational constraints. For example, when a transformer overload happens, the customers on the corresponding lateral will be penalized with extra charge due to their exceeding energy usage. The higher price encourages the customers to reduce their load (according to (4.30)). This concept will be demonstrated and discussed in the simulation results.

The optimization problem (4.28) is performed by the utility agent over $t = 1 : T$. (4.28) maximizes the utility company's profit with respect to the distribution gridconstraints. Optimization (4.30), which is performed by HANs at the residence, minimizes the customers electricity bill as well as disutility function. The Lagrangian multipliers, corresponding to nodal prices, are updated in each iteration. This process repeats until B_i^t is smaller than a specified threshold for every node i (a small positive number).

Convergence of iterative approach (4.28) can be obtained for the following three step size rules: constant step size, non-summable but square-summable step size, and step size given by harmonic series. Convergence of the subgradient method with these step size rules has been studied in the literature. The related results are summarized and discussed in [78].

In order to guarantee convergence, primal averaging is necessary if the objective function is neither strictly convex nor finite. It should also be used when the objective is not a function of all optimization variables [78]. The objective function (4.19) is strictly convex and finite. However, it is not a function of all optimization variables, which is a consequence of considering different device classes (utility functions are not defined for some appliance classes). Therefore, running average method is applied for all the variables, e.g. $\bar{E_{j,k}^{t}} = \frac{1}{l}\sum E_{j,k}^{t}$. Authors in [78] prove that the algorithm finds near-optimal schedules even when AMI messages (updated prices and residential load) are lost, which can happen in the presence of malfunctions or noise in the communications network. It is worth noting that when the primal objective function is not strictly convexity and/or finite, alternating direction method of multipliers (ADMM) can be used to guarantee the convergence [78].

4.3.2 Real-time pricing

As mentioned before, because of the highly random behavior of the residential customers a price adjustment in real-time is needed to reflect the actual residential load. Customers participate in the day-ahead market and purchase electricity as discussed in the last section. In the real-time, the price is calculated based on the actual residential load. The real-time price can be calculated using (4.2). This is similar to optimal power flow (OPF) in transmission system.

For a resident who participates in day-ahead market, in case that real-time price is higher than the day-ahead price, he will pay the same price as the day-ahead price. However, if the residence consumes more energy as he promised in the day-ahead, he has to pay for the extra energy with the real time price. In other words, the customers participating in the day-ahead market are charged with the minimum price between day-ahead and real-time price.

In order to encourage customers to accurately/honestly report their estimated energy consumption in day-ahead, a penalty can be set by the utility company to penalize large difference between day-ahead and real-time enegy consumption of the residences which can be expressed by:

$$\|E_{dh} - E_{rt}\| \leq \varphi \tag{4.32}$$

where E_{dh} is the hourly energy consumption scheduled by a residential customer in day-ahead and E_{rt} is the hourly demand of the residence in real-time. φ is a threshold set by the utility company.

Through encouraging the customers to participate in the day-ahead market, the utility company can have a better estimation of the residential load and plan to cope with potential violation in distribution system operational constraints such as transformer overload and congestion.

4.4 Simulation Results

The simulations are performed on a 2.66 GHz, 4 GB RAM PC. The software tools used for the simulations are MATLAB 2011b and ILOG CPLEX 12.2 under Windows 7 operation system. Performance of the proposed algorithm is demonstrated on a simple system with 30 residential customers. The configuration of the test system is shown in Figure 4.4 with 6 residential laterals and equal number of houses on each lateral. It is assumed that the system two An, two Bn, and two Cn phase laterals.

In our simulation, $b^t = c^t = 0$, and $a^t = 0.5$ are considered for the utility company cost function. Different types of customers are considered in the simulations. For

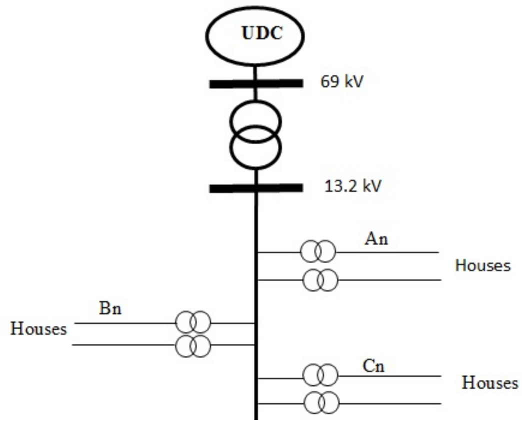


Figure 4.4: Topology of the test system

example, some customers are out of their houses during the working hours while some other stay in their house the entire day. Each household is also assumed to have schedulable appliances such as PHEV, air conditioner, washer/dryer, and dishwasher. Different houses use different weighting factors for utility functions corresponding to the residential appliances.

