ALGORITHM FOR OPTIMAL LOAD MANAGEMENT IN SMART HOME INTEGRATED WITH RENEWABLE ENERGY

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Engineering in Electrical Engineering

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วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรมหาบัณฑิต
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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for a Master's Degree.

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HUSSEIN SWALEHE : อัลกอลิทึมของการจัดการโหลดที่เหมาะสมสำหรับบ้านอัจฉริยะด้วยพลังงานหมุนเวียน (ALGORITHMS FOR OPTIMAL LOAD MANAGEMENT IN SMART HOME INTEGRATED WITH RENEWABLE ENERGY) อาจารย์ที่ปรึกษา : ผู้ช่วยศาสตราจารย์ ดร.บุญเรือง มะรังศรี, 175 หน้า.

หนึ่งในปัจจัยที่ส่งผลต่อระบบไฟฟ้าคือความต้องการการใช้งานที่เพิ่มขึ้น โดยปกติแล้วถ้าการใช้พลังงานไฟฟ้ามากขึ้นจะทำให้ระบบไฟฟ้าขาดความสมดุลแล้วจ่ายพลังงานไฟฟ้าไม่เพียงพอต่อผู้ใช้งาน ดังนั้นเพื่อให้ระบบมีเสถียรภาพและเพียงพอต้องความต้องการ ต้องมีการหาจุดที่เหมาะสมและดีที่สุดของอุปสงค์และอุปทาน จากการสำรวจในปี 2554 พบว่าผู้คนใช้พลังงานประมาณ 50% ของพลังงานทั้งหมด และจากนั้นค่าอุปสงค์ก็เริ่มเข้าใกล้ค่าอุปทานมากขึ้นทุก ๆ ปี ดังนั้นในงานวิทยานิพนธ์นี้จึงมีจุดประสงค์ในเรื่องการกำหนดเวลาเพื่อลดต้นทุนและโหลดสูงสุดจากอุปสงค์ที่เพิ่มขึ้นในบ้านอัจฉริยะที่ผสมผสานกับระบบพลังงานหวุนเวียน พลังงานหมุนเวียนเริ่มกลายเป็นส่วนสำคัญที่ช่วยเพิ่มระดับของการใช้พลังงานได้สูงขึ้น การจัดเก็บพลังงานนี้ก็เป็นอีกทางเลือกหนึ่งเช่นกัน โดยเฉพาะเทคโนโลยีทางด้านแบตเตอรี่และทางเลือกในการส่งออกพลังงานที่หลากหลาย รวมไปถึงการใช้ซอฟต์แวร์ประยุกต์ที่หลากหลาย อะกอลิทึมการจัดการความต้องการโหลดได้พัฒนาด้วยโปรแกรมสำเร็จรูปซึ่งจะช่วยลดควบคุมการใช้จ่ายโดยการจัดการการทำงานตามการควบคุมตามข้อมูลกลุ่มของผู้ใช้ เทคนิคที่ใช้ในการจัดการนี้คือ ผลการจำลองพบว่าเทคนิคนี้สามารถลดค่าไฟฟ้าได้ถึง 40% เมื่อไม่มีชุดพลังงานทดแทน แต่เมื่อมีชุดพลังงานทดแทนต่อร่วมด้วยจะสามารถลดค่าไฟฟ้าได้ถึง 53% และจะสูงถึง 66% เมื่อชุดพลังงานหมุนเวียนมีชุดกักเก็บพลังงานซึ่งได้นำไปเทียบกับราคาของ TOU แล้ว การลดค่าไฟฟ้าหมายถึงการลดความต้องการใช้ไฟฟ้าของผู้ใช้เฉพาะที่สามารถให้บริการได้ในช่วงที่มีความต้องการสูงสุด ในทางตรงกันข้าม WOA สามารถนำไปใช้ในการตั้งเวลาเครื่องใช้ไฟฟ้าในครัวเรือนในการลดค่าไฟฟ้าและการลดความต้องการสูงสุดจากด้านอุปสงค์ได้อีกด้วย

สาขาวิชา วิศวกรรมไฟฟ้า ลายมือชื่อนักศึกษา

ปีการศึกษา 2560 ลายมือชื่ออาจารย์ที่ปรึกษา

HUSSEIN SWALEHE : ALGORITHMS FOR OPTIMAL LOAD MANAGEMENT IN SMART HOME INTEGRATED WITH RENEWABLE ENERGY. THESIS ADVISOR : ASST. PROF. BOONRUANG MARUNGSRI, D.ENG, 175 PP.

SMART HOME/APPLIANCE SCHEDULING/RENEWABLE ENERGY/ BATTERY ENERGY STORAGE/OPTIMIZATION

One of the essential factor for the better operation of an electrical power system is load demand. Normally, higher load demand leads to instability and insufficient power supply. To make an electrical power system stable and sufficient, a good correlation between demand and supply should exist. A survey conducted during 2011 indicated that residential sector is consuming 50% of total energy. Also, the demand was seen to increase rapidly close to and sometimes beyond the supply. Hence, this research focuses on appliance scheduling for cost reduction and peak load reduction by increasing demand-side response in the smart home integrated with renewable energy. Renewable energy integration became a significant issue as renewable penetration levels increase and will require new generation support infrastructure; Energy storage provides one solution to this issue. Specifically, battery technologies offer a wide range of energy and power output abilities, making them ideal for a variety of integration applications. Peak shaving using distributed small (residential) energy storage can provide a reduction in peak loads and help renewable energy integration. A load management algorithm is developed in MATLAB which reduces both cost and peak load consumption by managing the operation according to utility controls and consumer preferences. The optimization problem was solved by using Whale Optimization Algorithm (WOA). The simulation results depicted a reduction of up to 40% in electric bill when scheduling electrical appliances without renewable energy source; up to 53% with renewable energy; and up to 66% when renewable energy with battery energy storage is considered with respect to Time-of-Use (TOU) pricing. The reduction in electric bill indicated the cutback of load demand from the specific user which can serve during severe peak demand. On the other hand, WOA can be adopted for appliance scheduling in the household, reduction of electric bill as well as cutback of peak demand from the demand side.

School of Electrical Engineering　　Student's Signature ______

Academic Year 2017　　Advisor's Signature ______

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LIST OF ABBREVIATIONS

AMI	Advanced Metering Infrastructure
AMR	Automatic Meter Reading
BESS	Battery Energy Storage System
BMS	Battery Management System
CPP	Critical Peak Pricing
DERs	Distributed Energy Resources
DG	Distributed Generation
DLC	Direct Load Control
DR	Demand Response
DSB	Demand Side Bidding
DoE	Department of Energy
DSM	Demand Side Management
EMS	Energy Management System
EPRI	Electric Power Research Institute
E/P	Performance Ratio
ESS	Energy Storage System
EV	Electric Vehicle
HAN	Home Area Network
HEMS	Home Energy Management System
IEA	International Energy Agency

LIST OF ABBREVIATIONS (Continued)

IPART	Independent Pricing and Regulatory Tribunal
LM	Load Management
MILP	Mixed Integer Linear Programming
PLMA	Peak Load Management Alliance
PG&E	Pacific Gas & Electric Company
PV	Photo-Voltaic
RES	Renewable Energy Sources
RTP	Real Time Pricing
SEA	Swedish Energy Agency
SA	Smart Appliance
SG	Smart Grid
SH	Smart Home
SM	Smart Meter
TLDC	Tariff with Load Component
TOU	Time of Use
VRB	Vanadium Redox Battery
WOA	Whale Optimization Algorithm

CHAPTER 1

INTRODUCTION

1.1 General Introduction

In the electrical power system, load demand plays an important role of maintaining the stability of the system. A good proportionality between demand (consumption) and supply (generation) should hold in order to avoid generation disturbances which later introduces negative effects in technical, economic and social areas (Davda, Desai, and Parekh, 2011). The rapid rise of energy needs has made electric utility companies to expand generation plants with respects to peak demand rather than average power in order to meet the consumer's demand (Goyal, and Shimi, 2017). This approach, unfortunately, renders power systems highly underutilized and customers' consumption patterns increasingly irresponsible. Additionally, it has driven utility companies to make huge long-term investments in new generation power plants which are mostly and typically based on traditional (conventional) energy sources. Such power plants – in addition to being capital intensive – lead to increased Greenhouse Gases (GHG) emissions that greatly affect the earth's temperature, changes in weather, sea level, and land use patterns (Swathi, Balasubramanian, and Veluchamy, 2016). Efficient utilization and special consideration of the optimal plant generation capabilities must be employed in order to improve the under-perfoming available generating plants without building new power plants (Abaravicius, 2007; Won and Song, 2013). Nowadays, load management has been accepted worldwide as the simplest, safest and cheapest technique that provide a better correlation between generation and load by performing load management practices on demand side loads through demand reduction or reshaping the load profile. Usually, load management practice aims to shift the load from on-peak period to off-peak period so as to reshape the load profile which in-turn reduces the total cost of electricity. Through energy management-based researches, an electrical engineer can cut costs of power system operation through utilization of optimal available generation capacity. Figure 1.1 depicts simple diagram of energy production, transport and distribution grid.

A survey conducted during 2011 indicated that 50% of total energy is being consumed by residential sector (SEA, 2005). Due to this reason, this thesis target on scheduling home appliances (HAs) in the smart home integrated with renewable energy. SH appliances are connected to HAN to coordinate power usage demanded the home under control. Load management is an essential key factor in SG for scheduling home appliances (HAs) in the smart home. A modern technology, with sophisticated metering infrastructure, can allow a two-way transmission of information between the utility company and the consumer through metering unit to enable a smooth aggressive load deviation (Qayyum et al., 2015). Regarding this direction, demand-response (DR) programs give incentives to significant costumers, generally in terms of money, to minimize their energy use during on-peak periods (Salma, 2012). Demand Response appear at a very fast timescale, approximately real-time, it results to a stable and sufficient power grid system and importantly minimizes electric cost and CO_2 emissions (Qayyum et al., 2015).

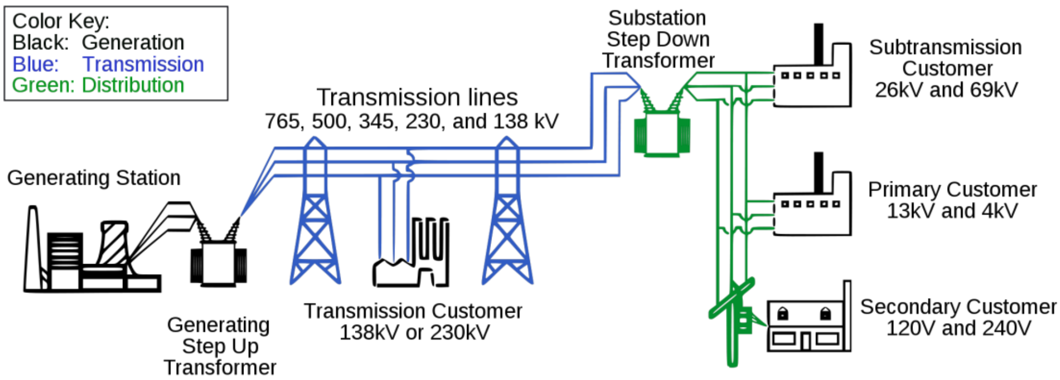


Figure 1.1 Simple diagram of energy production, transport and distribution grid (Capasso et al., 1994).

SG, in the growing power system technology, is currently considered as an upcoming solution to the most of the existing power systems. It comes in different names such as smart power grid or intelligent grid (Goyal and Shimi, 2017) to take over an old, disorganized and defenseless existing power system. An efficient performance of smart grid depends on the advanced technologies in electrical power, control, communication, information theory, bi-directional flows of electrical power and information which promotes an advanced and modern power system with cost-effective, safety and security. In smart grid, advanced energy-metering infrastructure (AMI) and energy monitoring are performed over a number of smart meters and sensors equipped all the way in smart homes. The part of communication as well as networking technologies ensure real time data collection and transmission to and fro both sides. In smart grid (SG) system, the load management is an essential factor to control energy management system. Through load management strategies in smart grid (SG), reduction of peak load during the peak period and control pricing of electricity unity can be achieved through customer participation in the smart home

(Tammam et al., 2013; Chen et al., 2013; Chen et al., 2012; Black and Tyagi, 2010; Palensky and Dietrich, 2011; Albadi and EI-Saadany, 2008; Caves, Eakin, and Faruqui, 2000). The usage of photovoltaic system causes a reduction of electric bill and the peak demand at home. Moreover, excessive generated energy can be added to the smart grid from the smart home (Ackerman et al., 2001; Pepermans, 2005; Twidell, 2003).

Smart Home is the computerized controls in homes and appliances that can be set up to respond to signals from the energy provider to reduce their energy use at times when the power grid is unstable from high peak load demand, or even to shift some of their power use (energy consumption) to times when power is available at a lower cost. Customer participation is an important feature in SH. The enabling component is a smart meter, which is also the bridge between smart home (SH) and SG. Smart meters no longer perform only as a data collector for utility companies, they play quite different roles for both customers and the grid. On the consumer side, smart meter serves as a controller in SH. In the future SH, the appliances are equipped with communication capabilities and are controlled by the smart meter through the in-home networking system. New smart appliances are deployed with the plug-and-play scheme with specific interfaces. All the information can be displayed through a controller on a displayable control panel. The SH control provides users many optional functions according to users' preferences, such as energy saving, loss reduction, money saving, and low carbon.

With small renewable generation and energy storage equipment, future SH operates like a small power system or a small connected MG. Also, the hybrid DC/AC distribution system will be realized and enhanced in the future SH to use both DC power and AC power. In short, the future SH will be a highly integrated system featuring high automation, customer preferences, low carbon and energy efficiency, which will bring us much convenience, health, relax, and sustainability. The effect of integrating renewables into the smart home results in a reduction of electricity bill, power loss and the peak demand of the home and export of energy to the smart grid in times when renewable energy production is more than the demand of the home.

1.2 Problem Statement

Load demand is an essential factor in the electrical power system. Demand (consumption) and supply (production) should constantly be balanced to avoid supply interruptions with all their negative technical, economic and social consequences. Problems with energy shortage and peak power shortage in the main grid in the past often were addressed at the generation side (power plants) and solved by building new power plants. However, a continuous expansion meets nowadays more and more economical (capital and fuel scarcity), Gestation period and environmental restrictions. The need for an option to handle peak load problem is by employing Load Management (LM). A survey conducted during 2011 indicated that residential sector is consuming 50% of total energy. Due to this reason, this thesis target on scheduling home appliances (HAs) in the smart home (SH). Smart home (SH) appliances are connected to home area network (HAN) to coordinate power usage demanded the home under control. Load management is an essential key factor in smart grid (SG) for scheduling home appliances (HAs) in the smart home (SH). The direction of how to handle peak demand problems together with new conditions of liberalized electricity markets moved more towards the demand side/customer in the smart home. The energy industry and policymakers acknowledge the demand side potentials in minimizing peak load and electricity cost are looking for the ways to influence consumer flexibility through different peak load reduction strategies. Demand Side Management can adopt the electrical energy consumption by acting on the behavior of the loads. Nowadays the control of loads is based on different tariff schemes to motivate the customer to move its consumption. Smart grid (SG) makes possible monitoring and control of those individual electrical loads.

The research focuses on the demand side in the smart home (SH) that could reduce peak load, and cost in the electrical system by using customer flexibility, i.e., by increasing the demand side response (DR) to signals coming from the energy market. The primary objective is to use different strategies to reduce peak load on the demand side considering their techno-economic, environmental and social. Modern metering and communication systems enable utilities (suppliers) to undergo direct load control measures and to perform demand response (DR). As the experiments with direct load control (DLC) at residential consumers show, these measures could be implemented without important comfort losses for the customers. However, the value of this type of demand-side actions needs to be expressed or quantified both for the customers and the supplier.

Load reduction strategies at the demand-side could govern the environmental performance of an energy system by reducing emissions and avoid the distortion of territories. Although, it should be indicated that the environmental effects depend on the prevalent generation and transmission system and could be different on different levels-regional, national and local. The implementation of these systems improves the use of renewable energy in the distribution network and can help to reduce peak load, power loss and consumer electrical bill.

1.3 Objective

The objective of this research is to come out with appliance scheduling program integrated with renewable energy, which reduces peaking in the electric grid and reduces individual household electricity bill in the community by increasing the demand side response to signals coming from the energy market.

Therefore, the specific objectives of this research are:

a) To propose a community-based appliance scheduling program to obtain cost savings with respect to Time-Of-Use (TOU) tariffs for individual households in the community by optimizing energy consumption.

b) To analyze the impact of this scheduling program on peak demand side and on the power profile of the community as a whole by considering their techno-economic, environmental and behavioral aspects during the peak period.

c) To find out how the integration of renewable energy will complement to meet the energy needs of the household.

1.4 Motivation of the Thesis

The energy industry acknowledges the potential for demand-side actions in reducing peak load and cost savings. It is looking for peak load reduction strategies to manage peak load situations. Traditionally, when considering load demand problems, the focus was on the larger industrial electricity users. The industrial sector has already adopted different load management strategies. However, in most countries, the non-industrial sector (residential, commercial and services) accounts for a very significant proportion of the total electricity use, e.g., in Sweden this non-industrial sector accounts for the half of the total electricity consumption (Swedish Energy Agency, 2005). Heating and air conditioning loads in this sector are often identified as the major contributors to system peaks. Furthermore, the increased number of household appliances may also lead to load shortages if used simultaneously. The residential, commercial, and service sector should be seriously considered when approaching peak demand problems and ensuring a well-functioning electricity market.

The existing knowledge on load demand variation in households and commercial buildings is fairly limited. New automated metering and communication technologies (e.g. 'smart meters') enable visibility of electricity use and provide strategically valuable information both for supply and demand side. Finally, there is a lack of communication between supply and demand sides leading to a lack of dialogue between wholesale and retail electricity markets. The demand side participation is essential to obtain this dialogue.

1.5 Thesis Contribution

The main contributions of this study can be summarized in the following categories:

a) Investigated the problem of scheduling of SH appliances operations in a given time range with a set of energy sources like national grid and local generation micro-grid. We formulated this problem as a primary objective functions problem. The first objective minimizes total energy cost and the second and third objective reduces the peak load of all the household appliances used in a 24-hours a day.

b) Proposed solutions based on Mixed Integer Linear Programming (MILP) and Whale Optimization Algorithm (WOA). MATLAB was used as a tool for obtaining the timing of appliance scheduling in the smart home.

c) Evaluated the performance of a residential energy model and optimized the performance of different types of load associated within.

d) Generated starting and ending times of the appliances that indicated the net import and export of energies to meet the demand of the home area network.

e) The proposed solution can be used for generating appliance scheduling plan in comparable time to be true as a real-time process for demand-side management.

1.6 Thesis Structure

The outlines of this thesis are as follows:

Chapter 1 provides the General Introduction, Problem Statement, Objectives of the Thesis, Motivation of the Thesis, Thesis Contribution, and Thesis Structure.

Chapter 2 explains the concept of Smart Grid and Smart Homes, Smart grid Infrastructure and its Applications, Smart Homes, Smart Appliances, Smart Meter, Energy Management System in Smart Home, Load Management (LM), Distributed Energy Resources in Smart Homes, Demand Response (DR), Benefits of LM and DR, Environmental Aspects, Barriers to LM and DR, Types of Residential Loads and its

Characteristics, Mixed Integer Linear Programming (MILP) and Whale Optimization Algorithm (WOA).

Chapter 3 In this chapter, appliance scheduling is formulated using MILP and WOA techniques for which use of decision variable and auxiliary binary decision variables are defined and applied. An extension to MATLAB is used in WOA and MILP is used to interface with INTLINPROG solver for obtaining optimized scheduling of appliances for minimizing peak load and cost of energy of the homes integrated with renewable energy sources.

Chapter 4 discusses the results obtained in Simulation and their usefulness in the case of electricty cost reduction of the homes and peak load reduction in the grid networks.

Chapter 5 concludes the results of the energy management system in the smart homes and the future works.

1.7 Chapter Summary

This chapter explained the focuses on the activities on the demand side in the smart home (SH) that could reduce peak load, and cost in the electrical system by using customer flexibility, i.e., by increasing the demand side response (DR) to signals coming from the energy market. The primary objective is to use different strategies to reduce peak load on the demand side considering their techno-economic, environmental and social. Also, depicts load reduction strategies at the demand-side that could govern the environmental performance of an energy system by reducing emissions and avoid the distortion of territories. The implementation of these systems improves the use of renewable energy in the distribution network and can help to reduce peak load, power loss and consumer electrical bill. Lastly, it direct to the objective, and scope of research including an outline of the thesis have been mentioned in this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Smart Grid and Smart Homes

Smart grid (SG), in the growing power system technology, is currently considered as an upcoming solution to the most of the existing power systems. It comes in different names such as smart power grid or intelligent grid (Goyal and Shimi, 2017) to take over an old, disorganized and defenseless existing power system (Yu, 2015). An efficient performance of smart grid depends on the advanced technologies in electrical power, control, communication, information theory, bi-directional flows of electrical power and information which promotes an advanced and modern power system with cost-effective, safety and security (Yu, 2015). In smart grid, advanced energy-metering infrastructure (AMI) and energy monitoring are performed over a number of smart meters and sensors equipped all the way in smart homes. The part of communication as well as networking technologies ensure real time data collection and transmission to and from both sides (Goyal and Shimi, 2017), (Yu, 2015). And thus, SG will be able to respond quickly to blackouts or broken pieces inside the entire power grid, and then protect working circuits from being affected in the grid so that large area power outages can be avoided (Yu, 2015). Besides, SG will also support more distributed power generation of renewable energy, such as solar, wind, and geothermal energy, through which the power system capacity will be increased, and the reliance on the fossil fuel will be decreased. Consequently, greenhouse gas (GHG) emissions can be controlled (Yu, 2015). In smart grid (SG) system, the load management is an essential factor to control energy management system. Through load management strategies in smart grid (SG), reduction of peak load during the peak period and control pricing of electricity unity can be achieved through customer participation in the smart home (Tammam et al., 2013; Chen et al., 2012; Chen et al., 2013; Black and Tyagi, 2010; Palensky and Dietrich, 2011; Albadi and EI-Saadany, 2008; Caves, Eakin, and Faruqui, 2000). The usage of photovoltaic system causes a reduction of electric bill and the peak demand at home. Moreover, excessive generated energy can be added to the smart grid from the smart home (Ackerman et al., 2001; Pepermans, 2005; Twidell, 2003).

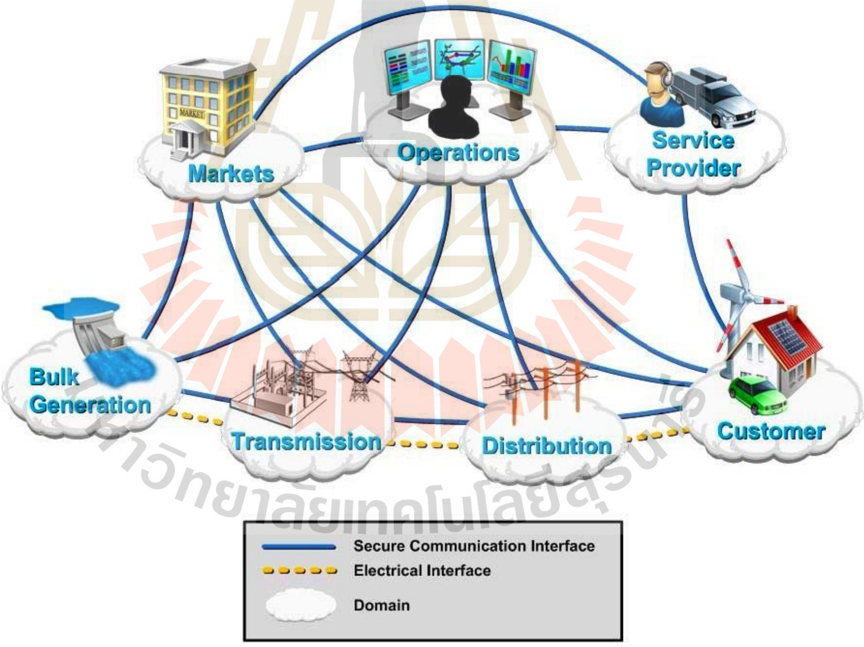


Figure 2.1 Smart Grid Structure (The National Institute of Standards and Technology USA, 2012).

More specifically, SG can be regarded as a large-scale and complicated power system that utilizes the advanced technologies in many fields to achieve a clean, efficient, reliable, and sustainable system. The intelligence penetrates into every component of the system from power generation to consumption by the customers. The realization of the ultimate SG requires incorporation of technologies in power system, information technology, communication, control theory, and computer science (Yu, 2015) (see Figures 2.1 and 2.2).

