Bangladesh University of Engineering and Technology

Generation Cost Minimization by Scheduling of Loads of a Substation Considering System Loss for Smart Grid

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February 2017

Declaration of Authorship

We, Partha Protim Saha & Shuvangkar Chandra Das, declare that this thesis titled "**Generation Cost Minimization by Scheduling of Loads of a Substation Considering System Loss for Smart Grid"** or any part of it has not been submitted elsewhere for the award of any degree or diploma.

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Certificate of Approval

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Acknowledgments

First of all, we would like to thank Almighty for giving us the strength, integrity and patience to complete this thesis.

We would like to express our sincere gratitude to our supervisor **Dr. Md. Forkan Uddin,** Associate Professor of the department of Electrical and Electronic Engineering, BUET for his continuous support, patience, motivation and immense knowledge. His guidance helped us all the time of the research and writing of this thesis. He shared his knowledge with us in interpreting subject topics and also valued our way of thinking to synthesize those topics. His suggestions pushed us towards the direction of better thinking, his brilliant reviews refined us in working out our research problems, and his support gave us spirit to continue our work at the time of our disappointment. We are extremely thankful and indebted to him for sharing expertise, and sincere and valuable guidance and encouragement extended to us. We take this opportunity to express gratitude to all of the department faculty members for their help and support. Their valuable reviews and remarks helped us a lot in refining our work.

We deeply thank our parents for the unceasing encouragement, support and attention. They always believe in ourselves even at the time when we were losing all hopes. We are grateful to them for their never-ending support and encouragement. We also place on record, our sense of gratitude to one and all, who directly or indirectly, have lent their hand in this thesis work.

Last, but not the least, we want to give thanks to the NEOS server which has helped us to solve our optimization problem [1].

Abstract

Reducing electricity generation cost and peak power demand is one of the key requirements for next generation Smart Grid. Load scheduling of electricity consumers is an effective way to reduce the peak power demand on the electricity grid. In this thesis, we consider scheduling of loads of a substation along with system losses in order to minimize the electricity generation cost. We also consider deployment of smart meters for autonomous demand side management within a neighborhood, where several users share a substation. Smart meters are connected to not only the power grid but also the local area network, which is necessary for handling two-way communications in a smart grid infrastructure. We model the system losses such as transmission loss, line loss, transformer loss to address the load scheduling problem. We formulate an optimization problem to determine the optimal schedule of the loads of different consumers in 24 hours of a day. The problem is found to be a non-linear integer problem. We solve the problem for various scenarios of the consumers, appliances and loads by using optimization tools CPLEX and MINOS. The numerical results show that optimal load scheduling reduces the generation cost significantly compared to the generation cost of the conventional system.

Dedication

Dedicated to our loving parents.

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List of Symbols

V_n user voltage

$I_{n,a}$ appliance current

$\theta_{n,a}$ appliance power factor angle

$P_{n,a}$ energy consumption for each appliance for one hour

e_n^h total hourly consumption for each user

ε_h total hourly consumption of a substation

I_n^h user current for one hour

$x_{n,a}^h$ binary decision variable

l_n length vector for each user

r_n radius vector of wire for each user

R_n resistance of the wire for each user

p_n^h line loss for each user for one hour

L_h total line loss for one hour

P_{cu}^h copper loss

R_s secondary winding resistance of transformer

R_p primary winding resistance of transformer

a turns ratio

P_{core} core loss of transformer

E_h total energy consumption

$T_{n,a}$ operating time period of appliance

Chapter 1
Introduction

In this chapter, we provide an introduction on smart grid, its background, definition of smart grid, its features and impact on the world. We also discuss on load scheduling, demand and peak demand. Later in this chapter, we provide the motivation behind our thesis and the contribution of our thesis.

1.1 Introduction to Smart Grid

A new vision termed 'smart grid' was floated since the early twenty first century (around 2007) mainly by the public bodies and regulators of electricity utilities in the North America against the backdrop of several events of massive blackouts that occurred in USA and Europe.

The smart grid vision is still in the stage of evolution. It comes from an idea that the large power grids which interconnect bulk and centralized power plants across the world are aging. So, a potential solution could be to make the system self-healing when events like blackouts occurs. It can be done through embedding (i) plug-in hybrid electric vehicles (that use high power density rechargeable alkaline batteries) and (ii) smart appliances (self-responsive to system condition) at the consumer end (iii) distributed small-scale generation resources including renewable sources. All of these can be communicated by the grid control centre by using the available distributed communication media such as mobile network, internet, broadband wireless systems, fiber optic networks, and power line carriers (PLC).

There are some conspicuous features of a smart grid. These are DERs (Distributed Energy Resources including storage devices), two-way communication and DR (Demand Response).

Smart grid is still a vision which aims at transforming the existing power system so that it can (a) accommodate small generations and storage devices (based on renewable or conventional) including battery, fuel cells, plug-in hybrid electric vehicles interfaced with the grid through power electronics besides the large central power plants, (b) spread out two-way communication using IT equipment and smart electrical devices to transmit server commands to consumers and receive consumers' response for more accurate operation and control of the system and (c) retain the characteristics of an uncontrolled system or an electricity market.

1.2 What is Smart Grid

A smart grid is an intelligent electricity network which integrates the actions of all users connected to it and makes use of advanced information, control, and communications technologies to save energy, reduce cost and increase reliability and transparency. Smart grids co-ordinate the needs and capabilities of all generators, grid operators, end-users, and electricity market stakeholders to operate all parts of the system as efficiently as possible.

Development of this new grid will require significant efforts in technology development, standards, policy and regulatory activities due to its inherent complexity.

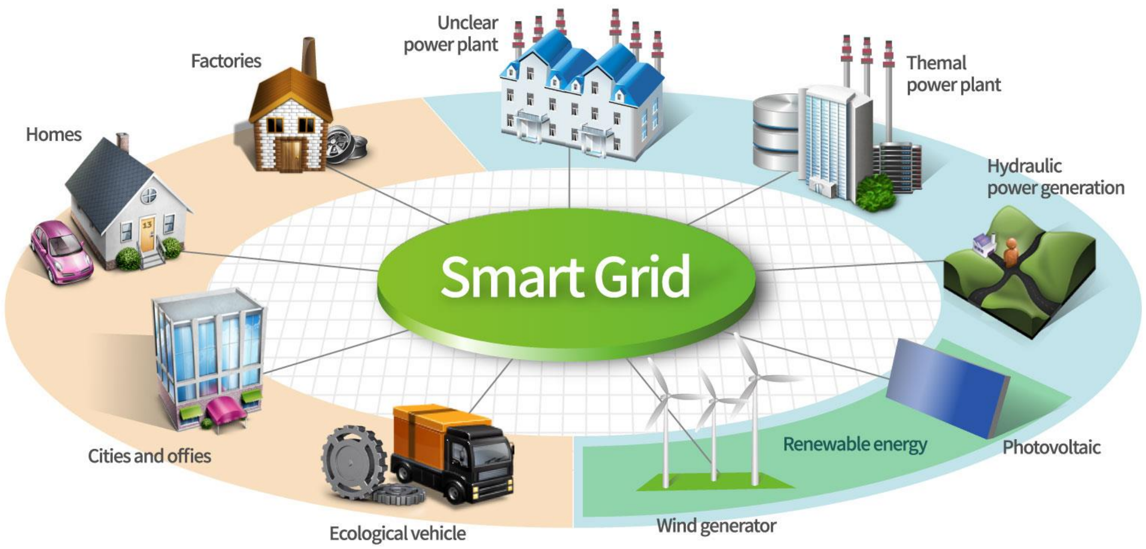


Figure 1.1: Smart Grid city

1.2.1 Impact of Smart Grid on the World:

We hope in the next two decades; a partnership of industry and government will reshape the electrical power grid in the United States and other countries. It will start building a smart grid that is more resistant to failure, more secure, more efficient and delivers power across the system at a lower cost to producers and consumers. Much of the existing electrical power infrastructure is aging and needs replacement. This infrastructure was built when demand was significantly lower not only for lighting and heating but for thousands of consumer and industrial applications. When the infrastructure will be expanded, and upgraded, it will also be made more capable. The smart grid will add monitoring, analysis, control and communication capabilities to the national power generation and distribution infrastructure. The aptly named smart grid makes everyone smarter. Energy producers, consumers and distributors will all have real-time information on the cost, demands and supply of power across the grid which enables an unprecedented level of control at every level of the system. The smart grid will also help to flatten the power distribution world. When the project is sufficiently far along, there will no longer be local energy markets. Massachusetts wind farms will be able to supply Las Vegas consumers with power at rates comparable to that of the Hoover Dam. Similar scenarios will be developed around the world [2].

Moreover, the smart grid will enable more widespread use of distributed generation by bringing generation closer to consumers. For example, could buy energy from the grid at night and sell it back during the day, providing a strong green incentive for consumers and contributing to a stronger grid. An advanced metering infrastructure (AMI) will enable consumer-friendly efficiency concepts like “prices to devices” under which prices are relayed to “smart” home controllers or end-consumer devices like thermostats, washer/dryers and refrigerators, which process the information and start or stop devices based on customer preference. By being able to monitor power distribution in real time (multiple times per second), rather than multiple times per minute (the current standard), producers will be able to accommodate energy needs more efficiently and minimize or avoid blackouts (the Department of Energy estimates that credit card operators lose $2.5 million per hour of blackout) [2].

A network which is more tightly monitored is also less vulnerable to deliberate manipulation and attacks. A smart grid will also help taking the peak out of peak demand. By allowing producers to better mention demand, the smart grid can minimize or eliminate the need for the Smart Grid. The grid operates now without a greater ability to anticipate when demand will peak or how high it will go. As a result, producers maintain Peaker plants that only operate during peak demand. The Peaker plants are expensive to operate. These generate additional greenhouse gases and make energy prices up, because the plants must be built and maintained but generally remain idle much of the time. National economies and the standard of living in the United States, as well as most of the world rests squarely upon the electrical infrastructure. In the coming decades expanding and modernizing that infrastructure may be one of the most important technological efforts [2].

1.2.2 Characteristics of Smart Grid

Customer participation:

The consumer will be offered different purchasing rate of electricity according to the total demand at a particular time. So, consumer will be more conscious of their usages pattern of electricity.

Coordination among different generation and storage units:

In this grid system, the user may also supply electricity to the grid from their renewable energy sources. This includes customer side distribution arrays. Smart grid will coordinate all the generation stations and small power sources.

Power quality package:

All customers do not need the same quality of power. The smart grid can supply varying grades and prices of power, like premium quality power, business quality etc. Advanced control mechanism such as rapid diagnosis of line faults, harmonic sources, switching surges etc. will be included in different package.

Optimizes asset utilization and operating efficiency:

A smart grid applies the latest technologies to optimize the use of its assets. For example, optimized capacity can be attainable with dynamic ratings. It allows assets to be used at greater loads by continuously experiencing and rating their capacities.

Maintenance efficiency can be optimized with condition-based maintenance, which signals the need for equipment maintenance at the right time. System-control devices can be adjusted to reduce losses and eliminate congestion. Operating efficiency increases when selecting the least-cost energy delivery system available through these types of system control devices.

Provides resiliency to disturbances, attacks and natural disasters:

Resiliency refers to the ability of a system to react to unexpected events by differentiating problematic elements while the rest of the system is restored to normal operation. These self-healing actions result in reduced interruption of service to consumers. It also helps service providers to manage the delivery infrastructure better.

Transmission and distribution losses:

Smart grid technologies can provide considerable benefits by reducing transmission and distribution losses. Also by optimizing the use of existing system smart grid provides benefit.

1.2.3 Key Features of Smart Grid

- ✓ **Advanced Metering Infrastructure(AMI):** It is an integrated system of smart meters, communications networks, and data management systems that enables two-way communication between utilities and customers. Customer systems include in-home displays, home area networks, energy management systems, and other customer-side-of-the-meter equipment that enable smart grid functions in residential, commercial, and industrial facilities [3].
- ✓ **Real Time Pricing(RTP):** Real-time pricing gives consumers information about the actual cost of electricity at any given time. Electricity prices change from hour to hour, but most consumers are forced to pay the same price no matter when they use electricity. Real-time pricing lets consumers adjust their electricity usage accordingly [4].
- ✓ **Demand Response(DR):** Demand response is a change in the power consumption of an electric utility customer to better match the demand for power with the supply. Demand response provides an opportunity for consumers to play a significant role in the operation of the electric grid by reducing or shifting their electricity usage during peak periods in response to time-based rates or other forms of financial incentives [5].
- ✓ **Smart Charging:** Smart charging is the intelligent charging of EVs, where charging can be shifted based on grid loads and in accordance to the vehicle owner's needs. The utility can offer EV owners monetary and/or non-monetary benefits in exchange for

enrolment in a program that permits controlled charging at the times when curtailment capacity is needed for the grid [6].

- ✓ **Distributed Generation Integration:** The integration of new sources of energy like wind power, solar-power, small-scale generation, or combined heat and power in the power grid is something that impacts a lot of stakeholders: network companies, the owners and operators of the DG units, other end-users of the power grid and not in the least policy makers and regulators [7].
- ✓ **Distributed Automation:** It is a Smart Grid technology that can be implemented on the electric grid's distribution system of local power lines and neighbourhood substations. It often offers the greatest bang for the buck. It improves reliability with real-time monitoring and intelligent control [8].

In the Fig. 1.2 below, we can see the functional integration map of a smart grid.