The optimization is performed over the 24 hours time horizon. Figure 4.5 shows the convergence of the approach on the feeder at 6:00 PM. Hourly nodal prices and residential appliance scheduling over 24 hours will be obtained at the point of convergence. It is worth noting that different time intervals, e.g. 15 minutes, can also be considered.

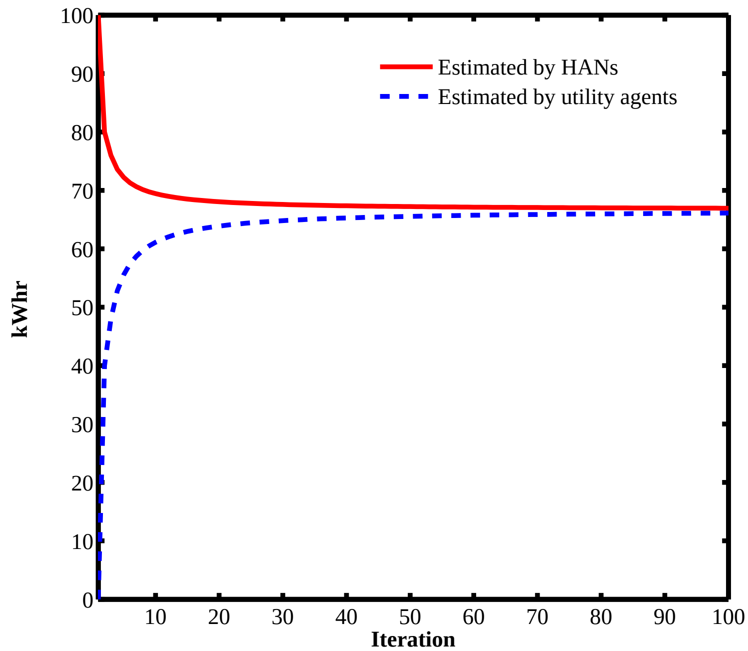


Figure 4.5: Convergence of the algorithm at the residential feeder

A small constant stepsize ($\beta = 0.15$) is chosen for the subgradient updates, coupled with dual and primal averaging, in order to obtain near-optimal dual and primal values in a finite number of iterations. As observed in Figure 4.5, the decentralized optimization is converged after several iterations. Note that the utility company and HANs exchange small size of information (price and residential energy consumption). The power schedule updates occur in parallel across all residential customers and therefore the computation time per iteration is the maximum time, over the utility company and all houses, to solve their optimization problem. Therefore, speed of the process doesn't depend on the number of the customers. Moreover, since simple models of residential appliances are considered, the optimization performed by HANs is very fast. In our test case, it takes 0.2 seconds for the algorithm to converge. Figure 4.6- Figure 4.9 show the effect of distribution system operational constraints on nodal prices. Figure 4.6- Figure 4.7 show the change in nodal price ($Cent/kWh$) on bus 6 due to distribution transformer capacity constraint. As shown in Figure

4.6, the aggregated load on node 6 is reduced to avoid transformer overload. When distribution transformer overload happens, the decentralized optimization approach automatically increases the nodal price on bus 6 (Figure 4.7). Therefore, some customers prefer to reduce their energy consumptions to save money. For example, if a customer has not assigned a high weighting factor for HVAC, the energy consumption of the HVAC will be reduced by HAN (the temperature deviates from the set point but still remains in the comfortable range). This is because the HAN minimizes the customer's utility bill as well as disutility function according to (4.30). Similar situation will happen in case of line congestion. For example, when a distribution line is congested, customers on the downstream nodes will be penalized with extra charge due to their exceeding energy consumption. The higher prices change the solution of (4.30) in such a way that the network operational constraint violation is prevented.

