OPTIMAL BEHAVIOR OF DEMAND RESPONSE AGGREGATORS IN POWER SYSTEM MANAGEMENT

A Dissertation by

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The following faculty members have examined the final copy of this dissertation for form and content, and recommend that it be accepted in partial fulfillment of the requirement for the degree of Doctor of Philosophy with a major in Electrical Engineering and Computer Science.

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To my beloved wife, Nazanin
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Energy plays a vital role in our life. In recent decades, managing demand and supply of energy and maintaining the balance has become more complicated due to some technical, financial and environmental factors like growing electricity demand, old infrastructure, volatile energy costs, and intermittent resources. Therefore, the energy dilemma must be tackled with comprehensive and practical solutions. Moving toward demand-side management (DSM) is one of the most recent approaches, which can help electrical utilities and governors to achieve their goals. This transition has been accelerated by inventing new devices, deregulating electricity markets, and empowering end-users to be aware of electricity price via the smart meters. The smart home concept is one of the critical components to implement DSM in power distribution networks, which includes different types of DERs such as PV, ESS, Electric Vehicle (EV), and controllable appliances. In this dissertation, a novel Smart Home Management System (SHMS) is presented to deploy smart control strategies to maximize the beneficial effects of DERs and household appliances. Besides, a mathematical model of residential energy management considering electricity bill, transformer asset management, and energy loss is introduced. This dissertation also develops an optimization approach of DR aggregator to alleviate transmission congestion in the presence of DR and DERs. In the third part, the impact of DR on reliability improvement and the efficiency of microgrids is studied.
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<tr>
<td>DG</td>
<td>Distributed generation</td>
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<td>ESS</td>
<td>Energy storage system</td>
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<td>DSM</td>
<td>Demand-side management</td>
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<td>DER</td>
<td>Distributed energy resources</td>
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<td>PV</td>
<td>Photovoltaic</td>
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<td>EIA</td>
<td>Energy information administration</td>
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<td>EV</td>
<td>Electric vehicle</td>
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<td>DOE</td>
<td>Department of Energy</td>
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<tr>
<td>DAH</td>
<td>Day ahead</td>
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<tr>
<td>RT</td>
<td>Real time</td>
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<td>EDRP</td>
<td>Emergency demand response program</td>
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<td>SHMS</td>
<td>Smart home management system</td>
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<td>LMP</td>
<td>Locational marginal price</td>
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<td>DLMP</td>
<td>Distribution systems, distribution LMP</td>
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<td>ODAF</td>
<td>Oil directed-air force</td>
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<td>LOL</td>
<td>Loss of life</td>
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NOMENCLATURE

\[ \Delta \theta_A \] Average ambient temperature

\[ \Delta \theta_{TO} \] Top oil rise over ambient temperature

\[ \Delta \theta_H \] Winding hottest-spot rise over top-oil temperature

\[ \Delta \theta_{TO,U} \] Ultimate top-oil rise over ambient temperature

\[ \Delta \theta_{TO,I} \] Initial top-oil rise over ambient temperature

\[ \tau_{TO} \] Oil time constant

\[ \Delta \theta_{H,U} \] Ultimate hottest-spot rise over top-oil temperature

\[ \Delta \theta_{H,I} \] Initial hottest-spot rise over top-oil temperature

\[ \tau_w \] Winding time constant

\[ \Delta \theta_{TO,R} \] Top-oil rise

\[ \Delta \theta_{H,R} \] Hottest-spot at rated load

\[ F_{AA} \] Aging acceleration factor

\[ F_{EQA} \] Equivalent aging factor

\[ F_{AA,r} \] Aging acceleration factor for interval

\[ I(jj) \] Current of branch-\( jj \)

\[ N(jj) \] Total number of nodes beyond branch-\( jj \)

\[ ie(jj,k) \] Nodes beyond branch-\( jj \)

\[ PLOSS(jj) \] Real power loss of branch
\( \beta \{ i \in (\varphi, \kappa) \} \)  
Real and imagine part of loss allocation factors

\( I_{MPP} \)  
Current at the maximum power point

\( \theta_2 \)  
Final temperature of the home

\( P_{\text{net}} \)  
Consumption of bus \( i \)

\( \lambda_k \)  
Energy cost of bus \( i \) at time \( t \)

\( I_{\text{EDRP}} \)  
Incentive applied in location \( i \) at time \( t \)

\( C_{P_{\text{max},i}} \)  
Maximum capacity of parking \( i \) at time \( t \)

\( E_{(i,i)} \)  
Self-elasticity of each DR programs price

\( \lambda_{\text{Energy}} \)  
Cost of energy

\( N_{\text{non}} \)  
Number of customers

\( NL \)  
Number of loads in a microgrid
CHAPTER 1:
INTRODUCTION

The smart grid is the vision for enhancing the efficiency of electricity utilization from the generation to consumption, together with effectively accommodating all DG and ESS opportunities and facilitating consumer cooperation in DSM programs. Integrating DER in power distribution network is one of the main achievements of moving toward a smart grid which is characterized by their small capacities and their connection to low and medium voltage electricity distribution grids. These technologies have the potential to not only deliver the electricity services to end users, but also new services and possibilities enabled by their distributed nature such as reliability improvement, loss reduction, etc. Concerning DER penetration, the New England Independent System Operator (NE-ISO) expected that they would provide approximately 2.855 GW by 202. They have forecasted that 800 MW of the total estimate will be supplied by solar photovoltaic (PV) [2]. In the residential level [3], the U.S. Energy Information Administration (EIA) projected that house/ building solar PV is expected to generate 25 GW in the year 2040. One of the essential elements of the future power grid is the smart homes[4]. Smart homes include different types of DERs such as PV, ESS, and Electric Vehicle (EV) and controllable devices. In an ideal smart home, all devices can be monitored or controlled via the central control system. So,
it's necessary to have an active, reliable and fast communication infrastructure [4], [5]. An ideal smart house is displayed in Figure 1.1

![Figure 1.1. A typical smart home components](image)

Smart grid technologies related to a house have been in rapid development, and the market share of these technologies is expected to rise notably. In a worldwide scale, market analysts expected that the market value of smart appliances reaches over 26.1 billion U.S.dollars in 2019 [5].

Recent advances in smart metering technology enable bidirectional communication between the utility operator and the end-users and facilitate the option of dynamic load adaptation. Toward this direction, DR programs provide incentives to large users, usually in the form of monetary rewards, to decrease their demand within peak periods.
Since the residential sector accounts for the largest share of the energy used in U.S., smart homes are the best sources to utilize DR program in the intelligent distribution networks. DR is a term defined as “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” by the U.S. Department of Energy (DOE).

For decades, DR has been implemented only in the form of direct-load control (DLC) for large size commercial or industrial loads. Nowadays, DR applications can be extended to engage residential customers due to new technology inventions in monitoring, two-way communication, and smart devices. An excellent classification of DR programs is shown in Figure 1.2.

![Demand Response Programs](image)

**Figure 1.2. Demand response program classification**

In DLC and load-interruptible programs, the electricity supplier provides different types of incentive such as monetary reward or discount rate to encourage consumers. The electricity
markets reports show price-based DR programs have become more practical, where participants receive financial incentives based on the amount of the curtailed load in response to electricity prices. When electricity tariff is variable, the customers shift the unnecessary tasks to off-peak hours or reduce the consumption like turning off the lights or changing the HVAC setting.

The impact of DERs, DR, and smart homes on the power system has been studied from different aspects in the literature. The results confirm that utilizing DER in power systems can be a double-edged sword:

a) Deployment of smart grid technologies, such as smart appliances with intelligent control, can deliver the full range of benefits to end-users and utilities in terms of electricity bills, asset management, and reliability

b) in the absence of an efficient strategy, the lifetime of power system components, electricity price, transmission congestion can be deteriorated.

The design of suitable DR mechanisms for smart homes and small-scale DERs entails significant challenges, due to the massive penetration of resources and the negligible impact of each single of them on the utilities’ decisions.

The aggregator mainly acts as an intermediary between end-users (DER owners, smart homes, and DR volunteers) and power companies who wish to serve end-users or exploit the services provided by these DERs. Since each aggregator represents a large number of end-users, it's authorized to negotiate with utilities on behalf of the home users.

From the system's perspective, DR would be useful if a large number of scattered DERs, DR resources, and flexible consumers could provide a coordinated response to its requirements. Thus,
the coordination of these resources by an aggregating entity, or DR aggregator, is essential to facilitate the interaction between the consumers and the companies.

Operators always seek to minimize the operating costs. Accordingly, they are willing to offer an incentive to aggregators in order to modify the consumption of end-users. On the other hand, aggregators sell DR services to the operator and provide compensation to customers to adjust their usage. Finally, end-users attempt to optimize the tradeoff between aggregator's offer and sacrificing their comfort. The interaction between smart homes, aggregator, and utilities is displayed in Figure 1.3.

![Figure 1.3 Structure and the interaction for the DR aggregator between DSO and smart homes](image)

From Figure 1.3 we can observe that the impact of aggregators on power system performances is highly related to the demand. Thus, smart homes need to be modeled in more details to find the optimal scheduling of DR resources to reach the utility goals as well as achieve customers satisfaction. A comprehensive framework for DR aggregators needs to be further investigated to pave the way for future smart grid implementation.
Objectives:

The goal of this work is to develop a model to optimize the behavior of DR aggregators to participate in power system management utilities and ISO.

This method decreases the negative impact of non-coordinated management of residential loads on the energy bill and the aging of power system devices. In this work, a mathematical approach is introduced to obtain the optimal scheduling of household appliances, charging/discharging PHEV, ESS, and other resources in a day. The model will be extended to relief transmission congestion under a contingency. The role of DR aggregators in maintaining balance in a microgrid will be discussed.

Scope of work:

This work focuses on three main areas.

- Developing a novel smart house energy management system based on DLMP considering energy loss and asset management
- Designing an optimal strategy for DR aggregators to alleviate transmission congestion in the presence of DERs
- proposing a novel concept for forming and operating of microgrids under contingencies considering DR and renewable resources

1.1 Smart House Energy Management System Based on Distributed Locational Marginal Pricing

- Proposing an analytical method to determine the impact of different variables on the aging of power distribution transformers
• Developing Smart Home Management Systems model in the presence of PHEV, PV, thermal appliances, energy storage, and controllable household appliances
• Introducing the smart home scheduling considering energy bill, power loss, and asset management

1.2 Congestion Management in the presence of DR Aggregators and DERs

• Studying the impact of Emergency Demand Response Program (EDRP) on transmission congestion
• Presenting a stochastic optimization model for DR aggregators to participate in the day-ahead congestion management under uncertainties of DERs, EDRP, and market prices

1.3 Utilizing of Demand Response approaches in microgrids

• Propose an optimal forming of flexible microgrids under contingencies
• Develop optimal operation of DERs and DR to improve the reliability of power distribution networks
CHAPTER 2:

LITERATURE REVIEW

Energy efficiency has been one of the main concerns of utilities, governments, investors, and other participants of the energy market in the recent two decades. Communication networks development, cutting-edge technologies, control devices, and DER integration has led to fundamental changes in power systems from the generation to end-users [1]. The utilities benefit from smart grid such as improved security, reduced peak loads, increased penetration of renewables, and lower operational costs [2]. On the other hands, customers can reduce their electricity bills through scheduling smart appliances and energy resources via Smart Home Management System (SHMS). DR programs like load shifting or peak shaving may bring remarkable opportunities for LSEs and end users regarding electricity price or increase the utilization factors of power system devices like power lines and transformers. [3, 4].

The residential consumers can reduce approximately 40% of energy consumption in the world by performing DR programs [6]. Therefore, electrical companies have been focusing on enabling technologies for DR activities in this sector [7, 8]. The typical smart home may include
different devices such as household appliances, Electric Vehicle (EV) with the capability of selling energy back to the grid (V2G) or injecting energy to home (V2H), distributed generation, solar panel, ESS, etc.[9].

There have been several studies that investigated the optimal scheduling of smart home devices to maximize the profits of customers and LSEs. In [10], a neural network based programming of PV, ESS was proposed, but the price variability and power system conditions were neglected. In [11] the customers schedule home appliances for bill reduction at the community level, whereas aggregators minimize the energy purchasing expense from utilities at the market level. The aim of [12] was decreasing the electricity bills of consumers by establishing a day-ahead decentralized coordination method with appliance scheduling and energy sharing. Basit et al. proposed an autonomous energy management-based cost reduction solution for peak load times that was solved through a step-wise approach [13]. The aim of the optimization problem of [14] was to minimize the total cost to meet the electrical energy needs of the household in a dynamic pricing environment. In [15], a stochastic dynamic programming framework for the optimal energy management of a smart home to minimize electricity ratepayer cost, satisfy home power demand and PEV charging requirements is presented. In [16], the impact of price-based DR strategies on smart household load pattern variations was assessed. The novelty of the [17] was that the monthly bill target preferred by the consumer is achieved through the optimal operation of appliances over a multi-day time horizon. In some papers, the profits of retailers and aggregators have been taken into account. Besides, a different incentive based peak load reduction strategy is also considered in [18] for load reduction and voltage improvement. In [19], a new market mechanism is introduced for congestion management in distribution systems. In [20] the effect of households' appliances scheduling on the lifetime of a distribution transformer and energy bill of
customers was assessed. In [21] a DLC based residential end-user coordination scheme is proposed to satisfy the distribution system operational limits. Paterakis et al. presented an optimal operation of a neighborhood of smart households regarding minimizing the total energy procurement cost and preventing power peaks that are harmful to distribution assets [22]. Amini et al. [23] proposed a systematic EV management for reducing power system loss. In [24] a smart home includes PV, ESS, and EV has been scheduled; however, the ability to inject power back to the house was neglected. In [25], customers’ satisfaction oriented strategy for residential heating, ventilation, and air-conditioning (HVAC) units was proposed. The potential of HVAC offering load balancing services through bi-directional LSE signals for power reduction or increase requirements was analyzed in [26,27].