In the future SG, many new facilities and infrastructure will become common and indispensable, such as the distributed generation of renewable energy resources, smart meters and sensors, electric vehicles, and grid energy storage (Omid, 2015; Yu, 2015). By integrating these new components, the power grid becomes truly intelligent, efficient, and automatic (Yu, 2015). New SG components are deployed using the plug-and-play interfaces, which increases the flexibility, scalability, and security of SG. Smart meters and sensors can be embedded into SG directly through the configured interfaces as simple as connecting a laptop to the Internet. In this way, a huge and complex SG system can be decomposed into many small parts with different features. For example, Distributed generation (DG) and grid energy storage (GES) are two new features in SG. DG makes it possible to incorporate more renewable energy generation, such as solar, wind, and tidal. GES is essential for optimal energy management, because it can not only store the extra energy, but also inject energy back to the grid when needed to avoid blackouts and reduce the cost (Yu, 2015).

Another important feature of SG is the two-way flows of electricity and information (Jason, 2012; Yu, 2015; Omid, 2015). In traditional power grids, both electricity and information flow is a unidirectional fashion. Electric power is generated from a centralized generation plant, and then travels through the transmission system and distribution networks to power users. Utility company collects the information of user consumptions and grid status, while power users have no access to acquiring the grid or market information. However, in SG two-way flows of electricity and information is supported, so that power customers are able to acquire the market information and the grid status and sell energy back to the grid (Yu, 2015). In this way, exchanges of information and power become more flexible, and higher efficient power management is enabled for more reliable power distribution. For example, the utility company could lower the electricity price so that the load peak is reduced by power injection from end customers. Also, by periodic information communications, the control center monitors the grid in real time, and customers acquire updated price information in real time. In short, two-way flows of electricity and information are the foundation of the real-time power control and many other SG applications.

The Smart Grid concept combines a number of technologies, end-user solutions and addresses a number of policy and regulatory drivers. It does not have a single clear definition.

The European Technology Platform (European Commission, 2006) defines the Smart Grid as:

"A Smart Grid is an electricity network that can intelligently integrate the actions of all users connected to it – generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies."

According to the (US Department of Energy, 2007):

"A smart grid uses digital technology to improve reliability, security, and efficiency (both economic and energy) of the electric system from large generation, through the delivery systems to electricity consumers and a growing number of distributed-generation and storage resources."

In Smarter Grids: The Opportunity (Department of Energy and Climate Change UK, 2009), the Smart Grid is defined as:

"A smart grid uses sensing, embedded processing and digital communications to enable the electricity grid to be observable (able to be measured and visualized), controllable (able to manipulate and optimized), automated (able to adapt and self-heal), fully integrated (fully interoperable with existing systems and with the capacity to incorporate a diverse set of energy sources)."

The literature (U.S. Department of Energy, 2009), (A Compendium of Modern Grid Technologies, 2009), (European Commission, 2009) and (World Economic Forum, 2009) suggests the following attributes of the Smart Grid:

- It enables demand response and demand side management through the integration of smart meters, smart appliances and consumer loads, micro-generation, and electricity storage (electric vehicles) and by providing customers with information related to energy use and prices. It is anticipated that customers will be provided with information and incentives to modify their consumption pattern to overcome some of the constraints in the power system (see Figure 2.2);
- It accommodates and facilitates all renewable energy sources, distributed generation, residential micro-generation, and storage options, thus reducing

the environmental impact of the whole electricity sector and also provides means of aggregation. It will provide simplified interconnection similar to plug-and-play;

- It optimizes and efficiently operates assets by intelligent operation of the delivery system (rerouting power, working autonomously) and pursuing efficient asset management. This includes utilizing asserts depending on what is needed and when it is needed;
- It assures and improves reliability and the security of supply by being resilient to disturbances, attacks and natural disasters, anticipating and responding to system disturbances (predictive maintenance and self-healing), and strengthening the security of supply through enhanced transfer capabilities;
- It maintains the power quality of the electricity supply to cater for sensitive equipment that increases with the digital economy;
- It opens access to the markets through increased transmission paths, aggregated supply and demand response initiatives and ancillary service provisions.

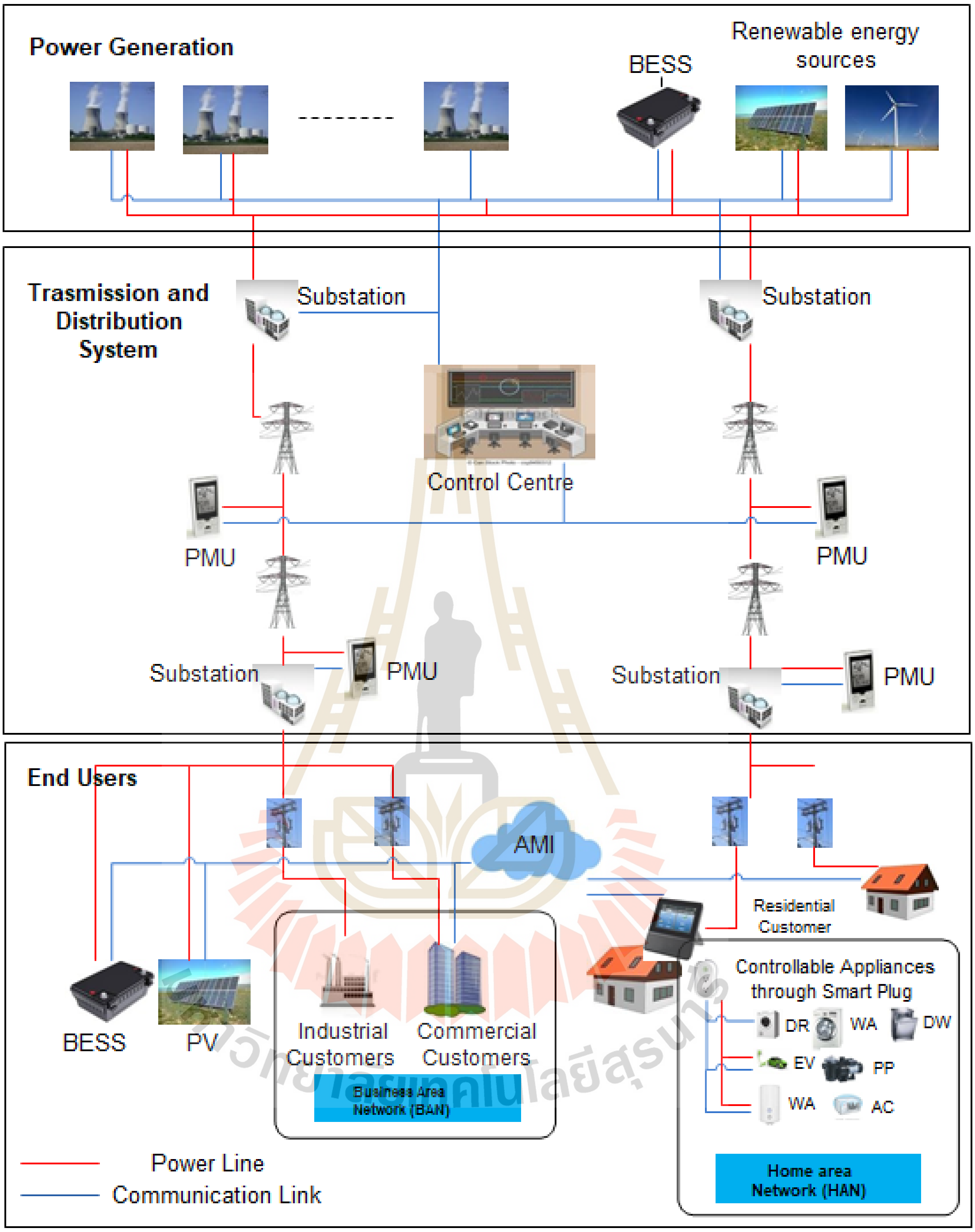


Figure 2.2 Conceptual design of a smart grid environment (Vivekananthan, 2014).

It can be clearly seen that effective two-way communication in a Smart grid will help in significantly reducing the peak demand as well as the overall consumption (Qayyum et al., 2015; Yu, 2015). Further, higher penetration of renewable energy generation technologies will reduce CO_2 emissions and the associated global warming (Ansu, 2013; Qayyum et al., 2015; Yu, 2015). Effective and well-planned operation of the smart grid will lead to reduced operational costs, increased reliability, power quality and operating efficiency while optimizing asset utilization (Yu, 2015; Qayyum et al., 2015).

2.1.1 Smart Grid Infrastructure $ Applications

Smart grid infrastructure: SG infrastructure is the foundation of SG, including a smart power system, information technology, and communication system (see Figure 2.3). The comparison between smart grid infrastructures from the traditional grid are given in Table 2.1.

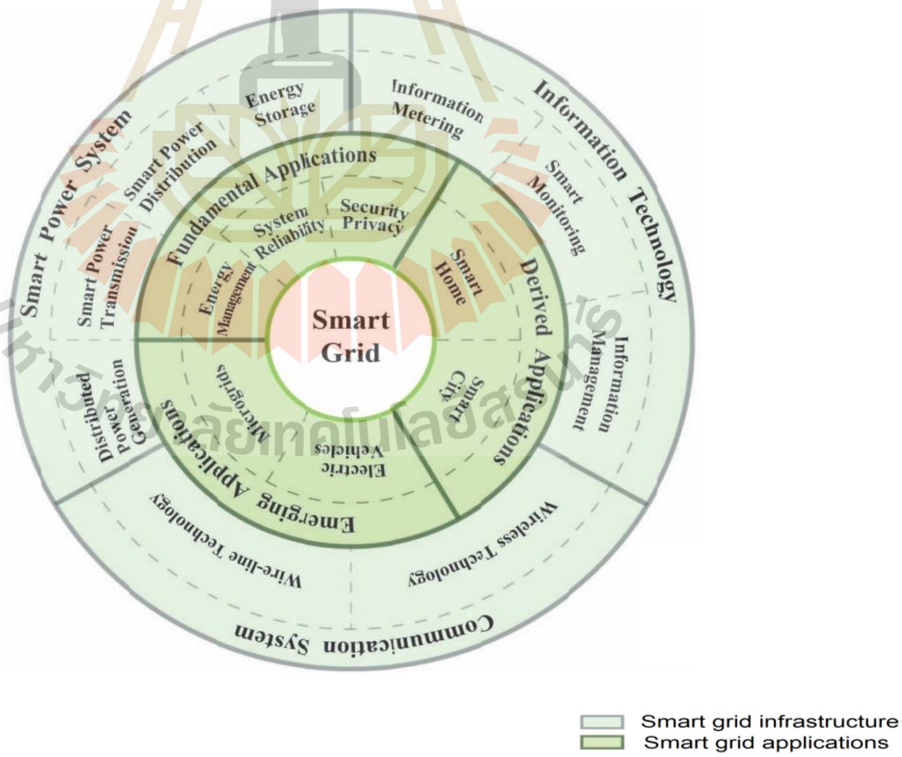


Figure 2.3 Smart Grid Infrastructure and Applications

(Yu, 2015).

a) Smart power system: provides a reliable and intelligent power system which consists of power generation, power transmission, power distribution, and energy storage.
b) Information technology: supports the advanced information metering, smart monitoring, and the corresponding information management.
c) Communication system: builds on the advanced communication infrastructure and technologies.

Smart grid applications. SG applications are further divided into fundamental applications and emerging applications:

a) Fundamental applications: focus on the technologies of energy management, system reliability, security and privacy, featuring demand-side management for energy efficiency improvement, user utility maximization, and system protection.
b) Emerging applications: introduce two new patterns in SG: electric vehicle (EV) and microgrid (MG), featuring energy management for large-scale support of EVs and DGs of renewable energy in MGs.
c) Derived applications: two examples are smart home (SH) and smart city, which are derived from SG, providing the impact of SG on human societies.

Table 2.1 Comparison between the traditional grid and the smart-grid.

TRADITIONAL GRID	SMART-GRID
Centralized Generation	Distributed Generation
No Energy Storage	Energy Storage
One-way Communication	Two-way communication
Electromechanical (Analog)	Digital
Manual Restoration	Self-healing
Failures and Blackouts	Adaptive and Islanding
Reactive Approach	Proactive Approach
Total control by Utility	Increased customer participation
Lack of real time monitoring	Extensive real time monitoring
Slow Reaction time	Extremely quick reaction time

2.2 Smart Home (SH)

Smart Home is the term normally used to define a household that uses a home controller to integrate the residence's various home automation systems (Rosslin, and Tai-hoon, 2010). Smart Home is the computerized controls in homes and appliances that can be set up to respond to signals from the energy provider to reduce their energy use at times when the power grid is unstable from high peak load demand, or even to shift some of their power use (energy consumption) to times when power is available at a lower cost. Customer involvement is the one among the critical attribute of the SH. The involvement of the customer is facilitated by a smart meter, which also connects the smart home (SH) and Smart Grid (SG). Besides the gathering of data for electric utility companies, smart meters perform crucial roles for both customers and the grid to which they are connected to. They act as controllers over consumer’s appliances. With the upcoming technologies of SH, each home appliance will be provided an ability to transfer information and monitored by the smart meter with the use of in-home networking system. Current developed appliances are equipped with application software’s and interfaces to provide an easy use to costumers. The programmed instructions can then be viewed to costumers through displays. The SH control can further give customers extra opportunities, such as energy saving, loss reduction, cost saving, and reduced carbon emission.

Depending on the type of appliances, devices, and networks that are installed and the level of automation desired, the smart home will have different levels of sophistication. Some of the configurations, combinations, and options for energy management in the smart home include a simple email notice for manual demand response by the consumer, and a smart meter directly communicating with a specific appliance to ask it to turn on and off (Association of Home Appliance Manufacturers, 2009). As a more sophisticated example, a smart meter communicates with an Energy Management System (EMS) home controller inside the house. The energy management system home controller could connect in home-smart appliances in different ways (wire or wireless), to the smart meter and the demand response backend system over the Internet using an existing broadband connection.

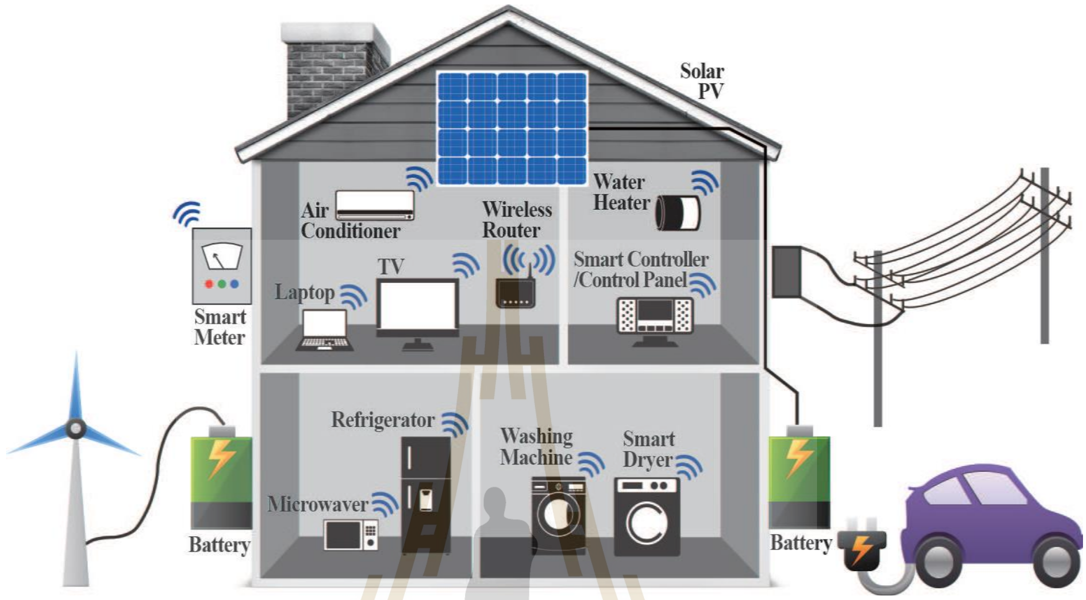


Figure 2.4 Future Smart Home (Swalehe, Chombo and Marungsri., 2018).

The concept of future SH is displayed in Figure 2.4 where a small renewable generation and energy storage system are equipped to make a future SH working as a small connected micro-grid (MG) (Abaravicius et al., 2006; Abaravicius, 2007; Barbose, and Goldman, 2004; Yu, 2015; Erol-Kantarci, and Mouftah, 2011; IPART, 2002; Swedish Energy Agency, 2006; Tsui and Chan, 2012; Watson, 2005; Wilma, Suschek-Berger, and Tritthart, 2008). Moreover, the use of hybrid DC/AC system can be added to support the future SH with the use of both DC power and AC power supply. Therefore, with the future SH, a reliable power supply will be available with an addition of automation, user preferences, and low emissions and cost-effective. The higher penetration of renewable energy into the smart home results in a minimization of electric bill, peak demand of the household and export of extra energy to the smart grid in times when renewable energy generation is more than the demand of the household (Ackerman et al., 2001; Pepermans, 2005; Twidell, 2003). Moreover, smart homes generally include a Home Energy Management System (HEMS), which optimizes the use of energy and gives the users feedback about their electric consumption (Al-sumaiti, Ahmed, Madgy, Sa., 2014). The HEMS incorporate and manages three subtasks:

- Optimization scheduling: find the most suitable time to use electric appliances considering the electric pricing fluctuation and the peak loading. It aims at minimizing the wasted energy and the electricity bills, while maintaining users' comfort;
- Control and automation: the design of microcontroller-based systems to control the HEMS interface and monitor the use of appliances and their consumption. This can be done using heuristic optimization methods, search algorithm and control using LabView;
- Communication: manages the wireless network part by providing dynamic information about the home energy consumption based on power line communication. A ZigBee interface is a perfect example of such communication system.

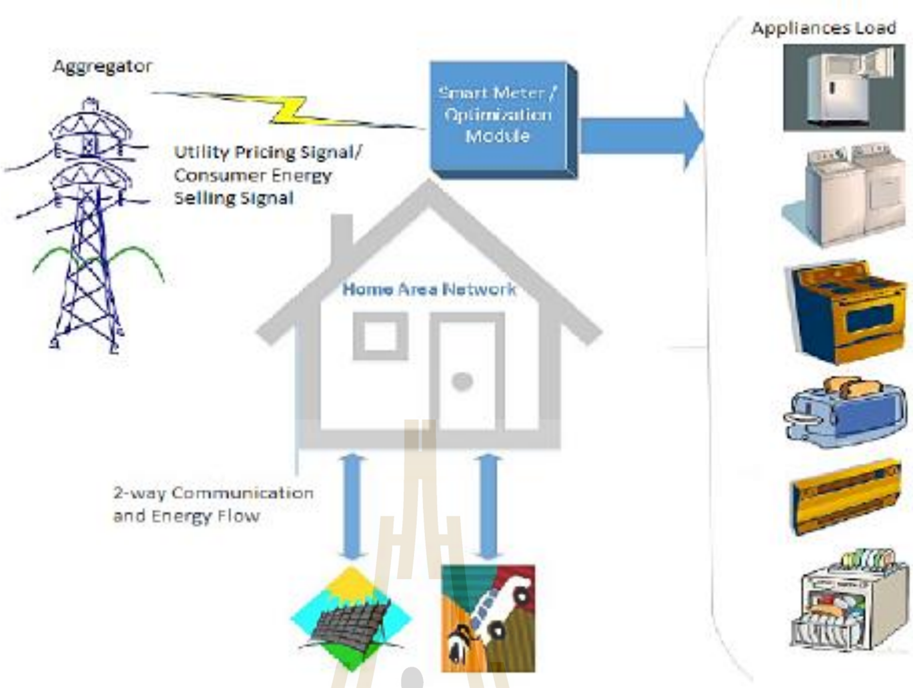


Figure 2.5 HAN model for appliance scheduling (Qayyum et al., 2015).

2.2.1 Smart Appliances

The term "Smart Appliance" with respect to the smart grid refers to a modernization of the electricity usage system of a home appliance so that it monitors, protects and automatically adjusts its operation to the needs of its owner (Association of Home Appliance Manufacturers, 2009). Some of the key features noted by (Association of Home Appliance Manufacturers, 2009) include the following:

- The capability to alter the requirement for electrical energy exploitation;
- Consumer is able to reverse all pre-programmed sets of instructions;
- To maintain stability of the system;
- To give alerts to end-users to shift to a convenient time with available cheaper prices;

- To provide an automatic reduction of usage based on the consumers pre-established guidelines;
- To develop the energy consumption profile from total home energy consumption approach to utilize the data to its best profit.

The two main reasons for a consumer accepting to adopt smart appliances are an economic gain to the consumer and environmental reasons, but the latter is among only a small percentage of consumers who are environmentally conscious or environmental advocators. Most consumers will readily accept to shift to smart appliances for economic gains rather than environmental gains (Wilma, Suschek-Berger and Tritthart, 2008). To trigger consumers to buy smart appliances, Wilma, Suschek-Berger and Tritthart, 2008, suggested a promotion of attractive tariff from utility to customers with an addition of other incentives.

All smart appliances are classified as receivers, and the means of controlling them are through transmitters such as the 'remote control or keypad' (Rosslin, and Tai-hoon, 2010). For instance, if an appliance is needed to be switched ON or OFF, the transmitter (the remote), should transmit a signal to the receiver (appliance) in the form of a code which may include an attention to the intended system, giving a unit number of the respective equipment and the instructions that contains a set of actions to be performed (Rosslin, and Tai-hoon, 2010).

2.2.2 Smart Meter (SM)

This is an intelligent device mostly used to monitor and control the energy usage in home. Its monitoring function is based on collecting measured energy data, perform energy analysis based on the algorithm uploaded on it, and later it can prepare a real-time energy usage (Costanzo, 2011). Such a device, smart meter (SM), performs more complicated monitoring functions compared to a normal automated metering reading (AMR). The advanced functions include power quality monitoring, remote customer debranching, dynamic service ratification, etc. Moreover, SM, can be combined into an Advanced Metering Infrastructure (AMI) to supply the real-time information and services to utilities and customers (Costanzo, 2011) (see Figures 2.6 and 2.7). In Table 2.2, the comparison between AMR and AMI are given.

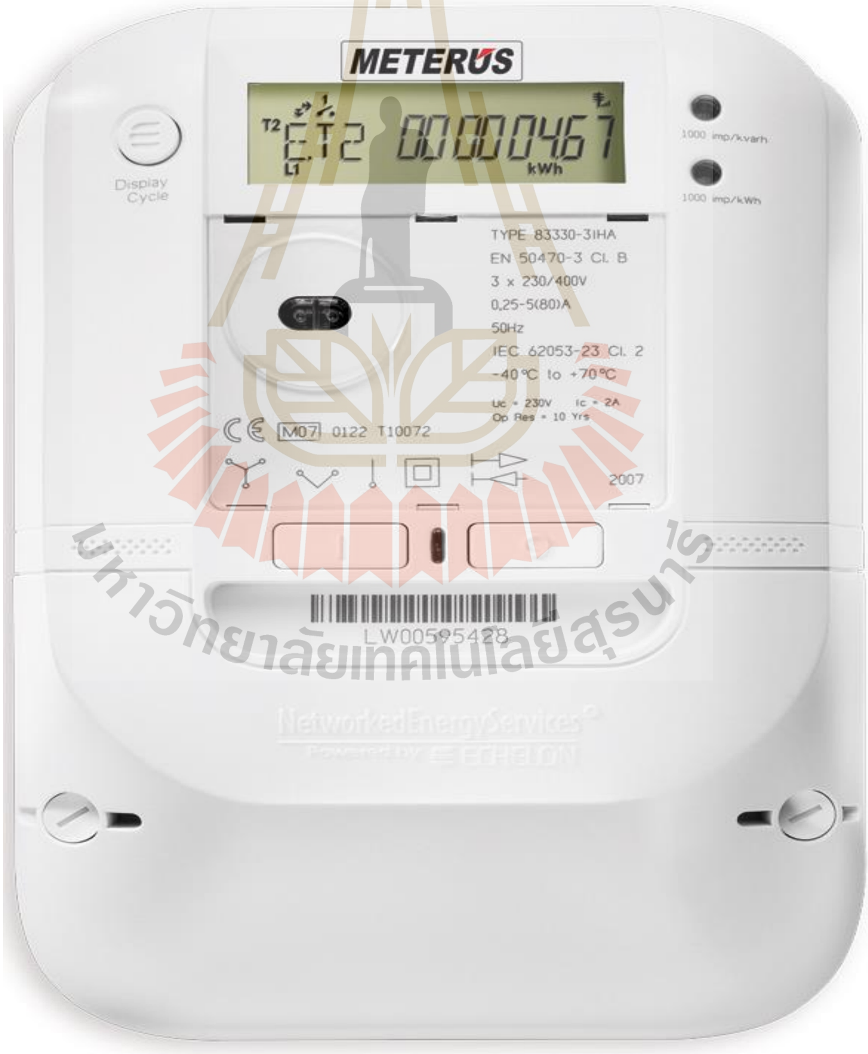


Figure 2.6 A Smart meter (Hancheng, 2016).