Figure 4.8- Figure 4.9 show the effect of phase balance constraints on the optimization results, i.e. residential load and nodal prices. Figure 4.8 exhibits the difference of loads on phases a and c ($\left|\sum_{i=1}^{N_a} P_{i,a}^t - \sum_{i=1}^{N_c} P_{i,c}^t\right|$) when the phase balance constraints is included. As shown in Figure 4.9, the nodal prices ($Cent/kWh$) on the phases change in such a way that (4.3)-(4.5) are satisfied. For example, if phase c has a higher load than phase a in such a way that $\left|\sum_{i=1}^{N_a} P_{i,a}^t - \sum_{i=1}^{N_c} P_{i,c}^t\right| > \gamma$, ($\gamma = 1.7\,kW$ in the simulations), the nodal prices on the laterals connected to phase c will increase while the nodal prices on the nodes supplied by phase a decrease. As the price changes, the result of optimization problem (4.30) for the residences located on the mentioned phases will change. Similar results will be obtained for phases $a - b$, and $b - c$.

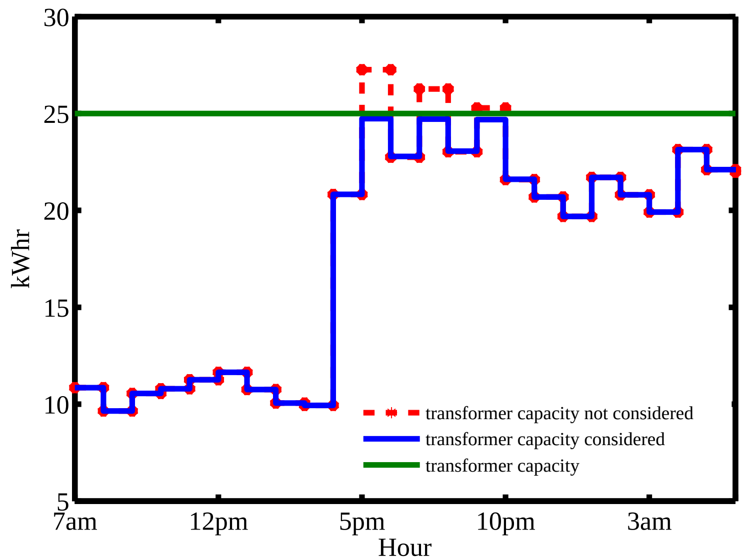


Figure 4.6: Effect of transformer capacity constraint on residential loads on node 6