Literature review reveals most of the papers have been covered energy bill, power loss, reliability improvement, peak to average, and congestion management. In other words, optimizing the profits of consumers and LSEs have rarely been studied and modeled simultaneously in one problem. Due to the radial topology, the current of branches, and resistance of distribution feeders the power loss is not neglected. Therefore, a new pricing mechanism needs to be designed to represent either energy price and power loss of distribution networks. By extending the locational marginal price (LMP) concept from transmission systems, the Distribution LMP (DLMP) is applied to cover the cost of power loss and energy in distribution networks.

This idea can provide a fair allocation of power loss among nodes and customers. In addition, improving the condition of power system elements can postpone new investments. This dissertation assesses the impact of the SHMS on the lifetime of a distribution transformer. To the best knowledge of authors, this is the first study in the literature which models a single SHMS includes PV, PHEV, small-scale ESS, and intelligent appliances in order to decrease energy bill
and power loss. Moreover, the uncertainty of outdoor air temperature, PV, and uncontrollable loads are modeled by Monte Carlo simulation. The internal temperature of the home and operation of appliances and energy resources are defined by two-stage stochastic optimization and solved by MILP.
CHAPTER 3:
TRANSFORMERS ASSET MANAGEMENT IMPROVEMENT USING DEMAND SIDE ENERGY MANAGEMENT SYSTEM

This chapter examines the consequences of overloading on the aging of power system components.

3.1. Finding the Most Influential Variables On Asset Management

In general, experiments are used to study the performance of processes and systems [8]. Figure 3.1 depicts a typical system with controllable and uncontrollable factors.

The objective of the experiment is to determine:

- Which variables are most influential on the response
- Where to set the influential controllable factors so that response is within an acceptable range
- Where to set the prominent controllable elements so that variability in response is small

Statistical design of experiments is the process of planning the research so that appropriate data that can be analyzed by statistical methods will be collected. Many tests involve the study of the effects of two or more factors. Factorial designs mean that in each complete trial or replication of the experiment all possible combinations of the levels of the factors are investigated. A $2^4$ factorial design for transformer loss of life is discussed in the following subsections.
3.2 2^4 Factorial Design For Transformer Loss Of Life

Four factors are chosen to analyze their effects on the transformer loss of life.

The daily load profile of a residential neighborhood with data granularity of 15 (96 intervals) minutes is given in Fig 3.2. High-resolution AMI data guarantee the calculation accuracy. The load has been given in per unit values. In order to generate the second level for the factorial design, peak shaving is applied to the load profile. Resulted load profile has been given in Figure 3.3. Load profile could also be affected by many other load management programs. Demand response, controlled electric vehicle charging, and distributed generators are some of the influential factors. All the above cases could have been considered as the second level to analyze their potential effect on transformer loss of life.

![Load profile - Level 1](image)

Figure 3.1: Transformer load profile- level 1

Transformer cooling type [10]: ONAN refers to the dissipation of heat from the oil to the atmosphere by natural circulation of the oil through the windings and cooling equipment, which is externally cooled by natural air. In contrast, Oil Directed-Air Force is a better way to improve heat dissipation by forcing oil through the winding as shown in Fig. 4 b. Regarding the transformer cooling type, the value of $m$ and $n$ are different. For the low level which represents the type of
ONAN, $m$ and $n$ are chosen to be 0.8. High level is assumed to be directed ODAF for which $m$ and $n$ are 1. Ambient temperature and oil time constant are two more factors which are of interest in this experimental design. Ambient temperature depends on the number of fans in the substation room and is given in two levels: Low ($20^\circ$C) and High ($40^\circ$C). Oil time constant is also divided into low (100) and high (300) levels. All the factors and their levels are summarized in Table I. As shown in table I, two levels "low" and "high" are represented by "0" and "1" in design matrix, respectively.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Level</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transformer Load profile</td>
<td>A</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Ambient Temperature</td>
<td>B</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Cooling Characteristic</td>
<td>C</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Oil Time Constant</td>
<td>D</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

Loss of life values for 16 combinations of four factors are given in Table 3.2.
3.3 Analysis

After analyzing data in Design-Expert® Software effect of each factor, the sum of squares, and their contribution to transformer loss of life have been given in Table 3.2.

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>Loss of Life (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.007435</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.011403</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0.008525</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0.012605</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0.009765</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0.017307</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0.010954</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0.018589</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.007157</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.0110556</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0.00823452</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0.0122496</td>
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<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0.00943626</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0.0168989</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.0106134</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.0181766</td>
</tr>
</tbody>
</table>
The last column (Contribution %) in this list measures the percentage contribution of each model term relative to the total sum of squares. Table III shows that the transformer load profile plays the most significant role in transformer LOL. Its contribution is 60.44%. The second most significant factor is cooling characteristic. Its contribution is 31.02%. The interaction between factors A and C is more significant than factor B. Impact of OTC in this model is negligible.

### 3.4 Asset Management of Power Distribution Transformers

Transformers represent the most substantial portion of the capital investment in transmission and distribution substations [1]. Annually, transformer aging incurs considerable cost to utilities in terms of both maintenance and replacement. Disposed assets could have been prevented from failure and maintained in service for a longer time if preventive and corrective actions had been put in place. There always are several factors accelerating asset aging which need to be analyzed.
and opposed on time. Before installing a particular asset into the grid, contributing factors to its loss of life need to be estimated. Expected LOL of a transformer is a function of customer demand, ambient temperature, and cooling characteristics [2]. Research on the impact of electricity consumption pattern on asset has gained momentum in recent years. Humayun et al. [3] quantified the improvement of transformer utilization through demand response based on transformer hottest-spot temperature. Aravinthan and Jewell [4] proposed a two-step methodology for scheduling electric vehicle charging to limit the burden on distribution and transmission assets. Mousaviagah et al. [5] presented a method to quantify the distribution transformer life extension caused by customer-owned distributed generators. A preliminary assessment of the impact of ambient temperature rise on distribution LOL was performed in [6] to model climate change and urbanization effects. Effect of load growth, cooling characteristics and top oil temperature on liquid-filled transformer loss of life was also reported in [7]. All of the above factors were analyzed separately; however, the major disadvantage of the one-factor-at-a-time strategy is that it fails to consider any possible interaction between the elements. The correct approach to dealing with several factors is to conduct a factorial experiment in which factors are varied together [8]. Recognizing what has been missing in the literature, this dissertation aims to figure this out by conducting a $2^4$ factorial design to analyze the joint effect of loading, cooling characteristics, ambient temperature, and oil time constant on transformer LOL. Each of the four contributing factors is defined in 2 levels, low and high, to make sixteen separate scenarios. Real-time 15-min AMI residential load data for one typical weekday in Canada are used for the first loading level. This profile is shaved during the peak time to generate the second loading level. Impact of each factor and their interaction on transformer LOL is statistically analyzed through Design-Expert® Software Version 9 and results show the significance of each factor.
3.5. Transformer LOL Calculation

According to IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators [9], transformer thermal model and aging equations are as follows:

3.5.1 Transformer Thermal Model

The following equation estimates the transformer winding hottest-spot temperature:

$$\theta_H = \theta_A + \Delta \theta_{TO} + \Delta \theta_H$$  (3.1)

where $\Delta \theta_A$ is the average ambient temperature during the load cycle, $\Delta \theta_{TO}$ is the top oil rise over ambient temperature, $\Delta \theta_H$ is the winding hottest-spot rise over top-oil temperature.

The top-oil rise and hottest spot temperature rise are:

$$\Delta \theta_{TO} = (\Delta \theta_{TO,U} - \Delta \theta_{TO,i})(1 - \exp^{-t/\tau_{TO}}) + \Delta \theta_{TO,i}$$  (3.2)

$$\Delta \theta_H = (\Delta \theta_{H,U} - \Delta \theta_{H,i})(1 - \exp^{-t/\tau_{w}}) + \Delta \theta_{H,i}$$  (3.3)

where, $\Delta \theta_{TO,U}$ and $\Delta \theta_{TO,i}$ are ultimate and initial top-oil rise over ambient temperature, respectively. $\tau_{TO}$ is oil time constant, $\Delta \theta_{H,U}$, and $\Delta \theta_{H,i}$ are ultimate and initial hottest-spot rise over top-oil temperature, respectively. $\tau_w$ is the winding time constant.

For the multi-step load cycle analysis with a series of short-time intervals, (2) is used for each load step, and the top-oil rise calculated for the end of the previous load step is used as the initial top-oil rise for the next load step calculation. $\Delta \theta_H$ is transient winding hottest-spot temperature rise over top-oil temperature.
The ultimate top-oil rise and ultimate hottest-spot rise can be calculated as given below

\[ \Delta \theta_{TO,U} = \Delta \theta_{TO,R} \left[ \frac{K_v^2 R + 1}{R + 1} \right]^n \]  
(3.4)

\[ \Delta \theta_{H,U} = \Delta \theta_{H,R} K_v^{2m} \]  
(3.5)

Where \( \Delta \theta_{TO,R} \) and \( \Delta \theta_{H,R} \) are the top-oil rise and hottest-spot at rated load, respectively; \( K_v \) is the ratio of ultimate to rated load; \( R \) is the load loss ratio; \( m \) is an empirically derived exponent used to calculate the variation of \( \Delta \theta_H \) with changes in load. \( n \) is an empirically derived exponent used to calculate the variation of \( \Delta \theta_{TO} \) with changes in load. These factors depend on the type of cooling of the transformer.

### 3.5.2 Transformer Aging

Aging acceleration factor \( (F_{AA}) \), the rate at which transformer insulation aging is accelerated compared with the aging rate at a reference hottest-spot temperature, is as given below

\[ F_{AA} = \exp \left( \frac{1500}{383} - \frac{1500}{273 + \theta_H} \right) \]  
(3.6)

The equivalent aging factor \( (F_{EQA}) \) for the total period can be calculated as follow,

\[ F_{EQA} = \frac{\sum_{r=1}^{N} F_{AA,r} \Delta t_r}{\sum_{r=1}^{N} \Delta t_r} \]  
(3.7)

where \( r \) is the index of the time interval, \( N \) is the total number of time intervals, and \( F_{AA,r} \) is the aging acceleration factor for interval \( \Delta t_r \).
The percent loss of life (LOL) of the transformer for \( t \) hours of operation can be obtained as follows:

\[
%\text{LOL} = \frac{F_{EQ} \times t \times 100}{\text{Normal insulation life}} \quad (3.8)
\]

Minimum normal insulation life expectancy is 180000 hours (20.55 yr.), with continuous service at the HST of 110°C. Normal percent loss of life for operation at a rated hottest-spot temperature of 110°C for 24 h is 0.0133%.

### 3.6 Distribution Loss Allocation Methods

In radial distribution systems, electric power flows from a substation to end users. Energy loss allocation to each customer is related to load level, the location of the node, and equivalent impedance. In this dissertation, a practical method called the “Exact Method” is implemented to allocate active power loss to nodes.