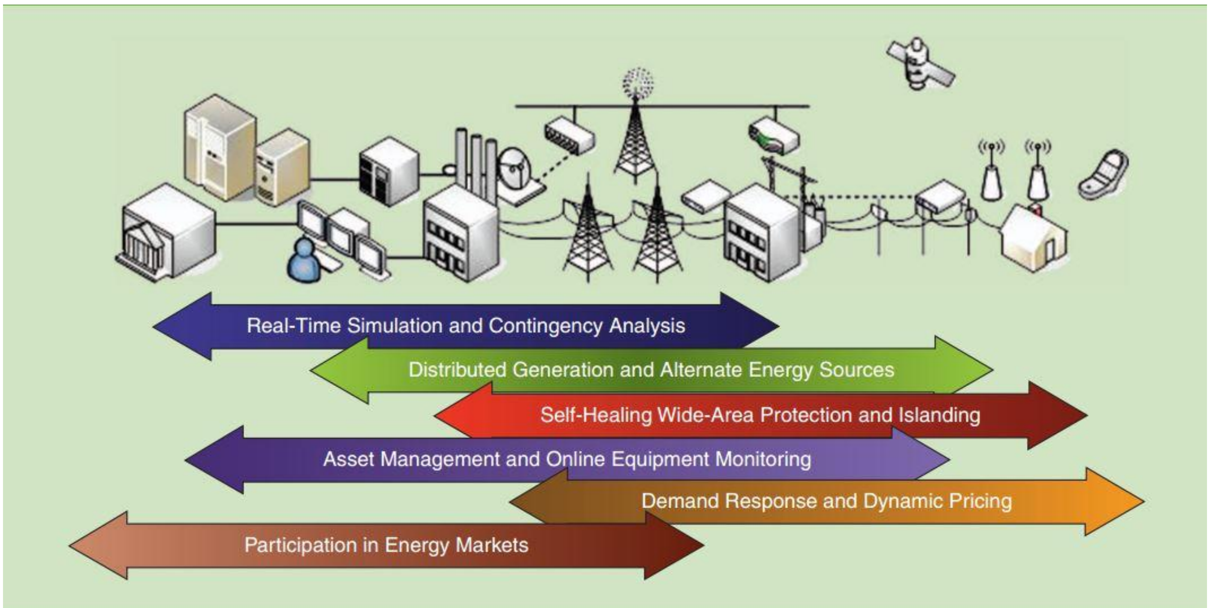


Figure 1.2: Functional integration map of a smart grid

1.3 Difference Between Existing Power Grid and Smart Grid

The existing power grids are generally used to receive power from a few central generators and transmit to a large number of users. In contrast, the smart grid uses two-way flows of electricity and information to create an automated and distributed advanced energy delivery network. Table 1.1 gives a brief comparison between the existing grid and the smart grid.

Modern information technologies enable smart grid capable of delivering power in more efficient ways. It also makes smart grid responding to wide-ranging conditions and events. It goes without saying that the smart grid could respond to events that occur anywhere in the grid, such as power generation, transmission, distribution, and consumption, and adopt the corresponding strategies. For example, once a medium voltage transformer failure event occurs in the distribution grid, the SG may automatically change the power flow and recover the power delivery service [9].

Table 1.1: Comparison between existing grid & smart grid

Existing Grid	***Smart Grid***
Electromechanical	Digital
One-way communication	Two-way communication
Centralized generation	Distributed generation
Few sensors	Sensors throughout
Manual monitoring	Self-monitoring
Manual restoration	Self-healing
Limited control	Pervasive control
Few customer choices	Many customer choices

In the below Fig. 1.3 & 1.4 show the relative differences between traditional power grid & the smart grid infrastructure.

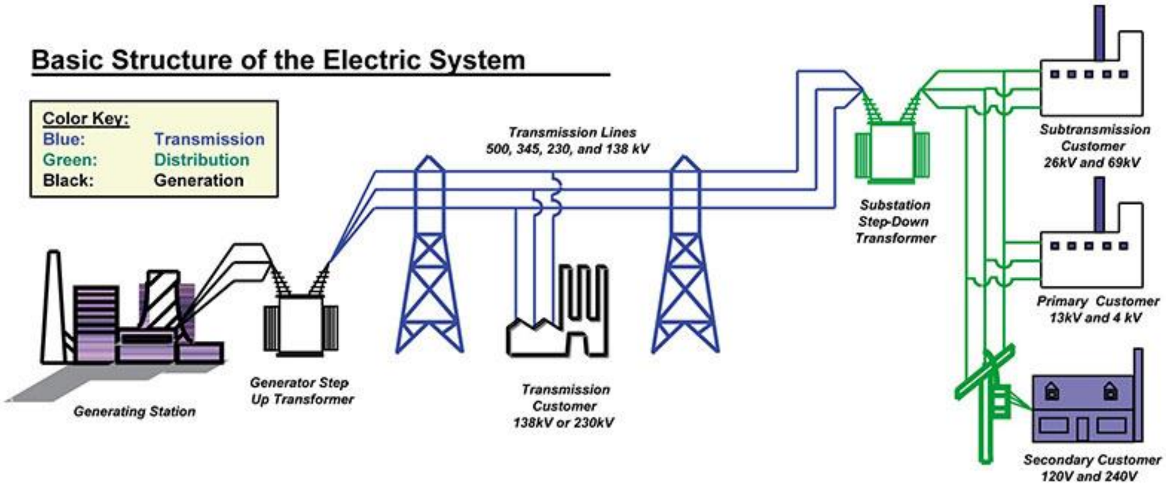


Figure 1.3: Traditional power grid

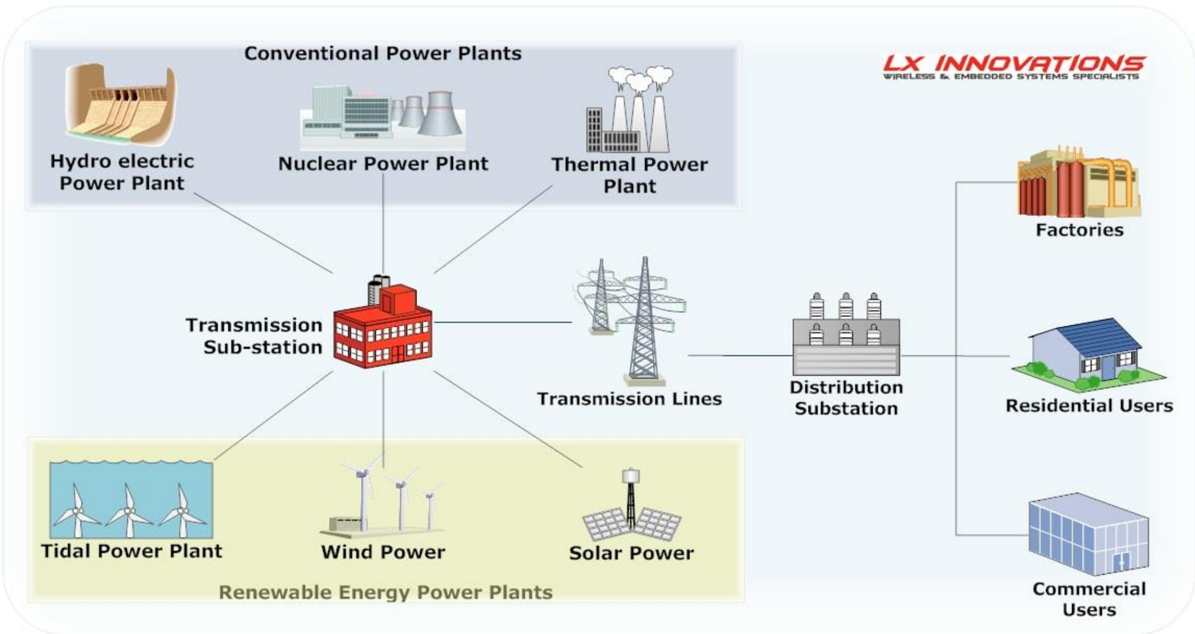


Figure 1.4: Smart grid

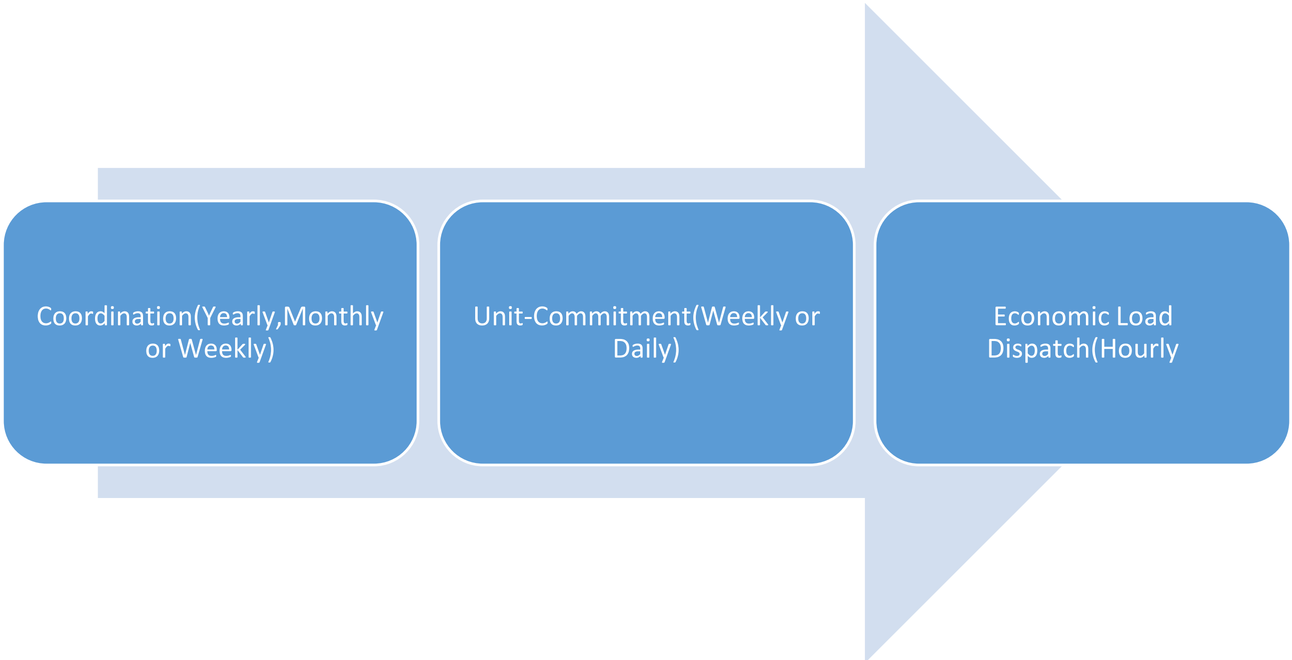
1.4 Load Scheduling

The electrical load schedule is an estimate of the instantaneous electrical loads operating in a facility, in terms of active, reactive and apparent power (measured in kW, kVAR and kVA respectively). The load schedule is usually categorized by switchboard or occasionally by sub-facility area [10].

Preparing the load schedule is one of the earliest tasks that needs to be done as it is essentially a pre-requisite for some of the key electrical design activities [10].

It provides the preliminary details of process/building / organization Load [10].

1.4.1 Parts of Load Scheduling



1.5 Demand and Peak Demand

Throughout the day and across seasons the demand for electricity is varied (Figure 1.5). Since electricity system infrastructure is designed to meet the highest level of demand, during non-peak times the system is typically underutilized. Building the system to satisfy occasional peak demand requires investments in capacity. This investment would not be needed if the demand curve was flatter. Smart grids can reduce peak demand by providing information and incentives to consumers to enable them to shift consumption away from periods of peak demand. Demand response in the electricity system is the mechanism by which end-users vary consumption in response to price or other signals. It can both reduce peak demand, but also provide system flexibility which enables the deployment of variable generation technologies. The first priority is reducing peak demand because demand at a system level is relatively predictable and ramps up and down slowly compared with variable generation. As demand response technology develops and human interactions are better understood, the availability, volume and response time of the demand-side resource will provide the flexibility necessary to respond to both peak demand and variable generation needs [9].

Peak demand has to be managed such that it can enable better system planning throughout the entire electricity system. This management can also increase options for new loads such as electric vehicles, for storage deployment and for generation technologies. These benefits are essential for new systems where demand growth is very high, and for existing and aging systems that need to maintain existing and integrate new technologies [9].

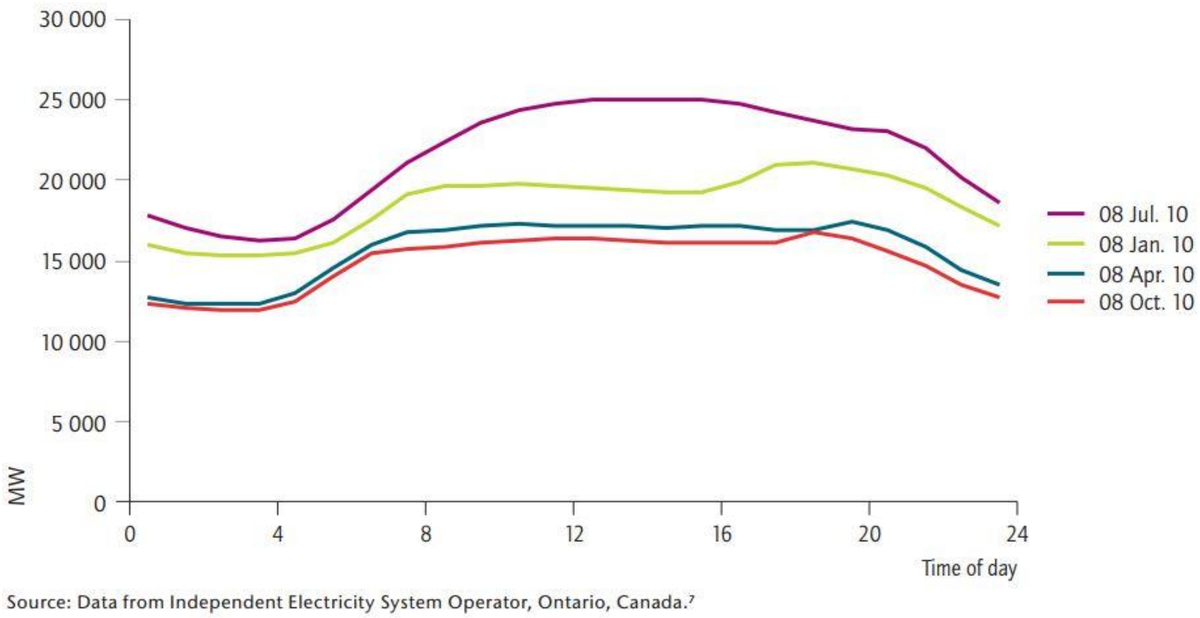


Figure 1. 5: Example of a 24-hour electricity system demand curve [9]

The demand for electricity varies throughout the day and across seasons. Smart grids can reduce the peaks and optimize system operation.