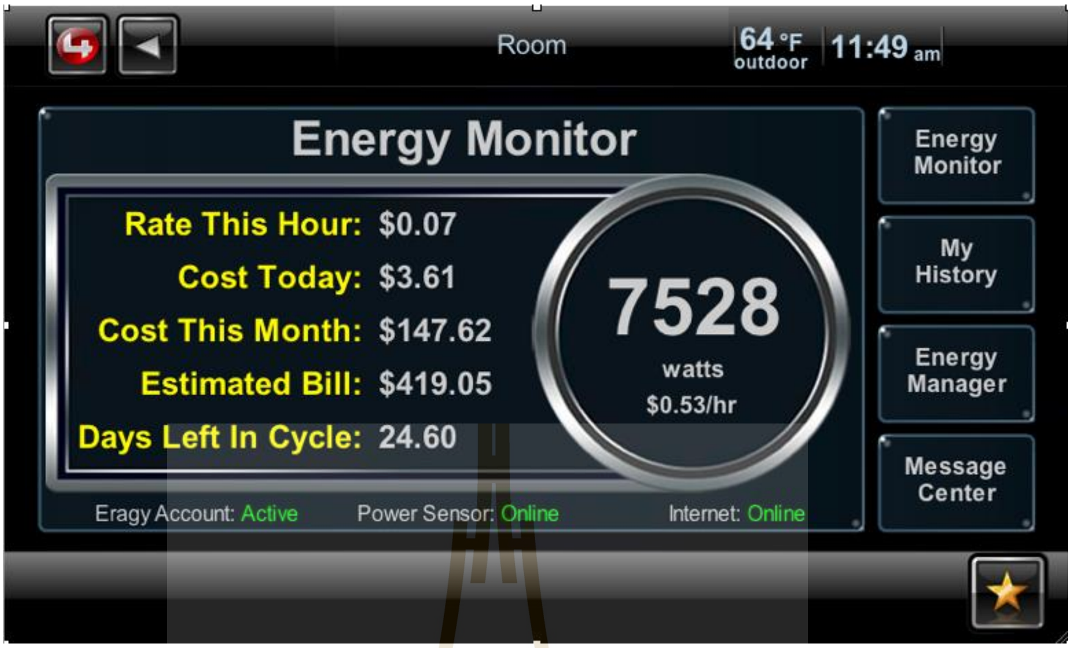


Figure 2.7 An In-Home display in Smart Meter (Longe, 2016).

Table 2.2 Comparison between AMR and AMI.

Automatic Meter Reading (AMR)	Advanced Metering Infrastructure (AMI)
One-way communication.	Two-way communication.
Information flow from AMR to utility	Information flow among home appliances, AMI and utility.
Interacts with neighborhood Area Network (NAN).	Interacts with NAN and Home Area Network (HAN) and or Business Area Network (BAN).
Consumer unable to control its electricity usage through Demand Response (DR).	DR can be implemented from the consumer side.
Benefits majorly utility provider.	Benefits both utility provider and consumer.
Simple architecture.	Complex architecture.
Negligible security risk.	High security risk.

Development of SM devices employs the use of advanced technologies which impacts the transfer of information between consumers and utility. Communication technology has been considered mostly in the advancement of SM due to its great impacts in social, economic and environmental point of use. In Neenan (2008), social benefits were observed as the principal outcomes of the SM with intelligent features. In many articles, regarding to the SM, the major concerns are market as well as social benefits. Technological concerns of the SM is yet wide spread. Moreover, most consumers have also seen to focus on economic benefits of SM rather than its performance. For that case, Neenan (2008), developed a study to identify and measure the social significances of the SM to the consumer. The factors considered to reflect social benefits were advancement in service reliability, existence and workability of feedback, the presence of demand/response, new products, service and macroeconomic impacts.

In technological advancement of SM, an overview of a SM accompanied with the investigation on the implementation of its functionalities was proposed by (Karnouskos et al., 2007). Investigation was also made to observe satisfaction in the adapted services. The power was given to the "internet of things" on which goods are available in the same marketplace. From that point of view, a SM is attached in the home gateway to merge the home appliances through home automation network (a communication between appliances and SM) with the utility via data exchange. Therefore, a SM is taken as a home gateway to connect the domestic appliances and utility through internet. Apart from using a SM for energy monitoring in domestic house, the work also suggested that a SM should be a multi-utilities device, meaning that, the device should be able to work in electric and thermal energy; and natural gas as well. The main advantage of SM to operate under multi-utilities is to provide assistance to customers for uncontrolled energy market. Technically, a multi-utilities SM must have overlapping layers such as Programmable HW, Embedded Middleware, Execution environment API, Service layers that assist a third person utility to upload its service codes. Furthermore, the work proposed a model for combining the hardware provider, service providers and SM end user.

Advanced measurement is of very advantageous in a smart grid. It takes place on monitoring of transformer health in the grid. The monitoring process involve measurement of the lines temperature, moisture content as well as computing of thermo images of electrical devices. Moreover, it should account for load capability and insulation aging factor. Proper actions taken based these measurements can minimize by 2.5 times the risk of failure implemented through properly selected maintenance strategy (Flynn, 2008).

Vis-a-vis energy dispatch matter related with AMI (Advanced Metering Infrastructure) as shown in Figure 2.8, (Bruno et al., 2009) presented a mathematical technique for solving a distributed-optimal power-flow problems with SM, distributed generation facilities and remote load control. With this work, the observations were made on the practicability of the utility to trim the end-user's load with remote signals. The mathematical approach was a modified one from the normal Optimal Power Flow (OPF) and was capable of taking into account the practicability to buy energy from different distributed providers and convey it to costumers with different needs. The chief outcome of the optimization was to diminish the running costs of the distribution companies by including two suitable strategies: (i) shedding – shedding a portion of energy such that the balance exists between generation and load, and (b) estimate the amount a portion of energy to be fed from distributed generators to balance the demand under the assumption of partial load shedding among the selected customers.

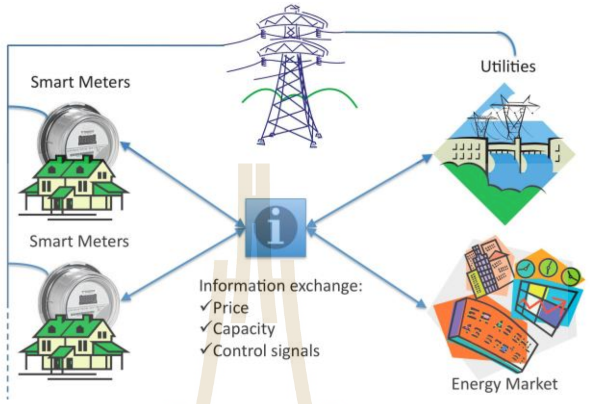


Figure 2.8 Advanced Metering Infrastructure

(Costanzo, 2011).

2.3 Energy Management System (EMS) in Smart Homes (SH)

Following the global fossil fuel crisis and the tension to minimize CO_2 outflow, several energy tariffs and services have been proposed by energy suppliers to motivate end-users to efficiently minimize or control their energy consumptions. Among of the techniques mostly undertaken to efficiently manage the load include load shifting or installation of DERs. On the other hand, inclusion of DERs such as solar system, small wind turbine and ESS in buildings has seen as a way toward making the greener energy consumption although they are complicated in control. Despite of advancement of SM in distribution networks, end-users are still encountering difficulties in doing efficient energy management due to their past habits. Moreover, the electricity bill is still the biggest problem to them. For example, in UK, the residential electricity bill was reported to reach £1200 per household per year in 2013 (OFGEM, 2014). To utilize the chance of assisting customers to manage their home appliances and DERs, advancement in modeling and evolution of HEMS and BEMS are needed to be done in industrial and academic levels (see an example in Figure 2.9).

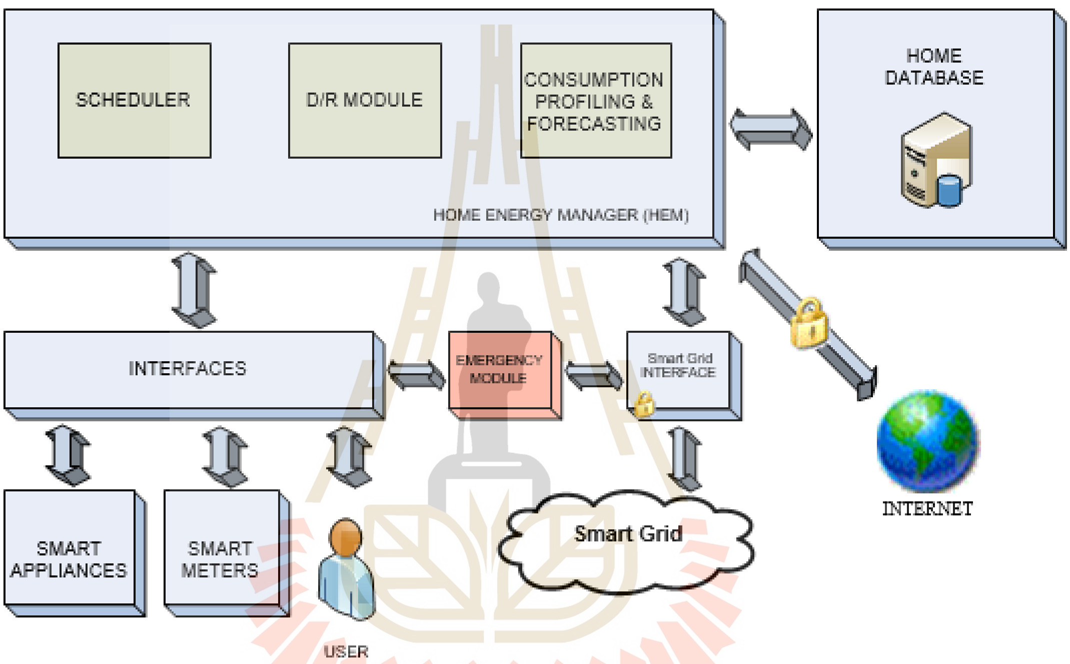


Figure 2.9 Home energy management system (HEMS) (Costanzo, 2011).

Suyang (2014) outlined that the EMS market including HEMS, BEMS, enterprises EMS etc. has reached $17.4 billion in 2013 and it was forecasted to attain $38.49 billion in 2018.with the Compounded Annual Growth Rate (CAGR) will be counted for 17.2%. Normally, EMS products do serve several functions to end-users such as monitor to the energy consumption of appliances and manage the operation states of appliances based on the environment and time factors. Extra features like shifting the spare green energy to heat water have been implemented and realized in

EMS as well. With the spread of the RTP, Demand Response Service (DRS) and other advanced tariffs or power services, more effective energy optimization functions, such like real-time monitoring & optimization functions, will be able to have core supporting techniques for further development.

2.3.1 Load Reduction Strategies

Reducing the load to balance the system, can be done based on different approaches depending on the existing technical and economic conditions. Killicote and Piette, (2005) explains three major strategies for load reduction – peak load management, demand response and energy efficiency. Moreover, it should be noted that the demand side can reduce the demand through energy savings, carrier switching or distributed generation, keeping in mind that no load demand is modified (see Table 2.3).

Table 2.3 Demand side activities affecting load demand (Abaravicius, 2004).

	Peak load management	**Demand response**	**Energy efficiency**	**Energy savings**	**Energy carrier switching**	**Distributed generation**
Activity level (periods)	daily/weekly	Dynamic, event driven	daily/weekly	daily/weekly	Permanent	Dynamic, event driven,
Primary motivation	Time of Use rates Load demand charges	Price Reliability Emergency	Conservation Environmental protection	Conservation Environmental protection	Conservation Environmental protection	Price Reliability Emergency
Design and technology, action	Low power demand appliances	Dynamic control capability	Efficient envelope, equipment and systems	Behaviour	Change of HVAC systems from electric to natural gas or district heating/cooling	Self-generation (micro chp, fuel cells)
Operations, actions	Demand limiting Demand shifting	Demand shedding Demand shifting	Integrated system operations	Behaviour		Self-generation

2.3.1.1 Load Management (LM).

Load management can be defined as a set of objectives designed to control and/or directly or indirectly modify the patterns of electricity use of various customers of a utility to reduce peak demand. This control and modification enable the supply system to meet the demand by making the best use of its available generation and transmission capacity (Paracha and Doulai, 1998). Load management is not usually a measure to save energy (power) but is used to run the power supply system more efficiently by preventing large peaks in demand. Energy is not conserved, but the load demand is moved from peak hours to times with smaller coincident load (Abaravicius, 2004).

Load management could be implemented on a daily basis, by limiting the demand or moving the usage (consumption) from peak to off-peak hours, or even on weekly by moving the usage from weekday to weekend. The main motivation for the demand side to participate in peak load demand management programs is the Time of Use (TOU) electricity pricing or load demand charges. The implementation requires low power demand appliances.

2.3.1.2 Demand Response (DR).

Demand response (DR) is action to reduce load when (Watson, 2005) either Contingency occurs that threaten supply-demand balance or Market conditions occur that raise supply costs.

Demand response is a dynamic, demand driven process. It is usually not set up as a daily action but takes place when there is a particular situation at the production or transmission side. The primary motivation is for the avoidance of a critical peak price, for system reliability and for handling emergency situations and preventing blackouts. DR requires dynamic control capability, to shed the loads or shift them to other periods (Abaravicius, 2007).

2.3.1.3 Energy Efficiency and Savings.

Implementation of energy efficiency measures can also contribute to the decrease of demand peaks. For example, use of more efficient lighting bulbs would both reduce the energy consumption and load demand. Often, with respect to load issues, energy efficiency is named ‘strategic conservation.' For such strategic conservation, utilities adopt focused programs to encourage efficient energy use to reduce demand, not only during peak periods but also at other times; this reduces average fuel cost and can postpone the need for future additional utility capacity (Bellarmine, 2000).

Energy efficiency and savings strategies are usually assessed on a daily and/or weekly basis for systems benefit. The implementation requires energy-efficient building envelopes and systems (appliances), as well as energy conscious behavior by users.

2.3.1.4 Change of Energy Carrier.

Here, a good example could be the conversion of heating from electricity to another heat source, e.g., district heating, wood pellets or natural gas. This measure significantly reduces the total electricity use of a building or household and decouples electricity demand from dependence on outdoor temperature. Electric heating is the most common source of heat in detached houses in Sweden, although district heat predominates in apartment blocks. Only about 8% of the detached houses in Sweden are connected to district heating (Swedish Energy Agency, 2006).

2.3.1.5 Distributed Energy Options.

The use of "Distributed generation," also called "decentralized" or "embedded generation" is one more way to decrease peak loads of a power system (i.e., particular end-use loads are supplied with local generation units instead of using the power from the grid). The distributed generation includes both supply side and demand side measures. A definition proposed by (Ackermann et al., 2001) refers to distributed generation as an "electric power source connected directly to the distribution network or on the end-user side of the meter."

Several reasons, such as the development of generation technologies, gradually requiring lower specific investments, the penetration of IT technologies and energy security create favorable conditions for an expansion of the distributed generation in future. (Pepermans et al., 2005) note the primary drivers for distributed generation in the US and Europe:

"Making use of distributed generation allows a flexible reaction to electricity price evolutions. Apparently, this is the primary driver for the US demand for distributed generation, i.e., using distributed generation for continuous use or for peaking use (peak shaving). In Europe, market demand for distributed generation is, at the moment, driven by heat applications, the introduction of renewables and by potential efficiency improvements".

However, the statement that there is a market demand for a distributed generation could be considered as exaggerated - there is rather an interest of some enthusiasts (Thörnqvist, 2007). LM and DR are directly aimed at load demand reduction, loss reduction, and cost reduction.

2.4 Load Management (LM)

Load management does not aim to decrease the overall electricity consumption, rather approaches (or replies to) the consumption pattern. That is the fundamental difference between load management and energy conservation. Load management strategies are designed to either reduce or shift demand from on-peak to off-peak times, while conservation strategies may primarily reduce usage over the entire 24-hour load period (PG&E, 1985). Load management measures could be applied both to energy demand and on supply sides.

The purpose of load management techniques is to reduce peak demand to level daily, seasonal or annual electricity demand. The techniques help to economize system operation by making the best use of its available generation and transmission (network) capacity. The subject divides between network and generation load management, depending on the current need in a system (IPART, 2002):

"Network Load Management includes activities that reduce the peak demand on the electricity network, thereby deferring or avoiding the need to augment the network. Generation Load Management includes activities that reduce the peak demand in the generation market, thereby avoiding the need to call on the most expensive electricity generators and deferring the need to build new power stations."

The typical and probably the most widely applied load management strategies are peak clipping, valley filling, and load shifting. (Gellings, 1993) emphasizes six load management strategies. In addition to the three mentioned, there are also strategic conservation, strategic load growth, and flexible load shape.

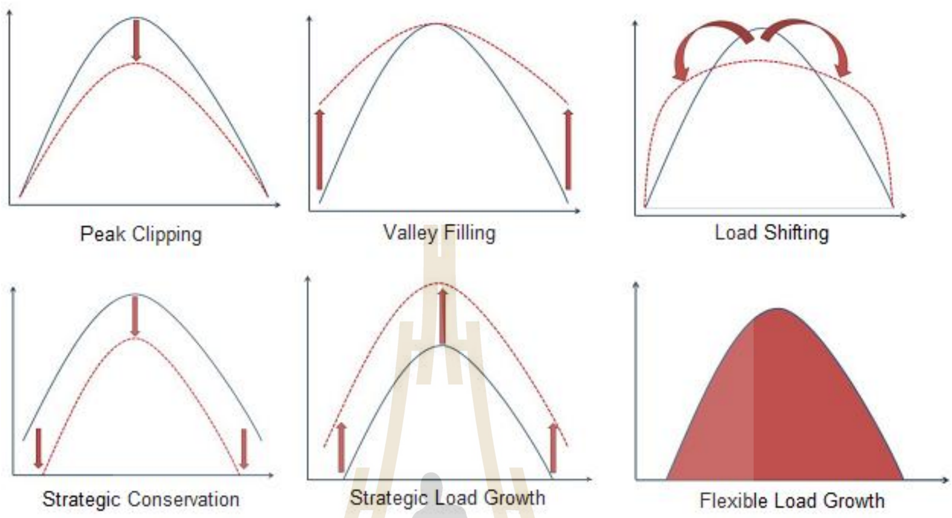


Figure 2.10 Load control strategies (Gellings, 1993).

The load management strategies showed in Figure 2.10 above could shortly be described in following way:

- Peak clipping – a reduction of the load during short usage peaks;
- Valley filling - building loads during the off-peak period;
- Load shifting - combines the benefits of peak clipping and valley filling by moving existing loads from on-peak hours to off-peak hours;
- Strategic conservation – decreasing the overall load demand by increasing the efficiency of energy use;
- Strategic load growth - increased electric energy consumption either to replace inefficient fossil-fuel equipment at the point of use or to improve consumer productivity and quality of life;

- Flexible load shape – specific contracts and tariffs with possibilities to flexibly control consumers' equipment.

2.5 Distributed Energy Resources in Smart Homes (SH)

DERs refer to the small power resources installed in the distribution network, which can generate or store energy through grid-connected devices (Jiayi, Chuanwen, and Rong, 2008) (see Figure 2.11). Since the DER systems are decentralized and mostly located close to the energy consumers (e.g. Homes & Buildings), the energy generated by or stored in the DERs can response the quick-change demands of the energy consumers in distributed network faster than the traditional centralized, long-distance and large-scale power plants (De Martini, Chandy, and Fromer, 2012). With the implementation of DERs, the end energy consumers can get the potentially cheaper and greener energy from the DERs as an alternative way rather than depend on the centralized power supplier only (Bayod-Rújula, 2009). Currently, the main stream commercially available DER systems are classified and introduced in (Galli, Scaglione, and Wang, 2011; Bergmann et al., 2010; Basu et al., 2012; Mohd et al., 2008), which are introduced in the following part as well.

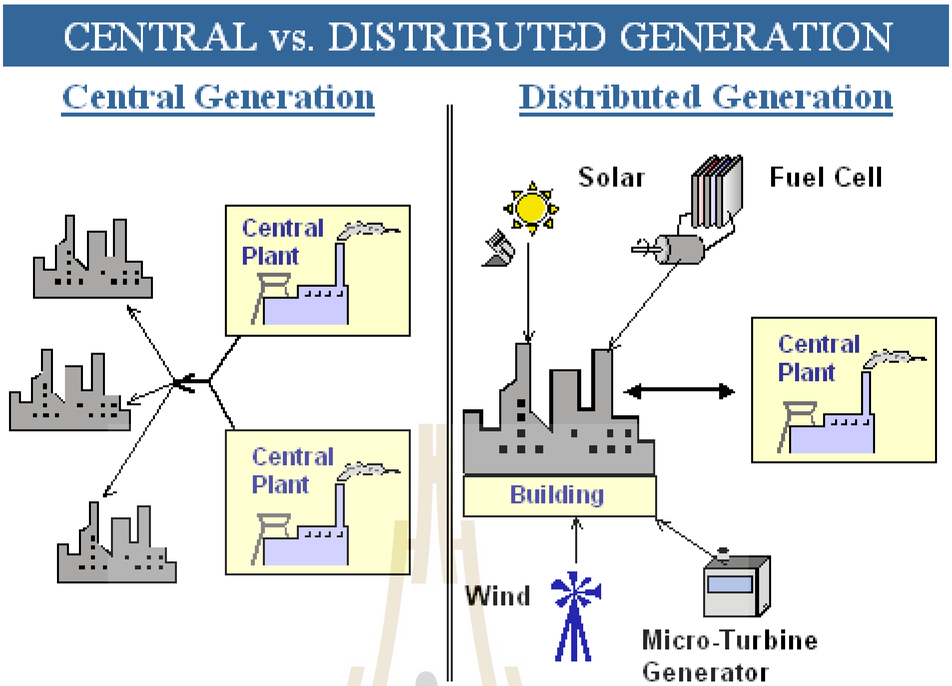


Figure 2.11 Comparison of the Centralized generation and Distributed generation (Longe, 2016).

2.5.1 Photovoltaic (PV) Systems

The PV system is a power system which converts the solar energy to electricity with the photovoltaic cells (Turner, 1999). For a completed PV system solution, a DC-AC converter is usually included to convert the electricity from DC to AC, which can feed to the grid directly (Teodorescu, Liserre, and Rodriguez, 2011). For some residential PV system such as standalone systems, the battery bank is necessary to ensure continuous power output during the night-time (Wang, and Zhang, 2010). According to the scale and location, PV systems are categorized into three kinds: Residential roof-top, commercial roof-top and ground-mount utility-scale systems, which are shown in Figure 2.12, respectively.

Although the PV technique has already existed for more than twenty years, there is an only little share of the market for the PV systems because of the high cost in the early periods. After entering the 21st century, the price of PV system kept dropping due to the continuous price reduction of PV array materials and the improvement of PV manufacturing efficiency (Luque, and Hegedus, 2011). From 2001 to 2012, the cost of PV system has dropped by more than 50%, i.e. $2.00 per watt (€1.52 per watt) (Feldman, 2014). Because of the price dropping of PV modules, the installation capacity of the PV system has increased correspondingly. The U.S PV installation capacity had increased from 4MW to 1.15GW between 1997 and 2008 – nearly 300 times. At the same time, the 10-year CAGR of global PV showed a great growth rate which was close to 55% (U. S. DOE, 2010). It should be noted that the remarkable increase of the PV system installation has not only benefited from the price drop of PV modules, but also from the government financial subsidies. For instances, US government provides 30% Federal tax Grant for PV system; UK government gives 13.88p/kWh FIT generation tariff to small solar PV system (capacity smaller than 4kW) and6.38p/kWh generation tariff for stand-alone solar PV system (capacity larger than50kW) and Chinese Government allows US$0.15 per kWh for PV system (Varma, Sanderson, and Walsh, 2011; Mulder et al., 2013; Zhang, and He, 2013).

Figure 2.12 Three main kinds of PV systems

(Allan, 2010; Becky, 2012; Systems, 2012).