#### 3.6.1. Exact method

This approach uses the results of a converged load flow based on the identification of nodes and branches [28]. In a radial distribution system, branch current can be written as:

\[
I(jj) = \sum_{k=1}^{N(jj)} \left[ \frac{P_{ie(jj,k)} + jQ_{ie(jj,k)}}{V_{ie(jj,k)}} \right]^* \quad (3.9)
\]

where \( I(jj) \) represents current of branch-\( jj \), \( N(jj) \) denotes total number of nodes beyond branch-\( jj \), \( ie(jj,k) \) represents nodes beyond branch-\( jj \) for \( k=1,2, \ldots, N(jj) \). Also, \( P, Q, \) and \( V \) represent real power, reactive power, and voltage of nodes \( ie(jj,k) \), respectively. The real power loss of branch-\( jj \) with sending end and receiving end voltages \( V_i \) and \( V_j \) is given by:
\[ PLOSS_{(jj)} = \text{Re}\{ (V_i - V_j)^* I_{(jj)} \} \]  \hfill (3.10)

\[ PLOSS_{(jj)} = \text{Re}\left( (V_i - V_j)^* \sum_{k=1}^{N_{(jj)}} \left[ \frac{P_{\{ie(jj,k)\}} + jQ_{\{ie(jj,k)\}}}{V_{\{ie(jj,k)\}}} \right] \right) \]  \hfill (3.11)

\[ \left[ \frac{V_i - V_j}{V_{\{ie(jj,k)\}}} \right]^* = \alpha_{\{ie(jj,k)\}} + j\beta_{\{ie(jj,k)\}} \]  \hfill (3.12)

\[ PLOSS_{(jj)} = \sum_{k=1}^{N_{(jj)}} \alpha_{\{ie(jj,k)\}} P_{\{ie(jj,k)\}} + \beta_{\{ie(jj,k)\}} Q_{\{ie(jj,k)\}} \]  \hfill (3.13)

where \( PLOSS_{(jj)} \) denotes real power loss of branch, \( \alpha_{\{ie(jj,k)\}} \) and \( \beta_{\{ie(jj,k)\}} \) represent real and imaginary part of loss allocation factors for the consumer at node \( ie(jj,k) \), respectively. Real power loss of branch \( jj \) allocated to customers connected to node \( ie(jj,k) \) is given by

\[ ploss\{jj,ie(jj,k)\} = \alpha_{\{ie(jj,k)\}} P_{\{ie(jj,k)\}} + \beta_{\{ie(jj,k)\}} Q_{\{ie(jj,k)\}} \]  \hfill (3.14)

The global value of losses to be supported by consumer connected to node \( l \) results from the sum of the losses allocated to it in each branch \( jj \) of the network is given (7):

\[ T_{plossi(l)} = \sum_{jj=1}^{N_{B}-1} ploss\{jj,l\} \text{ for } l = 2,3,...,N_{B}. \]  \hfill (3.15)

3.7 Implementing DLMP In Power Distribution Systems

The DLMP is similar to LMP in electricity wholesale market in which the cost of serving one additional unit of energy at a particular bus is displayed. DLMP of a node depends on load level, LMP, and allocated power loss which is given in (8)

\[ DLMP_{i,t} = LMP_i \left( 1 + \frac{T_{ploss_{i,t}}}{PLOSS} \right) \]  \hfill (3.16)
Consumers react to DLMP and choose whether to continue consuming or to reduce the load. This control method not only saves money for consumers but also improve the system security by load shifting and peak shaving.

3.8 Smart Home Management System

Electricity demand has generally been increasing over the last few decades. This trend has created some new obstacles for utilities, customers, and the environment.

In this work, a new SHMS under DLMP as a novel pricing mechanism is proposed to increase the profits of LSEs and customers from technical and financial points of view. From LSEs point of view, they intend to implement a proper plan to decrease power and sell more energy. From the end users points of view, they can reduce their electricity bills and earn more incentives proportionate to their contributions to energy loss reduction of the system. In the proposed approach, the energy bill of customers and power loss of the system are simultaneously decreased. First, household appliances such as wet appliances, Heating, ventilation and air conditioning (HVAC), EVs, ESS, and PV have been explicitly modeled. Monte Carlo simulation is used to deal with the uncertainties of the problem like outdoor temperature and renewable resources. To solve the two-stage stochastic problem, we employed Mixed Integer Linear Programming (MILP). Different scenarios are conducted to evaluate the impact of ESS capacities, availability of DERs, customers preferences, and different electricity tariffs on electricity bill and energy loss of the system. The results demonstrate the superiority of DLMP and the proposed method over existing pricing mechanism and the smart home management methods.

SHMS is implemented to determine the optimal scheduling of household appliances and operating ESS, PV, and EV considering signal price and customer preferences.
3.8.1. EV modeling

In this work, EVs are able to sell power back to the grid or supply the appliances, which is modeled by (3.17-3.21) [29].

\[ P_{t}^{EV,Ch} = P_{t}^{EV,CHRate}u_{t}^{EV} \] (3.17)

\[ P_{t}^{EV,Dis} = P_{t}^{EV,DisRate}(1 - u_{t}^{EV}) \] (3.18)

\[ SOC_{t}^{EV} = SOC_{t-1}^{EV} + \frac{P_{t}^{EV,Ch}}{BC_{EV}} - \frac{P_{t}^{EV,DisCh}}{BC_{EV}} \] (3.19)

\[ SOC_{t}^{EV,Min} \leq SOC_{t}^{EV} \leq SOC_{t}^{EV,Max} \] (3.20)

\[ SOC_{t}^{EV} = SOC_{t}^{EV,Desired} \quad \text{if} \quad t = T_{d}^{d} \] (3.21)

Where \( P_{t}^{EV,Ch} \) and \( P_{t}^{EV,Dis} \) represent charging and discharging power (kW) of EVs, respectively. \( P_{t}^{EV,CHRate} \) and \( P_{t}^{EV,DisRate} \) state charging and discharging rate of the battery, respectively. Equations (9) and (10) denote charging and discharging energy level of an EV depends on power rate and charging/discharging level of EV's battery at time \( t \). \( u_{t}^{EV} \) means binary variable (1 if EV is charging, else 0). Equation (11) imposes the state of energy at every interval \( SOC_{t}^{EV} \) to have the value that it had for the previous range \( SOC_{t-1}^{EV} \), plus the actual amount of energy that is transferred to the EV battery if it is charging at that interval, and minus the energy that is subtracted if the EV battery \( BC_{EV} \) is discharging during that interval. Constraint Equation (12) limits the SoC of the battery to be between a least state-of-energy limit \( SOC_{Min}^{} \) and the maximum battery capacity \( SOC_{Max}^{} \). Equation (18) represents the option
of having the EV charged at the desired level \( (SOC_{\text{EV,Desired}}) \) at the departure time of EV from home \( (T^d) \).

### 3.8.2 ESS

The main difference between EV and ESS models is the availability of ESS at the house within 24 hours of a day [30].

\[
P_{t,\text{Ch}}^{\text{ESS}} = P_{t}^{\text{EV,CHRate}} u_{t}^{\text{ESS}} \quad (3.22)
\]

\[
P_{t,\text{Dis}}^{\text{ESS}} = P_{t}^{\text{ESS,DisRate}} (1 - u_{t}^{\text{ESS}}) \quad (3.23)
\]

\[
SOC_{t}^{\text{ESS}} = SOC_{t-1}^{\text{ESS}} + \frac{P_{t,\text{Ch}}^{\text{ESS}}}{BC_{\text{ESS}}} - \frac{P_{t,\text{Dis}}^{\text{ESS}}}{BC_{\text{ESS}}} \quad (3.24)
\]

\[
SOC_{t}^{\text{ESS,Min}} \leq SOC_{t}^{\text{ESS}} \leq SOC_{t}^{\text{ESS,Max}} \quad (3.25)
\]

Where \( P_{t,\text{Ch}}^{\text{ESS}} \) and \( P_{t,\text{Dis}}^{\text{ESS}} \) represent charging and discharging power (kW) of energy storages, respectively. \( P_{t}^{\text{ESS,CHRate}} \) and \( P_{t}^{\text{ESS,DisRate}} \) state charging and discharging rate of the battery, respectively. \( u_{t}^{\text{ESS}} \) denotes binary variable (1 if ESS is charging, else 0). Equations (14) and (15) indicate charging and discharging energy level of an ESS depends on power rate and charging/discharging level of storage batteries at time \( t \). Equation (16) imposes the state of energy at every interval \( (SOC_{t}^{\text{ESS}}) \) to have the value that it had at the previous interval \( (SOC_{t-1}^{\text{ESS}}) \), plus the actual amount of energy that is transferred to the battery if it is charging at that interval, and minus the energy that is subtracted if the battery \( (BC_{\text{ESS}}) \) is discharging during that interval. Constraint (17) limits the SoC of the battery to be between a least state-of-energy limit \( (SOC_{\text{Min}}) \) and the maximum battery capacity \( (SOC_{\text{Max}}) \).
3.8.3 Small scale PV

Time series method is used for the forecasted amount of solar irradiance. Since solar irradiance varies a lot in different weather conditions, a stochastic approach is used to model the generation of PV in a day. The algorithm of modeling PV generation is shown in Fig.1.

The Beta distribution function is used to model the solar irradiance [31]. Based on estimated solar irradiance and possibilities, power generation of PV in each scenario is calculated as follows:

\[
T_{cell} = T_{amb} + S, \frac{T_{Nom} - 20}{0.8}
\]  
(3.26)

\[
I = S, [I_{sc} + k_c (T_C - 25)]
\]  
(3.27)

\[
V = V_{oc} + k_v T_C
\]  
(3.28)

\[
FF = \frac{V_{MPP} \cdot I_{MPP}}{V_{oc} \cdot I_{sc}}
\]  
(3.29)

\[
P_{t}^{Solar} = N \cdot FF \cdot V \cdot I
\]  
(3.30)

where \( V_{MPP} \) and \( I_{MPP} \) are voltage and current at the maximum power point, respectively. \( V_{oc} \) and \( I_{sc} \) are open-circuit voltage and short-circuit current in \( V, A \). \( T_{cell}, T_{amb} \) and \( T_{Nom} \) are the cell temperature, the ambient temperature and nominal operating temperature in °C, respectively. \( k_v \) is the voltage temperature coefficient in \( V/°C \), and \( k_c \) is the current temperature coefficient in \( A/°C \). \( N \) is the number of cells. \( P_{t}^{Solar} \) is the generation of the PV at hour \( t \).

3.8.4 Appliances

Due to the function of appliances and consumers preferences, household devices are classified as follows:
• **Non-controllable appliances**

This category includes those devices, which need to be operated at a particular time and cannot be modified such as television, light, or some specific appliances. The behavior of customers for power consumption varies on different days. Several factors such as weather conditions or weekday/weekend affect the load; therefore, Non-controllable demand can be considered as a stochastic variable. The uncertainty of customer behavior is can also be modeled by normal distribution [31].

\[
f_N(\text{load}) = \frac{1}{\sqrt{2\pi}\delta} e^{-(1-\mu)^2/2\delta^2}
\] (3.31)

In this case, the mean and variance of normal PDF are obtained similarly through the forecasted load and historical data. Hence, a normal distribution function is assigned for each hourly load demand.

• **Controllable appliances**

This category includes all appliances for which starting time can be shifted across the day in response to price variations or some technical issues without considerable impact on customers' comfort. Wet machines are capable of changing wash action and modifying cycle duration. Also, a dryer can change their consumption by delaying operation time. Air conditioners (AC) have more flexibility in adjusting the consumption by postponing start time and slightly violating temperature limits which set by customers. The specific parameters of devices are given in Table 1 [32].
Table 3.1

Characteristics of the household appliances

<table>
<thead>
<tr>
<th>Device</th>
<th>Rated Power (kW)</th>
<th>Duration Time (Hours)</th>
<th>Desired Start Time (Hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dishwasher</td>
<td>1.5</td>
<td>1</td>
<td>21-24</td>
</tr>
<tr>
<td>Clothes washer</td>
<td>2</td>
<td>2</td>
<td>18-22</td>
</tr>
<tr>
<td>Dryer machine</td>
<td>1.5</td>
<td>1</td>
<td>18-22</td>
</tr>
</tbody>
</table>

3.8.5 Thermal Appliances

HVAC can make a noticeable impact on residential consumption pattern, whereby they need to be modeled in more details. HVACs are considered as closed-loop temperature controlled devices operating to maintain the internal house temperature as set point. In this dissertation, acceptable bounds on the temperature, which will be specified by customers, are used as the comfort constraint in the scheduling process.

- **Thermostatic Model of a Home**

Thermal appliance operation model requires a dynamic thermal model that describes its heat exchange with the environment [33]. At the beginning of each time interval of the day, SHMS determines the appropriate output power of that range based on electricity price, outdoor air temperature, preferred temperature, and current temperature. First, the following equations (23-26) are used to determine how much energy is needed to reach the comfortable temperature during a time interval.

\[
P_t^{\text{Thermal}} = Q_t + mC(\theta_2^t - \theta_1^t)
\]  
(3.32)
where \( t \) is the duration time, \( m \) is the mass of the home air, \( C \) is heat capacity and \( \theta_1 \) and \( \theta_2 \) are the initial and final temperature of the home, respectively. Moreover, \( Q_l \) is the thermal conductivity of the house and is computed as follows:

\[
Q_l = k_l A_l (\theta_{out}^t - \theta_{in}^t) \quad l \in w, c, f
\] (3.33)

\[
\frac{1}{k_l} = \frac{1}{h_1} + \frac{1}{h_2} + \frac{e_1}{z_1} + \frac{e_2}{z_2} \quad l \in w, c, f
\] (3.34)

where \( \theta_{out}^t \) and \( \theta_{in}^t \) are the outdoor and indoor temperatures at hour \( t \), respectively. Also, \( A_l \) denotes is the area of the walls. \( z_1 \) and \( z_2 \) show coefficient of thermal conductivity of lined and middle layer, respectively. Moreover, \( e_1 \) and \( e_2 \) are the lined and intermediate layer thickness. \( k_i \) is the coefficients of thermal conductivity of the wall. The output power of the device for heating and air conditioning, the indoor temperature, and the outdoor air temperature constitute the historical data.