1.6 Motivation

Our main focus of the thesis work is to reduce generation cost applying load scheduling technique from the demand side. Mohesnian-Rad et al. [11] present an optimal, autonomous, and incentive-based energy consumption scheduling algorithm to balance the load among residential subscribers that share a common energy source. In this paper, they reduced Peak to average ratio and total cost. Yue et al. [12] consider the load demand scheduling problem of multiple end users. The objective of these end users is to minimize the electricity generation cost.

There are some lacking in their optimization problem. They do not consider appliance power factor which is an important parameter of every appliance. Power factor is important because it can lower utility charges and reduce system losses. Also, they don't consider distribution losses like conduction loss, transformer loss, switch gear loss etc. in these papers. For high loading condition, it is required to consider these losses. The total energy consumption model is not practical. So, we have tried to make our optimization problem as practical as we can.

Converting existing grid into smart grid is a continuous process and has to consider lot of real parameters of every appliance, transformer parameters, conduction losses etc. So, considering real scenario, we developed a real optimization problem to solve these problems

1.7 Contributions

Nowadays load changes frequently from KW range to MW Range. If we think about a tesla car which adds equivalent to 20KW load when connected. To handle the sudden change of demand a sophisticated and intelligent control system is necessary considering the appliance parameters and losses.

Our contribution is listed below:

1. We have considered appliance power factor. Then, we have considered conduction losses of the distribution wire. Also, we have included the transformer losses in the calculation.
2. By considering all these factors indicated above, we have formulated a more practical and real optimization problem.

3. Solving the problem, we have been able to reduce the generation cost by more than 30% compared to the previous problem.

Further, this research will contribute in different fields of the power systems.

1.8 Outline of the Thesis

- Chapter 1 contains primary introduction of the thesis. Also, there is a study about smart grid and load-scheduling. It shows the difference between the existing power grid and smart grid. This chapter also contains motivation behind this research and contribution of this research. At last, it includes the outline of the thesis work.
- Chapter 2 contains related works about the load-scheduling. It presents a literature review on load-scheduling and its impacts.
- Chapter 3 contains the system model, load model, and demand model. In this chapter, the problem formulation is shown. Also, analysis of the problem and complexity of the problem has been discussed later in the chapter.
- Chapter 4 contains the solution approach and numerical results of the simulation. Result analysis has been discussed. The advantage of optimal load scheduling has been presented.
- Chapter 5 includes a conclusion and some future expansion of load scheduling.

Chapter 2
Related Work

In this chapter, we are going to see some of the previous works on load scheduling of smart grid. The related work can be classified as (i) Demand management, (ii) Load management, (iii) Energy consumption management, and (iv) Demand response.

2.1 Demand Management and Optimizing Costs

There is a lot of scholarly articles dealing with the management of electricity and trying to optimize costs or minimize the demand on a power grid. Two topics of particular interest are Multi-Agent Home Automation Systems and Electricity Management Controllers. The purpose of these devices is to allow the agents, i.e. devices or appliances, to cooperate and coordinate their actions in order to find an acceptable near optimal solution for power management [13]. In their paper, they propose an algorithm to reduce energy costs by postponing or delaying starts of appliances all while taking into account the comfort of the inhabitant that lives in the residence. Cohen [14] demonstrates that it may be beneficial to a utility company to control the running of appliances to reduce the strain on the electrical grid during times of peak load. Using a dynamic programming approach, he shows how a utility company could level out the energy load throughout the day by controlling a residential area's usage of appliances, i.e. air conditioners and hot water heaters.

2.2 Load Management

There is a large body of literature on load management or load control. Hu, Chen and Bak-Jensen [15] discusses optimizing energy loads by managing consumer energy demand in Denmark. Denmark uses a time-of-use electricity rate schedule where electricity prices are set the day before through market trading and then those prices are implemented the following day [15]. Therefore, consumers know the time-of-use rate schedule beforehand. Using a linear program, they model the energy costs of a consumer during the day with an objective to minimize those costs. Since the consumers know the rate schedule, they can reduce the consumption near the price peaks in order to reduce the energy costs [15]. The authors show a price curve plotted against time with large price spikes. By using the LP, the authors show that program shifts energy consumption away from the peaks in order to reduce costs. Therefore, by shifting consumption, the end user will experience energy costs savings.

2.3 Load Side Demand Control

Luo, Kumar, Sottile, and Yingling [16], discuss an MILP formulation for load side demand control. Here the authors focus on the demand component of electricity costs instead of consumption costs. Their MILP considers loads that are on at time t then decides whether or not to shed those loads, when it needs to be shed, and when the operation of that load shall resume [16]. The MILP also looks at loads that are off and schedules when those loads are to resume again. The authors implement the model using constraints that set bounds to the minimum and maximum downtime for each of the loads, likewise for the up time. The authors also utilize three variables for each of the loads, one binary variable for off and on, another that tracks the time on, and lastly one that tracks the time off. By tracking the time off and time on, the authors can figure out the production of each of the loads over the time horizon. The model also utilizes a maximum demand constraint which enforces that the system demand must not exceed the max demand value. The authors apply their model to a coal mine case study where they model the electricity demand costs. Using demand control by shedding loads can reduce demand costs all while reducing any loss in productivity associated with load shedding [16]. Also, by preventing machines from constantly stopping and starting, the wear on the machines can be reduced. [16]

2.4 Energy Consumption Management

Mohsenian-Rad, Wong, Jatskevich, and Schober [18] propose a model similar to that proposed by Hu, Chen, and Bak-Jensen. Their model proposes the shifting of energy consumption as in [15], however, they propose that consumers will not change their consumption habits without incentive. They explain that most energy consumption in the United States occurs in buildings and there are two general approaches for energy consumption management in buildings: reducing consumption and shifting consumption [18]. In their paper, they propose the use of energy consumption devices similar to those proposed in [13] and [14] where there is an electronic controller in each household and in all households in the neighborhood are connected to one local controller. The algorithm they propose solves the energy consumption schedule for each household in the neighborhood, then communicates it back to the local controller. This process continues until each household achieves its own maximum payoff, or reduction in energy costs. The authors explain that the energy consumption schedule changes by shifting soft appliances such as dishwashers, clothes dryers, etc. [18]. By shifting these appliances, households are able to achieve the maximum payoff or cost savings. Hard appliances such as lighting, air conditioners, refrigerators, etc. are not allowed to be rescheduled in their model.

2.5 Load Shifting to Reduce Energy Consumption Costs

A model proposed by Middelberg, Zhang, and Xia [17] also utilizes the idea of load shifting to reduce energy consumption costs. The authors model a series of conveyor belts from a South African Colliery by using a binary integer programming method. Their objective is to reduce the operational electricity costs. In order to reduce electricity costs, the model shifts electricity demand from peak TOU periods to those periods that are less expensive or the off-peak periods [17] similar to [15] and [18]. By utilizing this approach, they show that with the South African case study, there was a 49% reduction in the cumulative energy costs during 5 weekdays in a high-demand season [17]. However, they also showed that the total energy that was consumed during peak TOU periods over the five days was reduced from 25% to 8% compared to the non-optimal data from the case study.

2.6 Reduce Energy Consumption Costs Using Production Optimization

Ashok and Banerjee [19], take the shifting principles proposed in [15] and [18] and applies that idea to an industrial setting. They propose a mixed integer linear program to reduce energy costs based on a case study for a typical flour mill. The authors use a myriad of constraints such as production, storage, process flow, sequential, maximum demand, downtime of machines, and electrical load to properly model a flour mill's production. The objective of the model is to reduce energy consumption costs while the constraints ensure that the flour production is optimized as well. They claim the proposed model is capable of analyzing the industry response to different tariffs, operational strategies like two or three shift operation, variation of equipment size or storage capacity and adoption of new technologies [19]. By implementing the model, the authors claim that in the case study the plant would experience an energy cost reduction of 29% by implementing their model. The cost savings is a result of spreading out the peak energy consumption times to take advantage of the part-peak and off peak electricity costs proposed by the time-of-use energy schedule they used for their case study.

2.7 Demand Management to Optimize Cost through RTP

Roos and Lane [20] propose a linear program that is applied to the industrial setting as in [19]. They propose that the purpose of this paper is to add more insight into the electricity cost saving potential of real-time pricing (RTP) through intelligent [20]. Instead of using a time-of-use schedule, the electricity prices are variable for specific time periods throughout the day. Since the utility company provides the consumer with the pricing information beforehand, Roos and Lane propose an intelligent demand system similar to the EMC devices proposed in [13] and [14]. Through linear programming optimization, the authors propose a load scheduling strategy that may result in minimum electricity costs to the end user [20]. The objective is to reduce the electricity costs to the end user under real-time pricing electricity rates. Through intelligent demand management which describes the optimal load scheduling, an end user could experience substantial electricity costs savings.

2.8 Reducing Electricity Costs by Load Shifting Using RTP

Mohseninan-Rad and Leon Garcia [21] propose a model for residential consumers that also uses real-time pricing (RTP) as discussed in [20]. The authors claim, the lack of knowledge among users about how to respond to time-varying prices and the lack of effective home automation systems are two major barriers for fully utilizing the benefits of real-time pricing tariffs [21]. Although the RTP schedule allows consumers to shift their higher energy demand appliances to times where energy rates are lower, these shifts are done manually by the consumer. The authors propose a model that will optimally schedule consumer appliances in order to minimize the consumer's total electricity costs. The authors make the assumption that each residential consumer is equipped with a smart meter with an energy scheduling unit similar to the EMC devices discussed in [13], [14], and [20]. The authors devise a linear program that reduces consumer electricity costs while also minimizing the time between when a device is called to turn on and when the linear program schedules the appliance to turn on. Since the electricity costs may not be known for the entire day to the end user, the authors propose an equation that predicts the electricity costs during the day based on past electricity cost data. By utilizing the schedule proposed by the linear program, an end user can experience reduced electricity costs.

2.9 Demand Response Using RTP

A model for demand response using real-time pricing was proposed by Conejo, Morales, and Baringo which applies to a household or small business. Similar to the pricing scheme in Denmark [15], the consumer knows beforehand the electricity rate they will receive for the following hour therefore, they can adjust their consumption pattern accordingly [22]. Using a linear program algorithm, the authors were able to provide electricity consumption results based on a typical 24 hours a day for a household or small business. They claim that by implementing their linear program algorithm into an EMS as discussed by [13], [14], [20], and [21], consumers would be able to reduce their energy consumption costs by optimizing their energy consumption patterns.

2.10 Reduce Operational Cost by Load Shifting

In [18], the authors stated that most of the energy consumption of the United States occurs in buildings. A paper by Braun [23] explains that "the use of a building's thermal storage for load shifting can significantly reduce operational costs, even though the total zone loads may increase" [23]. The author proposes using efficient cooling systems that utilize part load operation. Also, the model he proposes takes advantage of the thermal mass of the building, i.e. how well insulated it is, as well as a time-of-use electricity rate structure. Braun proposes a mathematical program where the objective is to reduce both the energy and demand costs of cooling a building by precooling the building during pre-workday hours. Essentially, the model precools the building before it will be occupied by workers during the working hours, i.e. cooling the building to some temperature lower than the normal thermostat set point such as 72 degrees. Therefore, for some hours of the working day, the building will not need to be cooled since the program relies on the thermal properties of the building structure. Also, by precooling the building in the early morning hours, the air conditioning system does not work as hard since there is no one in the building and the outside ambient temperature will not put a large thermal load on the building. Therefore, the model shifts the demand and energy charges by shifting the load to the early morning hours to precool the building and to take advantage of the off-peak energy rate. Hence, energy savings are realized by using efficient equipment utilizing part load operation as well as precooling the building during off-peak hours.

2.11 Summary:

Our model will deal with commercial load scheduling similar to the papers proposed by the authors we've discussed. Our model will shift the electrical loads from peak times to partial peak or low peak times similar to [15], [18], and [19], However, the models proposed by most of the authors in this review neglect to take into account the demand charges associated with running large electrical motors. In [17] they discuss reducing energy demand and energy consumption simultaneously similar to our model. The main difference is the application of the model proposed in [17] and the model we propose. The model for the commercial load scheduling problem is much more general and takes into account both the demand costs and consumption costs through the scope of a time-of-use schedule. As shown in many of the papers discussed previously, consumers can take advantage of the time-of-use schedule by shifting energy loads from peak periods to periods where electricity is cheaper. Also, similar to the model in [17], our model staggers start preventing large energy demand charges which can be quite substantial at times. By taking into account both the energy consumption costs and energy demand costs, we provide an integer program that can greatly reduce energy costs for a commercial or industrial firm that uses large machines with electrical motors.

Chapter 3
System Model

In this chapter, we are going to study the system structure, its modeling considering system losses (line losses and transformer losses etc.). Later in this chapter, we will see the final optimization problem after modeling which aims at reducing generation cost.

3.1 Energy Consumption Modeling

In this section, we will consider a smart power system. The system consists of loads, substation, Smart Load Scheduling Devices(SLSD), transformers etc. We illustrated the system in the figure given below.