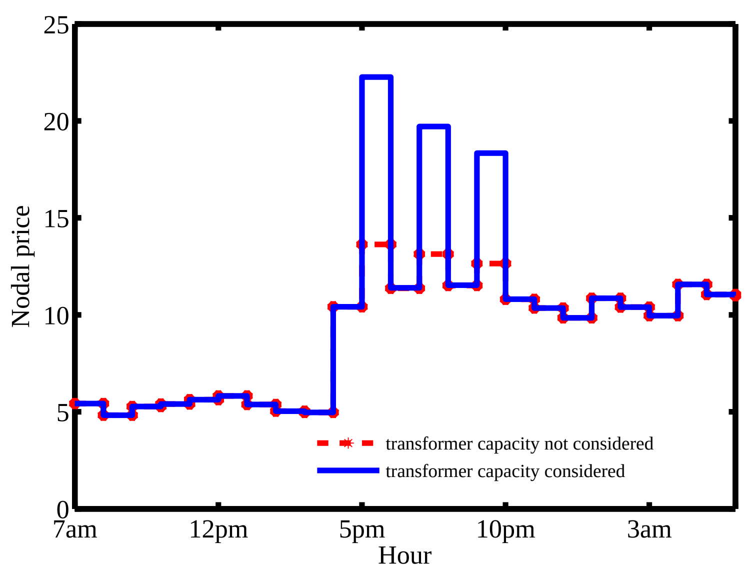


Figure 4.7: Effect of transformer capacity constraint on node 6 prices

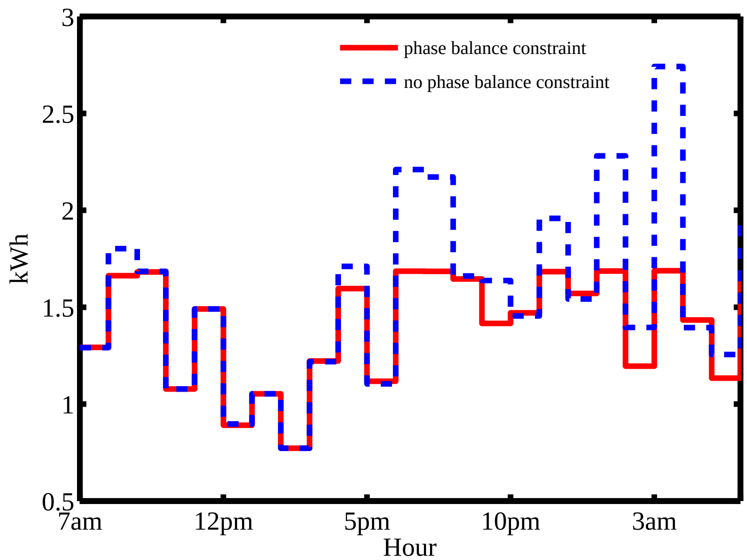


Figure 4.8: Effect of phase balance constraint on residential loads

It is worth noting that the distribution system operational constraints can also be included as soft constraints. In other words, the objective function of the utility company can include these soft constraints by assigning different weighting factors. Therefore, the operational constraints such as phase balance can be violated but the customers will have to pay more money depending on the weighting factors set by the utility company.

In the second stage, the day-ahead prices are updated according to the discussion in the last session. The customers who participate in the day-ahead market have the advantage to pay less for their promised energy consumption. This is to the benefit of both the customers and the utility company as it can prepare for the potential violation of the operational constraints. Moreover, to encourage the customers to honestly/accurately report their day-ahead demand, a penalty function based on the difference between hourly day-ahead and real-time demands can be set by the utility company.

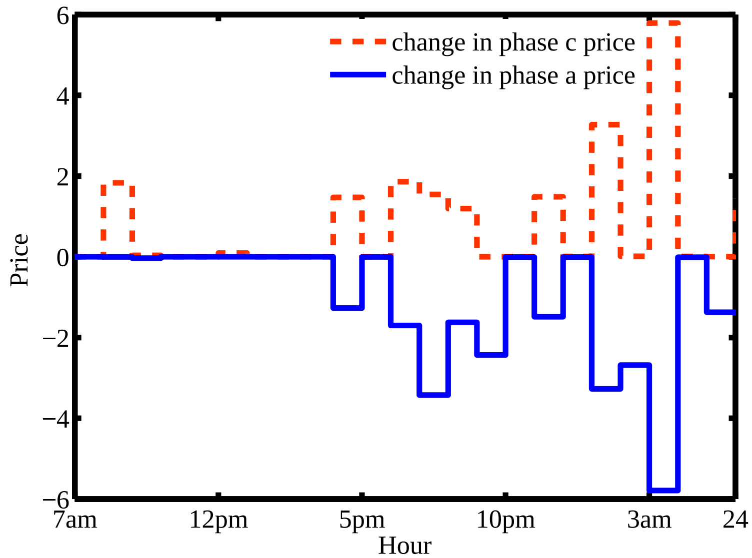


Figure 4.9: Effect of phase balance constraint on nodal prices

4.5 Alternative Objective Function

In this section, an alternative objective function is used to minimize the cost to the UDC and customers in distribution system. A UDC purchases electricity from market and sells it to the residential customers. The UDC tends to minimize its cost while ensuring that the distribution system operational constraints are satisfied. The following function is considered to model the UDC cost.

$$C^t = m^t(\sum_{i\epsilon N_b} P_i^t + \sum_{l\epsilon N_l} r_l \frac{(p_l^t)^2 + (q_l^t)^2}{V_l^t}) \tag{4.33}$$

where m^t is the locational marginal price at the substation (power supply provider). N_b and N_l are the number of distribution nodes and branches, respectively. P_i^t is the aggregated loads on node i at time t. r_l and x_l are resistance and reactance of distribution line l, and p_l^t and q_l^t are the active and reactive power flows on the lines, respectively. V_l^t is the voltage on node i at time t. The first terms in the cost functionC^t include the cost of supplying demand on every distribution node and the second term includes the cost due to active power loss on the lines. This is very similar to the Distribution Locational Marginal Price described in [5].