In this work, the output power of the AC depends on outdoor air temperature. Since the temperature is a stochastic variable, the power of AC is also an uncertain variable. The historical data illustrate the best function to model the stochastic behavior of outdoor temperature in winter is Beta distribution.

\[
f(T) = \begin{cases} 
\frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) + \Gamma(\beta)} \times T^{(\alpha - 1)} \times (1 - T)^{\beta - 1}, & 0 \leq T \leq 1, \quad \alpha, \beta \geq 0 \\
0, & \text{otherwise}
\end{cases} \] (3.35)

\[
\beta = (1 - \mu) \cdot \left( \frac{\mu \cdot (1 + \mu)}{\delta^2} - 1 \right)
\] (3.36)

\[
\alpha = \frac{\mu \cdot \beta}{1 - \mu}
\] (3.37)
Where $\mu$ and $\delta^2$ are mean and variance of air temperature. Similar to the PV, actual data processing achieves the average value that is the hourly average of forecasted air temperature and the deviation of air temperature. Based on the collocated data and given parameters, a Beta distribution function is fitted for an outdoor temperature of each hour [34]. Hourly temperature and relative humidity data from Meteorological Terminal Aviation Routine (METAR) weather reports of 43 weather stations located in the USA are used [35]. The numerical study shows the mean and variance of the error in temperature are 2 and 1.4, respectively. The histogram of the forecasted and real temperature error is displayed in Fig. 1.

![Figure 3.3: The histogram of the forecasted and real temperature error](image)

3.9 Problem formulation

The optimization problem is presented as MILP which has a two-stage objective function as in (30). In the two-stage stochastic problem, the final decisions (i.e. scheduled appliances, the operation of ESS and EVs) are made in the first stage by considering the analysis of scenarios and
making decisions about customer's convenience (setting the indoor temperature based on customer's desired temperature and outdoor temperature) in the second stage. Total cost is equal to energy bought from grid minus energy sold back to the network.

\[
Final\_Cost = \sum_{t=1}^{T} \left[ \left( P_{t}^{buy} \cdot DLMP_{t}^{buy} - P_{t}^{Sell} \cdot DLMP_{t}^{sell} \right) + \sum_{s=1}^{S} P_{t,s} \cdot TC_{t,s} \right]
\] (3.38)

Under this electricity tariff, the location of customers might affect their energy bills, which can decrease the fairness of the proposed strategy. In order to solve this issue, it's assumed utilities buy their surplus energy based on their contribution to loss reduction. This policy can motivate customers to modify their demand during peak hours and sell it back to the grid when DLMP is high. In this dissertation, DLMP of node \( i \) is calculated in Eq. (1)-(8) and sent to SHMS on node \( i \). MILP is applied to obtain the optimal scheduling of appliances and energy resources in a house and evaluate the impact of the implemented strategy on utilities and customers’ profits.

The proposed stochastic model of SHMS \( TC_{t,s} \) is defined as follows

\[
TC_{t,s} = P_{t,s}^{Thermal} \times DLMP_{t}
\] (3.39)

where \( P_{t,s}^{Thermal} \) represents the required energy to reach the desired indoor temperature.

3.9.1. First stage constraints

The balance between demand and energy resources in a home and import/export power from/to the grid is given in (32). In the first stage, forecasted data are considered for random variables

\[
P_{t}^{grid} + P_{t}^{ESS,Dis} + P_{t}^{EV,Dis} + P_{t}^{Solar} = P_{t}^{ESS,Ch} + P_{t}^{EV,Ch} + P_{t}^{sell} + P_{t}^{App}
\] (3.40)
Where $P_{grid}^t$ and $P_{sell}^t$ state the amount of energy bought /sold back from/to grid, respectively.

Upper and lower bound of power transactions are

$$P_{grid}^t \leq \kappa_b \times u_{grid}^t, \quad \forall t$$  \hspace{1cm} (3.41)

$$P_{sell}^t \leq \kappa_s \times (1 - u_{grid}^t), \quad \forall t$$  \hspace{1cm} (3.42)

Equations (33) and (34) represent the restriction of the power exchange. If the power of the grid is needed to be drawn, the system is not allowed to sell back higher than $\kappa_s$. According to the safety of appliances and capacity of smart meters, the customer cannot import energy from the grid greater than $\kappa_b$. Also, $u_{grid}^t$ denotes binary variable (1 if a network is supplying power during period $t$, 0 else).

### 3.9.2. Second stage constraints

Second stage constraints are defined to make sure the customers' satisfaction is not violated. HVAC can play a vital role in the electricity usage of a house under different desired indoor temperature and outdoor temperature.

$$\theta_{Desired}^t - \varepsilon \leq \theta_{in}^t \leq \theta_{Desired}^t + \varepsilon$$  \hspace{1cm} (3.43)

Where $\theta_{Desired}^t$ state the desired indoor temperature for homeowners and $\varepsilon$ represents a small positive value that is determined by assumption.

### 3.9.3. Methodology

The performance of SHMS and its algorithm for each hour $t$ is illustrated in Fig. 4.
To model the uncertainties of solar radiation, outdoor air temperature, and non-controllable loads in a day, we produce a forecasted solar irradiance and air temperature by time series method [31]. Moreover, the consumption pattern of smart homes is achieved through smart meter data [32]. Then, probability distribution function (PDF) of deviation between historical and the forecasted data in
each hour for the aforementioned variable parameters are calculated. In this research, the non-
sequential Monte Carlo Simulation (MCS) is applied to generate some scenarios for uncertain
sources based on the corresponding PDFs [37]. To represent possible states, the MCS generates
over 1500 scenarios. Since dealing with this number of scenarios is a time-consuming process, a
proper method needs to be applied to reduce scenarios with an accurate approximation. The
backward method is employed to determine a subset of the initial scenario set and assign new
probabilities to the preserved scenarios [38]. The number of scenarios has been reduced from 1500
to 15 new scenarios. According to the scenarios, the objective function is solved to obtain the
optimal scheduling of appliances and energy resources in each node. According to (1)-(8), DLMP
of nodes is calculated and send to SHMS as a price signal. The proposed module can modify its
schedule to decrease energy bills. This approach leads to reduce the total energy cost of the network.
Finally, the optimal scheduling of smart homes considering energy costs and power loss of the
systems is achieved.

3.10 Numerical results

In this dissertation, the IEEE 30-bus distribution network is used as the test case shown in Fig.
3.5[39]. The number of houses equipped with SHMS in each bus is given in Table II. The real-time
demand of an average house is given in Fig. 3.6 [32]. Electricity pricing data of Ontario on
December 5, 2011, is used in the numerical study is shown in Fig. 3.7[40]. As it discussed in Eq
(8), this price signal is used to calculate the hourly DLMP of nodes. The nearly 100 meter-square
household includes four habitats with different electric appliances, including fridge, TVs,
microwave, video game, computer, oven, etc. The desired indoor temperature is assumed 74 °F. A
bi-directional EV operation including both V2G (EV can inject energy back to the grid) and V2H
(meaning that a portion of the energy stored in EV battery is used to cover the household load
partly) options is considered. The Capacity of EV and ESS battery are assumed 5 kW, and initial SoC of EV is 50% at 6 P.M. The lower limit of EV state-of-energy is restricted to 20%-30% of SoC to avoid deep discharging. In addition, the battery should be fully charged at departure time. Charging and discharging rate of EV and storage batteries are 2 kWh and 0.5 kWh, respectively. For simplicity, some additional costs such as maintenance of PV and degradation of batteries are neglected. The parameters of thermal appliances and 1000 KVA distribution transformer and are listed in Table III and Table VI, respectively [32]. Acceptable bounds of the temperature are (73°F - 75°F). When the available energy from the resources is enough to supply the total demand, the excess of energy can be sold back to the grid and vice versa.

![IEEE 30 bus distribution test system](image)

**Figure 3.5 IEEE 30 bus distribution test system**

**Table 3.2**

<table>
<thead>
<tr>
<th>Node</th>
<th>25</th>
<th>26</th>
<th>27</th>
<th>28</th>
<th>29</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num. home</td>
<td>150</td>
<td>150</td>
<td>100</td>
<td>100</td>
<td>120</td>
<td>100</td>
</tr>
</tbody>
</table>
Figure 3.6: The real-time measured load demand of a smart home

Figure 3.7: Time of Use electricity price

Table 3.3
Thermal appliance problem inputs

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$\frac{1}{h_1}$</th>
<th>$\frac{1}{h_2}$</th>
<th>$\frac{mC}{w}$</th>
<th>$e_1$ (m)</th>
<th>$e_2$ (m)</th>
<th>$\lambda_1 \left( \frac{w}{m^2C} \right)$</th>
<th>$\lambda_2 \left( \frac{w}{m^2C} \right)$</th>
<th>Home Dimension (m$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>0.17</td>
<td>0.15</td>
<td>0.3</td>
<td>1</td>
<td>46</td>
<td>10<em>8</em>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parameter</td>
<td>$kc$</td>
<td>$kw$</td>
<td>$kf$</td>
<td>$t(h)$</td>
<td>$c$</td>
<td>$m^2$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value</td>
<td>2.926</td>
<td>2.832</td>
<td>1.72</td>
<td>1</td>
<td>1.12</td>
<td>1.2*240</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3.4
Secondary distribution transformer parameters

<table>
<thead>
<tr>
<th>Type of cooling</th>
<th>ONAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hottest-spot rise over ambient at rated load</td>
<td>80°C</td>
</tr>
<tr>
<td>Top-oil rise over ambient at rated load</td>
<td>55°C</td>
</tr>
<tr>
<td>Load loss at rated load to no-load loss</td>
<td>8</td>
</tr>
<tr>
<td>Winding time constant (min)</td>
<td>5</td>
</tr>
<tr>
<td>The oil time constant (min)</td>
<td>155</td>
</tr>
</tbody>
</table>

As it expressed in Eq. (8), due to the relation between DLMP and demand, consumers should pay the electricity price proportionate to their usage. Since the distance between the substation and a node is a multiple of the equivalent resistance, the location of a node is an important term to determine the contribution of the load to the total loss. The impact of two mentioned factors on DLMP of the system is measured.

Fig. 6 illustrated the correlation between demand, the location of a node and corresponded DLMPs. The red and blue lines represent demand and DLMP of nodes during peak hours, respectively. Although node 8 and node 9 are adjacent and their equivalent resistances are almost equal, the higher consumption of node 9 causes a significant difference between their DLMPs. In order to verify the impact of node’s location on DLMP, nodes 28 and 18 are compared to each other. Since node 18 is further from S/S than node 28, the DLMP of node 18 is noticeably higher than node 28. However, the consumption level of node 28 is higher than node 18 at that time.
Fig. 3.7 demonstrates the difference between the minimum and maximum levels of DLMPs among nodes during off-peak hours is less than peak hours. Since load level is lower in the off-peak hour and total loss is small, the contribution of each node to loss is negligible. Therefore, DLMP of each node is almost equal to the LMP of S/S and the variance of DLMP at the off-peak hour is less than peak hour.

Figure 3.8: Correlation between consumption and DLMP in power distribution system

Figure 3.9: Impact of total demand on DLMP in the network
There are two types of customers' preferences in charging strategy of EVs: 1) consumers are willing to charge their EV once arrive home, 2) consumers are willing to charge their EV with lower prices and inject power to the house during peak hours.

Charging EVs regardless of the electricity price and the situation of the network may lead to increase the power demand between 6pm-9pm. On the other hand, the electricity price during peak hours is at the highest level compared to midnight. Therefore, the energy cost of these customers is highly raised. In the first scenario, the new peak may reach 3.5 kW instead of the available peak power value of 1.5 kW in the residential demand. Consequently, the power loss of the power distribution system is significantly increased. The total energy loss of the network and electricity bill of the customer is 13.94 MWh and 43.4 dollars, respectively. The decomposition of smart home power demand via proposed SHMS strategy for consumers with V2G, ESS, PV, and household appliances depicts in Fig. 8. The negative part represents the amount of discharged energy to the house or grid. The green line shows how much energy needs to be purchased from the grid.
In the second scenario, SHMS prefers to charge the ESS and EV in the off-peak period. It is assumed that once the EV owner arrives home at 7 P.M., the EV is plugged in and the EV and ESS supply household power demand until the SoC of batteries reach the lower limit. Fig. 9 reveals this strategy may cause a new peak in off-peak periods of the system. The result also illustrates the EV owner charges the vehicle once the electricity price is dropped. Therefore, the EV demand is shifted to the off-peak period (1 a.m. to 3 a.m.). In this case, the total energy loss and electricity bill of customers are 13.695 MWh and 39.24$, respectively. Although the loss and electricity bill of customers is reduced compared to the previous scenario, the power loss and DLMP of the nodes during the new peak period is higher than the first strategy.

Since now, the traditional scheduling of resources and appliances have been investigated regarding the impact of user preferences on electricity costs. However, the contribution of customers to the power loss of the network has been neglected, and SHMS only considers electricity price to charge/discharge energy resources. In this dissertation, we proposed a smart
management system to determine optimal scheduling of household appliances to maximize social welfare. Therefore, some information such as ambient temperature, PV generation, the status of EV and ESS, and electricity prices are collected to provide a precise solution. The proposed schedule of appliances under the DLMP scheme is given in Fig 10.