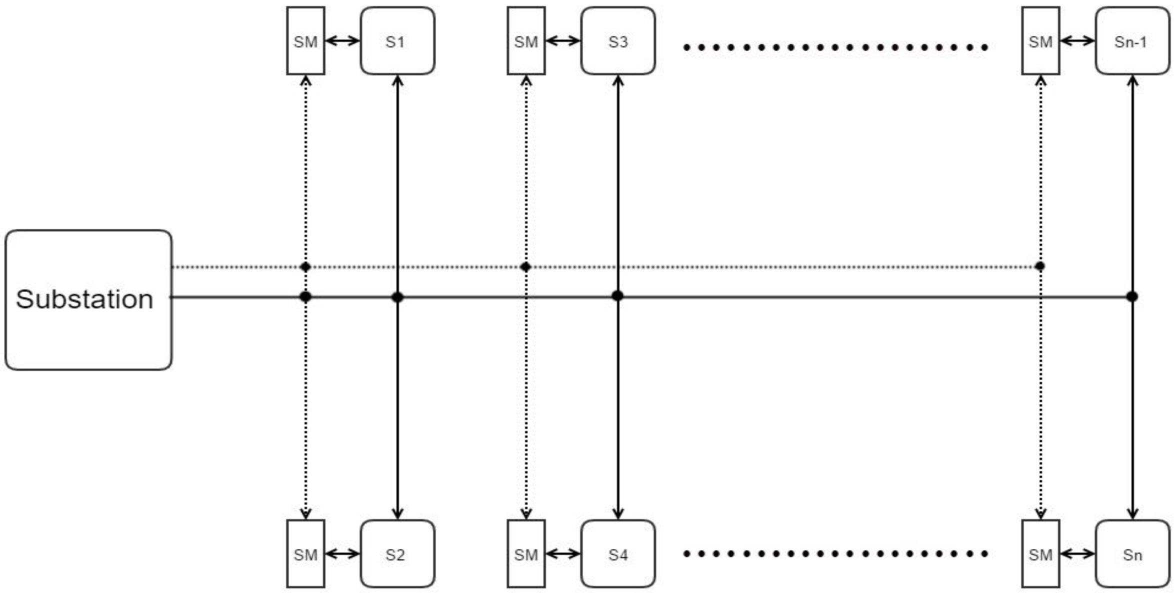


Figure 3.1: A sample smart grid system with n load subscribers

In this system, each subscriber has Smart Load Scheduling Devices(SLSD) which has bi-direction data flow with the household appliances. The meter is also connected to the Local Area Network(LAN) so that it can communicate with the central server. All the subscribers are connected to the substation. So, the convenience of the load scheduling and fewer data processing we consider each substation as our workspace. Thousands of subscribers consist of a substation so if each subscriber has 10 appliances on average, the processing time for load scheduling is less than processing the data centrally.

Let the number of the subscriber is denoted by N and for each subscriber $n \in N$. Let, A denotes the set of appliances such as light, fan, washing machine, refrigerator and for each appliance $a \in A$.

In this section, we will design a real substation power system considering all types losses and energy consumption. Energy consumption for each appliance for one hour

$$P_{n,a} = V_n I_{n,a} \cos(\theta_{n,a}) \text{x1Hr} \qquad (3.1)$$

where, $P_{n,a}$ is in kWh unit and $n \in \mathbb{N}$ is for each user and $a \in \mathbb{A}$ is for each appliance.

We consider appliance current $I_{n,a}$ which varies from appliance to appliance. Let the user voltage, V_n which is dependent on the distance from the substation to subscriber. Also, we consider the appliance power factor angle, $\theta_{n,a}$. For resistive load power factor is close to unity and for inductive and capacitive load the power factor is less than unity. Moreover, the maximum loading-profile of the households are resistive or inductive. In the data generation chapter, we will discuss different load profile of the household appliances. So, total hourly consumption for each user is denoted by e_n^h which is the summation of the energy consumption of all appliances of users.

$$e_n^h = \sum_{a \epsilon A} P_{n,a} \qquad (3.2)$$

$$e_n^h = \sum_{a \epsilon A} V_n I_{n,a} cos(\theta_{n,a}) \qquad (3.3)$$

where, $H = \{1,2,3,4, \ldots ..24\}$

The total number of elements of H is 24 hours and for each hour of the day is denoted by $h \in H$. Total hourly consumption of the substation considering all users and all appliances is

$$\mathcal{E}_h = \sum_{n \in \mathbb{N}} e_n^h \qquad (3.4)$$

$$\mathcal{E}_h = \sum_{n \in \mathbb{N}} e_n^h = \sum_{n \in \mathbb{N}} \sum_{a \epsilon A} P_{n,a} \qquad (3.5)$$

$$\mathcal{E}_h = \sum_{n \in \mathbb{N}} \sum_{a \epsilon A} V_n I_{n,a} cos\theta_{n,a} \qquad (3.6)$$

Using the equation (3.6), we can calculate the total energy consumption of a particular substation in kWh unit. But there are certain factors behind this energy consumption which has the in consideration for real energy consumption model a substation.

Apart from appliance consumption, there is substation and line loss component for a real system.

3.2 User Current Modeling:

Our main purpose of the thesis is load scheduling using optimization technique so that peak demand can be reduced significantly. In every power grid system, peak demand exists only a few hours of a day. For mitigating the peak demand the power generation company has to add new power generating station with the grid just for few moments of a day. Using optimization technique, we will schedule the appliance and reduce peak demand. For optimization, mathematical modeling language will be used to serve our purpose.

As every appliance has power factor angle which adds complexity in our calculation. But mathematical modeling language cannot solve vector sum of the currents of appliances. So, to simplify the calculation of the optimization process we will pre-calculate resultant current of users using MATLAB software.

So, one-hour user current is the vector sum of the appliance current $I_{n,a}^{h}$.

$$(I_n^h)^2 = \left(\sum_{a\in\mathbb{A}} I_{n,a} cos\theta_{n,a}\right)^2 + \left(\sum_{a\in\mathbb{A}} I_{n,a} sin\theta_{n,a}\right)^2 \quad (3.7)$$

Here, we include a binary decision variable $x_{n,a}^{h}$ for each appliance. If any appliance is operating at a particular hour $x_{n,a}^{h} = 1$. On the other hand, if appliance is not operating at that particular hour $x_{n,a}^{h} = 0$.

$$(I_n^h)^2 = \left(\sum_{a\in\mathbb{A}} I_{n,a} cos\theta_{n,a}\, x_{n,a}^{h}\right)^2 + \left(\sum_{a\in\mathbb{A}} I_{n,a} sin\theta_{n,a}\, x_{n,a}^{h}\right)^2 \quad (3.8)$$

3.3 Energy Loss Modeling

Electricity losses are in generally classified into two categories:

I. Technical loss: Technical loss can be variable or fixed loss.
II. Non-technical loss: Non-technical losses are theft, fraud, un-metered supply and mismanagement.

Losses in a grid is classified into few categories:

i. Generation loss

ii. Transmission loss
iii. Distribution loss

A substation is under the distribution loss which is the main concern of this thesis.

In our thesis, we will schedule the loads under a substation. So, the elements consisting a substation and households are (i) step down transformers, (ii) switch gear, (iii) circuit breakers, (iv) distribution line, (v) measuring meters, and (vi) appliances.

The main losses in a substation are (i) line loss, and (ii) transformer loss.

Line loss is mainly copper loss and transformer loss are categorized into few elements such as (a) copper loss and (b) core loss.

3.3.1 Line Loss Modeling

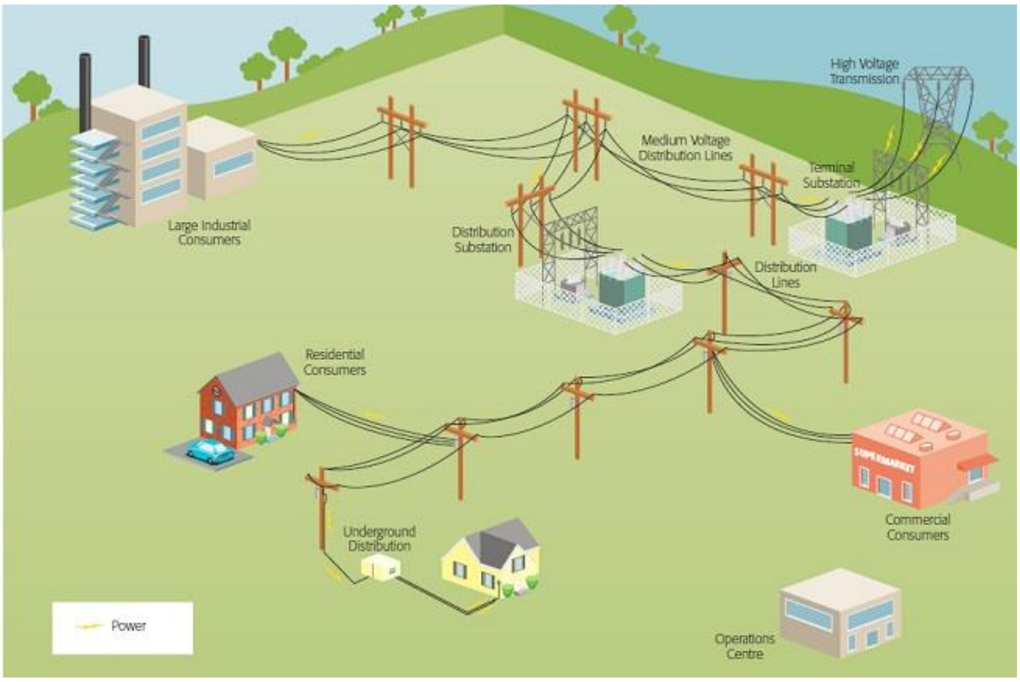


Figure 3.2: A Generic Substation Model

Fig. 3.2 shows a generic substation model. Commercial consumers, residential consumers, and large industrial consumers get the electricity from distribution station via distribution lines.

Electricity carrying lines are made of copper and aluminium in general. So, line loss is mainly the conduction loss due to the resistance of the material. Line loss of different user will be different due to the length line length from the substation and line current of the subscriber.

Line is proportional to the length and squared of line current and inversely proportion to the squared of line radius.

Let, length vector for each subscriber $l_n = [l_1, l_2, \dots \dots \dots \dots \dots \dots \dots \dots, l_n]$

Wire radius vector for each subscriber $r_n = [r_1, r_2 \dots \dots \dots \dots \dots \dots \dots .. r_n]$. Radius vector can be found from the AWG (American Wire Gauge) table. So, the resistance of the wire of each subscriber

$$R_n = \frac{\rho l_n}{\pi r_n^2} \qquad (3.9)$$

We get the line loss for each user for one hour

$$p_n^h = (I_n^h)^2 R_n \qquad (3.10)$$

Total line loss for one hour

$$L_h = \sum_{n \in \mathbb{N}} p_n^h = \sum_{n \in \mathbb{N}} (I_n^h)^2 R_n \qquad (3.11)$$

Here, I_n^h is the line current of each user for one hour time period.

3.3.2 Transformer Loss Modeling

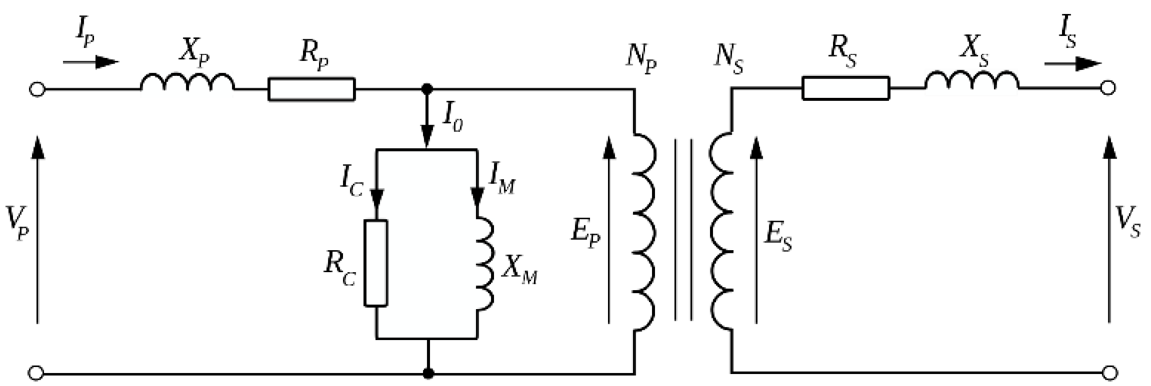


Figure 3.3: Equivalent circuit of a transformer

In the previous page, Fig. 3.3 shows an equivalent circuit of a transformer. It has two sides: primary and secondary. Np and Ns are number of turns of the coil in the primary and secondary respectively. Rp, Rs, Xp and Xs are resistance and reactance in the primary and secondary sides respectively. In the transformer, losses are due to the resistance Rc and reactance Xm. Transformer losses mainly categorize into 4 types:

1. **Copper loss**: Copper losses are the resistive heating losses in the primary and secondary windings of the transformer. They are proportional to the square of the current in the windings [24].

2. **Eddy current loss**: Eddy current losses are the resistive heating losses in the core of the transformer. They are proportional to the square of the voltage applied to the transformer [24].

3. **Hysteresis loss**: Hysteresis losses are associated with the rearrangement of the magnetic domains in the core during each half-cycle. They are a complex, non-linear function of the voltage applied to the transformer [24].

4. **Leakage flux loss**: The fluxes ϕ_{LP} and ϕ_{LS} which escape the core and pass through only one of the transformer windings are leakage fluxes. These escaped fluxes produce a leakage inductance in the primary and secondary coils and the effects of this inductance must be accounted for [24].

Eddy current loss and hysteresis loss are core loss. So, we will consider mainly core loss and copper loss of the power transformer.

Copper Loss

Copper loss is due to the primary and secondary side copper resistance.

Copper loss, $P_{cu}^{h} = I_s^2 R_s + I_p^2 R_p$

where,

R_p = the primary winding resistance

$R_s =$ and secondary winding resistance.