Benefiting from the factors mentioned above, the installation capacity of PV system is expected to keep a sustainable and rapid growth in the predictable future (Bayod-Rújula, 2009; Dincer, 2011; Larson et al., 2003). For the small/medium scale roof-top PV systems in residential and commercial buildings, there is still great room for growth (Braun et al., 2012; Castleton et al., 2010). Therefore, aiming to improve the monitor and control functions of such systems, the upcoming metering, control and optimization tools and components included in the smart home/ buildings solution will play an extremely important role for helping end users monitor and manage the PV systems (Allerding and Schmeck, 2011; Sechilariu, Wang, and Locment, 2013).

2.5.2 Energy Storage Systems (ESS)

The ESS is the system to store the energy through physical media for later use. The ESS can satisfy the demands of different storage applications from residential users to the wholesale energy market. Since the smart grid aims to build an environment-friendly and decentralized power grid, the ESS can act as a coordinator in the network to help maintain the stability of the grid. Due to the instability of the generation of the renewable generators, such as wind turbine and PV arrays, the power output is always changeable and thereby difficult to predict accurately. The power generation has difficulties to satisfy the changeable power demands once the ratio of renewable energy resources takes high share in the entire power generations, and thus may result in a power surge, frequency variation and other problems. With the assistance of ESS, the active/inactive power control, load shifting, and excess energy storage can be achieved, and improve the stability of the power grid and the efficiency of energy use (Suyang, 2014).

Figure 2.13 Energy Storage Systems

(Allan, 2010; Becky, 2012; Systems, 2012).

Currently, there are various techniques applied for the storage media in the energy storage systems, such as a battery, flywheel, a large capacitor, hydrogen and compressed air. Figure 2.13 gives several demonstration projects of energy storage systems with different techniques. In the low voltage (LV) distributed power network, with the consideration of cost and system working efficiency, the battery energy storage system (BESS) is recommended (Cheng, 2012). The BESS can store the spare energy generated by PV with the common DC bus and transmit the stored energy to residential house or grid through the DC/AC converter once necessary.

2.5.2.1 Battery Energy Storage and its Applications.

This one briefly describes the four considered battery technologies including their history, chemical characteristics, and their applications when integrated with renewable energy sources.

1. Lead-acid (Pb-A)

Pb-A batteries were first created in the 1860's and are one of the most mature, least expensive and widely used rechargeable battery technologies in the world today. The defining characteristics of lead-acid batteries include relatively low cost, technological maturity, low energy density, and limited cycle life. The open-circuit potential of the fully charged lead-acid cell is approximately 2.15 V however this value varies with temperature and decreases significantly as the battery is discharged (Linden and Reddy, 2010). The following reaction occurs in a lead-acid battery (Linden and Reddy, 2010).

$$Pb + PbO_2 + 2H_2SO_4 \rightarrow 2PbSO_4 + 2H_2O \quad (\text{discharge}) \tag{2.1}$$

The ideal applications include uninterruptable power supply and short duration grid support to prevent failure or instability that could result in large financial losses (Chen et al., 2009; Dell and Rand, 2001). The Electricity Storage Association (ESA) states Pb-A batteries are "fully capable and reasonable" for power applications and "feasible but not quite practical or economical" for energy applications (Electricity Storage Association, 2012). SANDIA national laboratory along with EPRI has identified several applications and several combinations of individual applications for Pb-A batteries in (EPRI, 2003; EPRI, 2004), all of which pertain to short/medium duration storage and infrequent deep discharge cycles. To enable comparison between Lead-acid (Pb-A) and other Energy Storage Technology (EST) some numeric values for several parameters are presented in Table 2.4.

Table 2.4 Numeric values of critical parameters for Lead-acid (Pb-A)

Lead-acid (Pb-A)	
Power (MW)	0-40 (Kyriakopoulos, 2015)
Capacity (MWh)	0.25-50 (Palizban, 2016)
Storage Period (Time)	Day-month (Baeyens et al., 2015)
Specific Energy (kWh/ton)	20 (Andrews and Jelley, 2013)
Energy Density (kWh/m^3)	70 (Wolf, 2014)
Efficiency (%)	70-90 (Kyriakopoulos, 2015)
Lifetime (# Cycles)	500-1000 (Jeong and Cho, 2015)
Power Cost ($/kW)	300-600 (Jeong and Cho, 2015)
Energy Cost ($/kWh)	200-400 (Kyriakopoulos, 2015)

Lead-acid (Pb-A) battery energy storage is employed by the following advantages: Can provide high current; Mature technology; and highly recycled. Some of the disadvantages are that they contain toxic substance and Short lifetime.

2. Lithium-ion (Li-ion)

Li-ion batteries are a recent technology with roots based at Bell labs in the 1960's and the first commercialization by Sony in 1990 (Chen et al., 2009). The defining characteristics of Li-ion batteries are high cycle life, high energy density, high efficiency, and high cost which have led to their use in small format consumer electronics. Figure 2.14 is intended to clarify the technical design of the battery. The basic intercalation reaction for Li-ion batteries is as follows in (2.2) (Scrosati and Garche, 2010):

$$yC + LiMO_2 \rightarrow Li_xC_y + Li_{1-x}MO_2, \;\; \mathrm{x} = 0.5, y = 6 \;\; (\mathrm{discharge}) \qquad (2.2)$$

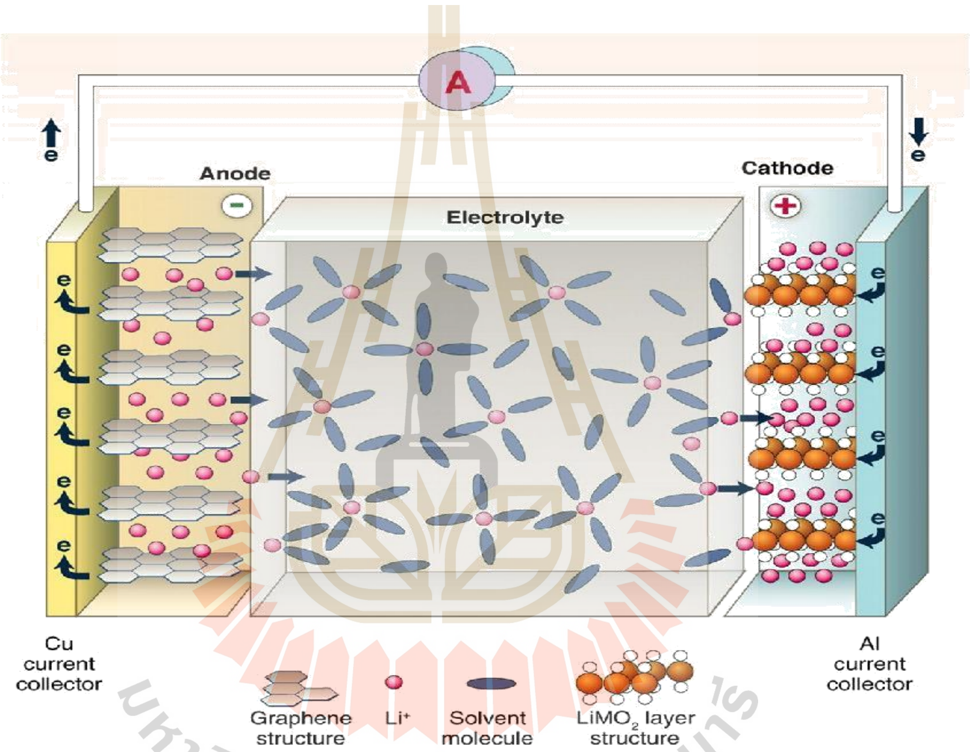


Figure 2.14 Schematic diagram describing the designing of a Lithium-ion (Xu, 2004).

Li-ion batteries possess high power capability, good cycle life, high energy density, and high efficiency; however, they are relatively expensive. The E/P ratio indicates ideal application in short and medium duration grid services. Li-ion power cell designs are the only suitable technology for second-timescale services.

Employing other battery technologies for these purposes would result in dramatic oversizing of the storage capacity. Due to high energy density, portable grid storage battery banks have been suggested for temporary or semi-permanent application for T&D deferral or other non-permanent applications (Altair-Nano, 2011). The ESA finds Li-ion batteries to fall under the same application category as Pb-A batteries with “fully capable and reasonable” rating for power applications (short duration storage) and “feasible but not quite practical or economical” for energy applications (long duration storage) (Electricity Storage Association, 2012). However, Referring to Figure 2.14, it becomes clear Li-ion outperform Pb-A batteries in all engineering consideration categories, but not maturity or cost. Because of these cost and life characteristics, the choice of lead-acid or lithium ion remains application specific. To enable comparison between Lithium-ion (Li-ion) and other Energy Storage Technology (EST) some numeric values for several parameters are presented in Table 2.5.

Lithium-ion (Li-ion) battery energy storage is employed by the following advantages: High efficiency; Low weigh, and small battery. One of the disadvantage is very expensive.

Table 2.5 Numeric values of critical parameters for Lithium-ion (Li-ion)

Lithium-ion (Li-ion)	
Power (MW)	0.001-0.1 (Sarbjit et al., 2014)
Capacity (MWh)	0.25-25 (Kauhaniemi, 2016)
Storage Period (Time)	Day-month (Baeyens et al., 2015)
Specific Energy (kWh/ton)	75-200 (Kyriakopoulos, 2015)
Energy Density (kWh/m^3)	300 (Wolf, 2014)
Efficiency (%)	85-100 (Sarbjit et al., 2014)
Lifetime (# Cycles)	1000-4500 (Zakeri, 2014)
Power Cost ($/kW)	175-4000 (Jeong and Cho, 2015)
Energy Cost ($/kWh)	500-2500 (Jeong and Cho, 2015)

3. Sodium-sulfur (Na-S)

Na-S batteries are another relatively new battery technology. In the 1980's NGK Insulators began work on developing Na-S for grid-scale applications and ultimately developed a grid-scale product that has seen exponential growth rates of implementation related to grid support and renewable energy applications (Dell and Rand, 2001; Beaudin et al., 2010; NGK Insulators, 2011). Na-S batteries are regarded as one of the lowest cost options for grid-scale energy storage (López, Agustín, and Navarro, 2009). The defining characteristics of Na- S batteries are high cycle life, high energy density, high pulse power capability, and average to low cost. Figure 2.15 shows the conceptual schematic of a Na-S Battery (NGK Insulators, 2011). The basic chemical reaction is a combination of positive sodium ions with the molten sulfur according to the following chemical equation (2.3):

$$2Na + 2S \rightarrow Na_2S_4 \quad (\text{discharge}) \tag{2.3}$$

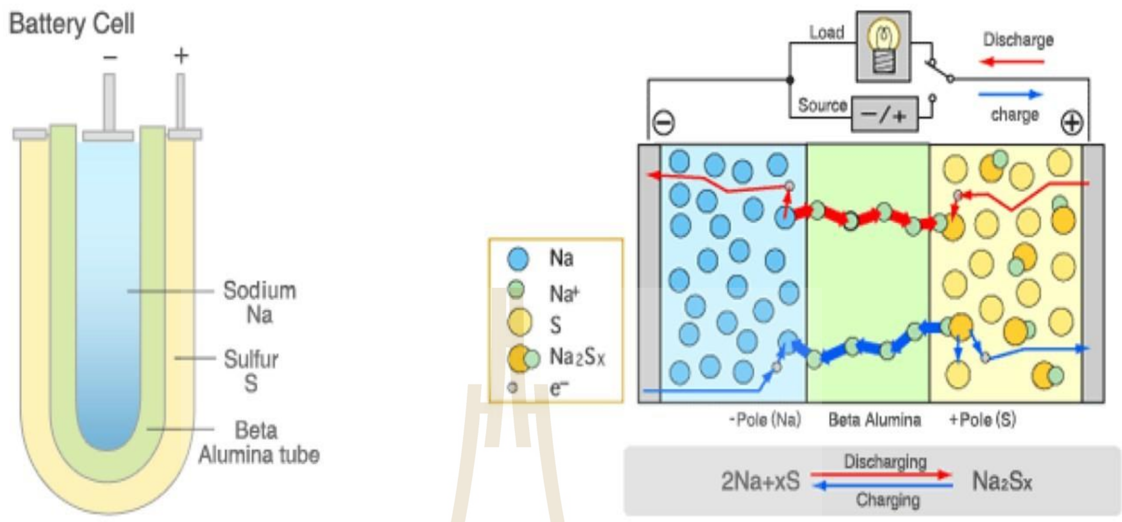


Figure 2.15 Sodium-sulfur battery schematic (NGK Insulators, 2011)

The E/P ratio for commercially available Na-S cells suggests its application to hour- timescale medium and long duration grid services. Na-S batteries are the only technology to receive "fully capable and reasonable" ratings from the ESA in both power and energy applications, suggesting this technology will become valuable in grid-storage applications (Electricity Storage Association, 2012). Due to the high cycle life, energy and power densities, reasonable cost, and being environmental effects of the battery, Na-S batteries are poised for several energy storage applications (Chen et al., 2009; Beaudin et al., 2010; Electricity Storage Association, 2012)). Unfamiliarity and production capacity (single vendor (Electricity Storage Association, 2012)) will be the limiting factors in deployment of this technology for grid-storage applications. It is evident from Table 2.6 and Figure

2.15 that Na-S has advantages over VRB in the storage duration lasting several hours. Beyond this however, the scalability of VRB gives it competitive advantage.

Table 2.6 Numeric values of critical parameters for Sodium-sulfur (Na-S)

Sodium-sulfur (Na-S)	
Power (MW)	1-50 (Sandia National Labratorie, 2016)
Capacity (MWh)	≤ 300 (Kauhaniemi, 2016)
Storage Period (Time)	Day (Castillo, 2014)
Specific Energy (kWh/ton)	150 (Andrews and Jelley, 2013)
Energy Density (kWh/m^3)	150-250(Wang, Dooner and Luo, 2014)
Efficiency (%)	75-90 (Kyriakopoulos, 2015)
Lifetime (# Cycles)	2500 (Jeong and Cho, 2015)
Power Cost ($/kW)	1000-3000 (Jeong and Cho, 2015)
Energy Cost ($/kWh)	300-500 (Kyriakopoulos, 2015)

4. Vanadium Redox Battery (VRB)

Development of the VRB began in the early 1980's at the University of New South Wales (Chen et al., 2009). The defining characteristics of the VRB include extremely large cycle life, independent energy and power construction, low to average energy density, moderate efficiency, moderate cost, and no self-discharge. A simple schematic of the VRB can be seen in Figure 2.16.

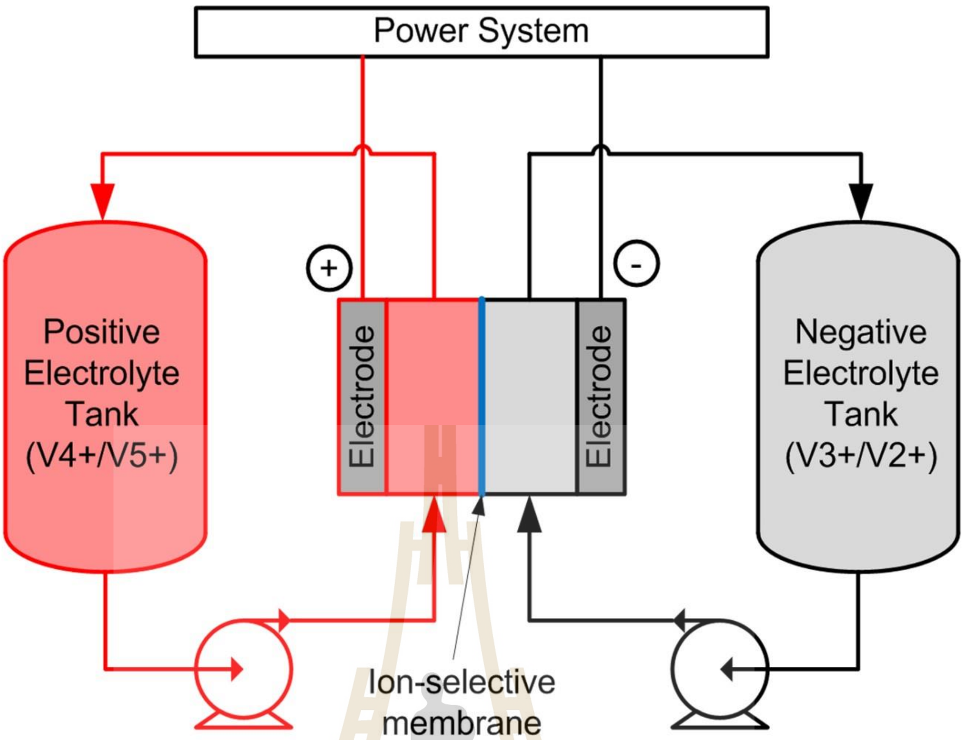


Figure 2.16 VRB schematic (Leadbetter, 2012).

VRB's has relatively low energy density, and small incremental cost for increasing the storage capacity. The E/P ratio suggests ideal application in medium to long duration storage systems. As it requires sufficient space and maintenance (e.g. pumps) this technology is ideally suited to centralized large-scale long duration storage. Although several VRB demonstration projects are operating, this technology has still not achieved commercial level. The ESA rates VRB (and other flow batteries) as "reasonable" for power applications and "fully capable and reasonable" for energy applications suggesting it could very well fulfill a hybrid role where long duration storage is the primary concern, and power quality improvement is a secondary concern (Electricity Storage Association, 2012). To enable comparison between VRB and other Energy Storage Technology (EST) some numeric values for several parameters are presented in Table 2.7.

Table 2.7 Numeric values of critical parameters for Vanadium Redox Battery (VRB)

Vanadium Redox Battery (VRB)	
Power (MW)	0.03-7 (Sarbjit et al., 2014)
Capacity (MWh)	< 10 (Kyriakopoulos, 2015)
Storage Period (Time)	Day-month (Baeyens et al., 2015)
Specific Energy (kWh/ton)	10-30 (Kyriakopoulos, 2015)
Energy Density (kWh/m^3)	25-35 (Wang, Dooner and Luo, 2014)
Efficiency (%)	75-85 (Sarbjit et al., 2014; Kyriakopoulos, 2015)
Lifetime (# Cycles)	12000 (Akinyele, 2014; Jeong and Cho, 2015)
Power Cost ($/kW)	600-1500 (Jeong and Cho, 2015)
Energy Cost ($/kWh)	150-1000 (Kyriakopoulos, 2015)

2.5.3 Electric Vehicle (EV)

The spread of EV and PHEV not only bring social and economic benefits, but also reduce the burden of the electrical power system. According to (Tokuda, 2012), it has mentioned that over 20 million of EV will be on the road by 2020 worldwide. Correspondingly, Pike's research suggests that the number of EV charging stations will hit 11 million globally by 2020 (Shahan, 2012). In the USA, which is the largest EV ownership country, it is planned to build a huge amount of fast charging stations to satisfy the fast-growing demands (Etezadi-Amoli, Choma, and Stefani, 2010). Along with the increasing number of EVs and accompanying EV charging stations, the relevant charging demands will increase either, which will significantly influence the stability and power quality of the distributed network. This is because of the high unit power rate of EV charging box/station and the generality of transportation user patterns (e.g. office workers have similar working periods during the week days).

As mentioned previously, the power grid operator will face new challenges in power flows, grid losses, and voltage profile patterns once a large number of EVs are connected to the power system. (Richardson, 2013; Lopes, Soares, and Almeida, 2011; Rosenfield, 2010) concluded that the power grid operator would face new peak loads caused by the EVs, and the existing grid equipment (e.g. Small Transformer in distribution grid) will have difficulties in handling the mass electric power, thus the power suppliers need to build more power plants to satisfy the increased demands. With the consideration of the proposed problems caused by the EVs, (Leemput et al., 2012; Peas Lopes Almeida and Soares, 2009; Musio, Lombardi, and Damiano, 2010; Aabrandt et al., 2012; Pillai et al., 2012; Chukwu, and Mahajan, 2014) specified a number of methods from the charging scheduling, centralized management, renewable energy integration and Vehicle-to-Grid (V2G) perspectives.

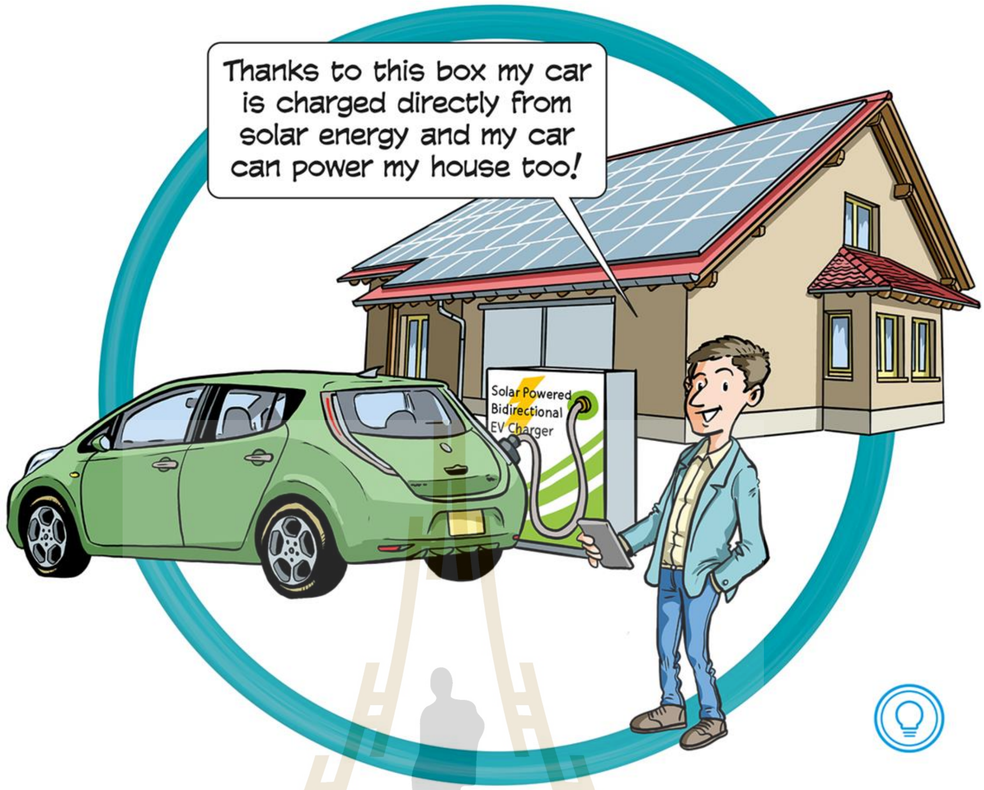


Figure 2.17 A Home Based EV Smart Charging System (TuDelft, 2017).

Aabrandt et al., (2012) proposed a smart charging method for the EVs in the distribution network based on the aggregator service, which can schedule the charging of the EVs by considering the prediction of required EV and the power grid loads. Moreover, Pillai et al., (2012) proposed a charging scheduling approach of EVs that can integrate with the wind system and other renewable energy systems in order to use the available capability of the distribution network efficiently. As shown in Figure 2.17, a home based EV smart charging system is presented, utilizing the Mixed Integer Linear Programming (MILP) to forecast the load consumption, PV generation prediction and the electricity price and optimize the EV charging to minimize the energy bill (Molina et al., 2012).

2.5.4 Other Systems

Apart from the DERs listed above, there are still a number of other DERs used with different techniques, such as CHP and Waste-to-energy. Those DERs mainly focus on the recycling and reusing of the wasted energy. For instances, the waste-to-energy system can collect the decomposers of the flora and fauna wastes and drive the turbine or fuel cells generating heat or electricity, and the CHP system reuses the exhausted heat from a generation for heating or other purposes (Psomopoulos, Bourka, and Themelis, 2009; Braun, Klein, and Reindl, 2006).

2.6 Demand Response (DR)

The concept of demand response (DR) is nowadays used by various agents in energy markets with different interpretations. In some cases, the concept is used as an umbrella to cover a multitude of actions. In another case, it simply defines a specific load control action.

Some of the common definitions are listed below:

(IEA, 2003)

"Demand response refers to a set of strategies which can be used in competitive electricity markets to increase the participation of the demand-side, or end-use consumers, in setting prices and clearing the market."

(Laurita, 2005)

"Demand Response is: Customers reducing their electricity consumption in response to either high wholesale electricity prices or system reliability events. Customers being paid for performance based on wholesale market prices."

(Harrington, 2003)

"At its most general level, demand response is the ability of (electricity) demand to respond to variations in market prices in "market" or "real" time. It can be achieved through demand reduction, by shifting load to a less expensive time period, or by substituting another resource for delivered electricity (such as gas or self-generation)."