![Figure 3.11: Total household power demand for consumers willing to charge EV with lower prices](image)

As it seen in Fig.10, the ESS is charged from 10 A.M to 4 P.M when PV generation exceeds the total household demand. The EV is charged once the electricity price is dropped regardless of the network situations. In the proposed method, SHMS decreases the charging rate of ESS or EV and extends charging time to 6 hours. According to Eq (13), the EV’s battery must be fully charged at departure time. Since the electricity price and demand between 7 P.M to 10 P.M are higher than midnight hours, the EV injects power to home during peak hours and switch to charge mode until reaching predetermined SoC. The EV battery SoC variation in this period is presented in Fig 11. Results reveal the proposed operation of EVs has correctly followed this strategy.
Figure 3.12: An example of the decomposition of smart house power demand via proposed SHMS

Fig. 16 displays the energy bill of customers compared to TOU pricing is decreased. It's assumed the LSEs buy the surplus energy of customers under TOU pricing and pay an additional incentive to household owners proportionate to their contribution to loss reduction. As a result, a smart customer can manage the consumption and sell the extra energy to the network during peak periods to receive higher monetary incentives. From LSEs point of view, the proposed method led to reducing the total energy loss of the network by 400kWh a day as is illustrated in Fig. 17.
3.11 Smart Home Management Strategy Considering Aging of Transformer

Transformers are generally the most expensive assets in a distribution system and play an eminent role in reliability [3]. Aging or deterioration of a transformer is a time function of temperature, moisture, and oxygen content. Operators have traditionally been leveraging
temperature as the only controllable factor in transformer management [4]. Overloading puts higher thermal stress on distribution transformers [5]. By online monitoring and limiting the loading of transformers up to their dynamic thermal rating (DTR) temperature of the transformer can be kept within the allowed range [6]. Advanced metering infrastructure (AMI) provides utilities with a bi-directional communication system to continuously measure the loading of transformers and send the control signal to smart homes to modify their consumption behavior[7].

Smart Home Management System (SHMS) enables homes to monitor and control smart devices through a communication infrastructure. [8, 9]. This system brings remarkable benefits for consumers and utilities such as reducing electricity bill, empowering consumers to participate in DR programs and improving the utilization of assets.

Research on presenting an optimal scheduling method for home appliances has gained momentum. In [10], a decision-support tool for smart homes was proposed to minimize electricity bill. In [11], the game-theoretic analysis is applied to home appliances scheduling problem to decrease peak-to-average ratio in consumption pattern. In [12] a novel method is evaluated to minimize the householder’s electricity bill without considering the preference of customers. To schedule thermostatically controlled loads, in [12] appliance commitment algorithm is presented based on price and load forecasts. In these studies, asset utilization factor has not been considered as an objective.

Significant load growth in recent years requires distribution transformers to be upgraded. According to the high capital costs, utilities are willing to increase the utilization of transformers and postpone the reinforcement. DR as a strategic solution can modify the loading of distribution transformers by peak shaving and load shifting. [13].
In the literature, various approaches to improve the aging of transformers via DR programs have been studied. Impact of Electrical Vehicle (EV) charging management along with load shifting on the aging of transformers was investigated in [14]. In [15] impact of charging electric vehicle on a residential transformer is evaluated. Load shaping as a solution was proposed to improve the usage of transformers. A demand response optimization model based on HST of the transformer is solved in [3]. The electricity price was not considered in scheduling the appliances. In [16] transferring load to neighbor substations and load curtailment are applied to limit the load on transformers.

There is a lack of studies on assessing the effect of scheduling the home appliances with considering customer comfort, Real-Time Pricing (RTP) and aging of transformers. Recognizing what has been missing in the literature, this dissertation aims to figure this out by presenting load shaping as a DR strategy assisted by SHMS to decline the transformer overloading problems with regard to customer preferences and electricity bill.

Figure 13 illustrates the HST of a distribution transformer under three mentioned strategies. The HST of transformers from midnight to morning is almost equal. In the second strategy, the load is shifted to off-peak period due to the lower electricity prices. According to Eq. 42 to Eq. 45, HST of the transformer will be raised during overloads. In scenario 1, HST reaches 162°C, which is reduced to 132°C (scenario 3) through implementing the proposed method and shifting unnecessary demands. Fig. 14 shows the LOL of a transformer has been decreased in the third scenario. The results reveal the LOL of a transformer has been reduced up to 20% under DLMP scheme. There is a direct relationship between the operation time of ACs and their set points. In order to study the impact of ACs operation time on loading of transformers, three set points have been examined. Figure 15 indicates the LOL of a low voltage transformer is highly reliant on ACs
set point. As a result, asset management improvement is one of the advantages of the proposed strategy for LSEs.

Figure 3.15: The hottest temperature of a distribution transformer under three different scenarios

Figure 3.16: The LOL of a distribution transformer under three strategies
3.12 Summary

In this chapter, a novel smart home management system was proposed to determine the optimal operation of a smart home. Mixed-integer linear programming (MILP) is used to solve the two-stage stochastic problem to find the optimal operation of ESS, EV, household appliances, and AC based on customer preference, outdoor temperature, and energy price. In the proposed pricing mechanism, the contribution of each node to the power loss of the system is calculated to determine a new pricing mechanism called DLMP. The LSEs use this index to identify and rank the nodes based on their impacts on power loss. Afterward, the most critical nodes are chosen to perform incentive-based or time-based DR programs. Several scenarios were examined to verify the proposed methodology. The impacts of PV, ESS, customer preference, and TOU pricing on electricity bills, asset management, and total power loss were also investigated. At the baseline scenario, it was assumed that consumers were willing to charge their EV once they arrive home. Compared to this case, the proposed strategy provided a more efficient operation using electricity bill and energy loss reduction, which was significant. The results also proved the proposed method could improve the asset management of the system by decreasing the HST of a transformer and
increasing the life of the low voltage transformers. The process can be easily adapted to larger formulations including Combined Heat and Power (CHP) and other controllable appliances for the extension of the smart household concept.
CHAPTER 4:

TRANSMISSION CONGESTION MANAGEMENT IN THE PRESENCE OF
DEMAND RESPONSE AGGREGATORS

Electricity grids are fundamental for delivering electricity from power plants to end-users. However, not all flows resulting from commercial transactions can be allowed. Due to physical constraints, many of these transitions occur in flows that exceed the maximum value that a system operator considers to be secure [14]. Congestion takes place when the transmission lines are not sufficient to transfer the power [15], [16]. To prevent such events, two congestion management approaches are used to maintain stability in the electricity grid. Congestion can be relieved through reconfiguration, upgrading the conductors, installing new lines, and some effective market-mechanism [10].

Small loads like residential or commercial customers need to be aggregated to become a sizeable tradable capacity block and enter the market through incentive-based programs. In some markets like CAISO, aggregators are able to adjust the load of participants remotely or shut down an appliance on short notice from a centralized control room which is called Direct Load Control (DLC) [12].
4.1. Demand Response for the alleviation of congestion

Traditionally, power transmission congestion is removed through up and downscaling generation capacity. Rescheduling the committed generators, using FACTS devices, performing DR programs, and operating DERs in power distribution networks are some other current approaches for transmission congestion management.

Transmission congestion may induce higher costs for consumers because operators must rely on higher-cost generation sources. Distributed energy resources and demand response programs are recognized as two main approaches to modify the load pattern of a bus during peak hours. This dissertation presents a cost/worth analysis approach for optimal management of power distribution networks to mitigate congestion. MILP is used to find the optimal amount of load curtailment and to relieve the congestion through a least-cost manner.

Congestion is the result of physical limitations of discrete transmission grid components that limit the amount of power that can flow over portions of the transmission lines without jeopardizing the reliability of the system. To supply local demands, more expensive units are supposed to be brought on-line. This situation can create “market power” for some of the market participants and may lead to electricity price spikes in restructured power systems.

In recent years, many studies have been carried out to develop congestion management in the restructured electricity industry. In [30], a comprehensive literature review of different approaches for congestion management in electricity markets is presented. In [32] a model for the optimal planning of DERs for congestion management in the electricity market is proposed. Also, a cost/worth analysis approach for optimal sizing of DERs to mitigate congestion and increase the security of the system is presented in [33]. A computational method for optimal power dispatch considering transmission congestion to minimize the summation of step bidding prices from
participated generators in electricity markets is discussed in [34]. In [35], a method is proposed for optimal rescheduling of Generation and Transmission switching has been used to reduce line loading in a congested transmission system. Another approach for congestion management is finding volunteer customer to curtail their consumption when transmission congestion occurred. Determining how much each load should be curtailed depends on the elasticity of loads, required incentive to satisfy customers, LMP and sensitivity of load to flow of congested line [36]. Applying Demand Response (DR) programs to manage transmission congestion in a least-cost manner are discussed in [37].

In this work, an optimal strategy for DR participants to relieve the transmission congestion is introduced.

4.2. problem formulation

The primary goal is to minimize the total energy cost subject to line thermal, voltage boundaries, and load curtailment limitations. The transmission network is managed by Independent System Operators (ISO) and Regional Transmission Operator (RTO). We assumed utilities have only two options to control the demand and supply in their areas: (1) reducing loads by performing load management programs, and (2) operating the small-scale distributed generations.

\[
\begin{align*}
\text{Min} & \left[ \sum_{t=1}^{T} \sum_{k=1}^{n_{bus}} (P_{\text{net},i}^k \lambda_k) + \sum_{t=1}^{T} \sum_{i=1}^{n} P_{\text{DG},i}^t \text{Cost}_{DG,i}^t + P_{\text{DRP},i}^t \text{Inc}_{EDRP,i}^t \right] \\
\end{align*}
\] (4.1)

Where \( P_{\text{net}} \) represents consumption of bus i (MW), \( \lambda_k \) states energy cost of bus i at time t ($/MWh), \( P_{\text{EV},i}^t \) is injected energy of parking lot i at time t (MW), \( \text{IN}_{\text{EV},i} \) is the incentive applied in location i at time t to EVs’ owners ($/MWh), \( P_{\text{EDRP}} \) represents reduced demand by EDRP program in location i at time t (MW) and \( \text{IN}_{\text{EDRP}} \) is the incentive applied in location i at time t to customers ($/MWh).
4.2.1. Constraints

\[ 0 \leq P_{EV,j}^i \leq P_{EV,\text{max}}^i \quad (4.2) \]

\[ 0 \leq P_{EDRP,i} \leq C_{EDRP\text{max},i} \quad (4.3) \]

\[ V_{\text{Max}} \leq V_i \leq V_{\text{Min}} \quad (4.4) \]

4.3. Modeling Emergency Demand response programs

Demand response (DR) is described electricity consumption pattern change from normal usage in response to spot market of electricity price changes over time via smart technology in response to cost saving and power system reliability maintaining [12].

Due to the strong relationship between loading of a bus and power flow of a transmission line, DR as a load-shaping tool may bring significant opportunities such as reducing the energy cost and preventing overloads for utilities [33].

4.3.1. Emergency demand response programs

DR is divided into time-based and incentive-based programs. In EDRP, which is classified as an incentive-based program, SHMS schedules the home appliances or shifts their starting time in response to incentives. Some devices like dishwasher, cloth washer, and HVAC have more flexibility to push the start time back. In EDRP, the utility pays monetary incentives to customers who plan to reduce their unnecessary portion of usage. Elasticity is defined as demand sensitivity concerning the price.

\[ E = \frac{\partial D}{\partial \rho} = \rho_0 \frac{dD}{D_0 \ d \rho} \quad (4.5) \]
In this dissertation, DR is mathematically modeled in response to network electricity price and incentive of utility under emergency cases. Equation (4.6) shows how much customers should consume electric power to achieve maximum revenue in 24 hours a day while they take part in DR programs.

\[
d(i) = \left[ d_0(i) + \sum_{j=1}^{24} E(i,i) \frac{d_0(i)[\rho(i) - \rho_0(i) + A(j)]}{\rho_0(i)} \right] \times \left[ \sum_{j=1}^{24} E(i,j) \frac{\rho(j) - \rho_0(j) + A(j)}{\rho_0(j)} \right] (4.6)
\]

\(d(i)\) denotes customer demand changes in 24 hours. \(d_0\) denotes load participation factor. \(E(i,i)\) denotes self-elasticity of each DR programs price in 24 hours interval. \(E(i,j)\) denotes cross elasticity of each DR programs prices in 24 hours interval. \(A(j)\) in $/MWh is the incentive which is paid in \(j\)-th hour. \(\rho_0\) and \(\rho(i,j)\) denote base default price.

Requesting a higher ratio of curtailment may lead to increase the resistance of customer. It means elasticity of load is decreased and utility should pay more incentive to satisfy the customers.

**4.4. Sensitivity analysis**

When a transmission line of a system is congested, each transaction from a generator to a demand affects the congested lines differently. Determination of the proper amount of capacity needed to support a transaction necessitates a calculation of how each transaction contributes to flow on the CSCs. A utility prefers to find the best-related buses to implement congestion management programs instead of focusing on all buses. Transmission line relief (TLR) and shift factor (SF) are known as the major indexes to measure the sensitivity of the flow on a transmission line to load changes. In this work, SF is used to evaluate the weight of buses in congestion management. Other names such as Power Transfer Distribution Factors (PTDF), Power Distribution Coefficients (PDCs), Effectiveness Factors, and Impedance Factors also known as shift Factors. SF is an
incremental amount of power flow on constraint \( j \) when an additional unit of power is injected at bus \( i \) and withdrawn at the reference bus.

\[
SF_i = \frac{\partial P_T^l}{\partial P_i} \quad (4.7)
\]

Where \( SF \) is the shift factor of bus \( i \), \( P_T^l \) states the flow of line \( l \) th, and \( P \) is a load of the bus in the location of \( i \).