I_p = Primary side current

Here, I_s (secondary current) is equal to the total user current under the substation.

$$I_s = \sum_{n\in\mathbb{N}} I_n^h \quad (3.12)$$

We know that in the power transformer nameplate there is voltage rating. Like a power transformer is transforming 11KV voltage into 220V. So, from voltage rating, we can easily calculate turns ratio.

$$\text{Turns ratio } a = \frac{V_p}{V_s} = \frac{N_p}{N_s} = \frac{I_s}{I_p}$$

$$\text{Primary side current } I_p = \frac{I_s}{a}$$

$$\text{Copper loss } P_{cu}^h = I_s^2 (R_s + \frac{R_p}{a})$$

$$P_{cu}^h = (\sum_{n \in \mathbb{N}} I_n^h)^2 (R_s + \frac{R_p}{a}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.13)$$

Core Loss:

Hysteresis and eddy current losses are major core loss parameters. These losses are constant for various loads.

$$Let, hysteresis\ loss = P_{hy}$$

$$\&\ eddy\ current\ loss = P_{eddy}$$

$$\text{So, core loss } P_{core} = P_{hy} + P_{eddy} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.14)$$

3.3.3 Substation Miscellaneous Loss

Substation miscellaneous losses are in generally (a) switchgear and (b) circuit breaker losses.

These losses are negligible considering other losses. So, we will neglect these losses for simplifying the system model.

Substation Hourly Consumption

Total energy consumption = Appliance consumption + Line loss+ Transformer loss

= Appliance consumption +Line loss + (Transformer copper + Transformer core loss)

$$E_h = \mathcal{E}_h + L_h + (P_{cu}^h + P_{core}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.15)$$

where, core loss P_{core} is a constant parameter. $\mathcal{E}_h, L_h, P_{cu}^h$ are variables

3.4 Generation Cost Modeling

Cost function can be modeled as $Cost(E_h) = \sum_{h \in H_{day}} B(E_h) + \sum_{h \in H_{night}} C(E_h)$ [11]

where, H_{day} is the set of day time

$$H_{day} = \{5,6,7,8,9,10,11,12,13,14,15,16,17,18\}$$

H_{night} is the set of night time

$$H_{night} = \{19,20,21,22,23,0,1,2,3,4\}$$

B= per unit cost of electricity during day time

C= per unit cost of electricity at night

3.4.1 Appliance Operating Condition

The user will provide operating time period of the appliances, $T_{n,a}$ $where\ n \in N\ and\ a \in A$.

For continuity of the appliances, we assume another set $H^c_{n,a} = \{\ 2,3,4 \dots \dots \dots H - T_{n,a}\ \}$

3.5 Load Scheduling Problem

In our load scheduling problem, we are minimizing the cost. The cost function Cost (E_h) is given below which is to be minimized.

Minimize $Cost(E_h) = \sum_{h \in H_{day}} B(E_h) + \sum_{h \in H_{night}} C(E_h)$ (1)

Subject to:

$$(I^h_n)^2 = \left(\sum_{a \in \mathbb{A}} I_{n,a} cos\theta_{n,a}\, x^h_{n,a}\right)^2 + \left(\sum_{a \in \mathbb{A}} I_{n,a} sin\theta_{n,a}\, x^h_{n,a}\right)^2 \quad \forall\ h \in H, n \in N \qquad (2)$$

$$E_h = \mathcal{E}_h + L_h + (P^h_{cu} + P_{core}) \quad \forall\ h \in H \qquad (3)$$

$$\mathcal{E}_h = \sum_{n \in \mathbb{N}} \sum_{a \epsilon A} V_n I_{n,a} cos\theta_{n,a} x^h_{n,a} \quad \forall\ h \in H \qquad (4)$$

$L_h = \sum_{n\in\mathbb{N}}(I_n^h)^2 R_n \qquad \forall h \in H \qquad (5)$

$R_n = \frac{\rho l_n}{\pi r_n^2} \qquad n \in N \qquad (6)$

$P_{cu}^h = (\sum_{n\in\mathbb{N}} I_n^h)^2(R_s + \frac{R_p}{a}) \qquad \forall h \in H \qquad (7)$

$P_{core} = P_{hy} + P_{eddy} \qquad \forall h \in H \qquad (8)$

$\sum_{h\in H} x_{n,a}^h \geq T_{n,a} \qquad \forall n \in N, a \in A \qquad (9)$

$\sum_{h_c\in H_{n,a}^c} x_{n,a}^{h_c} \geq T_{n,a}\ x_{n,a}^{h_c}\left(1 - x_{n,a}^{h_c-1}\right) \qquad \forall n \in N, a \in A, h_c \in H_{n,a}^c \qquad (10)$

Eqn. (1) is representing the cost function of total energy consumption. This minimization problem has some constraints. Eqn. (2) to eqn. (8) has been discussed before in this chapter. Eqn. (9) represents a constraint where decision variable $x_{n,a}^h$ is greater than or equal to the duration of operation of an appliance ($T_{n,a}$). $T_{n,a}$ is parameter which is taken as input from the user. Eqn. (10) represents another constraint which is for continuity for the duration of operation of an appliance. $x_{n,a}^{h_c}\left(1 - x_{n,a}^{h_c-1}\right)$ is the starting point of the appliance that means from when the appliance is running.

3.6 Problem Analysis and Complexity:

The cost function $Cost(E_h)$ indicating the cost of generating or providing energy by the substation at each hour $h \in H$. We first notice that in general

$$Cost_{h_1}(E) \neq Cost_{h2}(E), \qquad \forall\, h_1, h_2 \in H \ \&\, h_1 \neq h_2$$

In other words, the cost of the same energy can be different at different times of the day. In particular, the cost can be less during the night compared to the daytime.

The cost function $Cost(E_h)$ is a convex function [4]. So, it has only one global optimum point. A convex function can be a piece-wise linear function or a smooth differential quadratic function.

The cost function we assume is general and represents either the actual energy cost or simply a cost model by proper load scheduling.

- In our optimization problem, the objective function is linear but the constraints are non-linear.
- The decision variable $x_{n,a}^{h}$ is 3 dimensional. So, if we consider N=1000 families, A =10 appliances, H=24 hours, then the number of variable would be 240K. Similar case will happen for rest of the variables.

No. of Variables: Our problem has mainly two variables which are $x_{n,a}^{h}$ and I_{n}^{h}. As a result, there are also some variables which are related to these two main variables. So, $\varepsilon_h, L_h, E_h, P_{cu}^{h}$ all are variables.

No. of Parameters: Parameters are those whose values are known. In our problem, we have parameters. These are B, C, appliance current $I_{n,a}$, user voltage V_n, power factor angle $\theta_{n,a}$, operating time of appliance $T_{n,a}$, resistance of wire R_n.

No. of Constraints: Constraints are the conditions which will be imposed on the objective function to minimize our electricity generation cost. In our problem, we have nine constraints.

Our optimization problem is considered for all H, N and A.

3.7 Summary

In this chapter, we have studied on energy consumption modeling, user current modeling, loss modeling. Then we have showed the optimization problem considering system losses and other constraints. The analysis and complexity has been discussed later in this chapter.

Chapter 4
Solution Approach and Numerical Results

In this chapter, we have provided the approach of the simulation of our optimization problem. Then after we have shown the results we got after simulation. Later brief analysis of these results is given.

The idea behind the smart grid is an integrated intelligent network system which will solve the problems of the conventional grid system. To make a grid smarter and safer is a continuous process and requires many construction changes and adding intelligence to the existing grid [25]. If we consider the present grid system, the building blocks of a smart grid are shown below:

a. Grid
b. Software tool
c. Communication
d. Intelligent load
e. People awareness

If we consider a substation has 1000 families and each family have on average of 20 appliances. The total number of the appliance is 20000. The local server has to schedule the appliance with a view to making to demand curve flat whole period of a 24 hours' span.

So, to schedule the appliances we used a software tool to optimize the cost function. There are two purposes of the optimization

1. Reduce generation cost
2. Reduce peak demand and make the demand curve flat

4.1 Optimization

Maximizing or minimizing some function with respect to some constraints to determine the best choice of the different options is known as optimization [26]. So, optimization is an important mathematical program to optimize the resources. A grid without intelligence cannot be fully smart. It must have the capability of decision making. So, to make a grid smart programming approach is used. Optimization and artificial intelligence are mainly used to integrate intelligence in the grid network.

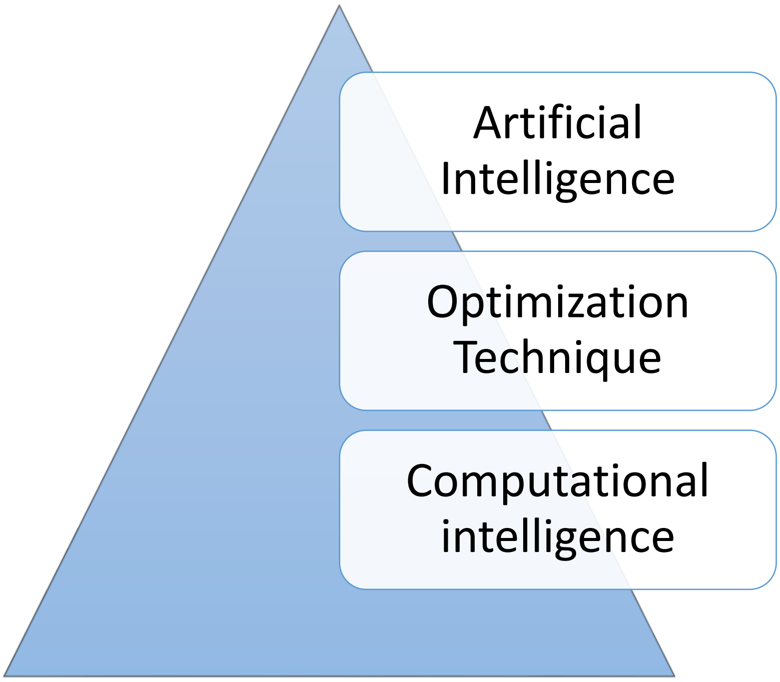


Figure 4.1: Features of optimization

4.1.1 How Optimization Works

The physical structure for the optimization requires a server and a processing unit to perform the optimization program. The server performs the data storage functionality. We all data available in a certain period of a day, the optimization program calculates according to predefined algorithms to find out the minimum and cost and optimum time schedule for each appliance. So, the process is based on only the data of a certain day.

4.1.2 How Artificial Intelligence Works

Artificial intelligence is the buzzword of the 21st century which mimics the human brain to solve a particular problem. Artificial intelligence is a software program which learns to solve problem as the same way a human child learn to overcome different problems. In the area of smart grid, artificial intelligence can bring revolution as it mimics human brain, so it will give a better result than optimization tool. But the main disadvantage of the artificial intelligence is, it requires much time to learn the way of solving and find out the minimum generation cost just like a human child needed to learn anything.

Artificial intelligence is out of scope in this thesis, for faster decision we will use different optimization tool.

4.1.3 Building Block of Optimization

The optimization problem requires few mandatory blocks to perform the operation. In the image given below is the main building block of optimization.

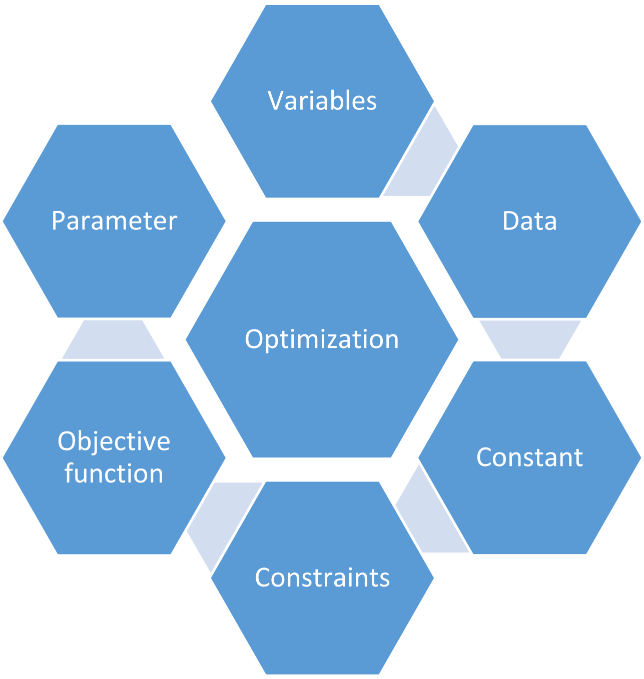


Figure 4.2: Building block of optimization

4.2 Optimization Solver

The use of optimization software requires that the function f is defined in a suitable programming language and connected at compile or run time to the optimization software. The optimization software will deliver input values in A, the software module realizing f will deliver the computed value f(x) and, in some cases, additional information about the function of derivatives [27].

In this manner, a clear separation of concerns is obtained: different optimization software modules can be easily tested on the same function f, or a given optimization software can be used for different functions f [27].

The following tables provide a list of optimization software organized according to license and business model type.

As we all know, there are many algorithms approaching solving problems. Here is a list of algorithms commonly used in solvers for a different type of problems.

4.2.1 MINOS

MINOS is a software package for solving large-scale optimization problems (linear and nonlinear programs) [28]. It is especially effective for linear programs and for problems with a nonlinear objective function and sparse linear constraints (e.g., quadratic programs).

4.2.2 CPLEX

The IBM ILOG CPLEX Optimizer solves integer programming problems, very large linear programming problems using either primal or dual variant of the simplex method or the barrier interior point method, convex and non-convex quadratic programming problems, and convex quadratically constrained problems (solved via second-order cone programming, or SOCP) [29].

4.3 Proprietary Software for Optimization

In our thesis, we will use Freeware software. The name of the software is AMPL. AMPL is a powerful language designed specifically for mathematical programming. To solve the optimization problem, the software package requires few files.