(Piette et al., 2005)

"Demand Response can be defined as (1) load response managed by others for reliability purposes, (2) load response managed by others for procurement cost minimization purposes (e.g., load bidding), and (3) price response managed by end-use consumers for bill management."

There are two principal points of view (leading to particular interests) when describing demand response as a process:

- Of the consumer: (i) automated response and load control systems (making processes less labor intensive, etc.), (ii) energy supply without significant interruptions or loss of comfort, (iii) saved money.
- Of the supplier: (i) effective pricing mechanisms, (ii) automatic load reduction, (iii) risk management.

Different demand response strategies/methods (direct load control, self-control and indirect control) have different prerequisites and results. In many cases, it is important to harmonize (combine) indirect load control (pricing, etc.), self-control (automation, e.g., load guards, etc.) and direct load control (demand shifting or shedding on HVAC systems, processes, etc.) in Demand Response programs.

Three levels of Demand Response automation are as follows: (a) Manual Demand Response: Involves manually turning off lights or equipment; this can be a labor-intensive approach. (b) Semi-Automated Response: Includes the use of building energy management control systems for load shedding, where facilities staff initiates a preprogrammed load shedding strategy. (c) Fully-Automated Demand Response: Undertaken at a building or facility through receipt of an external communications signal; specialists set up a pre-programmed load shedding strategy which is automatically initiated by the system without the need for human intervention.

Proven technological solutions are one of the key challenges to advancing demand response. The technology, first of all, has to enable the effective communication between utility and consumer equipment:

"Demand responsive control systems integrate the controls for the distributed (demand responsive) energy system with electronic communication and metering technology to facilitate one-way or two-way communication between utility and customer equipment. These technologies are used to reduce energy consumption (by dimming lights, raising air-conditioning setpoints, etc.) in response to peak electricity demand emergencies and/or prices."

"If the load is participating in more advanced demand response programs such as demand bidding or buyback, time-of-use or real-time pricing, the metering package might also need to have the ability to receive price and send response signals from and to the load-serving entity and/or the transmission provider."

As it is described at the beginning of this chapter, DR and LM are very similar in their strategies and methods. The major difference is that the LM is a plan that operates on a "regular" basis (daily or weekly according to preset plan), while DR typically responds to "emergency" events in the system (see Figure 2.18). Therefore, such above-described strategies as TOU rates and TLDC would rather refer to load management, while the remaining ones would be more appropriate for demand response.

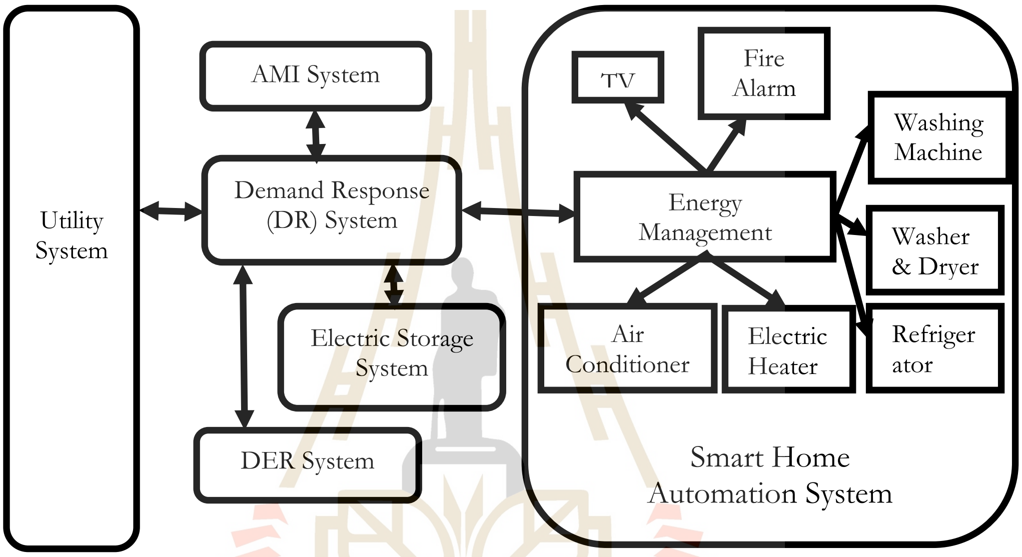


Figure 2.18 Systems related to demand response (DR) systems.

2.6.1 DR Options

Two main categories of DR options are possible in the real-world electricity environment based on the way in which the load adjustments are made. They are the price response demand options and the incentive-based options, as illustrated in Fig. 2.19.

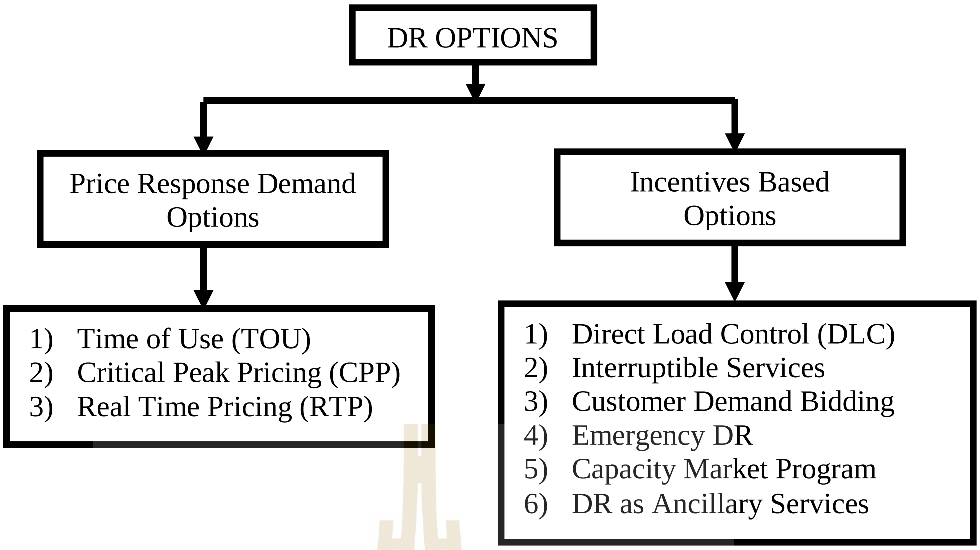


Figure 2.19 Available DR Options

An incentive-based DR is established by electric utilities when the utility has the direct control of residential loads. Customers are provided with an incentive separately or as a reduced rate in their electricity bill. This group of options functions when adverse network conditions exist or when a high wholesale price spike occurs. In contrast, price response demand options refer to the changes in usage of electricity in response to the electricity price variation. Customers tend to reduce their consumption in order to reduce the cost of their consumption during times of high electricity prices (U. S. Department of Energy, 2006). Here, the customer response is entirely voluntary. Details of both techniques are discussed next.

2.6.1.1 Incentives-Based Options.

Incentive-based programs are market based and give the electric utility the authority for appliance control. Participating customers are provided with a reward (U. S. Department of Energy, 2006). Examples of incentive-based programs include:

1. Direct Load Control

In a direct load control scheme, the electric utility remotely shuts down or adjusts residential appliances on short notice. Customers are provided with rebates or reduced bills for the forced load adjustments.

2. Interruptible Services

In the interruptible services approach, the electric utility provides flexibility to customers to adjust their loads during critical conditions. Curtailment options are broadcast to the customers in advance with appropriate retail tariffs and discounts or rebates. Customers automate their loads for control according to curtailment options. If the customers fail to curtail their loads, penalties are applied to the customers.

3. Customer Demand Bidding

In customer demand bidding, an opportunity is given to residential customers to offer bids based on the wholesale price or an equivalent price signal. The electric utility selects load based on the bids and remotely controls loads of selected customers.

4. Emergency DR

In an emergency DR scheme, customer load adjustments are conducted during a power shortfall and incentives are provided for affected customers.

5. Capacity Market Program

In a capacity market program, customers offer bids according to possible load curtailments in the capacity market as a replacement for expensive generators. The electric utility selects the customers based on the bids and sends prior notice of curtailment. Customers automate their loads for control in order to match with the prior notice for curtailment. Penalties may apply if the customers fail to curtail their loads during the given time.

6. DR for Ancillary Services

Unlike the capacity market program, customers in a DR for ancillary services scheme bid for load curtailment as operating reserves. Upon the acceptance of bids by the ancillary services market, offers are provided to customers during selected dispatch time steps. Finally, loads are subjected to control based on the offers.

2.6.1.2 Price Response Demand Options.

1. Time-of-Use (TOU) tariff

TOU pricing is designed to reflect the utility cost structure where rates are more expensive during peak periods and cheaper during off-peak periods. Both the supplier and the end-user benefit from successfully designed TOU rates. Examples of defined peak periods are shown in Figure 2.20.

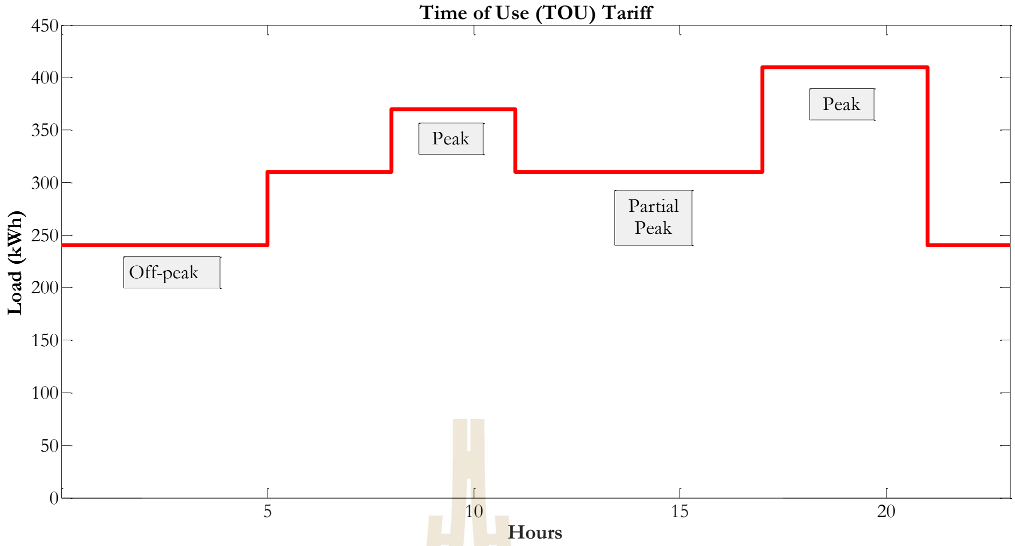


Figure 2.20 Time of Use Pricing

2. Real Time Pricing (RTP)

The principle of RTP is that the consumer (end-user) price is linked to the wholesale market price. RTP might also be called dynamic pricing. The principal feature is that timing and prices are not set in advance (IEA, 2003).

As defined by Barbose and Goldman, 2004, "Under real-time pricing (RTP) tariffs, retail electricity consumers are charged prices that vary over short time intervals (typically hourly) and are quoted one day or less in advance, to reflect contemporaneous marginal supply costs (see Figure 2.21). These tariffs differ significantly from those used by electric utilities, which are based on prices that are fixed for months or years at a time to reflect the average, embedded supply costs, with little or no differentiation with respect to the timing of consumption".

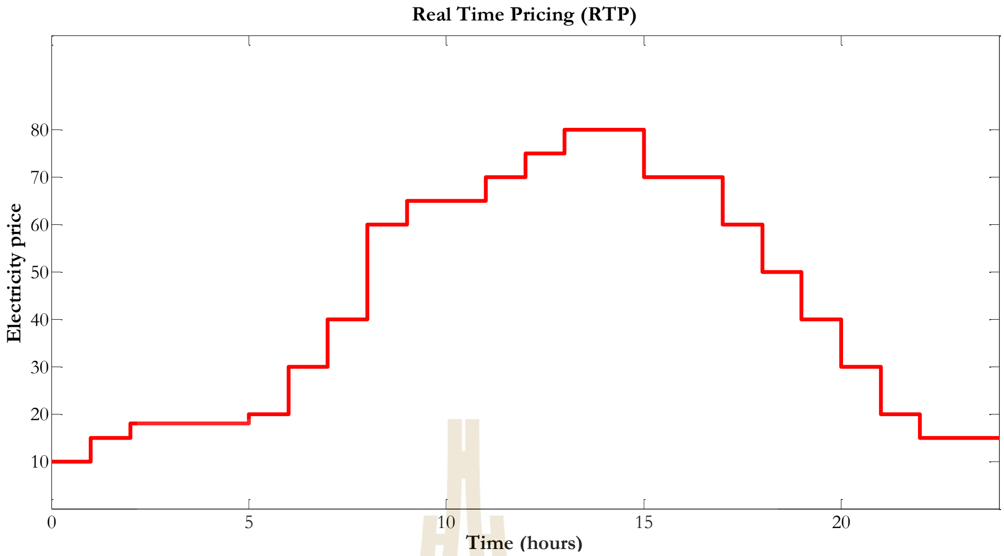


Figure 2.21 Real-time Pricing

3. Critical Peak Pricing (CPP)

CPP could be called a combination of TOU and RTP. It uses a unique, increased rate on selected days with high demand prediction, aiming to reduce demand when it is most critical. Generally, a day-ahead notification is given to customers to allow them to make voluntary energy reduction when the CPP days are called. An example of CPP situation is shown in Figure 2.22. On CPP days participating customers face up to five times higher peak prices and are compensated by lower than normal rates for non-CPP days (PG&E, 2007).

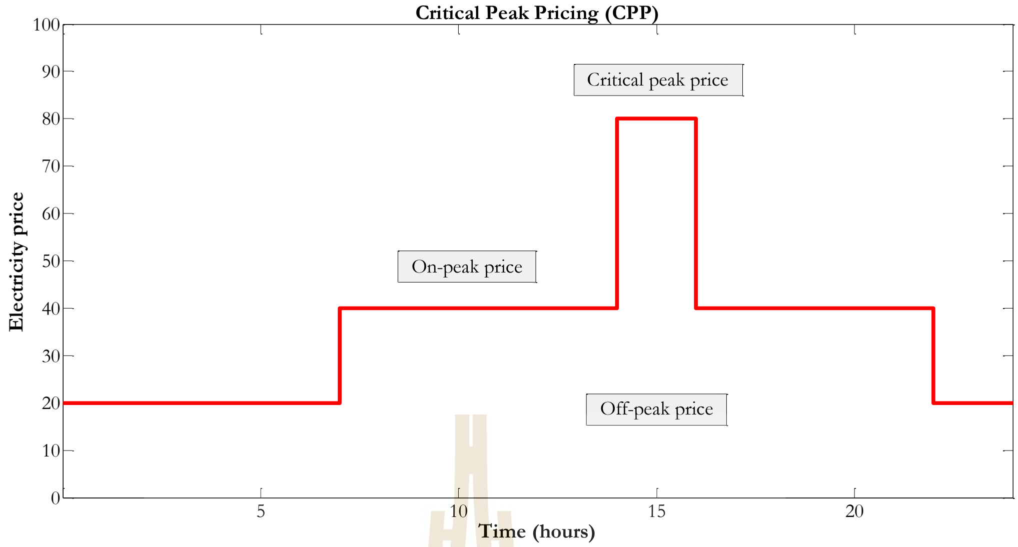


Figure 2.22 Critical-peak Pricing

2.7 Benefits of Load Management and Demand Response

Load management and demand response require an individual "sacrifice" of consumer comfort and freedom. However, the implementation of LM and DR strategies can provide some technical, economic, environmental and social benefits.

The significant advantages of an electricity market are:

- Increased overall economic efficiency**:** When consumers change their electricity usage behavior and reduce or shift on-peak usage and costs to off-peak periods, it results in the more efficient use of the electric system;
- Market power mitigation: DR programs help relieve market power of traditional and new energy suppliers especially when there are limited supplies and/or transmission constraints that might lead to market power;
- Improved system reliability: During emergency conditions, DR enhances electric system reliability;

- Reduced price volatility (risk management): Prices in wholesale markets vary from day to day, and hour to hour. DR reduces suppliers' and consumers' risk in the market;
- Reduction of average energy prices to all consumers: DR implementation can lower costs for generation, transmission and distribution charges and help reduce wholesale market prices;
- Consumer service: DR helps users understand and manage their electricity use better;
- Environmental impact: Demand response can contribute to reducing environmental impacts by reducing or delaying additional power plant developments and by allowing the utilization of the existing generation capacity more efficiently.

2.8 Environment Aspects

Usually, the term "load management" is considered to be solely a technical and marketing measure for improving the economic performance. Research has mostly been devoted to issues such as harmonizing the relations between supply and demand, optimizing power generation and transmission, and increasing the security of supply. These economic and technical effects, however, influence environmental performance as well. Research has rarely identified or emphasized this impact.

Load management can be used to achieve the following effects in electrical power systems:

- Decrease the operation of peak units;

- Ensure optimal operation of base generation units. Reducing the frequency of restarting power plants and ramping their production up and down. Start-ups often require burning fuel at a suboptimal temperature and/or without generating electricity. Similarly, ramping (changing the output from a generating unit) may cause fuel to be burned sub-optimally. Eliminating startups and reducing ramping would reduce emissions (Holland and Mansur, 2003);
- Avoid or postpone addition of generation and network capacity;
- Allows an increase in new renewable energy generation with variable output. Since the "new" renewable electricity generation technologies, such as wind and solar, have variable output, load management can, in principle, help to absorb peak production and fill troughs at least production. The solid biomass plant is best for base-load supply. In this case, the higher reliance on base power units could be a tool to increase the renewables' share in the total mix.

These measures, in principle, may affect the environment, (i) by reducing fossil carbon and radioactive emissions, and (ii) by avoiding the land use for a new generation and transmission infrastructure.

2.9 Barriers to LM and DR

In spite of the beneficial possibilities, the demand side strategies have, their penetration into the market meet various constraints, starting from customer understanding of energy use, economic valuation, technical options to policymaking. (Levy and Piette, 2005) note some main challenges and barriers to advancing DR, namely the need of jointly understood the terminology, understanding, and quantification of the value of DR, transparent pricing, awareness by policymakers, delivery/marketing, development and penetration of DR enabling technologies.

(Electric Power Research Institute, 2002) underline such constraints for DR development as program design and unreliability (unproductiveness) of customer behavior:

“As regulators and energy companies struggle to gain control, existing demand response programs are being challenged to provide capabilities that the technologies, incentive structures, and operating plans just cannot support. While many of the problems are severe and often challenge program continuity, the solution lies in improved program design and not the development of new technology.”

Consumer attitude and awareness problem are one of the most important. (Moezzi et al., 2004) emphasize that “electricity customers have been collectively trained on and formed by a century of primarily flat, fixed rates, or otherwise predictably-priced power. Consumer views on electricity service and pricing, as well as business practices reflect this history”.

It is a big challenge to make DR a reliable resource. Many energy experts note that whenever they talk to utilities about DR, one of the first things to hear from system operators is that the DR is not the resource they could count on. It is not like having a “button to push” so the load would instantaneously disappear. DR programs are not set up this way. This simultaneously leads to the conclusion that utilities did not seek to understand what the consumers want and so the utilities create DR programs in their own isolation.

DR is also a function of what is going on the marketplace. Emergency or crisis situations, e.g., the one that was in California in 2000 – 2001, motivated consumers to participate in DR. Even though they did not understand the issue well, they participated. However, the expectations and motivations are different during the crisis and without it. 4-5 years later the interest decreased.

Demand-side activities for electric load reduction have a potential to provide significant benefits in the electricity market, but at the same time meets various barriers. Research on energy demand-side raises diverse and complex questions. The next chapter of this thesis presents the results of the performed research of the author and his colleagues.

2.10 Types of residential loads and its characteristics

In residential energy management system, scheduling of different types of load can only be realized after having complete data of load type and their characteristics including cycle durations, energy consumed in every mode. In a particular home area network (HAN), the load may include:

- Appliances;
- Electric vehicle (EV);
- Energy storage devices or battery management system (BMS).

The energy usage of these loads in residential sector has been summarized in Figure 2.23. Household appliance load can be further sub-categorized into manageable and non-manageable loads as shown in Table 2.8 below. Mostly in the literature of energy management system, it is a manageable load which has all the focus mainly because of its high energy consumption and predictability in its operation. In (Agnetis, Pascale, Detti, and Vicino, 2013) and (Chen, Wang, Heo, and

Kishore, 2013), the manageable load has been further categorized as shown in Figure 2.23.

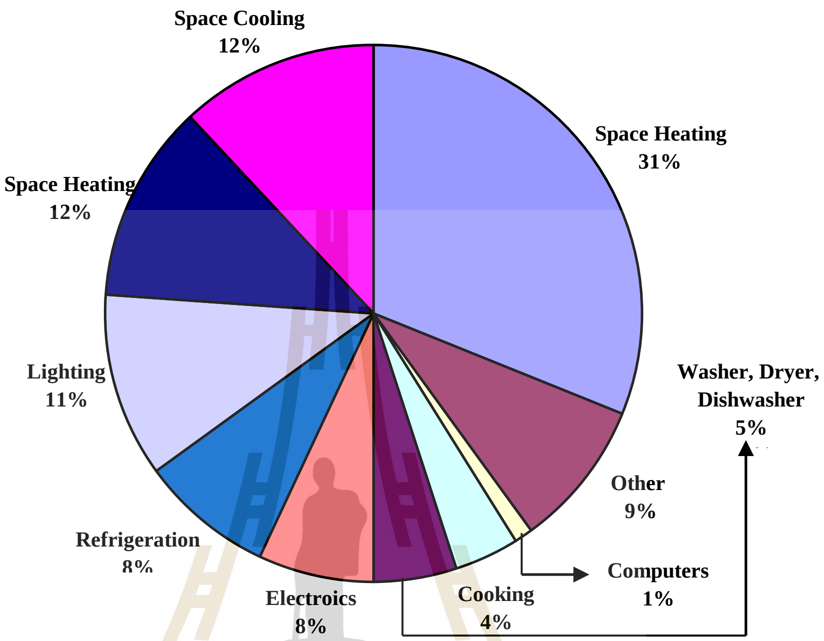


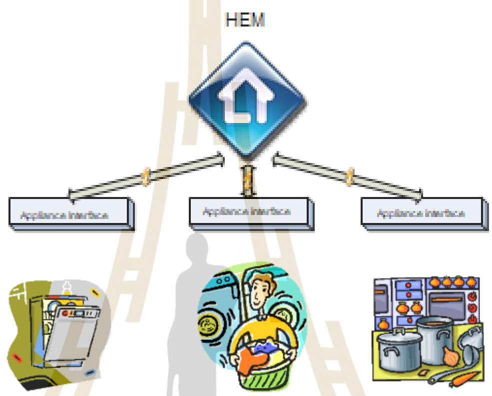
Figure 2.23 A typical electric energy usage in residential sector

(The National Academies, 2015).

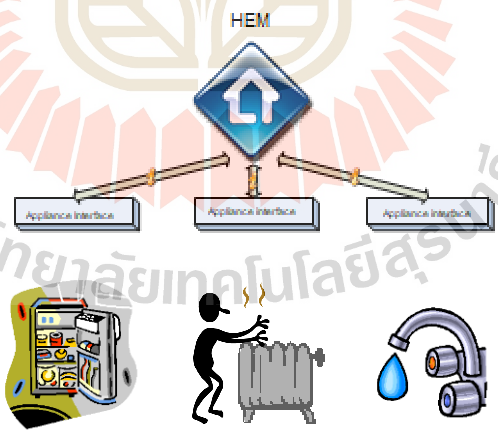
Table 2.8 Load types and its Characterictics

No.	Category	Types of loads	Home appliance
1	Manageable	Shiftable	Washing Machine, Dish Washer
2	Manageable	Interruptible	Water heater, Refrigerator
3	Manageable	Weather Based	Air Conditioner, Electric Heater
4	Non-manageable	Auxiliary	TV, laptops, lights

(a)



(b)



(c)

Figure 2.24 Home load categorization (Costanzo, 2011): (a) Auxiliary; (b) Shiftable; (c) Interruptible.

- Weather-based load refers to the appliances that to be operated continuously throughout the day. Examples of this baseload are an air conditioner, electric heater, etc. Such as air conditioner and electric heaters which depend upon weather and power absorption of premises.
- Non-shiftable load refers to the appliances which must be turned ON immediately when it is needed, and it cannot change its working time period.
- Shiftable load refers to the appliances which can complete its task within the preferred time interval, (flexible delay having certain consumption cycle with specified energy consumption profile), e.g., washing machine, dishwater, etc. Further, the shiftable load can be divided into two type's namely interruptible and non-interruptible loads.
  - Interruptible load refers to the appliances that can be given discrete time intervals to complete its working cycle. E.g., water heater, refrigerator (for example, water heater and refrigerator they are either ON with fixed energy consumption or OFF. However, their ON cycle duration depends upon user preference setting).
  - Non-interruptible load refers to the appliances that are turned ON exactly once to complete its job (for example, water heater and refrigerator they are either ON with fixed energy consumption or OFF. However, their ON cycle duration depends upon user preference setting).