### 4.5. Local marginal pricing calculation

In deregulated electricity markets, LMP or nodal price is commonly used to reflect the minimal value of the electricity in different locations.

LMP is the marginal cost of supplying the next increment of electric energy at a specific bus considering the generation marginal cost and the physical aspects of the transmission system.

When the line flow constraints are not included in the evaluation or the capacity of elements is assumed to be large enough, LMPs at all buses equal to MCP of the system. If transmission losses are ignored, a difference in LMP would appear when lines are congested.

The LMP at bus \( i \) can be calculated as follows:

\[
\lambda_i = \lambda_{\text{Energy},i} + \lambda_{\text{Loss},i} + \lambda_{\text{Congestion},i} \quad (4.8)
\]

\( \lambda \) is the summation of the \( \lambda_{\text{Energy}} \), \( \lambda_{\text{Loss}} \), and \( \lambda_{\text{Energy}} \) which represent the cost of energy, loss, and congestion, respectively. In this dissertation, the value of losses is neglected and \( \lambda_{\text{Loss}} \) is assumed to be zero.
\[ \lambda_{\text{Congestion},i} = -\sum_{k}^{NC} \mu_k \ SF_{j,k} \] (4.9)

Where NC represents the total number of transmission constraints, \( \mu_k \) is the shadow price of transmission constraint (S/MWh) which is associated with the binding constraint, and \( SF_{j,k} \) is the shift factor of \( j \) to transmission constraint \( k \).

As it can be seen in Eq (4.8), the LMP of congestion consists of two terms: (1) SF, and (2) shadow price. To calculate SF, an injection of power at one bus and a withdrawal at another bus is considered. The SF is the ratio of the change in the flow on a line to a change in the injection and a corresponding change in the withdrawal.

Shadow Price of a transmission constraint is the significant system cost to relieve a marginal MW of congestion in that constraint. Shadow Price is used to pay Financial Transmission Right (FTR) holders. Shadow Price should be large enough to stimulate customers who have a huge effect on congestion to cooperate in load management and use all available energy.

4.6. Objective function

In this dissertation, utilities have two options to manage the consumption and local generation in their area: (1) reducing loads by implementing EDRP. The primary purpose of this dissertation is to minimize the objective function considering the constraints of the system.

\[
\text{Min} \left[ \sum_{t=1}^{T} \sum_{k=1}^{nbus} (P_{\text{net},i} \lambda_k) + \sum_{t=1}^{T} \sum_{i=1}^{n} P_{EV,i}^t \ln_{EV,i} + P_{EDRP,i}^t \ln_{EDRP,i} \right] 
\] (4.10)

Where \( P_{\text{net}} \) represents consumption of bus \( i \) (MW), \( \lambda_k \) states energy cost of bus \( i \) at time \( t \) ($/mWh), \( P_{EV,i} \) is injected energy of parking lot \( i \) at time \( t \) (MW), \( \ln_{EV,i} \) is the incentive applied in location \( i \)
at time $t$ to evs’ owners ($/\text{mwh}$), $P_{EDRP,i}$ represents reduced demand by EDRP program in location $i$ at time $t$ (MW) and $in_{edrp}$ is the incentive applied in location $i$ at time $t$ to customers ($$/\text{MWh}$).

ACOPF is used to calculate the shift factors of buses by changing the demand of a bus and monitoring the flow of the congested line. Congestion cost can be estimated based on SF and shadow price. The available capacity of the parking lot in each bus and bidding curves of customers to participate in EDRP are calculated based on (3) and (2), respectively. GA as an optimization tool is applied to solve the problem to relieve the congestion in a least-cost manner.

4.7. Simulation results

Fig. 1 depicts a test case to study the proposed approach. The parameters and flows of the 14-bus power system are shown in Table I. Characteristics of generators are illustrated in Table II. shadow price of the system has been considered 2500$/\text{MW}$ [21]. The marginal cost of the system before congestion is 13.54 $$/\text{MWh}$.

To evaluate the impact of the proposed method, the generator 4 is failed and congestion at line 2-4 at peak hour has occurred
Figure 4.1 IEEE 14 buses test system

Table 4.1

<table>
<thead>
<tr>
<th>Line</th>
<th>R(p.u)</th>
<th>X(p.u)</th>
<th>Line</th>
<th>R(p.u)</th>
<th>X(p.u)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-2</td>
<td>0.05</td>
<td>0.2</td>
<td>5-6</td>
<td>0.08</td>
<td>0.3</td>
</tr>
<tr>
<td>1-5</td>
<td>0.08</td>
<td>0.3</td>
<td>6-11</td>
<td>0.05</td>
<td>0.25</td>
</tr>
<tr>
<td>2-3</td>
<td>0.05</td>
<td>0.25</td>
<td>6-12</td>
<td>0.05</td>
<td>0.1</td>
</tr>
<tr>
<td>2-4</td>
<td>0.05</td>
<td>0.1</td>
<td>6-13</td>
<td>0.1</td>
<td>0.3</td>
</tr>
<tr>
<td>2-5</td>
<td>0.1</td>
<td>0.3</td>
<td>9-10</td>
<td>0.12</td>
<td>0.26</td>
</tr>
<tr>
<td>3-4</td>
<td>0.07</td>
<td>0.15</td>
<td>9-14</td>
<td>0.05</td>
<td>0.25</td>
</tr>
<tr>
<td>4-5</td>
<td>0.12</td>
<td>0.26</td>
<td>4-5</td>
<td>0.05</td>
<td>0.1</td>
</tr>
<tr>
<td>4-8</td>
<td>0.05</td>
<td>0.25</td>
<td>10-11</td>
<td>0.05</td>
<td>0.25</td>
</tr>
<tr>
<td>4-9</td>
<td>0.05</td>
<td>0.1</td>
<td>13-14</td>
<td>0.05</td>
<td>0.1</td>
</tr>
</tbody>
</table>
### Table 4.2

Characteristics of generators

<table>
<thead>
<tr>
<th>Generator</th>
<th>A ($/MWh)$^2$</th>
<th>B ($/MWh$)</th>
<th>C ($/h$)</th>
<th>$P_{\text{max}}$ (MW)</th>
<th>$P_{\text{min}}$ (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>0.013</td>
<td>10</td>
<td>0</td>
<td>200</td>
<td>0</td>
</tr>
<tr>
<td>G2</td>
<td>0.018</td>
<td>20</td>
<td>0</td>
<td>200</td>
<td>0</td>
</tr>
<tr>
<td>G3</td>
<td>0.18</td>
<td>12</td>
<td>0</td>
<td>150</td>
<td>0</td>
</tr>
<tr>
<td>G4</td>
<td>0.015</td>
<td>15</td>
<td>0</td>
<td>250</td>
<td>0</td>
</tr>
<tr>
<td>G5</td>
<td>0.021</td>
<td>20</td>
<td>0</td>
<td>300</td>
<td>0</td>
</tr>
</tbody>
</table>

Shift factor of buses has been computed according to (5) which shown in Table III. In this case, buses 3, 4, and 5 with higher SF have been considered as candidate buses for implementing the congestion management approaches. The LMP of buses after congestion is shown in Table IV.

As it mentioned before, the willingness of customers to participate in this program is decreased by increasing the curtailment ratio. In this dissertation, the elasticity of curtailing 2% to 4% of demand in peak hour is changed from 0.004 to 0.006, respectively. The proposed incentive for EDRP in each bus is illustrated in Fig. 2 to Fig. 4. Since the initial demand of bus 4 is less than bus 3 and 5, incentive rate of bus 4 is more than two other buses. Therefore, the ISO should pay more incentive for curtailing 1 MW (2% of demand in bus 4) compared to the same amount in bus 3 (about 1% of initial demand). The optimal capacity of EDRP and parking, lots by minimizing the objective function, have been illustrated in Fig4.6 and Fig.4.7.
Table 4.3
Shift factor of different buses

<table>
<thead>
<tr>
<th>Bus</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>SF</td>
<td>-0.005</td>
<td>0.021</td>
<td>0.035</td>
<td>0.026</td>
<td>0.0012</td>
</tr>
</tbody>
</table>

Table 4.4
Market clearing results under a congestion

<table>
<thead>
<tr>
<th>Bus</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>LMP\text{_Energy}($/MWh)</td>
<td>418</td>
<td>544</td>
<td>456</td>
</tr>
<tr>
<td>LMP\text{_Congestion}($/MWh)</td>
<td>1428</td>
<td>2261</td>
<td>1642</td>
</tr>
<tr>
<td>LMP($/MWh)</td>
<td>1846</td>
<td>2805</td>
<td>2098</td>
</tr>
</tbody>
</table>

Fig. 6 shows the contribution of EDRP and parking lots to mitigate the congested line. Blue and red charts represent PHEV parking lot and EDRP, respectively. The total capacity of each bus demonstrates bus 4 with higher SF has more potential to alleviate the congested line compared to buses 3 and 5. In bus 4, the contribution of EDRP is less than the parking lot because the incentive rate of EDRP is considerably raised in higher capacities. On the other hand, we have to utilize more EDRP in bus 5 due to the limited parking capacity.

Fig. 7 illustrates the amount of incentive for each bus. Blue and red charts represent PHEV parking lot and EDRP, respectively. Due to the limited capacity of the parking lot in bus 5, the utility has to pay more incentive to EDRP players.

The LMP of the system after implementing this approach has been decreased to 14.67 $/MW.
4.8. Summary

This work proposed an efficient approach for managing transmission congestion in the least cost manner by utilizing EDRP and parking lots. This method respects economic factors such as congestion shadow price, the incentive for parking lots and EDRP to calculate the final costs of each program. The results proved the total cost of the system has been decreased and the
transmission congestion relieved. Furthermore, the results illustrated when the capacity of parking is not adequate, the utility should pay more incentive to EDRP participants to achieve the required demand. moreover, the elasticity of demand has a high impact on the incentive and the contribution of EDRP to mitigate the congested line.
CHAPTER 5:

IMPROVING THE RELIABILITY OF MICROGRIDS BY PERFORMING
DEMAND RESPONSE UNDER CONTINGENCIES

Microgrid system has been implemented to improve the network reliability and reduce the impact of outages on end-users. Determining the most efficient boundaries of microgrids under contingencies is one of the main challenges of utilities from safety and security points of view. Currently, most researches have been focused on the pre-defined boundary or static microgrids regardless of system conditions and priority of customers. In this dissertation, a novel concept for designing and operating of resilient microgrids to improve reliability and reduce the energy not supplied is proposed. Compared to current approaches, boundaries of the proposed flexible microgrids can be extended or shrunk based on generation and demand levels, technical constraints, and customer comfort.

Furthermore, the DR program is utilized to maintain the balance between generation and consumption in the microgrid. In this work, the Genetic Algorithm (GA) and Mixed-Integer Linear Programming (MILP) are simultaneously applied to the model and solve two-stage optimization considering utilities' profits and customers' satisfaction. In planning level, GA is utilized for sitting and sizing of distributed generations and placement of switches. In operation level, MILP is used to select target switches as boundaries of optimal microgrids, the model priority of customers, and determine the contribution of each load in the DR program. The case study is also presented, and
final results show the superiority of the proposed method compared with traditional fixed boundaries method in microgrids.

5.1. Traditional Reliability improvement approaches in power distribution networks

In power distribution systems, the reliability is calculated based on the duration and frequency of interruptions. Sustained and momentary interruptions impose negative impacts on systems safety, economic activities, and customers' comfort [41]. Also, electric utilities are directly subjected to heavy penalties by the regulatory agencies when reliability indices of customers are undermined [42]. Therefore, a significant challenge for electric utilities is how to design more reliable and efficient system to reduce the effects of outages. There have been numerous research works on reliability improvement of power distribution systems. Currently, common approaches can be divided into two main categories: (1) reducing the frequency of interruptions, as measured by System Average Interruption Frequency Index (SAIFI) and Momentary Average Interruption Frequency Index (MAIFI), such as undergrounding and preventive maintenance; (2) decreasing the average duration of interruptions as measured by System Average Interruption Duration Index (SAIDI) from improving Fault Location, Isolation and Restoration process (FLISR) [3]. In [42, 44-47], the switch placement problem was formulated to enhance system reliability, but they did not consider the impact of Distributed Generators (DGs). Tadayon and Golestani proposed the switch placement method by an immune algorithm with considering tie lines as only alternative resources [8]. Bezerra et al. [49] suggested a multi-objective optimization approach for switch placement based on particle swarm optimization. In all mentioned papers above, there was no guarantee to restore critical loads in downstream feeders as long as the faulted section is repaired. Nowadays, increasing the penetration rate for small-size DGs in distribution systems can help utilities to restore critical loads located in downstream parts [50-54]. This aim can be established
if the capacity of DG is more than total consumption in the islanded network. One of the main shortcomings of traditional distribution systems was lack of observability and controllability. In recent years, most of these problems have been solved by developing two-way communication, installing smart meters, and utilizing small distributed energy resources (DERs) such as wind turbines and electric vehicles. Accordingly, traditional outage management methods have been changed and moved toward smart microgrid [55-58].