Table 4.1: Files needed for AMPL solver

File name	File Format
Model file	.mod
Data file	.dat
Run file	.run

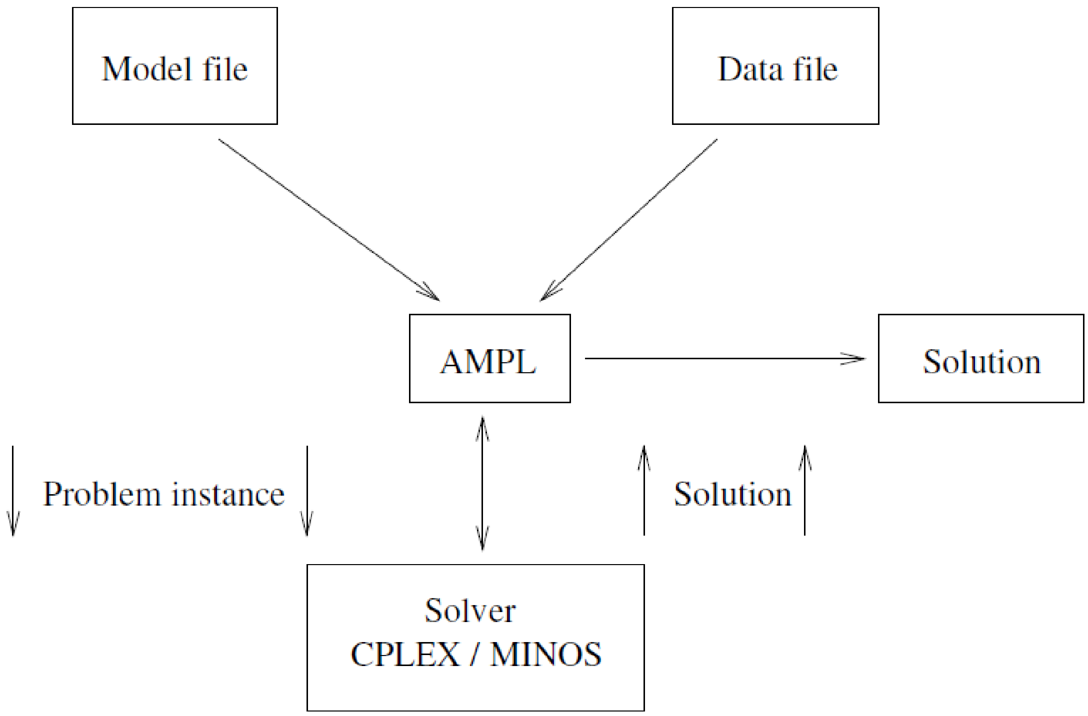


Figure 4.3: Flow chart of solving a problem through AMPL

4.3.1 Model File

Contains definition of indices, parameters, decision variables, objection functions, constraints.

4.3.2 Data File

The data file contains the parameter value, set elements, constraints values etc.

4.3.3 Run File

The run file contains which variable will be printed and which will not be printed etc.

We used AMPL to develop our model and run file. Using MATLAB 2016 we developed the run file.

In the optimization problem, if we consider 1000 subscriber and each subscriber has 20 appliances for 24 hours, the number of variable would be 480000 under one set. Unfortunately, the student version of AMPL limits upto 300 variables. For this reason, we used NEOS server to solve our optimization problem. In the below section, we will show few analytical results of our solution.

4.4 Power System and Parameters

In our system model, we needed few parameters. Some of these parameters are provided by users and some are provided by distributors.

The electricity generation cost varies different time of day. In the peak hour generation cost is higher than normal hour. Generation cost also varies depending on temperature.

Table 4.2: Parameters of the optimization problem

Parameter Name	Parameter Symbol
Electricity production cost during day time(USD/Unit)	B
Electricity production cost during night time(USD/Unit)	C
Average current through each appliance	$I_{n,a}$
Voltage across each user	V_n
Wire resistance of each user	R_n
Power factor angle of each appliance	$\theta_{n,a}$
Operating time of the appliance	$T_{n,a}$

4.5 Baseline Case

While calculating baseline case, we use the data generated by MATLAB. Appliance current $I_{n,a}$ is less than 1 ampere. User voltage V_n varies between 200 and 220 volts. Power factor of cosine is almost 1.00 for each case and power factor of sine varies between .01 and .31. Operating time period of appliance is considered 1 hr., 2 hrs. and 3 hrs. for different cases. Using these randomly generated data we calculate the cost for the baseline case.

4.6 Numerical Results

In this section using random function, we generate the appliances' data, and randomly schedule the data and calculate the generation cost for baseline case. Then using the online solver, we find out the optimized generation cost. In the below section, we will demonstrate the generation cost for a different number of subscribers and appliances.

4.6.1 Case I

<u>3 subscribers each having 4 appliances</u>

In our model, the example power system at Fig. 3.1 is assumed to have 3 load subscribers, N=3 and each subscriber is selected randomly to have 4 appliances, A=4. Such appliances include refrigerator-freezer (daily usage: 1.32 kWh), electric stove (daily usage: 2.01 kWh), heating (daily usage: 7.1 kWh), dishwasher (daily usage: 1.49 kWh) etc. [4]. In Fig. 4.4.1, we see that optimized cost is less than the baseline case cost in each sample. Fig. 4.4.2 shows that percentage of cost reduction for different samples.

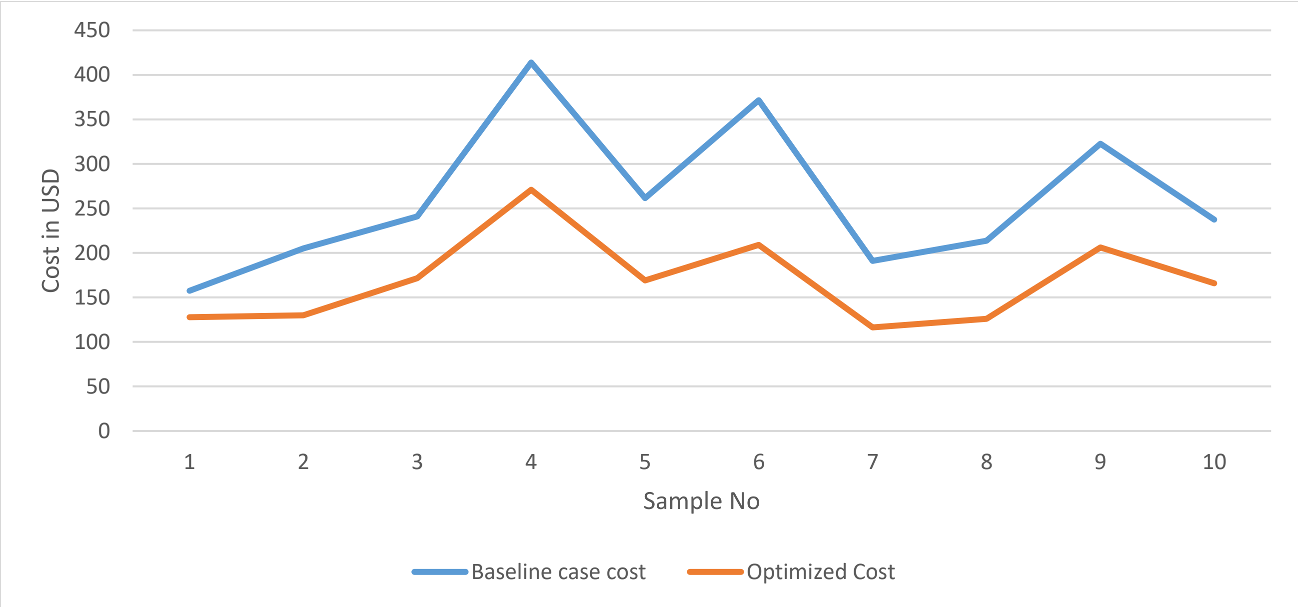


Figure 4.4.1: Comparison between baseline case cost and optimized cost for 3 subscribers & 4 appliances

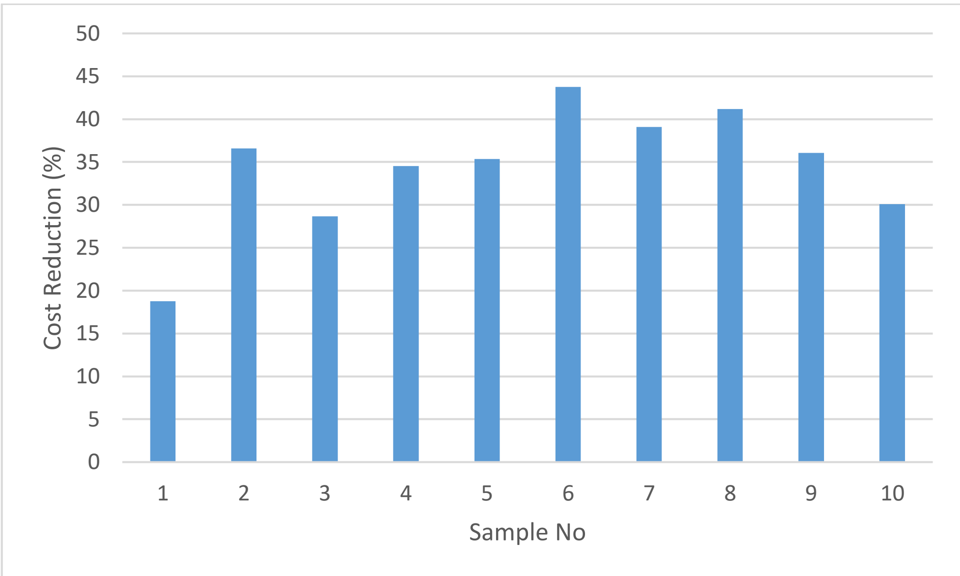


Figure 4.4.2: Percentage of cost reduction for different samples in case I

4.6.2 Case II

<u>5 subscribers each having 3 appliances</u>

In our model, the example power system at Fig. 3.1 is assumed to have 5 load subscribers, N=5 and each subscriber is selected randomly to have 3 appliances, A=3. Such appliances include electric stove (daily usage: 2.01 kWh), heating (daily usage: 7.1 kWh), dishwasher (daily usage: 1.49 kWh) etc. [4]. In Fig. 4.5.1, we see that optimized cost is less than the baseline case cost in each sample. Fig. 4.5.2 shows that percentage of cost reduction for different samples.

Figure 4.5.1: Comparison between baseline case cost and optimized cost for 5 subscribers & 3 appliances

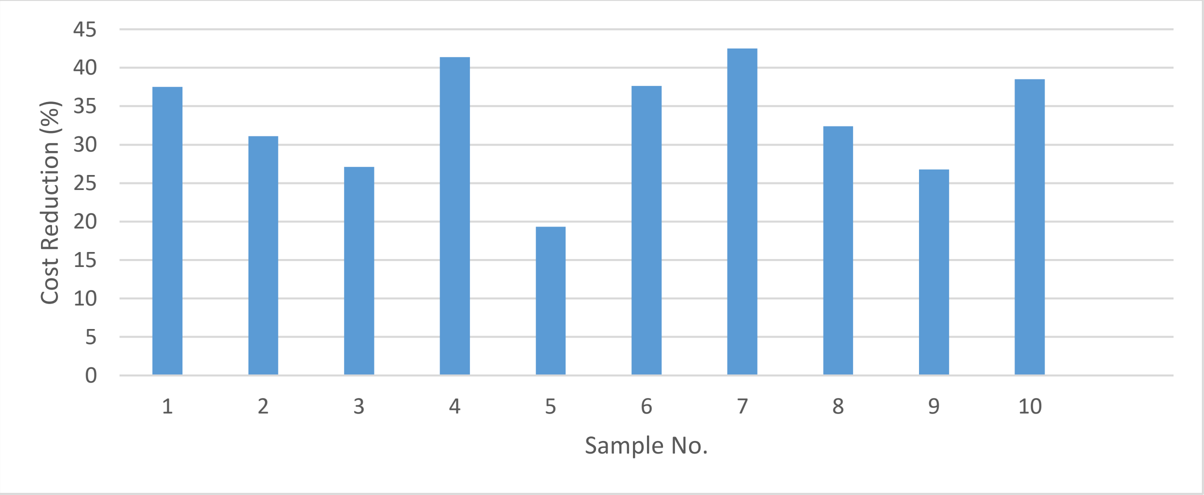


Figure 4.5.2: Percentage of cost reduction for different samples in case II

4.6.3 Case III

<u>10 subscribers, each having 4 appliances</u>

In our model, the example power system at Fig. 3.1 is assumed to have 10 load subscribers, N=10 and each subscriber is selected randomly to have 4 appliances, A=4. Such appliances include refrigerator-freezer (daily usage: 1.32 kWh), electric stove (daily usage: 2.01 kWh), heating (daily usage: 7.1 kWh), dishwasher (daily usage: 1.49 kWh) etc. [4]. In Fig. 4.6.1, we see that optimized cost is less than the baseline case cost in each sample. Fig. 4.6.2 shows that percentage of cost reduction for different samples.