Similar to the last formulation, a social welfare optimization is proposed to minimize the cost to the UDC while taking customers' satisfaction into account. Mathematically, the social welfare maximization problem is formulated as follows:

$$\begin{gathered}
\min\, Z = \textstyle\sum_{t=1}^{T} C^t + \sum_{i,j,k} u(x_{i,j,k}) \\
s.t. \\
A.P_l = P_i \\
|I_l| < I_l^{max} \\
V_{min} \leq |V_i| \leq V_{max} \\
class\,(2) - class\,(5)\, constraints
\end{gathered} \tag{4.34}$$

where x and $u(x)$ are the energy consumption and utility function of appliance k in house j which is on node i. A is the reduced node incidence matrix of the system. I_l and V_i are the current on the lines and voltage on the nodes, respectively. This optimization problem considers the thermal limits of the lines and voltage limit of the nodes. Constant power factors for every node are considered. Voltage limit constraint can be formulated as a linear function of active and reactive power flows as follows:

$$2\sum_{l \epsilon \alpha_k^i} (r_l p_l + x_l q_l) \leq \delta_{max} \tag{4.35}$$

$$\delta_{max} = \Delta V_{max}(V_s - \Delta V_{max}) \tag{4.36}$$

where α_i^s is the path reaching bus i from substation s. ΔV_{max} is the maximum allowed deviation of voltage magnitude on node i from voltage at substation (V_s).

In addition to the network operational constraints, the constraints associated with class (2)-class (5) residential appliances are also considered in the optimization. The convex problem (4.34) has a separable structure. Therefore, it can be solved in a decentralized way through dual decomposition and sub-gradient method. The Lagrangian function for (4.34) is given by:

$$L = Z + \lambda_i^t (P_i - A.P_l) \tag{4.37}$$

where λ_i^t is the lagrangian multipliers (scaled nodal prices) associated with active power balance on the nodes. As observed in (4.37) the optimization problem has two components. One optimization can be performed by the UDC and the other can be done by the loads on each node. The residential company sends λ_i^t to every node. All the loads connected to the node receive the price and perform their optimization. The optimization performed by the UDC is as follows:

$$\min \sum_{t=1}^{T} [m^t \sum_{l \epsilon N_l} r_l \frac{(p_l^t)^2 + (q_l^t)^2}{V_l^t}) - \lambda_i^t . A.P_l] \tag{4.38}$$

$$s.t.$$

$$|I_l| < I_l^{max} \tag{4.39}$$

$$2 \sum_{l \epsilon \alpha_k^i} (r_l p_l + x_l q_l) \leq \delta_{max} \tag{4.40}$$

The second term of objective function (4.37) which is performed by residential HANs is as follows:

$$\min \sum_{t \epsilon T} [m^t \sum_{i \epsilon N_b} P_i^t + \lambda_i^t . P_i^t + \sum_{i,j,k} u(x)]$$

$$s.t.$$

$$class\,(1) - class\,(5)\,constraints$$

The Lagrangian multipliers for every node are updated according to the following equation:

$$\lambda_i^t\,(l+1) = \max\left[\lambda_{p,i}^t\,(l) + \beta_i(P_i(l) - A.P_l(l)), 0\right], \forall i \tag{4.41}$$

We can split P_i^t among the residences on node i as follows:

$$P_i^t = \sum_{i,j} P_{ij}^t$$

where P_{ij} is the purchased active power by house j on node i. Therefore the optimization in every house is formulated as follows:

$$\min \sum_{t \epsilon T} (m^t + \lambda_i^t) P_{ij}^t + \sum_{i,j,k} u(x) \tag{4.42}$$

$$s.t.$$

$$\sum_{i,j,k} x^t + p_{const}^t = P_{ij}^t + P_b^t + P_r^t$$

$$class(2) - class(5)\, constraints$$

where p_{const}^t is the energy consumption of non-schedulable appliances in a house at time t. P_b^t and P_r^t are the battery output power and power generated by rooftop solar panel. This model is shown in Figure 4.10. Every household solves the optimization (4.42) and returns P_{ij}^t to the UDC.

The optimization (4.42) is a deterministic optmization which is performed by the HANs. Every household has to solve it's own optimization problem and return P_{ij}^t to the utility company. P_{ij}^t shows the amount of power that a house wants to purchase from the utility company. The challenge in this problem is that the forecasted energy consumed by non-schedulable loads and energy generated by rooftop solar panels can be inaccurate. The uncertain parameters can be given as intervals:

$$p^t_{const} \epsilon [p^t_{const,min}, p^t_{const,max}]$$
$$p^t_r \epsilon [p^t_{r,min}, p^t_{r,max}]$$