The microgrid is defined as a group of interconnected loads and DERs that acts as a single controllable entity which enables the system to operate in both grid-connected or island mode [59]. Implementing microgrids may bring some significant opportunities to a network such as improving the reliability of a system, reducing the outage costs and increasing social welfare [60-65]. Existing literature discussed the boundaries of microgrids are pre-defined and priority of loads are not taken into account [55, 60-62]. Due to variable generations in renewable resources and different importance of loads, static boundaries concept is no longer fulfill the expectations of customers and utilities. In this dissertation, a new idea of forming and operating an island called flexible microgrid is introduced.

In contrast with static microgrid, form, and the boundary of a flexible microgrid depends on various factors such as generation and demand level or importance of customers. Smart outage management system needs to collect real-time data from loads and generators to select target switches as boundaries of microgrids. The boundaries of microgrids can be changed based on a new situation of a system over the contingency. At the first step, the location of switches and DGs' size should be optimized. These two factors have a significant impact on the efficiency of microgrids; however, investment and maintenance costs of them must be taken into account. In
the first stage of optimization, GA is used to determine the optimal sizing and sitting of DGs and switch placement.

In order to maintain the balance between supply and demand in a microgrid, several methods have been introduced. Performing DR is one of the most efficient and practical approaches to achieve this goal [66]. DR reassembles loads in the timing to obtain the desired load reduction in a microgrid under different contingencies [67]. In this paper, an incentive-based DR program is chosen to curtail part of usage in a microgrid [68-69]. Due to the importance of customers, different outage costs, expected incentive for participants, and constraints of the network, an optimization model is required to solve the DR problem. In this dissertation, order, MILP is used to address the second stage of optimization at which the optimal contribution of loads in the DR program with respect to objective function and constraints of the system is calculated.

To surmount the shortcomings of the former studies [55-64] this dissertation proposes a comprehensive framework for modeling and solving two-stage optimization in resilient microgrids. The main contribution of this dissertation is to design optimal forming of flexible microgrids and perform DR program with the aim of improving system reliability and maximizing social welfare. In addition, this dissertation introduces a novel concept to merge a group of microgrids or divide a large microgrid into smaller ones to enhance the performance of the outage management system. Also, the expected incentive for DR participants and the potential cost saving of performing DR under a contingency is quantified. Moreover, optimal placement of switches and sizing of DGs in the presence of DR to create flexible boundaries are obtained. To the best knowledge of the authors, this is the first time study in the literature designing flexible microgrids under a contingency by optimizing the boundaries of microgrids and determining restored/curtailed customers simultaneously.
5.2 Demand response program modeling in microgrids

The capability of the system to manage the demand of end users to control energy consumption is one of the main opportunities of smart grids [70]. Operators pay incentive to volunteers as compensations for participating in DR program. When a shortage occurred in a microgrid, utilities are allowed to curtail a part of the load based on the pre-signed agreements. Thus, system operators would be able to support customers with higher priorities with higher reliability requirements, such as industrial units, hospitals, and fire stations. The proposed DR model and incentive scheme for participants are discussed in more details below.

5.2.1. Encouraging customers to Participate in the DR program

In this program, utilities are authorized to shed high demand appliances of residential customers such as air-conditioner directly or send a control signal to commercial or industrial customers [71]. As part of agreements, participants are paid in advance for agreeing to reduce power usage upon request [72]. In both cases, the utility pay incentive to customers. In this dissertation, DR is economically modeled in response to network electricity price and incentive of utilities under contingencies.

a. Determining Reward for participants

Elasticity is defined as demand sensitivity to the price [45]. It means utility should provide more incentive for a higher amount of curtailment.

\[
E = \frac{\partial D}{\partial \rho} = \frac{\rho_0}{D_0} \frac{dD}{d\rho} \tag{5.1}
\]

Where \( E \) is the elasticity of the demand, \( \rho_0 \) represents nominal electricity price ($/MWh), and \( D_0 \) denotes initial demand value (MW).
In this proposed method, the economic effect of DR is modeled in response to network electricity price and incentive of utility in emergency cases. Equation (5.2) shows how much customers should change the consumption level to achieve maximum revenue and convenience when taking part in DR programs [73].

\[
A(i) = \frac{\Delta d(i) \rho_0(i)}{E(i)}
\]  

(5.2)

\[
d(i) = d_0(i) + E(i) \frac{A(i)}{\rho_0(i)}
\]  

(5.3)

where \(d(i)\) denotes the required demand for utility, \(d_0\) represents initial demand of load \(i\), \(E(i)\) denotes self-elasticity, and \(A(i)\) is required reward to motivate load to decrease the consumption of load \(i\) from \(d_0\) to \(d\) in $/MWh.

Survey results have demonstrated that participants are only willing to curtail or shift some loads such as air conditioner or wet appliances [74, 75]. It is assumed operators are allowed to curtail the load of customers up to 20% of current usage during contingencies. In this dissertation, MILP is applied to determine the optimal combination of restored/interrupted loads in each microgrid with respect to profits of customers and utilities, which are discussed in the following section.

5.3 Reliability assessment of the power distribution network

Reliability indices are used to evaluate the performance of the outage management system in utilities. In this section, the process of calculating reliability indices is explained.

5.3.1 Classifying loads in a radial distribution network based on restoration time

When a fault occurs in a distribution system, each load might experience a specific outage
duration based on its location. So, loads can be classified into four categories. Figure 5.1 demonstrates the restoration time for each zone after a fault.

The main grid can supply loads #1. The restoration time is equal to fault location and isolation time. Restoration time for loads #2 is equal to the summation of fault location, isolation, and repair time. The available DG can supply load #3. The restoration time is equal to the summation of fault location, isolation, and required time to run the DG. The last term depends on the technology of DGs.

In some cases, the available generation of DG is not adequate to supply load #4. Accordingly, this load is interrupted. The restoration time for this load is similar to load #1.

5.3.2 Calculating reliability indices

According to IEEE Std. 1366, reliability indices of power distribution networks can be divided into three main categories: time-based indices, frequency-based indices, and energy based indices. In this method, Energy Not Supplied Cost (ECOST) is used to determine the interruption cost of a system.

\[ ECOST = \sum_{i=1}^{N} r_i L_{avg,i} CDF_i \]  \hspace{1cm} (5.4)

where \( r_i \) represents restoration time for each interruption event, and \( L_{avg,i} \) denotes average interrupted load for each event. In this dissertation, Customer Damage Function (CDF) is used to estimate the outage cost. CDFs are usually based on normalized customer interruption cost data based on survey and are estimated for different customer sectors [71].

In order to measure the reliability of distribution systems, ENS and Average System Interruption Duration Index (ASIDI) are also presented. ASIDI indicates the total duration of interruption for
the load during a pre-defined period. The calculation of this index is based on load rather than customers affected. ASIDI is sometimes used to measure distribution performance in areas that serve relatively few customers having relatively large concentrations of load, predominantly industrial/commercial customers. Theoretically, in a system with homogeneous load distribution, ASIDI would be the same as SAIDI [77]. Mathematically, it is given in (5).

\[
ASIDI = \frac{\sum r_i L_i}{L_T}
\]  \hspace{1cm} (5.5)

where \(L_i\) indicates the power of load \(i\).

5.4 Problem Formulation

In this section, the problem formulation for minimizing the outage cost of utilities and improving the reliability of the system by restoring higher priorities loads in the presence of the DR program is discussed. Optimal combinations of the restored/curtailed loads problem are formulated as a MILP problem and solved by MATLAB.

5.4.1. Proposed MILP formulation for DR problem

The proposed MILP formulation for optimal sectionalizing switch placement in distribution networks is presented in (6–9). In contrast to heuristic approaches, MILP formulations guarantee convergence to the global optimum solution.

The objective of the proposed DR problem is to minimize the total system cost in terms of customers incentive cost. On the other hand, DR is performed to improve the performance of microgrids through shedding or shifting loads and energizing important consumers during contingencies. Therefore, deciding how many DR volunteers should be involved and how much energy is needed to be curtailed requires trading off between DR incentive and CDF of essential
customers. In order to determine the contribution of each participant in DR, an optimization problem should be solved. Equation (6) shows the objective function for minimizing the total incentive of DR participants.

\[ \text{Min } \sum_{i=1}^{N_{\text{cur}}} \Delta d_i \cdot A(\Delta d_i)_i \]  \hspace{1cm} (5.6)

Where \(N_{\text{cur}}\) represents the number of curtailed load and \(\Delta d\) shows the amount of reduced demand of load \(i\).

Figure 5.1. Restoration time of loads in different zones

\[ \sum_{i=1}^{N_{\text{cur}}} \Delta d_i \cdot A(\Delta d_i)_i < \sum_{j=1}^{N_{\text{non}}} L_i \cdot CDF_i \]  \hspace{1cm} (5.7)

\[ \Delta d_i < 0.2 \cdot L_i \]  \hspace{1cm} (5.8)

\[ \sum_{k=1}^{NL} (L_k - \Delta d_k) \leq P_{DG} \]  \hspace{1cm} (5.9)

where \(N_{\text{cur}}\) represents the number of curtailed load, \(N_{\text{non}}\) shows the number of customers, which are not interrupted in a microgrid, \(NL\), is the number of loads in a microgrid, and \(P_{DG}\) represents total DER generation in a microgrid. Equation (5.7) describes the total incentive of DR should be less than the total penalty which should be paid to interrupted customers. Equation (5.8) imposes a limit on the curtailing power by 20% of customers' usage. Constraint (5.9) forces the balance
between supply and demand in each microgrid.

### 5.5.2. Objective function

This dissertation aims to decrease outage cost of the system by installing switches, determining optimal sizing and sitting of distributed generation in the planning stage, and performing DR in operation stage. As a result, the total cost of the new installment, incentives, and interruption costs will be minimized. The objective function of this dissertation is given in (10).

\[
\text{Min} \sum_{i=1}^{\text{load}} \left[ (L_i \cdot t \cdot \text{CDF}) + (A_i) \right] + P_{DG} \cdot \text{Cost}_{DG} + N_{\text{Switch}} \cdot \text{Cost}_{\text{Switch}}
\]  

(5.10)

The first term of the objective function represents ECOST, which contains load level, restoration time, and CDF of each type of consumers. The second term \((A)\) shows the proposed rewards of DR participants, which is related to elasticity of loads and amount of curtailment. As discussed above, these two terms are used to determine the optimal forming of microgrids per fault. In addition, investment cost includes capital and maintenance costs of installed switches and DGs are taken into account in the third term. Moreover, technical constraints of the network such as voltage deviation of nodes and thermal limitation of branches are given in (5.11) and (5.12), respectively.

This problem is solved using GA by integer representation of individual solutions. Each chromosome gives a possible solution in which genes represent candidate locations for the placement problem. As shown in Fig 5.2, the string represents the position of switches, which can be either 0 (no switch installed) or 1 (switch is installed). In the second part, the location and size of DGS are presented. In this dissertation, four types of DGs (50, 100, 150, and 200 kW) is assumed. Each cell could contain either 0 (no DG placed), 1 (50 kW), 2 (100 kW), 3 (150 kW),
or 4 (200 kW). GA is used to find the optimal planning decisions. Equation (5.10) is considered as the fitness function of GA. Also, elitism rate is assumed to be 0.1. Crossover and mutation rates are considered to be 0.95 and 0.01, respectively.

![Sample string representation for optimal planning problem in GA](image)

Figure 5.2. Sample string representation for optimal planning problem in GA

### 5.6. Methodology

In traditional fault restoration methods, the closest switches to faults are opened and created some pre-defined islands. In this dissertation, switches are not only used to isolate the outage, but also designed the optimum forming of microgrids. Figure 5.3 illustrates a difference between static and flexible microgrids.

Suppose that a fault is occurred in feeder bus 10 and switch 5 creates the microgrid #1. Due to switch locations, two more microgrids can also be formed. The corresponding loads and DGs data are given in Table 5.1, and all possible forms of microgrids are presented in Table 5.2.

In the traditional process, the closest switch to the fault is opened, and microgrid #1 is created. The aggregated demands and resources show that microgrid #1 is not capable of operating and restoring current loads independently. Therefore, all customers will experience an outage. As mentioned before, the proposed method takes all conditions of the system into account and then makes optimal decision about the status of switches. In this case, if switch 6 was opened, customers in microgrid #2 could be restored and system total energy not supplied decreased. This situation is not limited to generation shortage.

In some cases, due to the uncertain and stochastic generation of renewable resources operators
prefer to have at least one traditional DER in a created microgrid to avoid some stability and reliability issues. In this method, adjacent microgrids can be merged into each other to add a conventional DG to microgrids. However, in all scenarios outage costs must be taken into account.

Figure 5.3. Example of flexible microgrid concept

<table>
<thead>
<tr>
<th>Table 5.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load and DG data</td>
</tr>
<tr>
<td>Load</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>DG</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
Table 5.2
Characteristics of microgrids

<table>
<thead>
<tr>
<th>Target Switches</th>
<th>5 Open, 6 Close</th>
<th>5 Open, 6 Open</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microgrid Num</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Load</td>
<td>7, 8, 9, 10, 11</td>
<td>10, 11</td>
</tr>
<tr>
<td>Total consumption(kW)</td>
<td>4400</td>
<td>1425</td>
</tr>
<tr>
<td>DG</td>
<td>4, 6</td>
<td>4</td>
</tr>
<tr>
<td>Total generation(kW)</td>
<td>2500</td>
<td>1500</td>
</tr>
</tbody>
</table>
Figure 5.4. Flowchart of the proposed algorithm to find the optimal forming of flexible microgrid

This methodology can help operators to find the optimal combination of open/close switches to achieve microgrids that are more efficient. The proposed algorithm to design the optimal forming of microgrids under a fault is shown in Fig 5.4.