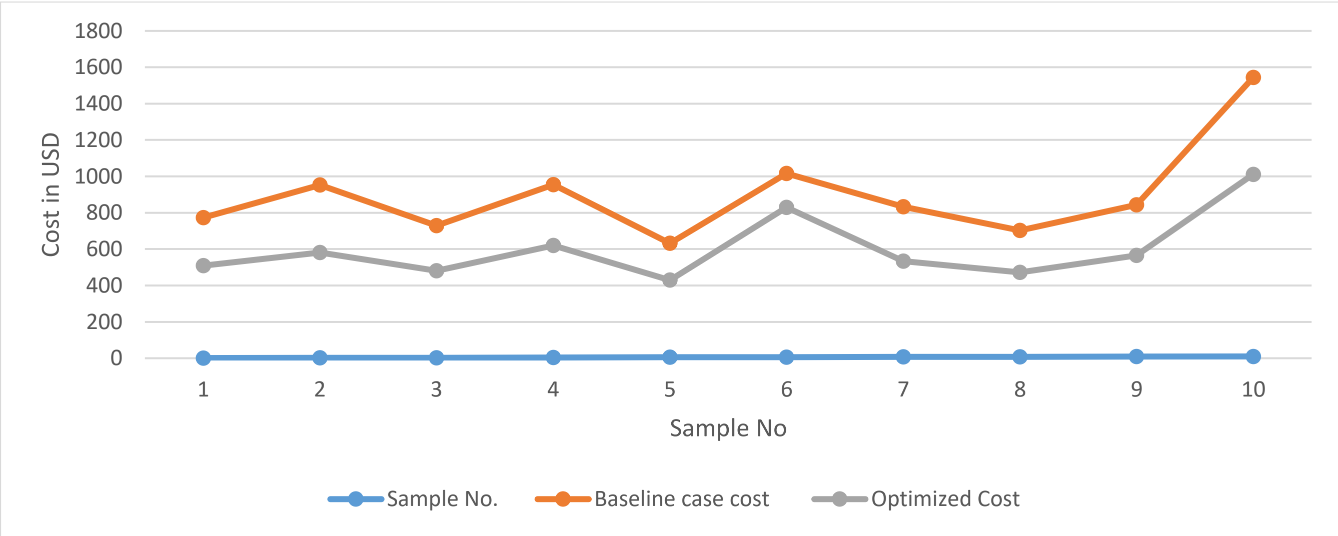


Figure 4.6.1: Comparison between baseline case cost and optimized cost for 10 subscribers & 4 appliances

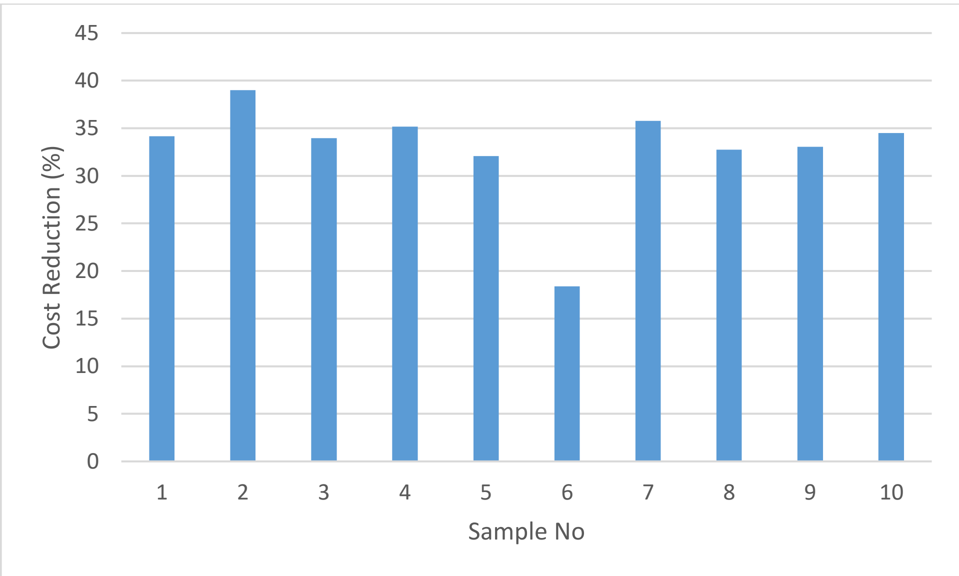


Figure 4.6.2: Percentage of cost reduction for different samples in case III

4.6.4 Case IV

<u>20 subscribers, each having 5 appliances</u>

In our model, the example power system at Fig. 3.1 is assumed to have 20 load subscribers, N=20 and each subscriber is selected randomly to have 5 appliances, A=5. Such appliances include refrigerator-freezer (daily usage: 1.32 kWh), electric stove (daily usage: 2.01 kWh), heating (daily usage: 7.1 kWh), dishwasher (daily usage: 1.49 kWh), clothes dryer (daily usage: 2:50 kWh) etc. [4]. In Fig. 4.7.1, we see that optimized cost is less than the baseline case cost in each sample. Fig. 4.7.2 shows that percentage of cost reduction for different samples.

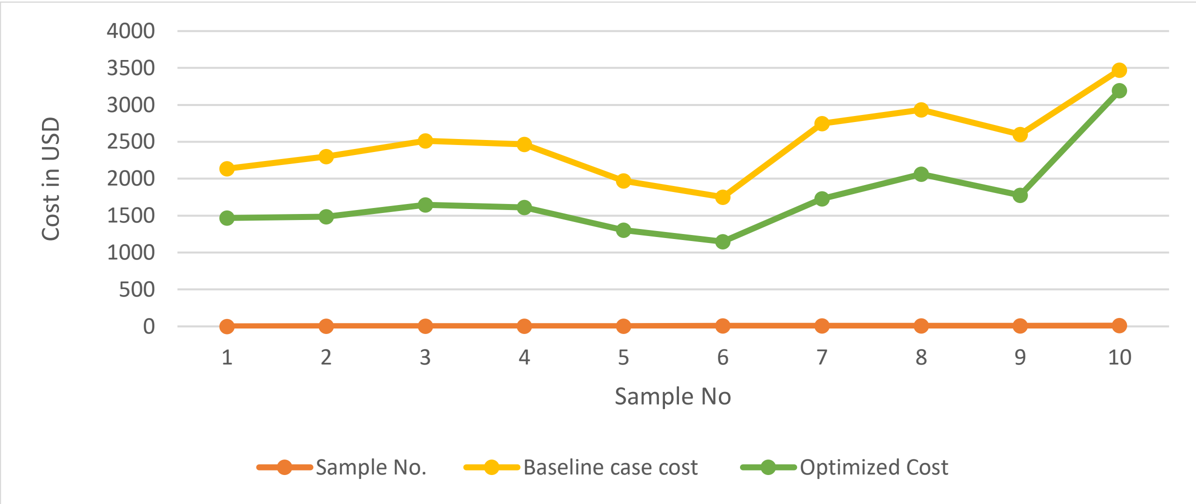


Figure 4.7.1: Comparison between baseline case cost and optimized cost for 20 subscribers & 5 appliances

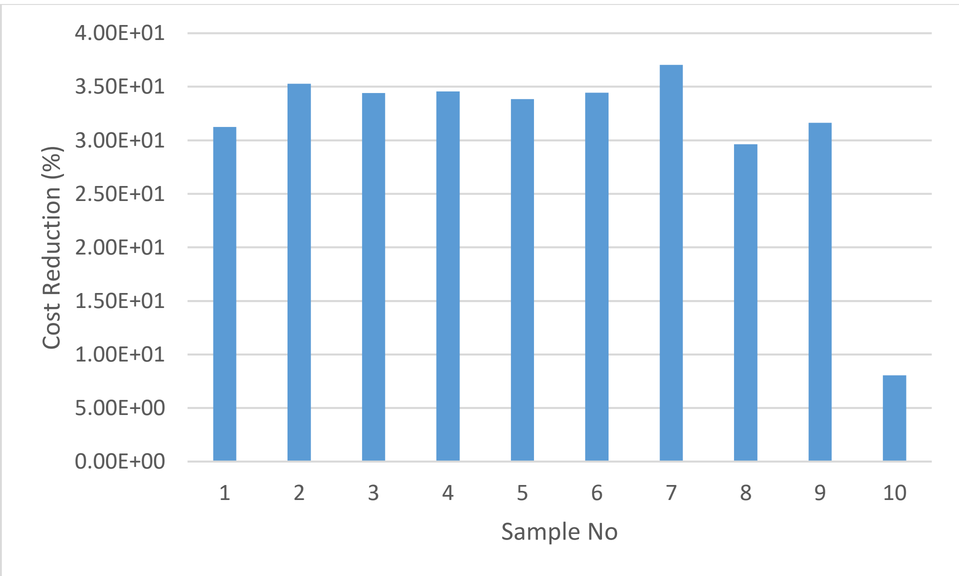


Figure 4.7.2: Percentage of cost reduction for different samples in case IV

4.6.5 Case V

<u>50 subscribers, each having 6 appliances</u>

In our model, the example power system at Fig. 3.1 is assumed to have 50 load subscribers, N=50 and each subscriber is selected randomly to have 6 appliances, A=6. Such appliances include refrigerator-freezer (daily usage: 1.32 kWh), electric stove (daily usage: 2.01 kWh), heating (daily usage: 7.1 kWh), dishwasher (daily usage: 1.49 kWh), PHEV (daily usage: 9.9 kWh), clothes washer (daily usage: 1.94 kWh), etc. [4]. In Fig. 4.8.1, we see that optimized cost is less than the baseline case cost in each sample. Fig. 4.8.2 shows that percentage of cost reduction for different samples.

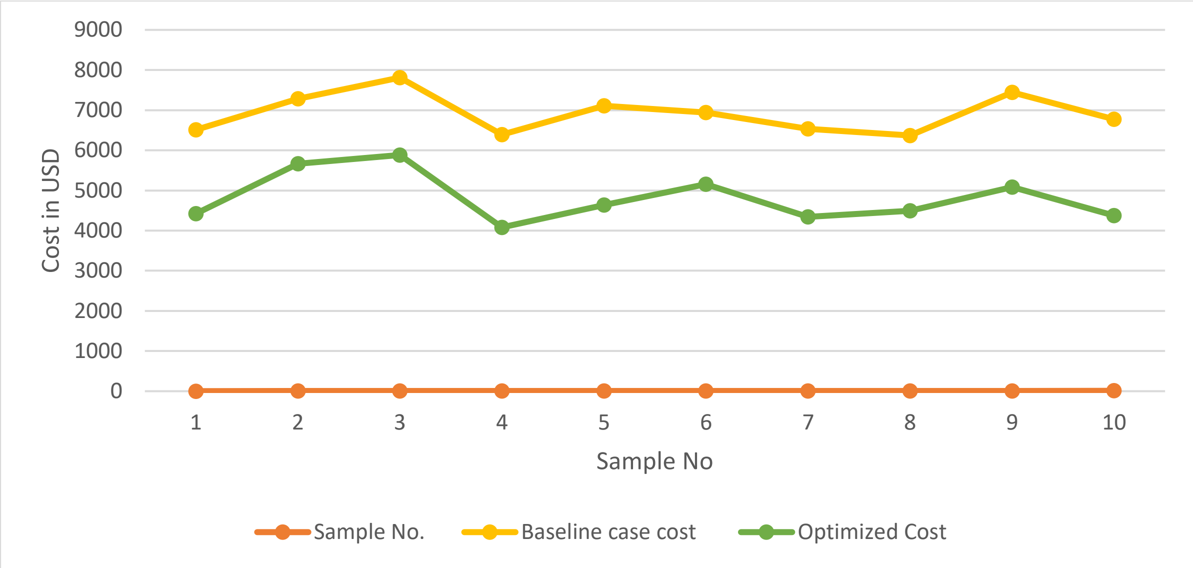


Figure 4.8.1: Comparison between baseline case cost and optimized cost for 50 subscribers & 6 appliances

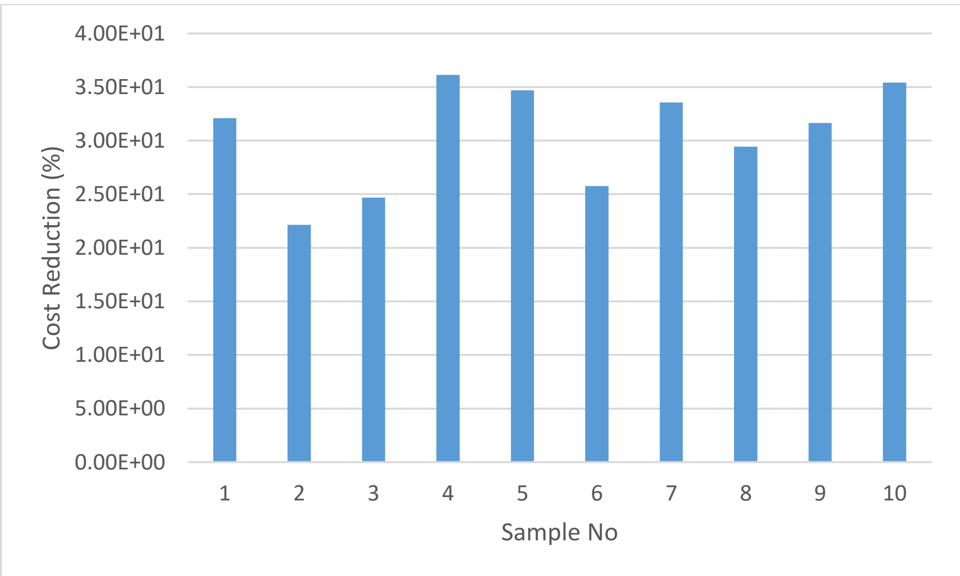


Figure 4.8.2: Percentage of cost reduction for different samples in case V

4.7 Cost Reduction at Different Cases

From the below graph we can see that the average percentage of generation cost decreases when the subscribers and appliances increase. This is because increasing number of subscribers and appliances increase the losses in the system. This indicates that considering all the losses in smart grid is necessary for higher loading condition.