One of the ways to cope with these uncertainties is to use stochastic programming in the household. However, stochastic programming is a computational intense approach and thus is not suitable for our iterative approach. In addition, we prefer to avoid sophisticated algorithms at the residence. A model based on certainty equivalent is developed to avoid complex algorithms. Consider the following stochastic programming problem:

$$\begin{aligned} &\min \; Ef_0(x, \omega) \\ &s.t. \\ &Ef_i(x, \omega) \leq 0 \end{aligned} \tag{4.43}$$

where $x \epsilon R^n$ is the optimization variable, and ω is a random variable. Based on Jensen's inequality we have:

$$Ef_i(x, \omega) \geq f_i(x, E\omega)$$

Now, consider the problem (4.44) obtained by replacing the random variable in each function by its expected value. This problem is sometimes called the certainty equivalent of the original stochastic programming problem (4.43), even though they

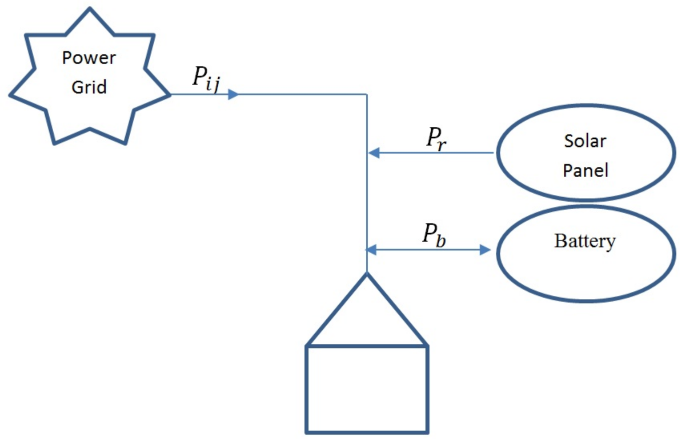


Figure 4.10: Smart home model

are equivalent only in very special cases. By Jensen's inequality, the constraint set for the uncertainty equivalent problem is larger than the original stochastic problem (4.43), and its objective is smaller. It follows that the optimal value of the uncertainty equivalent problem gives a lower bound on the optimal value of the stochastic problem (4.43).

$$\begin{gathered} \min\ f_0(x, E\omega) \\ s.t. \\ f_i(x, E\omega) \leq 0 \end{gathered} \tag{4.44}$$

This approach is used in this study. In order to show how this approach works, it is implemented on a simple 7-bus system shown in 4.11. First, we assume that the aggregated residential load on each bus is 100 kw. Then, we solve the optimization problem (4.38) without considering demand response to obtain nodal prices for different nodes. The nodal prices for buses 1, 2, and 7 are shown as example. Note that the price on node 1 is the LMP (reference price). This is similar to the energy price in transmission LMP. The price on each node is $LMP+\lambda_i$ where lambda includes the shadow prices for active power loss, and system operational constraints such as secondary transformer limit, line flow limit, and voltage constraints. As observed in Figure 4.12 the prices on nodes 2 and 7 are different. This is because the loss shadow price is included in λ_2 and λ_7.

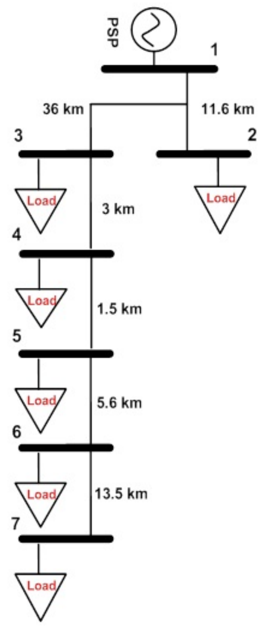


Figure 4.11: Test system

If we consider the demand response, then we will be able to control the loads by changing λ_i. For example, if a violation in system operational constraints such as secondary transformer capacity constraint happens, λ_i will increase in such a way that customers reduce their electricity consumption. Figure 4.13 shows the result of the decentralized optimization problem on node 7 when customers participate in the demand response program. Figure 4.14 shows the nodal prices on node 7 ($LMP+\lambda_7$). Suppose that the capacity of secondary transformer on node 6 is 180 kW. As Figure 4.13 shows, the transformer is overloaded when transformer capacity constraint is