After collecting system data, GA proposes chromosomes include switch places, size, and location of DGs in the test case. In order to calculate the reliability of the system, it is assumed a fault has occurred on feeder $i$. Based on the location of fault and switches, all possible forms of microgrids are created. In this dissertation, the status of adjacent switches of each microgrid is changed as
much as possible to restore critical loads make a microgrid more flexible and profitable. Due to the available data, the adequacy of the local generators is assessed. If available DGs could meet demand, DR program would not be performed. In this case, the outage cost is equal to zero. If generation level is less than customers' consumption, DR program is applied to restore more critical loads. To this end, MILP is used to determine how much demand should be shed (6-9). This procedure is repeated for all possible microgrids and reliability indexes are calculated concerning outage duration and interruption cost for different sectors of loads. Finally, the best forms of dynamic microgrids, outage cost, DR incentive, and reliability indexes of the system per fault are obtained. In each random chromosome which is generated by GA, the objective function(10) is calculated. GA operators (mutation and crossover) create a new population, and this process is repeated to find the optimal location of switches, size, and location of DGs, DR program in each microgrid and target switches per fault.

5.7. Numerical Results

The well-known PG&E 69-bus distribution system is selected as the test system [78]. CDF of loads is depicted in Fig 5. 6[79]. Blue, red, and green lines represent residential, commercial, and industrial loads, respectively. The capital cost of a switch has assumed $3,000 [80]. In this dissertation, the elasticity of different sectors of customers has been taken from [73], and failure rate and repair time of sections are taken from [78].
5.7.1 Allocation of Switches as boundaries of flexible microgrids

Based on the introduced objective function in (10), the optimal location of switches in a power distribution network is obtained.

- Implementing static microgrids

To highlight the superiority of the proposed method, we have assumed boundaries of a microgrid in operation stage is pre-defined. In this case, GA has introduced the location of switches and DGs in the planning stage. As discussed above, only closest switches to the fault are opened in operation stage. The location of switches and reliability indexes are shown in Table III. Also, the size and location of DGs are illustrated in Table IV.

- Implementing flexible microgrids

In this scenario, the location of switches and faults are not the only factor of shaping the microgrids. In some pre-defined boundaries based on the availability of DR and balance between demand and suppliers, merging a group of islands or partitioning a large island to smaller ones
may lead to restore higher priority loads and increase the profit of utilities. In this case, boundaries are flexible, and the shapes of microgrids are related to constraints and utilities' goals. The location of switches and reliability indices are shown in Table V.

- Flexible microgrids versus static microgrids

Fig. 7 and Fig. 8 illustrate the superiority of the proposed method comparing to static microgrids. The results show that by implementing flexible microgrids, ASIDI and the final cost of the system have been improved by almost 10% and 12%, respectively.

Moreover, the number of installed switches in flexible microgrids is less than the one in static microgrids.

Table 5.3
Location of switches and reliability indices of static microgrids

<table>
<thead>
<tr>
<th>Location of Switch</th>
<th>3, 4, 7,8, 11, 17,22,30,33, 38, 40,44, 55, 61</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASIDI (hour)</td>
<td>1.0552</td>
</tr>
<tr>
<td>ENS (kWh)</td>
<td>86086</td>
</tr>
<tr>
<td>Final Cost ($)</td>
<td>254010</td>
</tr>
</tbody>
</table>

Table 5.4
Sizing and sitting of DGs

<table>
<thead>
<tr>
<th>Bus Num.</th>
<th>40</th>
<th>44</th>
<th>47</th>
<th>69</th>
<th>21</th>
<th>66</th>
<th>64</th>
<th>31</th>
<th>35</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity</td>
<td>150</td>
<td>200</td>
<td>50</td>
<td>150</td>
<td>200</td>
<td>100</td>
<td>50</td>
<td>150</td>
<td>150</td>
</tr>
</tbody>
</table>
Table 5.5
Location of switches and reliability indices of flexible microgrids

<table>
<thead>
<tr>
<th>Location of Switches</th>
<th>3, 4, 7, 8, 11, 17, 22, 32, 38, 43, 59</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASIDI (hour)</td>
<td>0.9456</td>
</tr>
<tr>
<td>ENS (kWh)</td>
<td>78829</td>
</tr>
<tr>
<td>Final Cost ($)</td>
<td>226310</td>
</tr>
</tbody>
</table>

Inflexible microgrids, to create desired boundaries, operators can change the target switches. The performance of microgrids is increased by selecting optimal boundaries instead of installing extra switches. Thus, the required switches are decreased.

5.7.2 Performing DR program in flexible microgrids

As it mentioned in section II, operators can perform DR programs through Advanced Metering Infrastructure to restore higher priority customers and improve the efficiency of resilient microgrids. In this dissertation, MILP is applied to determine the optimal combination of curtailed/restored loads in each island. The flexibility of microgrids' boundaries along with DR can increase the performance of the fault restoration process considerably. Numerical results are demonstrated in Table VI.

In order to highlight the impact of performing DR on different types of loads, reliability indices for each sector have been calculated which are given in Table 7. Fig. 8 illustrates the ASIDI of residential, commercial and industrial customers. The green and blue charts represent flexible microgrids with and without performing DR, respectively. The impact of DR on industrial and...
commercial loads are meaningfully more than residential loads. Due to the lower priority of residential customers and their higher willingness to participate in the DR program, they would be the first option to be curtailed. Operators prefer to pay incentive to residential customers instead of paying the penalty to critical loads. Accordingly, the total profit of a utility will be increased.

Figure 5.7. Final outage costs of utilities in two scenarios
Figure 5.8. ASIDI of customers in two scenarios

Table 5.6

Reliability indices of flexible microgrids by performing DR

<table>
<thead>
<tr>
<th>Reliability indices</th>
<th>First scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASIDI (hour)</td>
<td>0.937</td>
</tr>
<tr>
<td>ENS (kWh)</td>
<td>76518</td>
</tr>
<tr>
<td>Final Cost ($)</td>
<td>210250</td>
</tr>
</tbody>
</table>
Table 5.7
Reliability indices for each sector of loads

<table>
<thead>
<tr>
<th></th>
<th>Flexible microgrids without DR</th>
<th>Flexible microgrids with DR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASIDI-Res(h)</td>
<td>0.9872</td>
<td>1.037</td>
</tr>
<tr>
<td>ASIDI-Com(h)</td>
<td>0.9661</td>
<td>0.9224</td>
</tr>
<tr>
<td>ASIDI-Ind(h)</td>
<td>0.891</td>
<td>0.781</td>
</tr>
<tr>
<td>ENS-Res(kWh)</td>
<td>37615</td>
<td>36355</td>
</tr>
<tr>
<td>ENS-Com(kWh)</td>
<td>27907</td>
<td>26356</td>
</tr>
<tr>
<td>ENS-Ind(kWh)</td>
<td>14406</td>
<td>12828</td>
</tr>
</tbody>
</table>

Figure 5.9. ASIDI of different sectors after performing DR programs

Fig. 10 demonstrates the significant impact of DR programs on final costs of utilities. Utilizing flexible boundaries and DR program simultaneously led to decrease the final costs of utilities to 19% comparing to static microgrids.
Figure 5.10. Effect of performing DR on utilities costs

Table 5.8
Reliability indices of static and flexible microgrids in scenario two

<table>
<thead>
<tr>
<th>Reliability indices</th>
<th>Static</th>
<th>Flexible</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASIDI (hour)</td>
<td>1.0831</td>
<td>0.9735</td>
</tr>
<tr>
<td>ENS (kWh)</td>
<td>88410</td>
<td>81153</td>
</tr>
<tr>
<td>Final Cost ($)</td>
<td>265530</td>
<td>235830</td>
</tr>
</tbody>
</table>
Table 5.9
Reliability indices for different sectors

<table>
<thead>
<tr>
<th></th>
<th>Flexible microgrids without DR</th>
<th>Flexible microgrids with DR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASIDI-Res(h)</td>
<td>1.036</td>
<td>1.0373</td>
</tr>
<tr>
<td>ASIDI-Com(h)</td>
<td>1.0257</td>
<td>0.972</td>
</tr>
<tr>
<td>ASIDI-Ind(h)</td>
<td>0.91</td>
<td>0.761</td>
</tr>
<tr>
<td>ENS-Res(kWh)</td>
<td>37318</td>
<td>37659</td>
</tr>
<tr>
<td>ENS-Com(kWh)</td>
<td>29627</td>
<td>28077</td>
</tr>
<tr>
<td>ENS-Ind(kWh)</td>
<td>14806</td>
<td>13406</td>
</tr>
</tbody>
</table>

a) Renewable resources are not able to operate on an island independently

To evaluate the effectiveness of the proposed concept, sensitivity analysis is performed. It is assumed that renewable resources can only work in the presence of at least one conventional DG in a microgrid due to their nature fluctuation in the generation.

According to the location of a fault, some created microgrids may include only renewable resources. In this scenario, the configuration of the test system, location, and type of DGs are considered as constraints for the objective function. Flexible boundaries are changed to add a diesel generator to the microgrids. Reliability indices for static and flexible boundaries microgrids are given in Table VIII. ASIDI and the final cost of the system by performing DR can be decreased to 11.3% and 13.6%, respectively.
According to the limitation of operators to utilize renewable resources in microgrids, some created microgrids are not able to keep running. Therefore, the reliability of the system would be deteriorated. The comparison of final cost between the two mentioned scenarios is depicted in Fig. 11, which shows the final cost of utilities has been increased in the second scenario.

![Figure 5.11. Comparison of final costs in two scenarios](image)

**5.8 Summary**

This dissertation proposed a novel method to design and operate flexible microgrids in the presence of DR programs under various contingencies. GA and MILP have been simultaneously applied to solve the two-level optimization problem. As the main contribution of this dissertation, in order to create the optimal forming of flexible microgrids under certain contingency, planning and operation stages were explicitly modeled and optimized simultaneously to achieve the most profitable approaches.

The proposed method has obtained the location of remote switches, and sitting and sizing of
DGs in the planning stage. In addition, contribution of customers in DR programs, financial trading between utilities and customers like incentive, and microgrids boundaries per fault have been determined in operation level. Moreover, MILP has been used to deal with the complexity of the DR problem with different variables and constraints. First, priority lists of customers who are willing to participate in the DR program are created. Then, based on the current consumption of microgrid, DR incentive, and CDF of customers, the contribution of each customer in the load shedding plan is obtained to achieve the highest social welfare.

Moreover, the proposed method is able to evaluate the performance of all possible forms of microgrids by merging adjacent microgrids into one joined-microgrid or dividing to smaller ones. The numerical results verified utilizing this concept led to improving reliability indexes by 15%. The proposed method studied performing of DR program on reliability indexes of residential, commercial, and industrial customers. The results demonstrated reliability could be significantly improved by implementing microgrids with flexible boundaries comparing to traditional static microgrids. Furthermore, by performing the DR program, the reliability of customers especially industrial and commercial sectors has been increased by 20%.
CHAPTER 6:

CONCLUSION AND FUTURE WORK

In this research, a new analytical model was proposed to analyze the impact of demand response aggregators on asset management and energy loss. The analytical model was employed to calculate the electricity bills of customers and the total energy loss of distribution networks. The optimal scheduling of household appliances and DERs were determined to minimize the sum of the total cost of customer bill and utilities' costs. Results of case studies show the importance of efficient smart home management on power system performance.

In this dissertation, we have also proposed an optimal strategy for DR participants to relieve the transmission congestion. This method considers economic factors such as congestion shadow price, the incentive for EV owners, and participants of EDRP to calculate the cost of each program. The results have proved that the total costs of the distribution system have been decreased and transmission congestion can be relieved by utilizing the proposed approach.

Our work gives insight on how to design and operate flexible microgrids to improve reliability and reduce the energy not supplied. Compared to current approaches, boundaries of the proposed flexible microgrids can be extended or shrunk based on generation and demand levels, technical constraints, and customers' comfort. Furthermore, the DR program is utilized to maintain the balance between generation and consumption in the microgrid. In this work, we applied the Genetic Algorithm (GA) and Mixed-Integer Linear Programming (MILP) to model and solved
two-stage optimization considering utilities' profits and customers' satisfaction. In planning level, GA is utilized for sitting and sizing of distributed generations and placement of switches. In operation level, MILP is used to select target switches as boundaries of optimal microgrids, the priority of customers, and determine the contribution of each load in the DR program. The case study is also presented, and final results show the superiority of the proposed method compared with traditional fixed boundaries method in microgrids.

This work is an initial step towards more efficiently and systematically incorporating DR program into power system management and electricity markets. The following research directions can be further explored:

- Working towards an inference and a decision-making tool to receive electrical signals and act on the power distribution system
- Developing a stochastic optimization model for DR aggregators to participate in the day-ahead congestion management under uncertainties of DERs, EDRP, and market prices.
- Designing an optimal procurement strategy for DR aggregators in wholesale electricity markets
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