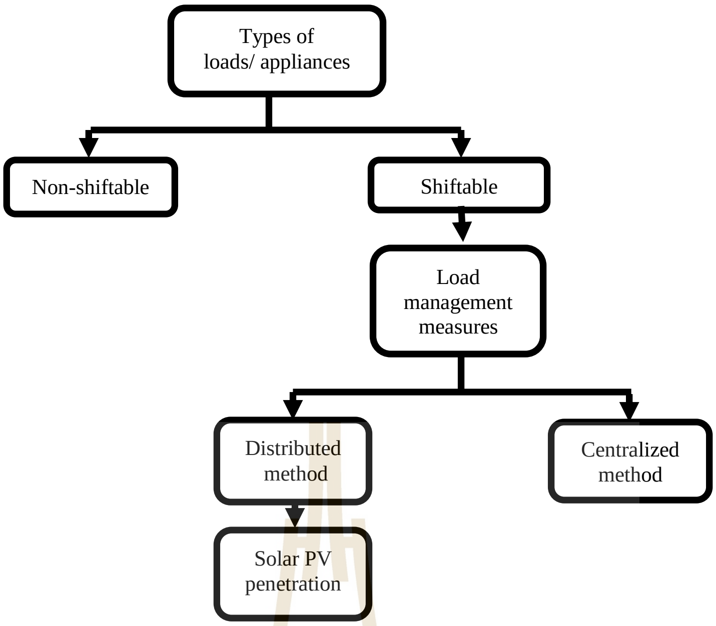


Figure 2.25 Overview of the proposed Scheduling Process

2.11 Mixed Integer Linear Programming (MILP)

Linear programming (LP, or linear optimization) is a mathematical method for determining a way to achieve the best outcome (such as maximum profit or lowest cost) in a given mathematical model for some list of requirements represented as linear relationships (Schrijver, 1998). Linear programming is a specific case of mathematical programming (mathematical optimization). More formally, linear programming is a technique for the optimization of a linear objective function, subject to linear equality and linear inequality constraints. Its feasible region is a convex polyhedron, which is a set defined as the intersection of finitely many half spaces, each of which is defined by a linear inequality. Its objective function is a real-valued affine function defined on this polyhedron. A linear programming algorithm finds a point in the polyhedron where this function has the smallest (or largest) value if such a point exists. Linear programs are problems that can be expressed in the canonical form:

$$\min_x \ f^T x \text{ subject to} \begin{cases} x(\text{intcon}) \text{ are integers} \\ A.x \le b \\ Aeq.x = beq \\ lb \le x \le ub. \end{cases} \tag{2.4}$$

$$x = \text{intlinprog}\left(f, \text{intcon}, A, b, Aeq, beq, lb, ub\right) \tag{2.5}$$

Where x represents the vector of variables (to be determined);

f and b are vectors of (known) coefficients;

A is a (known) matrix of coefficients;

$(.)^T$ is the matrix transpose;

$f^T x$ is the objective function to be minimized;

$Ax \le b$ are the inequalities constraints;

intcon refers to the vector of integer constraints;

Aeq is the linear equality constraint matrix;

beq is the linear equality constraint vector; and

lb and *ub* refers to the lower and upper bounds.

Linear programming can be applied to various fields of study. It is used in business and economics but can also be utilized for some engineering problems. Industries that use linear programming models include transportation, energy, telecommunications, and manufacturing. It has proved useful in modeling diverse types of problems in planning, routing, scheduling, assignment, and design.

Integer programming (IP) adds additional constraints to linear programming. In particular, it adds the requirement that some or all of the variables take on integer values. This seemingly innocuous change greatly increases the number of problems that can be modeled, but also makes the models more difficult to solve. In fact, two seemingly similar formulations for the same problem (one integer and the other one linear) can lead to radically different computational experience. Integer programming is NP-hard.

Table 2.9 Logical conditions to Binary conditions. All variables $\in\{0,1\}$

Logical condition	Binary condition
At most *N* of *a*, *b*, *c*, …	$a+b+c+\ ...\ \leq N$
At least *N* of *a*, *b*, *c*, …	$a+b+c+\ ...\ \geq N$
Exactly *N* of *a*, *b*, *c*, …	$a+b+c+\ ...\ = N$
If *a* then *b*	$b \geq a$
If *a* then not *b*	$a+b \leq 1$
If not *a* then *b*	$a+b \geq 1$
If *a* then *b*, and if *b* then *a*	$a=b$
If *a* then *b* and *c*; *a* only if *b* and *c*	$b \geq a$ and $c \geq a$
If *a* then *b* or *c*	$b+c \geq a$
If *b* or *c* then *a*	$a \geq b$ and $a \geq c$
If *b* and *c* then *a*	$a \geq b+c-1$

MIP (Mixed Integer Programming) is a generalization of LP in which the variables of the linear model are an integer. In some cases, the variables could also be binary. The binary modeling can be very tricky sometimes because our thinking is not used to. In Table 3.1 are presented some useful transformations of logical conditions to binary conditions.

The “INTLINPROG” uses this basic strategy to solve mixed-integer linear programs. intlinprog can solve the problem in any of the stages. If it solves the problem in a stage,intlinprog does not execute the later stages.

1. Reduce the problem size using Linear Program Preprocessing;
2. Solve an initial relaxed (noninteger) problem using Linear Programming;
3. Perform Mixed-Integer Program Preprocessing to tighten the LP relaxation of the mixed-integer problem;
4. Try Cut Generation to further tighten the LP relaxation of the mixed-integer problem;
5. Try to find integer-feasible solutions using heuristics; and
6. Use a Branch and Bound algorithm to search systematically for the optimal solution. This algorithm solves LP relaxations with restricted ranges of possible values of the integer variables. It attempts to generate a sequence of updated bounds on the optimal objective function value.

2.12 Whale Optimization Algorithm (WOA)

Seyedali and Andrew in (2006), proposed an innovative nature based meta-heuristic optimization technique known as Whale Optimization Algorithm (WOA) that models the general behaviors of humpback whales. Usually, whales are considered as talented animals in movement. The WOA is motivated by the special hunting characteristic of humpback whales (Mirjalili and Lewis, 2016). In general, the humpback whales aim to hunt krills or small fishes near the sea area. They use a genuine technique called bubble net feeding. With this technique, they swim around the target and build up a peculiar bubble beside a circle or 9-shaped path (Mirjalili and Lewis, 2016).

The mathematical model and optimization algorithms, WOA can be expressed into three categories as: (a) Encircling prey, (b) Bubble net hunting method, and (c) Search the prey.

Figure 2.26 Bubble-net feeding behavior of humpback whales (Mirjalili and Lewis, 2016).

2.12.1 Encircling Prey

Humpback whales can recognize the location of prey and encircle them. Since the position of the optimal design in the search space is not known a priori, the WOA algorithm assumes that the current best candidate solution is the target prey or is close to the optimum. After the best search agent is defined, the other search agents will hence try to update their positions towards the best search agent.

This behavior is represented by the following equations (2.6) and (2.7) (Mirjalili and Lewis, 2016):

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \times \vec{D} \tag{2.6}$$

$$\vec{D} = \left| \vec{C} \times \vec{X}^*(t) - \vec{X}(t) \right| \tag{2.7}$$

Where t indicates the current iteration;

$\vec{A}$ and $\vec{C}$ are coefficient vectors;

X^* is the position vector of the best solution obtained so far; and

$\vec{X}$ is the position vector.

It is worth mentioning here that X^* should be updated in each iteration if there is a better solution.

The vectors $\vec{A}$ and $\vec{C}$ are calculated by Mirjalili and Lewis in (2016) as follows in equation (2.8) and (2.9):

$$\vec{A} = 2 \times \vec{a} \times \vec{r} - \vec{a} \tag{2.8}$$

$$\vec{C} = 2 \times \vec{r} \tag{2.9}$$

Where equation (2.6) show the best solution position and the position of the vector. The current iteration is expressed by t. $\vec{C}, \vec{A}$ are the vectors coefficients. $\vec{a}$ decreased from 2 to 0 directly. $\vec{r}$ is a random vector [0, 1].

2.12.2 Bubble Net Hunting Method

This one is classified into two categories as Shrinking encircling prey and Spiral position updating.

- **Shrinking Encircling Prey**

Here $\vec{A} \in [-a, a]$ whereby $\vec{A}$ is reduced from 2 to 0. Here the position is set down at random values in between [-1, 1]. The current position of $\vec{A}$ is achieved between original position and position of the current best agent.

- **Spiral Position Updating**

A spiral equation is then created between the position of whale and prey to mimic the helix-shaped movement of humpback whales as follows in equation (2.10):

$$\vec{X}(t+1) = \vec{D} \times e^{bl} \times \cos(2\pi l) + \vec{X}^* \tag{2.10}$$

In the two paths above, whales swim around the prey during hunting simultaneously. 50% probability is accounted for above two methods (Mirjalili and Lewis, 2016) to update whale's positions.

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A} \times \vec{D} & if\ \ p < 0.5 \\ \vec{D}' \times e^{bl} \times \cos(2\pi l) + \vec{X}^* & if\ \ p < 0.5 \end{cases} \tag{2.11}$$

Where $D' = \left| \vec{X}^* - \vec{X}(t) \right|$ express the whale and the prey distance known as the best solution. b is constant, $l \in [-1,\ 1]$. P is random number [0, 1].

2.12.3 Search for Prey

The same approach based on the variation of the A^* vector can be utilized to search for prey (exploration). In fact, humpback whales search randomly according to the position of each other. Therefore, we use $\vec{A}$ with the random values greater than 1 or less than −1 to force search agent to move far away from a reference whale. In contrast to the exploitation phase, we update the position of a search agent in the exploration phase according to a randomly chosen search agent instead of the best search agent found so far. This mechanism and $|\vec{A}|>1$ emphasize exploration and al- low the WOA algorithm to perform a global search. The mathematical model is as follows:

$$\vec{D}=\left|\vec{C}\times\vec{X}_{rand}-\vec{X}\right| \tag{2.12}$$

$$\vec{X}(t+1)=\vec{X}_{rand}-\vec{A}\times\vec{D} \tag{2.13}$$

$\vec{X}_{rand}$ is a random position vector (a random whale) chosen from the current population.

CHAPTER 3

METHODOLOGY

3.1 Introduction

In this chapter, appliance scheduling is formulated using MILP technique and Whale Optimization Algorithm (WOA) for which use of decision variable and auxiliary binary decision variables are defined and applied. An extension to MATLAB in WOA is used during simulation, while MILP is used to interface with INTLINPROG solver for obtaining optimized scheduling of appliances for minimizing peak load and cost of energy of the homes integrated with renewable energy sources (Solar PV modules) and battery energy storage (Lithium-ion).

3.2 Scheduling of Smart Homes Energy Consumption

Cumulative load demand for appliances depends on how they are scheduled (used) over the time. For example, if all appliances start at the same time, the coincident demand could be very high to surpass the maximum limits imposed by the electricity distributors and sometimes adversely affect the home electrical system. Therefore, the appliance use should be appropriately spread over the time to keep the peak demand to a minimum and also usage cost of electricity to a minimum and, yet comfort is not sacrificed. In order to reduce the electricity price and make better use of the energy provided by the grid, one has to control the power consumption patterns of electric time-shiftable appliances in a smart home environment. An appliance is defined as time-shiftable when its power consumption time can be shifted to a preferred working period. To minimize the electricity cost, a residential power management system is implemented through the optimal scheduling of home appliances. A scheduled plan is realized in which the power usages of the different appliances are arranged to match the times of the day where the electricity price is minimum.

To define the scheduling of home appliance load as to when appliances start and end (called appliance window) in 24-hour time scale in a day, we define the following terms:

3.2.1 Set of Appliances

A, represents the set of electrical appliances used in the smart home Then, A = {heater1, dishwasher, washing machine, heater2, Iron, PV panels}. In this case, i denotes the index of the appliance shown in the set A.

3.2.2 Duration of Operation

A day of 24 hours is divided into 24-time slots. Thus, each time slot represents an interval of 60 minutes. The appliances can be set to start at any time within this time frame and end its cycle of operation before or on 24th time slot; surely not later this time. All the time slots are represented by their starting times. The end time slot will be obtained by adding 60 minutes to the starting time.

3.2.3 Execution Window of each Operation

Appliances must start in a user-specified window. Therefore, users specify the desired execution window for each appliance, i.e., the interval when the appliance can run. More precisely, for each appliance, there is a minimal starting time (before that it cannot start), and a maximal ending time (by then it has to be finished). The schedule is free to switch on the appliances at any time as long as it respects the starting and ending time constraints within the range.

3.2.4 Defining Problem

The appliance execution period of 24 hours is considered here which is divided into m equals to 24-time slots of 60 minutes each. *N* denotes the set of the number of appliances for scheduling, and *ni* indicates their corresponding number of the set of un-interruptible load profile for each appliance for $i = 1, 2, 3, \ldots, N$. If a single appliance is to be used on more than one occasion at different times, it will be treated as differently like appliance-1 and appliance-2, with the same load profile or different. We are now equipped to define appliance use by name (having its fixed corresponding load profile), that is some load phases *j* in use of appliance *i* during the time slot *k*. Therefore, P_{ij}^{k} represents load variable assigned to an appliance *i* having load phase *j* during the time slot *k*.

The optimal load management problem is a linear optimization problem. It consists of a linear objective function defined by nonlinear constraints. The optimal load management problem requires the solution of linear equations, describing optimal and/or secure operation of the home network. The general optimal load management problem can be expressed as a constrained optimization problem as follows:

$$\min = \{ f(x) | x \in X \}$$
$$\textit{Subject to } g(x) \geq 0 \qquad (3.1)$$
$$h(x) = 0$$

Where *f(x)* is the objective function, *g(x)* is the inequality constraint function, and *h(x)* is the equality constraint function.

3.2.5 Decision Variables

The typical unit for P_{ij}^{k} is kW, but when this is multiplied by a factor of (60/60=1), its unit will be changed into kWh. The load profiles P_{ij}^{k} are real (i.e., continuous) decision variables. In addition to P_{ij}^{k} we need the support of auxiliary binary decision variable to indicate whether a particular load profile is being processed or not. {0, 1} denotes binary decision variables. $X_{ij}^{k} = 1$, if an appliance *i* and its load phase *j* are being processed during the time slot *k*, otherwise. $X_{ij}^{k} = 0$. It can be, alternatively, stated that in the time interval of operation of appliances in their respective windows, the binary variable. $X_{ij}^{k} = 1$ and beyond the window, it is $X_{ij}^{k} = 0$.

$$X_{ij}^{k} = \begin{cases} 1 & \textit{if appliance is ON} \\ 0 & \textit{if appliance is OFF} \end{cases} \qquad (3.2)$$

3.2.6 Objective Function

The objective of the load scheduling is to minimize the total electricity cost for operating the appliances based on 24-hours ahead TOU electricity tariff. Let C^{k} denote electricity TOU tariff for time slot *k*. Then the total cost of electricity consumption function fc is given by the following equation:

$$\min \sum_{k=1}^{m} C^k \left(\sum_{i=1}^{N} \sum_{j=1}^{ni} P_{ij}^k X_{ij}^k \right) \tag{3.3}$$

The syntax for the MILP in MATLAB is given as follows in (3.6):

$$\min \sum_{k=1}^{m} C^k \left(\sum_{i=1}^{N} \sum_{j=1}^{ni} P_{ij}^k X_{ij}^k \right) = \begin{matrix} C^1 \\ C^2 \\ C^3 \\ . \\ . \\ . \\ C^{24} \end{matrix} \times \begin{bmatrix} p_{1,1} & p_{1,2} & p_{1,3} & . & . & p_{1,24} \\ p_{2,1} & p_{2,2} & p_{2,3} & . & . & p_{2,24} \\ p_{3,1} & p_{3,2} & p_{3,3} & . & . & p_{3,24} \\ p_{4,1} & p_{4,2} & p_{4,3} & . & . & p_{4,24} \\ p_{5,1} & p_{5,2} & p_{5,3} & . & . & p_{5,24} \end{bmatrix} \tag{3.4}$$

$$= \begin{bmatrix} C^1 \times p_{1,1} & C^2 \times p_{1,2} & C^3 \times p_{1,3} & . & . & C^{24} \times p_{1,24} \\ C^1 \times p_{2,1} & C^2 \times p_{2,2} & C^3 \times p_{2,3} & . & . & C^{24} \times p_{2,24} \\ C^1 \times p_{3,1} & C^2 \times p_{3,2} & C^3 \times p_{3,3} & . & . & C^{24} \times p_{3,24} \\ C^1 \times p_{4,1} & C^2 \times p_{4,2} & C^3 \times p_{4,3} & . & . & C^{24} \times p_{4,24} \\ C^1 \times p_{5,1} & C^2 \times p_{5,2} & C^3 \times p_{5,3} & . & . & C^{24} \times p_{5,24} \end{bmatrix} \tag{3.5}$$

Hourly electricity price fluctuation: the TOU tariffs are dynamic and fluctuate hourly depending on the energy generation, consumption and the peak hourly loads. The defined electricity cost value named C^k is given by the following 1×24 matrix by Rafkaoui in (2016) as shown in Fig 3.1:

C^k = [0.09, 0.08, 0.08, 0.09, 0.1, 0.1, 0.08, 0.1, 0.11, 0.11, 0.11, 0.11, 0.11, 0.11, 0.09, 0.1, 0.12, 0.11, 0.12, 0.11, 0.12, 0.11, 0.12, 0.11]

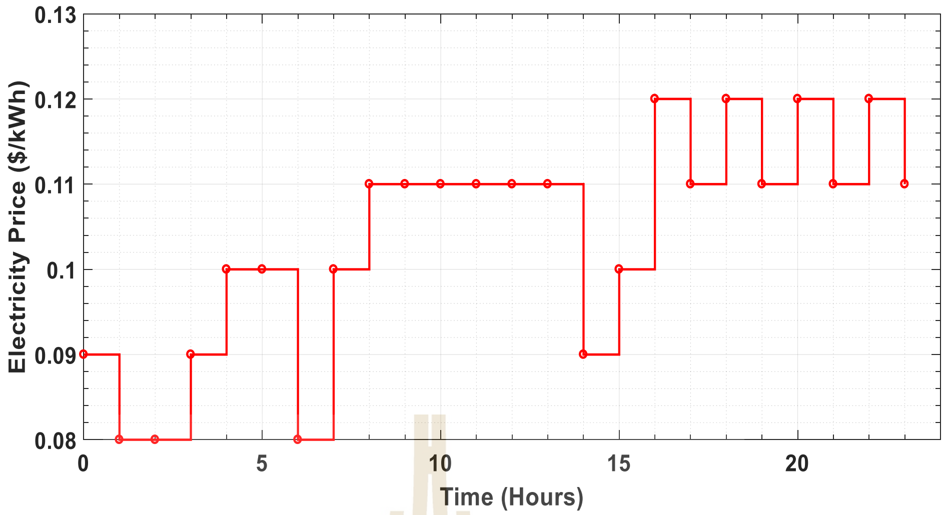


Figure 3.1 Electricity Price (Rafkaoui, 2016).

Where P_{ij}^{k} represents continuous decision variable which is used to indicate the load assigned to phase j of the appliance i during the time slot k. Once first load phase starts, it will sequentially complete all the phases, uninterruptedly. The corresponding auxiliary binary variable $X_{ij}^{k} \in \{0, 1\}$ is used with P_{ij}^{k} as on/off switch to estimate the time slot k when the appliance first phase starts till all its load phases end. The appliance will start once on the time scale and will not restart again. Therefore, optimization will be on the binary variable X_{ij}^{k} for all values of which appliance i and its load phases (load profile) j are known, and the only k is unknown. This will provide an optimal layout of appliances with their respective start and end slot time with the objective to minimize energy cost in TOU tariff.

The above equation has a different variant if renewable energy (PV) is integrated:

$$\min \sum_{k=1}^{m}\sum_{i=1}^{N}\sum_{j=1}^{ni}\left(C^{k}P_{ij}^{k}X_{ij}^{k}-g^{k}G_{ij}^{k}X_{ij}^{k}\right) \tag{3.6}$$

Where C^k represents Time-of-Use (TOU) tariff; g represents feed-in tariff; and G_{ij}^{k} is the power produced by PV panel consisting of different phases j at a time k.

If solar PV modules are added, then the equation will be as follows:

$$\min \sum_{k=1}^{m}\sum_{i=1}^{N}\sum_{j=1}^{ni}\left\{C^{k}P_{ij}^{k}-g^{k}\times r\times PR\times A\times T_{ij}^{k}\right\}X_{ij}^{k} \tag{3.7}$$

$$= \begin{matrix} C^{1} \\ C^{2} \\ C^{3} \\ . \\ . \\ . \\ C^{24} \end{matrix} \times \begin{bmatrix} p_{1,1} & p_{1,2} & p_{1,3} & . & . & p_{1,24} \\ p_{2,1} & p_{2,2} & p_{2,3} & . & . & p_{2,24} \\ p_{3,1} & p_{3,2} & p_{3,3} & . & . & p_{3,24} \\ p_{4,1} & p_{4,2} & p_{4,3} & . & . & p_{4,24} \\ p_{5,1} & p_{5,2} & p_{5,3} & . & . & p_{5,24} \end{bmatrix} - \begin{matrix} g^{1} \\ g^{2} \\ g^{3} \\ . \\ . \\ . \\ g^{24} \end{matrix} \times 0.16\times 0.75\times 4\times \begin{matrix} T^{1} \\ T^{2} \\ T^{3} \\ . \\ . \\ . \\ T^{24} \end{matrix} \tag{3.8}$$

Where r is the solar panel yield or efficiency equals to 16%, PR value is the performance ratio equals to 75%, A variable is the area of the photovoltaic modules 4 m^2, T is the hourly irradiation; and g^k is the feed-in tariff.

As a micro-grid component in the objective function is constant as it has only assigned fixed possible starting and ending time. The optimization will be achieved through appliance scheduling only. The PV profile will be superimposed on the demand curve of the appliances. It makes easy to determine time-wise usage of power either to supplement appliance demand to reduce load or export power where possible, when PV supply load is more than the appliances demand.

The above equation has a different variant if renewable energy (PV) is integrated with battery energy storage:

$$\min \sum_{k=1}^{m}\sum_{i=1}^{N}\sum_{j=1}^{ni}\left\{C^k P_{ij}^k - g^k (r \times PR \times A \times T_{ij}^k - P_{Bt})\right\} X_{ij}^k \tag{3.9}$$

Where r is the solar panel yield or efficiency equals to 16%, PR value is the performance ratio equals to 75%, A variable is the area of the photovoltaic modules 4 m^2, T is the hourly irradiation, g^k is the feed-in tariff; and P_{Bt} is the output power of the battery energy storage used when no renewable energy is generated in the smart home.

3.2.7 System Constraints

The constraints are grouped into energy constraints and timing constraints as indicated in equations (3.10) - (3.12).

To make sure that load phases of appliances fulfill their energy requirements, the following constraint is imposed:

$$\sum_{i=1}^{N}\sum_{j=1}^{ni} P_{ij}^k = E_{ij} \qquad \forall\{i, j\} \tag{3.10}$$

Where E_{ij} is the energy requirement for appliance i with load phase j and m are the available time slots in a day (in our case m = 24). These are technical specifications for the appliances. Time interval of load profile readings is 60 minutes each (= 1 hr).

Energy bounds: ensures the energy allocated in phase j for appliance i in any time slot k belongs to the allowed range [α, β].

$$\alpha_{ij} \le P_{ij}^{k} \le \beta_{ij} \qquad \forall\{i, j, k\} \tag{3.11}$$

The load safety constraint puts an upper limit to the peak coincident load demand of all appliances not exceeding a certain pre-defined limit P_{peak}^{k} .

$$\sum_{i=1}^{N}\sum_{j=1}^{ni} P_{ij}^{k} \le P_{peak}^{k} \qquad \forall\{k\} \tag{3.12}$$

The peak signal P_{peak}^{k} is provided by the grid operator, which is a demand response signal.