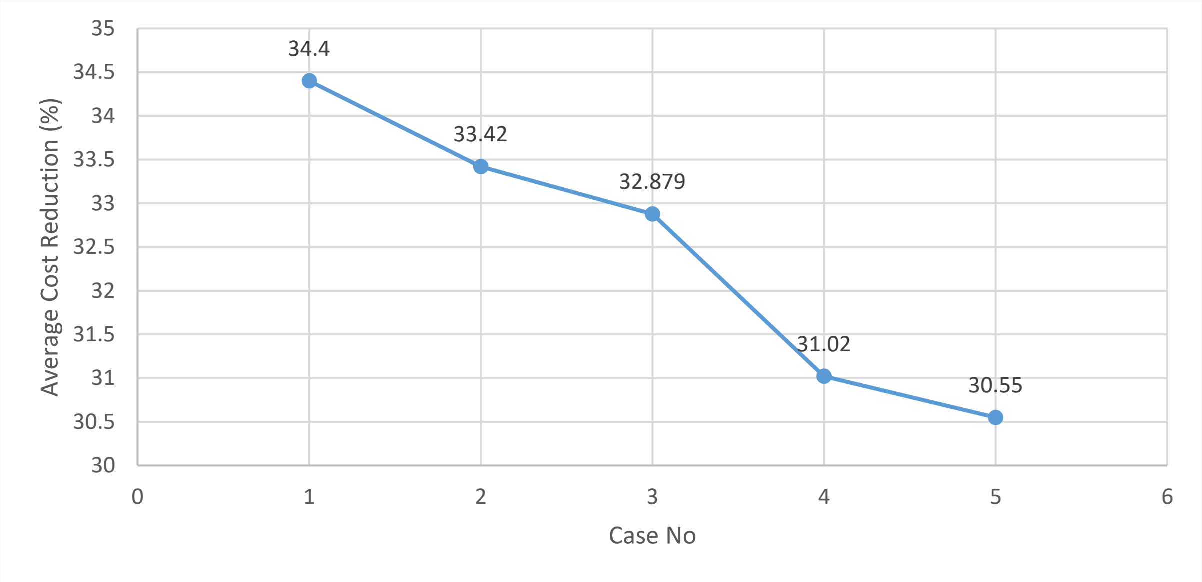


Figure 4.9: Average percentage of cost reduction for different cases

4.8 Cost Comparison Without Loss and With Loss

Suppose, we consider a case with 10 load subscribers and each subscriber has 4 appliances. Fig. 4.10 shows the comparison of cost without loss and with loss for baseline case cost. Fig. 4.11 shows the comparison of cost without loss and with loss for optimized cost. We see cost with loss is more than that of without loss.

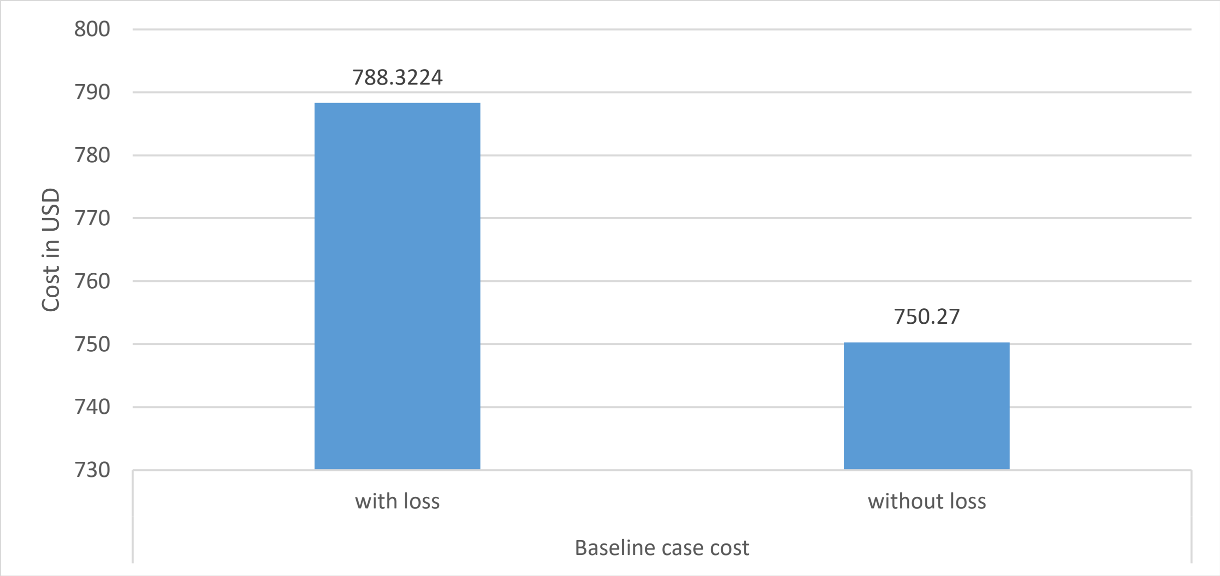


Figure 4.10: Comparison of cost without loss and with loss for baseline case cost

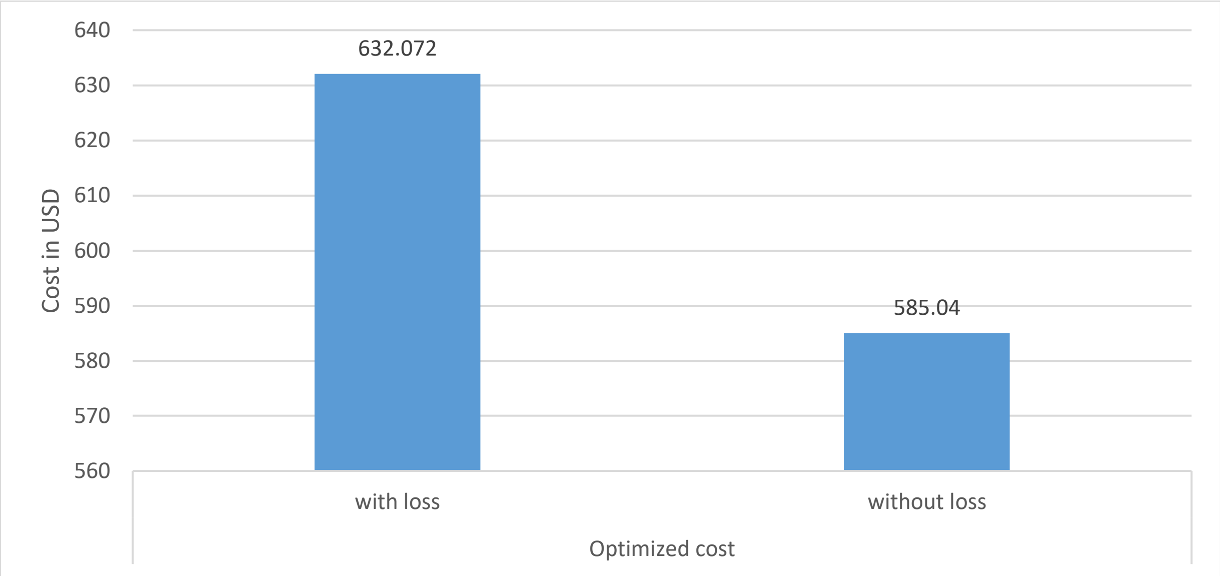


Figure 4.11: Comparison of cost without loss and with loss for optimized cost

4.9 Summary

In this chapter, we have discussed on solution process of optimization. Also, we have got introduced to solver for optimization like MINOS, CPLEX. Then numerical results and its analysis are given for different cases.

Chapter 5
Conclusion and Future Work

In this chapter, we have discussed the conclusion of our thesis. Some future expansion of this model is also demonstrated.

5.1 Conclusion

In this paper, we proposed a load scheduling problem considering generation loss, transmission loss, line loss and other losses. An effective optimization problem of our system model has been established considering some constraints. By using MATLAB, we generated data file which is later used in solver to solve the optimization problem. Since we used the student version of solver we could not solve above 300 variables, as a result we had to get the results through NEOS solver on the internet. The results show that our optimization is reducing the generation cost significantly (around 30-35%). So, we can say our optimization is cost-effective.

Our proposed architecture is also effective for monitoring and optimizing energy utilization. The system design concentrates on single phase electric distribution system. Moreover, our system can provide some solution faced by the existing power grid in Bangladesh such as wastage of energy.

5.2 Future Research Scope

The following thesis works can be undertaken as expansions of our model:

1) With minor modifications, our system can be used for line fault and power theft detection by using different sensors.
2) This model will help to reduce the energy wastage and save a lot of energy for future use.
3) Two-way communication is possible between user and power station. Cloud computing can be used to create database and monitor the consumption of large area.
4) It is possible to enhancement the system in future to suit this for three-phase electric distribution system.
5) We will reduce peak demand which also reduces generation cost.
6) Combining Artificial Intelligence with optimization, we fulfill the human demand on time.

Bibliography

[1] "NEOS Server for Optimization", *Neos-server.org*, 2017. [Online]. Available: https://neos-server.org/neos/.

[2] 2011. [Online]. Available: https://www.ieee.org /documents/ieee_smart_grid_ whitepaper_ sept2011.pdf.

[3] "Advanced Metering Infrastructure and Customer Systems - SGDP Program", *Smartgrid.gov*. [Online]. Available: https://www.smartgrid.gov/ recovery act/ deployment _ status/sdgp_ami_systems.html.

[4] "Frequently Asked Questions: Real-Time Pricing | Galvin Electricity Initiative", *Galvinpower.org*. [Online]. Available: http://galvinpower.org/power-consumers/act/real-time-illinois/faq.

[5] "Demand Response | Department of Energy", *Energy.gov*. [Online]. Available: https: // energy.gov/oe/services/technology-development/smart-grid/demand-response.

[6] S. Trochaniak, "What is Smart Charging? (with infographic)", *FleetCarma*, 2015. [Online]. Available: http://www.fleetcarma.com/what-is-smart-charging/.

[7] "Wiley: Integration of Distributed Generation in the Power System - Math H. Bollen, FainanHassan", *As.wiley.com*,2011. [Online]. Available: http://as.wiley.com/WileyCDA/ Wiley Title/productCd-0470643374.html.

[8] "Distribution Automation (DA) - NEMA", *Nema.org*. [Online]. Available: https://www. nema.org/Policy/After-the-Storm/Pages/Distribution-Automation.aspx.

[9] X. Fang, S. Misra, G. Xue and D. Yang, "Smart Grid — The New and Improved Power Grid: A Survey", *IEEE Communications Surveys & Tutorials*, vol. 14, no. 4, pp. 944-980, 2012.

[10] [Online]. Available: http://www.openelectrical.org/wiki/index.php?title=Load_Schedule.

[11] A. Mohsenian-Rad, V. Wong, J. Jatskevich and R. Schober, "Optimal and autonomous incentive-based energy consumption scheduling algorithm for smart grid", *2010 Innovative Smart Grid Technologies (ISGT)*, 2010.

[12] S. Yue, D. Zhu, Y. Wang and M. Pedram, "Distributed load demand scheduling in smart grid to minimize electricity generation cost", *2014 IEEE PES General Meeting | Conference & Exposition*, 2014.

[13] S. Abras, S. Pesty, S. Ploix and M. Jacomino, "An Anticipation Mechanism for Power Management in a Smart Home using Multi-Agent Systems", *2008 3rd International Conference on Information and Communication Technologies: From Theory to Applications*, 2008.

[14] A. Cohen and C. Wang, "An optimization method for load management scheduling", *IEEE Transactions on Power Systems*, vol. 3, no. 2, pp. 612-618, 1988.

[15] W. Hu, Z. Chen and B. Bak-Jensen, "Optimal Load Response to Time-of-Use Power Price for Demand Side Management in Denmark", *2010 Asia-Pacific Power and Energy Engineering Conference*, 2010.

[16] Z. Luo, R. Kumar, J. Sottile and J. Yingling, "An MILP Formulation for Load-Side Demand Control", *Electric Machines & Power Systems*, vol. 26, no. 9, pp. 935-949, 1998.

[17] A. Middelberg, J. Zhang, and X. Xia, "An optimal control model for load shifting--With application in the energy management of a colliery", *Applied Energy*, vol. 86, no. 7, pp. 1266--1273, 2009.

[18] A. Mohsenian-Rad, V. Wong, J. Jatskevich and R. Schober, "Optimal and autonomous incentive-based energy consumption scheduling algorithm for smart grid", *2010 Innovative Smart Grid Technologies (ISGT)*, 2010.

[19] S. Ashok and R. Banerjee, "An Optimization Model for Industrial Load Management", *IEEE Power Engineering Review*, vol. 21, no. 10, pp. 63-63, 2001.

[20] J. Roos and I. Lane, "Industrial power demand response analysis for one-part real-time pricing", *IEEE Transactions on Power Systems*, vol. 13, no. 1, pp. 159-164, 1998.

[21] A. Mohsenian-Rad and A. Leon-Garcia, "Optimal Residential Load Control with Price Prediction in Real-Time Electricity Pricing Environments", *IEEE Transactions on Smart Grid*, vol. 1, no. 2, pp. 120-133, 2010.

[22] A. Conejo, J. Morales and L. Baringo, "Real-Time Demand Response Model", *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp. 236-242, 2010.

[23] J. E. Braun, “Load Control Using Building Thermal Mass”, *Transactions-American Society of Mechanical Engineers Journal of Solar Energy Engineering*, vol. 125, no. 3, pp. 292--301, 2003.

[24] Rahman, "Transformers", *Slideshare.net*, 2014. [Online]. Available: https: //www.slideshare.net/towfiqeee/transformers-31083011.

[25] Utilityproducts.com, 2012. [Online]. Available: http:// www.utilityproducts.com /articles /2012/11/power-networks-made-safer-and-more-efficient.html.

[26] "Mathematical optimization", *En.wikipedia.org*. [Online]. Available: https:// en. wikipedia .org/ wiki/Mathematical_ optimization.

[27] "List of optimization software", *En.wikipedia.org*. [Online]. Available: https:// en. wikipedia.org/wiki/List_of_optimization_software.

[28] "MINOS 5.5", *Sbsi-sol-optimize.com*. [Online]. Available: http://www.sbsi-sol-optimize .com/asp/sol_product_minos.htm.

[29] "CPLEX", *En.wikipedia.org*. [Online]. Available: https://en.wikipedia.org/wiki/CPLEX.