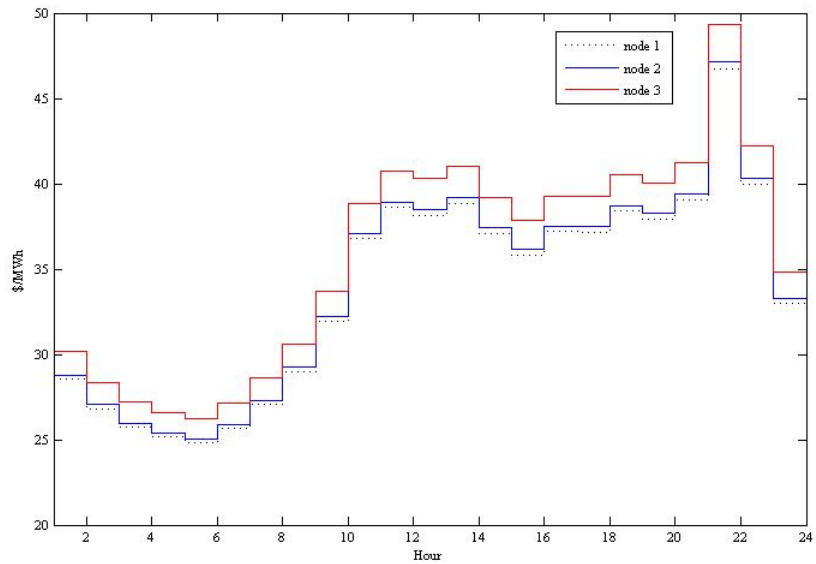


Figure 4.12: Nodal prices

not considered in the optimization. However, when this constraint is included in the optimization, λ_7 on node 7 increases in such a way that the customers reduce their energy consumption according to 4.42.

Note that this approach is performed in day-ahead. Therefore, a real-time adjustment is discussed in the last section is needed to cope with the uncertainties associated with residential loads.

4.6 Review

In this chapter, a two-stage pricing mechanism is proposed for residential demand response management. In the first stage, day-ahead prices and residential load schedule are obtained through a decentralized optimization. Day-ahead pricing is important as it helps the utility company to have a good estimation on the load for the next day. The decentralized optimization is developed using dual decomposition and sub-gradient method. The objective of the day-ahead optimization is minimizing the cost to the utility company and residential customers while maintaining he customer satisfaction. Two different functions are proposed to formulate the cost to the UDC. Five different classes of the residential appliances are considered and detailed models are developed accordingly. Since the energy consumption of non-schedulable residential loads is challenging to forecast, a normal distribution function is used to model the uncertainty of the estimation. As an important contribution of the work, distribution system operational constraints such as equipment capacity, line flow limits, phase balance, and voltage limit constraints are taken into account in the pricing mechanism. Effect of the operational constraints on the nodal prices are demonstrated and discussed.

Due to the highly random energy consumption at the residence, the second stage of pricing is used to adjust the price in real-time. The real-time price reflects the actual residential load. The proposed approach encourages the customers to participate in the day-ahead demand response management program.