3.3 Mixed Integer Linear Programming (MILP)

Linear programming (LP, or linear optimization) is a mathematical method for determining a way to achieve the best outcome (such as maximum profit or lowest cost) in a given mathematical model for some list of requirements represented as linear relationships (Schrijver, 1998). Linear programming is a specific case of mathematical programming (mathematical optimization). More formally, linear programming is a technique for the optimization of a linear objective function, subject to linear equality and linear inequality constraints. Its feasible region is a convex polyhedron, which is a set defined as the intersection of finitely many half spaces, each of which is defined by a linear inequality. Its objective function is a real-valued affine function defined on this polyhedron. A linear programming algorithm finds a point in the polyhedron where this function has the smallest (or largest) value if such a point exists. Linear programs are problems that can be expressed in the canonical form:

$$\min_x \ f^T x \text{ subject to} \begin{cases} x(\text{intcon}) \text{ are integers} \\ A.x \le b \\ Aeq.x = beq \\ lb \le x \le ub. \end{cases} \tag{3.13}$$

$$x = \text{intlinprog}\left(f, \text{intcon}, A, b, Aeq, beq, lb, ub\right) \tag{3.14}$$

Where *x* represents the vector of variables (to be determined);

f and *b* are vectors of (known) coefficients;

A is a (known) matrix of coefficients;

$(.)^T$ is the matrix transpose;

$f^T x$ is the objective function to be minimized;

$Ax \le b$ are the inequalities constraints;

intcon refers to the vector of integer constraints;

Aeq is the linear equality constraint matrix;

beq is the linear equality constraint vector; and

lb and *ub* refers to the lower and upper bounds.

Linear programming can be applied to various fields of study. It is used in business and economics but can also be utilized for some engineering problems. Industries that use linear programming models include transportation, energy, telecommunications, and manufacturing. It has proved useful in modeling diverse types of problems in planning, routing, scheduling, assignment, and design.

Integer programming (IP) adds additional constraints to linear programming. In particular, it adds the requirement that some or all of the variables take on integer values. This seemingly innocuous change greatly increases the number of problems that can be modeled, but also makes the models more difficult to solve. In fact, two seemingly similar formulations for the same problem (one integer and the other one linear) can lead to radically different computational experience. Integer programming is NP-hard.

Table 3.1 Logical conditions to Binary conditions. All variables $\in \{0,1\}$

Logical condition	Binary condition
At most N of a, b, c, …	$a+b+c+\ ...\ \leq N$
At least N of a, b, c, …	$a+b+c+\ ...\ \geq N$
Exactly N of a, b, c, …	$a+b+c+\ ...\ = N$
If a then b	$b \geq a$
If a then not b	$a+b \leq 1$
If not a then b	$a+b \geq 1$
If a then b, and if b then a	$a=b$
If a then b and c; a only if b and c	$b \geq a$ and $c \geq a$
If a then b or c	$b+c \geq a$
If b or c then a	$a \geq b$ and $a \geq c$
If b and c then a	$a \geq b+c-1$

MIP (Mixed Integer Programming) is a generalization of LP in which the variables of the linear model are an integer. In some cases, the variables could also be binary. The binary modeling can be very tricky sometimes because our thinking is not used to. In Table 3.1 are presented some useful transformations of logical conditions to binary conditions.

The “INTLINPROG” uses this basic strategy to solve mixed-integer linear programs. intlinprog can solve the problem in any of the stages. If it solves the problem in a stage,intlinprog does not execute the later stages.

1. Reduce the problem size using Linear Program Preprocessing;
2. Solve an initial relaxed (noninteger) problem using Linear Programming;
3. Perform Mixed-Integer Program Preprocessing to tighten the LP relaxation of the mixed-integer problem;
4. Try Cut Generation to further tighten the LP relaxation of the mixed-integer problem;
5. Try to find integer-feasible solutions using heuristics; and
6. Use a Branch and Bound algorithm to search systematically for the optimal solution. This algorithm solves LP relaxations with restricted ranges of possible values of the integer variables. It attempts to generate a sequence of updated bounds on the optimal objective function value.

3.4 Whale Optimization Algorithm (WOA)

Seyedali and Andrew in (2006), proposed an innovative nature based meta-heuristic optimization technique known as Whale Optimization Algorithm (WOA) that models the general behaviors of humpback whales. Usually, whales are considered as talented animals in movement. The WOA is motivated by the special hunting characteristic of humpback whales (Mirjalili and Lewis, 2016). In general, the humpback whales aim to hunt krills or small fishes near the sea area. They use a genuine technique called bubble net feeding. With this technique, they swim around the target and build up a peculiar bubble beside a circle or 9-shaped path (Mirjalili and Lewis, 2016).

The mathematical model and optimization algorithms, WOA can be expressed into three categories as: (a) Encircling prey, (b) Bubble net hunting method, and (c) Search the prey.

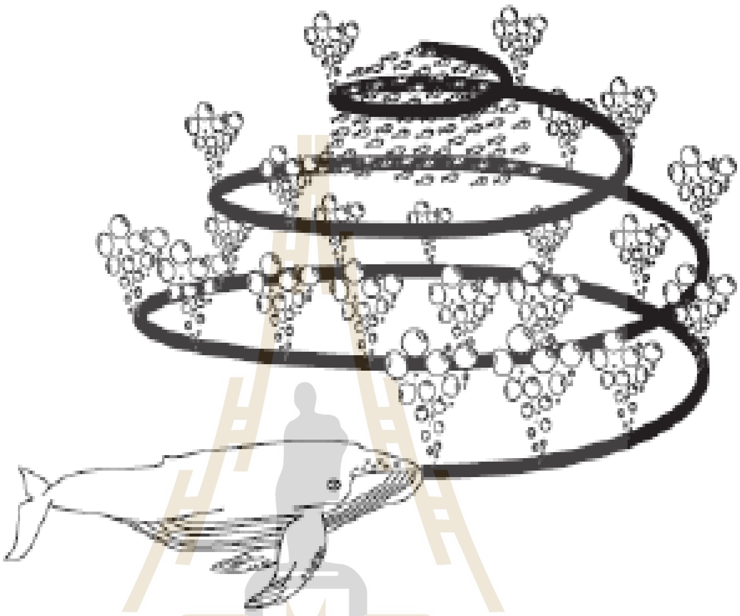


Figure 3.2 Bubble-net feeding behavior of humpback whales (Mirjalili and Lewis, 2016).

3.4.1 Encircling Prey

Humpback whales can recognize the location of prey and encircle them. Since the position of the optimal design in the search space is not known a priori, the WOA algorithm assumes that the current best candidate solution is the target prey or is close to the optimum. After the best search agent is defined, the other search agents will hence try to update their positions towards the best search agent. This behavior is represented by the following equations (3.15) and (3.16) by Mirjalili and Lewis in (2016):

$$\vec{X}(t+1)=\vec{X}^*(t)-\vec{A}\times\vec{D} \tag{3.15}$$

$$\vec{D}=\left|\vec{C}\times\vec{X}^*(t)-\vec{X}(t)\right| \tag{3.16}$$

Where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, X^* is the position vector of the best solution obtained so far, and $\vec{X}$ is the position vector. It is worth mentioning here that X^* should be updated in each iteration if there is a better solution.

The vectors $\vec{A}$ and $\vec{C}$ are calculated by Mirjalili and Lewis in (2016) as follows in equation (3.17) and (3.18):

$$\vec{A}=2\times\vec{a}\times\vec{r}-\vec{a} \tag{3.17}$$

$$\vec{C}=2\times\vec{r} \tag{3.18}$$

Where equation (3.15) show the best solution position and the position of the vector. The current iteration is expressed by t. $\vec{C},\vec{A}$ are the vectors coefficients. $\vec{a}$ decreased from 2 to 0 directly. $\vec{r}$ is a random vector [0, 1].

3.4.2 Bubble Net Hunting Method

This one is classified into two categories as Shrinking encircling prey and Spiral position updating.

- **Shrinking Encircling Prey**

Here $\vec{A}\in[-a,a]$ whereby $\vec{A}$ is reduced from 2 to 0. Here the position is set down at random values in between [−1, 1]. The current position of $\vec{A}$ is achieved between original position and position of the current best agent.

- **Spiral Position Updating**

A spiral equation is then created between the position of whale and prey to mimic the helix-shaped movement of humpback whales as follows in equation (3.19):

$$\vec{X}(t+1) = \vec{D} \times e^{bl} \times \cos(2\pi l) + \vec{X}^* \tag{3.19}$$

In the two paths above, whales swim around the prey during hunting simultaneously. 50% probability is accounted for above two methods (Mirjalili and Lewis, 2016) to update whale's positions.

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A} \times \vec{D} & if \;\; p < 0.5 \\ \vec{D}' \times e^{bl} \times \cos(2\pi l) + \vec{X}^* & if \;\; p < 0.5 \end{cases} \tag{3.20}$$

Where $D' = \left|\vec{X}^* - \vec{X}(t)\right|$ express the whale and the prey distance known as the best solution. b is constant, $l \in [-1, 1]$. P is random number [0, 1].

3.4.3 Search for Prey

The same approach based on the variation of the A^* vector can be utilized to search for prey (exploration). In fact, humpback whales search randomly according to the position of each other. Therefore, we use $\vec{A}$ with the random values greater than 1 or less than −1 to force search agent to move far away from a reference whale. In contrast to the exploitation phase, we update the position of a search agent in the exploration phase according to a randomly chosen search agent instead of the best search agent found so far. This mechanism and $\left|\vec{A}\right| > 1$ emphasize exploration and al- low the WOA algorithm to perform a global search. The mathematical model is as follows:

$$\vec{D} = \left| \vec{C} \times \vec{X}_{rand} - \vec{X} \right| \tag{3.21}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \times \vec{D} \tag{3.22}$$

$\vec{X}_{rand}$ is a random position vector (a random whale) chosen from the current population.

The input data to the proposed WOA is the number of appliances to be scheduled n, the population size of a whale N, and the maximum number of iterations it_{max}. The WOA beginning by producing N solutions from the random population in the search environment [0, 100], for every position the fitness function Fit_i is examined by using the above equations (3.3), (3.7), and (3.9). Then the fitness function F_{best} with respect to its best whale position y_{best} are obtained. The values of A and C parameters are evaluated based on a parameter to diminish from 2 to 0, then the position of every whale is updated with respect to parameter p. The preceding procedures continued until the stopping criteria are achieved. The last and final step is to translate values into binary to represent the switching state of the appliances. The implementation of WOA is described by flowchart given in Fig 3.3.

Algorithm: WOA Algorithm for Appliance Scheduling

Input: n : number of appliances, N : population size of whales, it_{max} : maximum number of iterations.
Output: y_{best} Optimal cost values.
Generate a population of N whales y_i, $\text{i} = 1, 2, \ldots.., N$
$t = 1$
for all y_i do // parallel techniques **do**
Calculate fitness function Fit_i for y_i from equation (3.3)
end for
Determine the best fitness function F_{best} and its position whale y_{best} .
repeat
    for For every Value of a decrease from 2 to 0 **do**
        for $i = 1$: N **do**
            Evaluate C and A using equations (3.17) and (3.18) respectively.
            $p = rand$
            if $p \geq 0.5$ **then**
                Update the solution using equation (3.19)
            else
                if $|A| \geq 0.5$ **then**
                Update the solution using equation (3.22)
                else
                Update the solution using equation (3.16)
                end if
            end if
        end for
    end for
    $t = t + 1$
until $H < it_{max}$

Figure 3.3 Pseudo-code of the WOA algorithm.

CHAPTER 4

SIMULATION RESULTS AND DISCUSSION

4.1 Introduction

This chapter demonstrates the simulation results carried out by the Mixed Integer Linear Programming (MILP) and Whale Optimization Algorithm (WOA) for the analysis of the optimal load management in smart home integrated with renewable energy sources and the MATLAB simulation for the appliance scheduling of appliances with and without renewable energy sources is considered by penetrating the battery energy storage.

4.2 Minimization of the Household Electricity Bill

The optimization of the appliance scheduling of the household electricity cost (bill) is accomplished using a MILP and WOA with respect to TOU tariff. The TOU tariff used during simulation for both MILP and WOA is as shown in Figure 4.1. MILP and WOA are implemented to undergo the cutback of the usage time of five different appliances (equipment) with different daily power consumptions. The electric appliances selected is a common smart home based-environment. It was used to schedule five (5) different shiftable appliances (i.e., Heater, washing machine, Iron, Dishwasher, and Heater 2) each with different daily energy consumption as shown from Table 4.1. Preferred working hours for operating an appliance (equipment) was taken into account to ensure total constant power supply from either utility (grid).

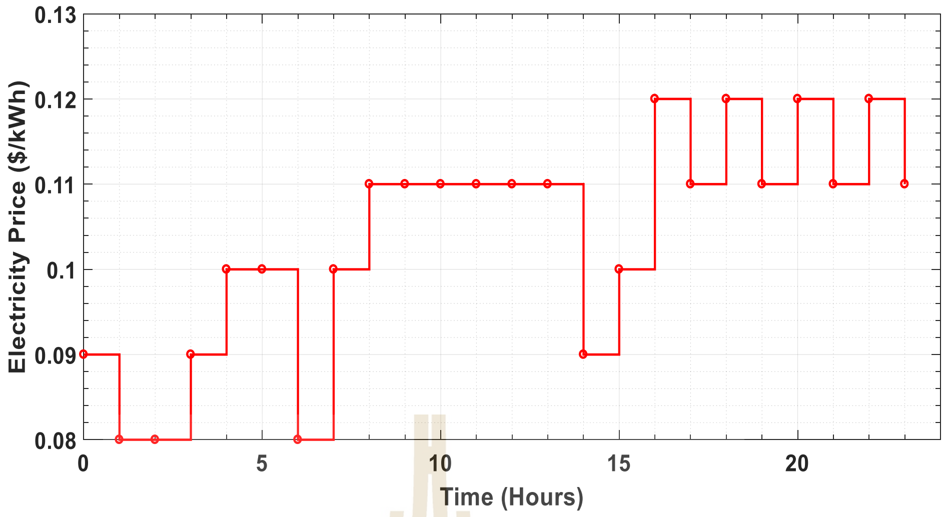


Figure 4.1 TOU Electricity Price (Rafkaoui, 2016).

Table 4.1 Appliances and Power Consumption Patterns.

Appliances	Types	Daily Power	Energy Consumption Patterns
Heater 1	Shiftable load	1100 W	Preferred hours: 7 a.m-9 a.m: 300 Wh, 10 a.m: 200 Wh
Washing Machine	Shiftable load	500 W	Preferred hours: 12 p.m: 500 Wh
Iron	Shiftable load	400 W	Preferred hours: 9 a.m: 500 Wh, 1 p.m: 300 Wh
Dish Washer	Shiftable load	400 W	Preferred hours: 12 p.m-2 p.m: 400 Wh
Heater 2	Shiftable load	800 W	Preferred hours: 9 a.m: 500 Wh, 2 p.m: 300 Wh

4.3 Optimization of the Residential Electricity Bill (Cost) by MILP

4.3.1 Optimization of the Residential Electricity Bill without Solar PV integration by MILP

The optimization of the appliance scheduling problem for cost reduction of the household for the 24-hours a day based on TOU tariff was performed by using a MILP techniques. It was used to schedule five (5) different shiftable appliances (i.e., Heater 1, washing machine, Iron, Dishwasher, and Heater 2) each with different daily energy consumption as shown from Table 4.1. Preferred working hours for operating an appliance (equipment) was taken into account to ensure total constant power supply from either utility (grid).

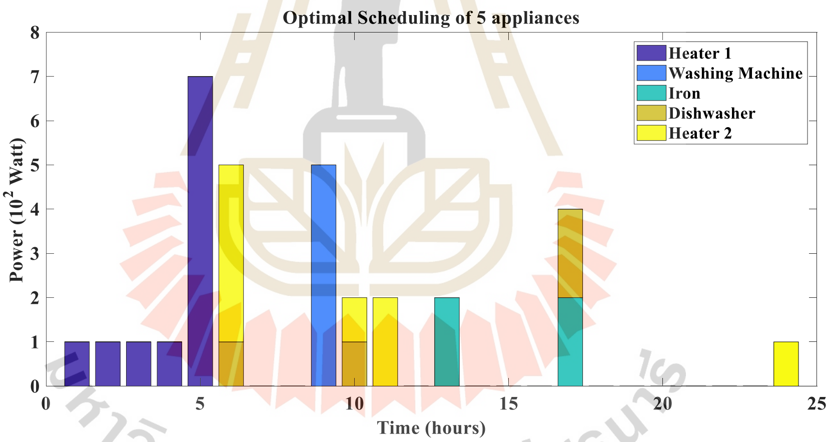


Figure 4.2 Optimal scheduling of appliances by MILP

The effectiveness and the efficiency of the MILP algorithm based on TOU tariff of the appliance scheduling problem for 24-hours a day was tested by comparing the electricity cost (bill) of the homes from the base case (i.e, before optimization) and after optimization. Table 4.2, give out the comparison of the simulation results of electricity bill (cost) of the household before MILP optimization and after MILP optimization with respect to TOU tariff. The optimization problem was done in MATLAB as seen from Figure 4.2. The simulation results shows that MILP minimizes electricity bill of the household for some amount and can be adopted for load management in smart homes.

Table 4.2 Cost Comparison without PV Integration by MILP

TOU Tariff: Hourly Electricity Price Fluctuation		
Appliances	Bill before MILP ($)	Bill after MILP ($)
Heater 1	0.099	0.096
Washing Machine	0.055	0.046
Iron	0.032	0.027
Dish Washer	0.048	0.015
Heater 2	0.064	0.063
Total	0.298	0.247

4.3.2 Optimization of the Residential Electricity Bill with Solar PV integration by MILP

The household appliances can be supplied by the power generated from the solar PV modules. Also, solar PV can be used to reshape the peak load during peak period as well as reducing the electricity bill of the homes. It was taken into account that the energy generated from the solar PV modules as shown in Figure 4.3, can either be applied to power the home appliances, stored or can be sold back to the utility (electricity grid) in times when the generated power is greater than the demand of the home. Also, if the solar power generated from the smart home exceed the demand of the home, the total hourly load was accounted as negative during simulation process. The negative value indicates that the power is in excess. The TOU billing method was used for the optimization process.

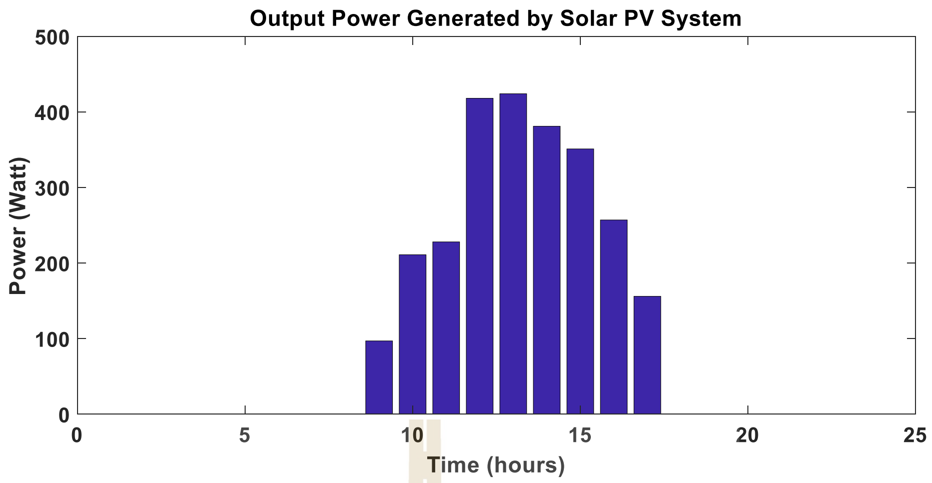


Figure 4.3 Solar PV Module Power Output generated from the SH

In this case, the impact of penetrating renewable energy sources (Solar PV) in the smart home for electricity cost reduction was examined. The optimization was carried out in two different cases. First case was the base case (before optimization) and the second case was optimizing by MILP with integrating with renewable energy sources (MILP + solar PV) with respect to TOU tariff. Table 4.3, shows the comparison of the simulation results of electricity bill (cost) of the household before MILP optimization and after MILP with renewable energy source (solar PV) based on TOU tariff. Figure 4.4 indicate the optimal scheduling of appliances with the integration of Solar PV modules.

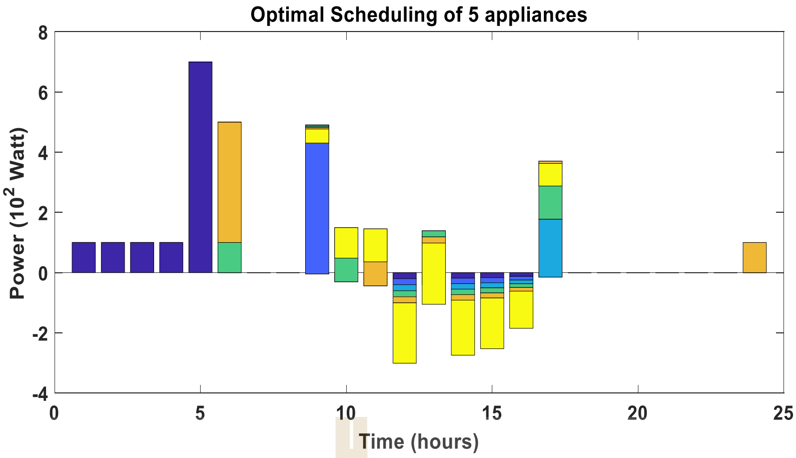


Figure 4.4 Optimal scheduling of appliances with the integrationof Solar PV modules by MILP

The graph depicts that the smart home appliances was powered by a part of the solar energy produced in the home and another part was left to be resold to the electricity utility. Table 4.3 sum up the solar power distribution. The objective function was equal to 0.227 $.

Table 4.3 Cost Comparison with PV Integration by MILP

TOU Tariff: Hourly Electricity Price Fluctuation		
Appliances	Before MILP ($)	MILP with solar PV ($)
Heater 1	0.099	0.089
Washing Machine	0.055	0.041
Iron	0.032	0.025
Dish Washer	0.048	0.014
Heater 2	0.064	0.058
Total	0.298	0.227

It can be shown from Table 4.3, that optimizing by MILP with solar PV (i.e., MILP + Solar PV) has major impact in case of minimizing the electricity cost than optimizing only with MILP. The extra energy from the solar PV that sold back to the grid and charge the battery energy storage in times when the PV generate more energy than the demand of the home was taken into consideration. The assumption made during simulation was that feed-in tariff (price of the energy sold back to the grid) equals to TOU tariff. A summary of the comparison of the Scheduling optimization of different cases is given from Table 4.3.

4.3.3 Optimization of the Residential Electricity Bill with Solar PV integration and Battery energy storage by MILP

Renewable energy integration became a significant issue as renewable penetration levels increase and will require new generation support infrastructure; Energy storage provides one solution to this issue. Specifically, battery technologies offer a wide range of energy and power output abilities, making them ideal for a variety of integration applications. Peak shaving using distributed small (residential) energy storage can provide a reduction in peak loads and help renewable energy integration. In this case it is assumed that the output power from the battery energy storage is used to supply the power for two hours only after the being full charged from the solar PV modules of the household.

It can be shown from Table 4.4, that optimizing by MILP with solar PV (i.e., MILP + Solar PV + Battery) has major impact in case of minimizing the electricity cost than optimizing only with MILP or MILP with Solar PV. The objective function was equal to 0.218 $.

Table 4.4 MILP Cost Comparison of the PV Integration and battery energy storage

TOU Tariff: Hourly Electricity Price Fluctuation		
Appliances	Before MILP ($)	MILP with solar PV and Battery storage ($)
Heater 1	0.099	0.087
Washing Machine	0.055	0.040
Iron	0.032	0.023
Dish Washer	0.048	0.013
Heater 2	0.064	0.055
Total	0.298	0.218

Table 4.5 MILP Cost Comparison of the Scheduling Optimization

24-Hours Electricity Bill of the Appliances ($)	
Pricing	TOU tariff
Base Case ($)	0.298
MILP without PV ($)	0.247
MILP with PV ($)	0.227
MILP with PV + Battery ($)	0.218
MILP with PV + Battery and energy selling ($)	0.200

From Table 4.5, the results of electric bills from in base case are seen to be the greater. But for the case of optimization with PV and Battery energy storage with respect to TOU tariff, MILP gives better savings in electric bills compared to MILP with PV. As seen in Table 4.5, the remained electric bill after optimization with PV, Battery and energy selling, MILP performs better than both cases.

4.4 Optimization of the Residential Electricity Bill (Cost) by WOA

4.4.1 Optimization of the Residential Electricity Bill without Solar PV integration by WOA

The optimization of the appliance scheduling problem for cost reduction of the household for the 24-hours a day based on TOU tariff was performed by using a WOA algorithm. It was used to schedule five (5) different shiftable appliances (i.e., Heater 1, washing machine, Iron, Dishwasher, and Heater 2) each with different daily energy consumption as shown from Table 4.1. Preferred working hours for operating an appliance (equipment) was taken into account to ensure total constant power supply from either utility (grid).