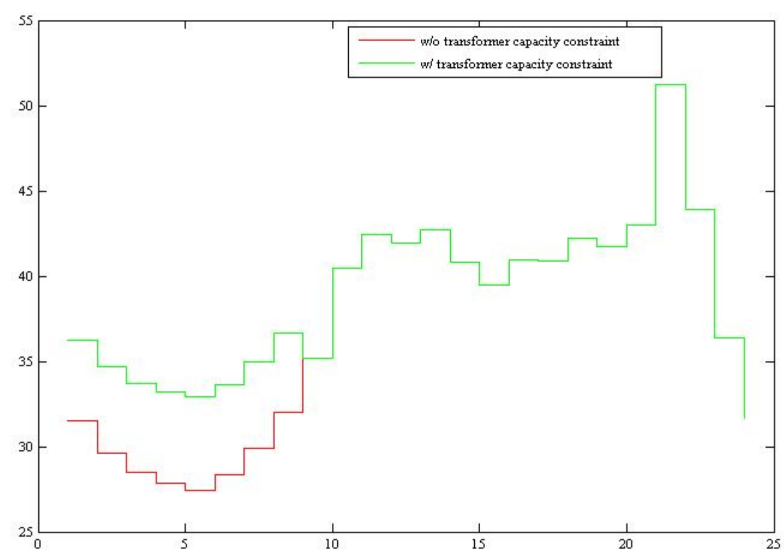


Figure 4.13: Load on node 7

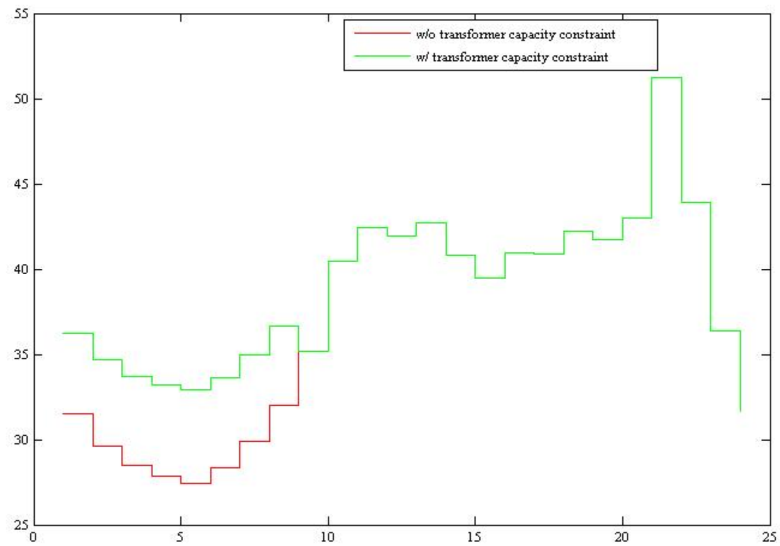


Figure 4.14: Nodal price on node 7

Chapter 5

Conclusion

In this dissertation, two important featuers of future smart dristribution gird is addressed and efficient approches are proposed to improve reliability and reduce cost.

5.1 Distribution System Restoration and Reconfiguration

In order to improve reliability of the system a fast and accurate procedure for distribution system reconfiguration and restoration in proposed first. This is a MIP-based approach which can be easily implemented for any given distribution system with different objective functions. Two particular objectives are minimizing the number of switching operations to isolate fault and remove overload condition, and minimizing the active power loss. The set of constraints include power balance, line flow limits, voltage limit, battery units constraints, and radiality of the system. The key issue of the DSR is to maintain the radiality of the system during reconfiguration process. A DFS-based approach is proposed to formulate radiality constraint for MIP. This approach detects all the possible cycles and loops generated by different combinations of switches. Then, the optimization can guarantee the radiality of the distribution system by opening at least one switch in each loop. This leads to a fast reconfiguration for large systems as the cycle detection approach is performed in off-line. This approach can also be applied to weakly-meshed system be removing the radiality constraint for particular cycles in the system. The study also shows that the charge/discharge of CES units can affect the result of reconfiguration through changing the line flows, voltage magnitudes, etc.

Due to the insufficient measurements and demand response programs in distribution grids load uncertainty will be an important factor for a reliable reconfiguration. Two different methods based on FMIP and SMIP are proposed to deal with the uncertainties in recognizing loads. It is shown that FMIP and SMIP lead to robust and optimal results which are feasible for many different load scenarios. Specially, since FMIP is much faster, it is recommended to use this approach for real-time applications.

5.2 Decentralized Residential Response Management

In this dissertation, a two-stage pricing mechanism is proposed for residential demand response management. In the first stage, day-ahead prices and residential load schedule are obtained through a decentralized optimization. Day-ahead pricing is very important as it helps the utility company to have a good estimation on the load for the next day. The decentralized optimization is developed using dual decomposition and sub-gradient method. The objective of the day-ahead optimization is minimizing the cost to the utility company and residential customers while maintaining he customer satisfaction. Five different classes of the residential appliances are considered and detailed models are developed accordingly. Since the energy consumption of non-schedulable residential loads is challenging to forecast, a normal distribution function is used to model the uncertainty of the estimation. As an important contribution of the dissertation, distribution system operational constraints such as equipment capacity, line flow limits, and phase balance are taken into account in the pricing mechanism. Effect of the operational constraints on the nodal prices are demonstrated and discussed.

Due to the highly random energy consumption at the residence, the second stage of pricing is used to adjust the price in real-time. The real-time price reflects the actual residential load. An extension to this work can be achieved through including distributed renewable resources owned by the utility company and/or residents. The demand response management program should help to maximize the utilization of these stochastic energy resources.

An extension to the current dissertation work can be to integrate distribution system reconfiguration and demand response program. This helps the system to be more economic and reliable.

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Vita

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