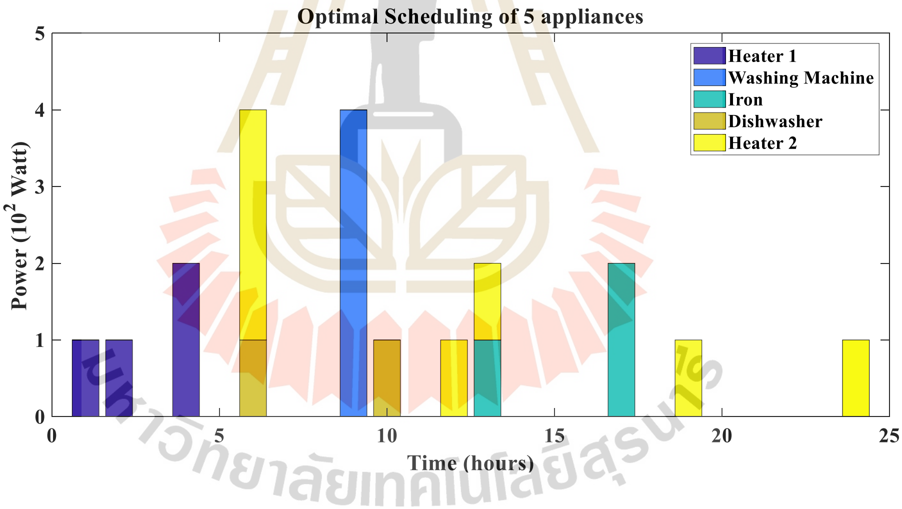


Figure 4.5 Optimal scheduling of five appliances by WOA

The effectiveness and the efficiency of the WOA algorithm based on TOU tariff of the appliance scheduling problem for 24-hours a day was tested by comparing the electricity cost (bill) of the homes from the base case (i.e, before optimization) and after optimization. Table 4.6, give out the comparison of the simulation results of electricity bill (cost) of the household before optimization and after WOA optimization with respect to TOU tariff. The optimization problem was done in MATLAB as seen from Figure 4.5. The simulation results shows that WOA minimizes electricity bill of the household better than MILP and can be adopted for load management in smart homes.

Table 4.6 WOA Cost Comparison without PV Integration

TOU Tariff: Hourly Electricity Price Fluctuation		
Appliances	Bill before WOA ($)	Bill after WOA ($)
Heater 1	0.099	0.091
Washing Machine	0.055	0.041
Iron	0.032	0.031
Dish Washer	0.048	0.024
Heater 2	0.064	0.055
Total	0.298	0.242

4.4.2 Optimization of the Residential Electricity Bill with Solar PV integration by WOA

In this case, the impact of penetrating renewable energy sources (Solar PV) in the smart home for electricity cost reduction was examined. The optimization was carried out in two different cases. First case was the base case (before optimization) and the second case was optimizing by WOA with integrating with renewable energy sources (WOA + solar PV) with respect to TOU tariff. Table 4.7, shows the comparison of the simulation results of electricity bill (cost) of the household before WOA optimization and after WOA with renewable energy source (solar PV) based on TOU tariff. Figure 4.6 indicate the optimal scheduling of appliances with the integration of Solar PV modules.

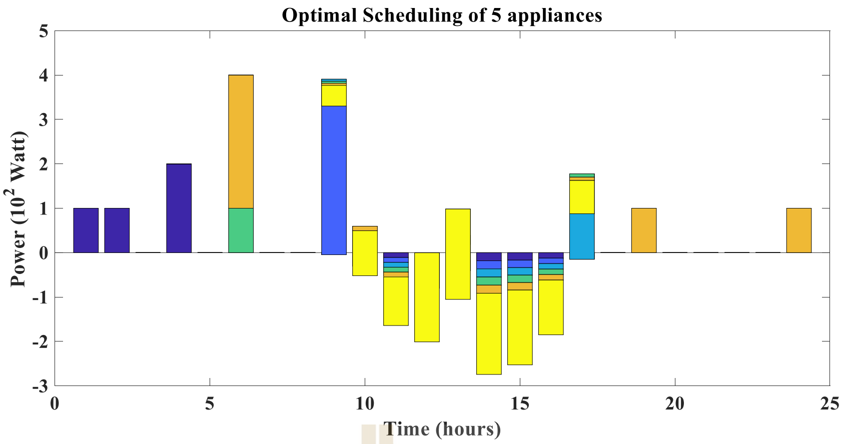


Figure 4.6 Optimal scheduling of appliances with the integration of Solar Pvmodules by WOA

The graph depicts that the smart home appliances was powered by a part of the solar energy produced in the home and another part was left to be resold to the electricity utility. Table 4.7 sum up the solar power distribution. The objective function was equal to 0.196 $.

Table 4.7 WOA Cost Comparison with PV Integration

TOU Tariff: Hourly Electricity Price Fluctuation		
Appliances	Before WOA ($)	WOA with solar PV ($)
Heater 1	0.099	0.073
Washing Machine	0.055	0.039
Iron	0.032	0.024
Dish Washer	0.048	0.021
Heater 2	0.064	0.039
Total	0.298	0.196

It can be shown from Table 4.7, that optimizing by WOA with solar PV (i.e., WOA + Solar PV) has major impact in case of minimizing the electricity cost than optimizing only with WOA. The extra energy from the solar PV that sold back to the grid and charge the battery energy storage in times when the PV generate more energy than the demand of the home was taken into consideration. The assumption made during simulation was that feed-in tariff (price of the energy sold back to the grid) equals to TOU tariff. A summary of the comparison of the Scheduling optimization of different cases is given from Table 4.7.

4.4.3 Optimization of the Residential Electricity Bill with Solar PV integration and Battery energy storage by WOA

Renewable energy integration became a significant issue as renewable penetration levels increase and will require new generation support infrastructure; Energy storage provides one solution to this issue. Specifically, battery technologies offer a wide range of energy and power output abilities, making them ideal for a variety of integration applications. Peak shaving using distributed small (residential) energy storage can provide a reduction in peak loads and help renewable energy integration. In this case it is assumed that the output power from the battery energy storage is used to supply the power for two hours only after the being full charged from the solar PV modules of the household.

It can be shown from Table 4.8, that optimizing by WOA with solar PV (i.e., WOA + Solar PV + Battery) has major impact in case of minimizing the electricity cost than optimizing only with WOA or WOA with Solar PV. The objective function was equal to 0.191 $.

Table 4.8 WOA Cost Comparison of the PV Integration and battery energy storage

TOU Tariff: Hourly Electricity Price Fluctuation		
Appliances	Before WOA ($)	WOA with solar PV and Battery storage ($)
Heater 1	0.099	0.085
Washing Machine	0.055	0.040
Iron	0.032	0.021
Dish Washer	0.048	0.012
Heater 2	0.064	0.033
Total	0.298	0.191

Table 4.9 WOA Cost Comparison of the Scheduling Optimization

24-Hours Electricity Bill of the Appliances ($)	
Pricing	TOU tariff
Base Case ($)	0.298
WOA without PV ($)	0.242
WOA with PV ($)	0.196
WOA with PV + Battery ($)	0.191
WOA with PV + Battery and energy selling ($)	0.160

For validation, the results of WOA algorithm was compared with those of MILP. The results are shown in Table 4.10.

Table 4.10 Cost Comparison of the electric bills from MILP and WOA

24-Hours Electricity Bill of the Appliances ($)		
Pricing	TOU tariff	
	MILP	WOA
Base Case ($)	0.298	0.298
Optimization without PV ($)	0.247	0.242
Optimization with PV ($)	0.227	0.196
Optimization with PV + Battery ($)	0.218	0.191
Optimization with PV + Battery and energy selling ($)	0.200	0.160

From Table 4.10, the results of electric bills from MILP and WOA in the base case are seen to be the same. But for the case of optimization with PV and without PV with respect to TOU tariff, WOA gives better savings in electric bills compared to MILP. Also, PV with battery energy storage, WOA gives better savings in electric bills compared to MILP. As seen in Table 4.10, the remained electric bill after optimization with PV, Battery and energy selling, WOA performs better than MILP in both cases.

4.5 Chapter summary

This chapter has exhibited the results of the appliance scheduling in the smart homes integrated with renewable energy sources and battery energy storage by using MILP and WOA simulation software. The optimum parameters of the appliance scheduling have also been enforced in MATLAB software. For discussion purpose, the next chapter has been discussed and innovated the final concept to be concluded for the optimal load management in smart home system.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

Reducing the environmental impact such as increased Greenhouse Gases (GHG) emissions that greatly affect the earth's temperature, changes in weather, sea level, land use patterns and responding effectively and efficiently to the energy demand (cost and peak load reduction) is crucial towards achieving sustainability. WOA and MILP methods were used to optimize and reduce the daily electricity cost through appliance scheduling. The scheduling optimization was implemented respectively with respect to Time-of-Use (TOU) billing method depending on the type of electricity price fluctuation. Moreover, the optimization was done in three different ways, i.e., optimization without solar PV, optimization integrating with solar PV and optimization with solar PV and battery energy storage. Simulation results depicted that optimizing the scheduling of the electric appliances through MILP and WOA minimizes the cost up to 53% and by up to 66% when renewable energy, battery energy storage and energy selling is taken into account with respect to TOU pricing. Also, in terms of scheduling, WOA showed that it can be adopted for scheduling appliances in households for both electric bill and peak load reduction. The reduction in electric bill indicates the cutback of load demand from the specific user which can serve during severe peak demand. Moreover, the great saving of electric bills indicates a better performance of WOA.

5.2 Future work

Finally, the results obtained demonstrated the efficiency of the WOA to achieve the appliances optimal scheduling, but the algorithm could further be improved. In this project, the utility function, which represent the satisfaction level of the consumer was not considered. The algorithm and optimization method could be enhanced to take into account the user's time of preference to use a particular appliance. Different pricing method could also not only apply to the electric gird but also to the selling of the surplus of solar energy.

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APPENDIX A

List of Publications

ARTICLES IN JOURNALS

Hussein Swalehe., Pius Victor Chombo., and Boonruang Marungsri. (2018). **Appliance Scheduling for Optimal Load Management in Smart Home Integrated with Renewable Energy by using Whale Optimization Algorithm**, Accepted to be published by Greater Mekong Subregion Academic and Research Network (GMSARN) International Journal, Vol. 12, No. 2, pp. 65-75.

ARTICLES IN CONFERENCES

Hussein Swalehe., Pius V. Chombo., Kelvin M. Minja., Novatus M. Kimenyuka., Elifuraha R. Mmary., Narupon Promvichai., Uthen Leeton., and Boonruang Marungsri. (2017). **System Reconfiguration for Technical Power Loss Reduction in the Distribution Network by using Genetic Algorithm**, Accepted to be published by 2017 IEEJ PE&S – IEEE PES Thailand Symposium on Advanced Technology in Power System, Bangkok, Thailand, pp. 141-145.

Hussein Swalehe., and Boonruang Marungsri. (2018). **Intelligent Algorithm for Optimal Load Management in Smart Home Appliance Scheduling in Distribution System**, Accepted to be published by 2018 EEAAT – IEEE iEECON 6th International of Electrical Engineering Congress, Krabi, Thailand, pp. 119-123.

H. Swalehe, P. V. Chombo, and B. Marungsri / GMSARN International Journal 12 (2018) 65 - 75

Appliance Scheduling for Optimal Load Management in Smart Home Integrated with Renewable Energy by Using Whale Optimization Algorithm

Hussein Swalehe*, Pius Victor Chombo, and Boonruang Marungsri

Abstract— *One of the essential factor for the better operation of an electrical power system is load demand. Normally, higher load demand leads to instability and insufficient power supply. To make an electrical power system stable and sufficient, a good correlation between demand and supply should exist. A survey conducted during 2011 indicated that residential sector is consuming 18% of total energy. Also, the demand was seen to increase rapidly close to and sometimes beyond the supply. Hence, this paper focuses on appliance scheduling for cost reduction and peak load reduction by increasing demand-side response in the smart home integrated with renewable energy. A load management algorithm is developed in MATLAB which reduces both cost and peak load consumption by managing the operation according to utility controls and consumer preferences. The optimization problem was solved by using Whale Optimization Algorithm (WOA) technique. The simulation results depicted a reduction of up to 40% in electric bill when scheduling electrical appliances without renewable energy source; and up to 53% when renewable energy is considered with respect to Time-of-Use (TOU) pricing. The reduction in electric bill indicated the cutback of load demand from the specific user which can serve during severe peak demand. On the other hand, WOA can be adopted for appliance scheduling in the household, reduction of electric bill as well as cutback of peak demand from the demand side.*

Keywords— **Load Management; Demand response; Smart home; Time-of-Use (TOU) pricing; Whale Optimization Algorithm (WOA).**

1. INTRODUCTION

In the electrical power system, load demand plays an important role of maintaining the stability of the system. A good proportionality between demand (consumption) and supply (generation) should hold in order to avoid generation disturbances which later introduces negative effects in technical, economic and social areas [1]. The rapid rise of energy needs has made electric utility companies to expand generation plants with respects to peak demand rather than average power in order to meet the consumer's demand [2]. This approach, unfortunately, renders power systems highly underutilized and customers' consumption patterns increasingly irresponsible. Additionally, it has driven utility companies to make huge long-term investments in new generation power plants which are mostly and typically based on traditional (conventional) energy sources. Such power plants – in addition to being capital intensive – lead to increased Greenhouse Gases (GHG) emissions that greatly affect the earth's temperature, changes in weather, sea level, and land use patterns [3]. Efficient utilization and special consideration of the optimal plant generation capabilities must be employed in order to improve the under-performing available generating plants without building new power plants [4] - [5]. Nowadays, load management has been accepted worldwide as the simplest, safest and cheapest technique that provide a better correlation between generation and load by performing load management practices on demand side loads through demand reduction or reshaping the load profile.

Usually, load management practice aims to shift the load from on-peak period to off-peak period so as to reshape the load profile which in-turn reduces the total cost of electricity. Through energy management-based researches, an electrical engineer can cut costs of power system operation through utilization of optimal available generation capacity. A survey conducted during 2011 indicated that 18% of total energy is being consumed by residential sector [6]. Due to this reason, this paper target on scheduling home appliances (HAs) in the smart home integrated with renewable energy. Smart home (SH) appliances are connected to home area network (HAN) to coordinate power usage demanded the home under control. Load management is an essential key factor in smart grid (SG) for scheduling home appliances (HAs) in the smart home. A modern technology, with sophisticated metering infrastructure, can allow a two-way transmission of information between the utility company and the consumer through metering unit to enable a smooth aggressive load deviation. Regarding this direction, demand-response (DR) programs give incentives to significant costumers, generally in terms of money, to minimize their energy use during on-peak periods [6]. Demand Response appear at a very fast timescale, approximately real-time, it results to a stable

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and sufficient power grid system and importantly minimizes electric cost and CO2 emissions [7].

Smart grid, in the growing power system technology, is currently considered as an upcoming solution to the most of the existing power systems. It comes in different names such as smart power grid or intelligent grid [2] to take over an old, disorganized and defenseless existing power system. An efficient performance of smart grid depends on the advanced technologies in electrical power, control, communication, information theory, bi-directional flows of electrical power and information which promotes an advanced and modern power system with cost-effective, safety and security. In smart grid, advanced energy-metering infrastructure (AMI) and energy monitoring are performed over a number of smart meters and sensors equipped all the way in smart homes. The part of communication as well as networking technologies ensure real time data collection and transmission to and fro both sides. In smart grid (SG) system, the load management is an essential factor to control energy management system. Through load management strategies in smart grid (SG), reduction of peak load during the peak period and control pricing of electricity unity can be achieved through customer participation in the smart home [8]-[14]. The usage of photovoltaic system causes a reduction of electric bill and the peak demand at home. Moreover, excessive generated energy can be added to the smart grid from the smart home [15]-[17]. A recent and well performing technique, Whale Optimization Algorithm (WOA) is employed for optimizing scheduling of appliances. Its high exploration and convergence behaviors toward solution in different iterations makes it unique in problem solving against other conventional techniques.

2. THE SMART HOME (SH)

"Smart Home is the term normally used to define a household that uses a home controller to integrate the residence's various home automation systems" [18]. Smart Home is the computerized controls in homes and appliances that can be set up to respond to signals from the energy provider to reduce their energy use at times when the power grid is unstable from high peak load demand, or even to shift some of their power use (energy consumption) to times when power is available at a lower cost. Customer involvement is the one among the critical attribute of the SH. The involvement of the customer is facilitated by a smart meter, which also connects the smart home (SH) and Smart Grid (SG). Besides the gathering of data for electric utility companies, smart meters perform crucial roles for both customers and the grid to which they are connected to. They act as controllers over consumer's appliances. With the upcoming technologies of SH, each home appliance will be provided an ability to transfer information and monitored by the smart meter with the use of in-home networking system. Current developed appliances are equipped with application softwares and interfaces to provide an easy use to costumers. The programmed instructions can then be viewed to costumers through displays. The SH control can further give customers extra opportunities, such as energy saving, loss reduction, cost saving, and reduced carbon emission.

The concept of future SH is displayed in Fig. 1 where a small renewable generation and energy storage system are equipped to make a future SH working as a small connected micro-grid (MG) [19]-[27]. Moreover, the use of hybrid DC/AC system can be added to support the future SH with the use of both DC power and AC power supply. Therefore, with the future SH, a reliable power supply will be available with an addition of automation, user preferences, and low emissions and cost-effective. The higher penetration of renewable energy into the smart home results in a minimization of electric bill, peak demand of the household and export of extra energy to the smart grid in times when renewable energy generation is more than the demand of the household [15]-[17].

Smart Appliances

"The term 'Smart Appliance' with respect to the smart grid refers to a modernization of the electricity usage system of a home appliance so that it monitors, protects and automatically adjusts its operation to the needs of its owner" [28]. Some of the key features noted by [28] include the following:

- The capability to alter the requirement for electrical energy exploitation.
- To give alerts to end-users to shift to a convenient time with available cheaper prices.
- To provide an automatic reduction of usage based on the consumers pre-established guidelines.
- To maintain stability of the system.
- Consumer is able to reverse all pre-programmed sets of instructions.
- To develop the energy consumption profile from total home energy consumption approach to utilize the data to its best profit.

The two main reasons for a consumer accepting to adopt smart appliances are an economic gain to the consumer and environmental reasons, but the latter is among only a small percentage of consumers who are environmentally conscious or environmental advocators. Most consumers will readily accept to shift to smart appliances for economic gains rather than environmental gains [29]. To trigger consumers to buy smart appliances, [29] suggested a promotion of attractive tariff from utility to customers with an addition of other incentives.

All smart appliances are classified as receivers, and the means of controlling them are through transmitters such as the 'remote control or keypad' [18]. For instance, if an appliance is needed to be switched ON or OFF, the transmitter (the remote), should transmit a signal to the receiver (appliance) in the form of a code which may include an attention to the intended system, giving a unit number of the respective equipment and the instructions that contains a set of actions to be performed [18].

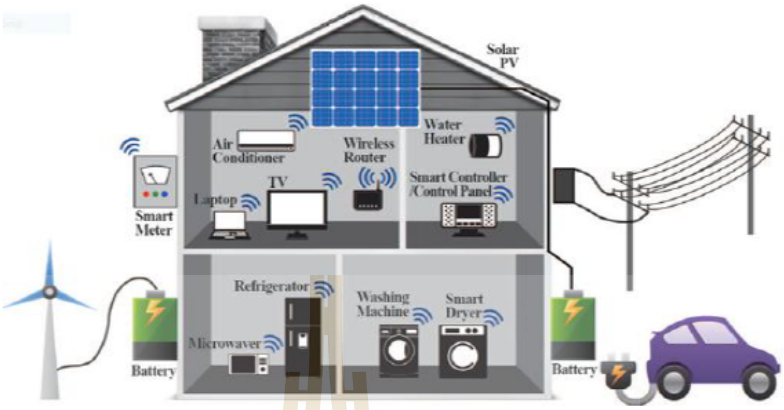

Fig.1 The concept of future smart home (SH)

3. LOAD MANAGEMENT (LM)

Paracha and Doulai (1998) [30] described load management as a set of goals aimed to manage, control or monitor the utilization of electical energy of various customers either by switching ON or OFF directly from the grid through grid operator during peak period or indirectly (demand response) from customer participation to reshape the load profile. This action helps the grid to gain stability between supply and demand and to make the best operation of its existing capacities in generation and transmission systems[4], [31].

Strategies for Load Management on Demand Side

There exist several strategies applicable for load management on demand side such as valley filling, peak clipping, and load shifting. Others are strategic conservation, strategic load growth, and flexible load shape. The operation of these strategies is shown on Fig. 2.

The descriptions of the above-mentioned strategies are given below:

- Peak clipping- this minimizes utility loads in case of peak demand periods and reconnect during off-peak.
- Valley filling- building loads during off-peak period
- Load shifting- transferring of loads from on-peak period to off-peak periods and vice versa
- Strategic load growth- increase customer usage resulting in sales increment beyond valley filling
- Flexible load shape- incentive contracts and tariffs (i.e, RTP, TOU, etc) with possibilities to shift consumer's equipment from on-peak period to off-peak period

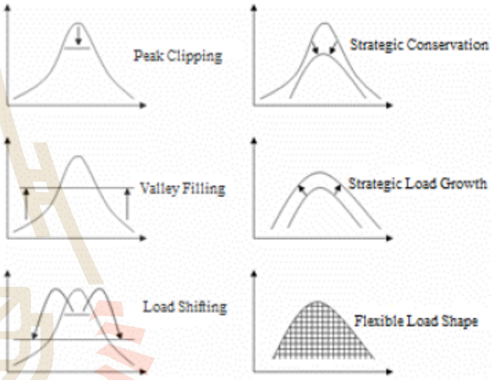

Fig.2 Load control strategies [32].

Among of the above-mentioned strategies, load shifting strategy is highly preferred and opted for scheduling since it gives a chance for a load to be reconsidered when removed during on-peak period. With this strategy, the reduced load is scheduled-in again in off-peak period.

Load Management Measures

Normally, the classification of load management measures falls into two classes which are direct load control (DLC) and indirect load control (ILC). The first class, DLC, secures the technological standards (AMI) applicable in smart grid as well as smart homes (like sensors and smart meters positioned at each customer to be monitored) that enable the grid operator to turn OFF the equipment during on-peak period and turn ON during off-peak period.

The second class, ILC, is positioned on either statute or economic policies. Based on this class, certain tariffs and pricing mechanisms are set to motivate customers to reduce their demands during on-peak periods. These are:

Time-of-use(TOU) tariff

This tariff is applied to direct the billing system on periods of cheaper prices (off-peak) and expensive prices (peak). With the successfully invented TOU billing system, both the utility and the consumer benefit.

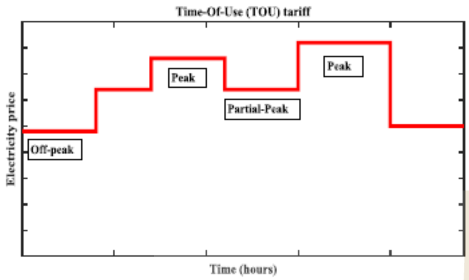

Fig.3. Time of use pricing.

Interruptible load tariff (ILT)

In Interruptible load tariff (ILT), consumer signs an incentive contract from the utility company to turn OFF the appliances during on-peak period or during emergence. And most of the time, this incentive contract is in the form of monetary reward to encourage the consumer to minimize their demand timely when required by the utility.

Tariff with load demand component (TLDC)

With (TLDC), end-user is requested to manage the load demand at a lower level due to a part of electricity bill build upon the highest documented hourly load demand price.

Real-time pricing (RTP)

This tariff associates the end-user's rate with the large-scale market rate. It is sometimes known as dynamic billing system. The principal characteristics are that the timing and costs are not set in advance [33].

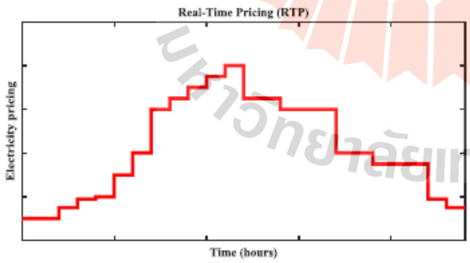

Fig.4. Real-time pricing.

Critical peak pricing (CPP)

This incorporates the principal characteristics of both TOU and RTP tariffs. It accounts a unique, extended price on chosen days with accelerated demand indicator, aimed to reduce the load in critical levels. Usually, an upcoming signal is given to end-users to let on them to make voluntary energy minimization when CPP days are called.

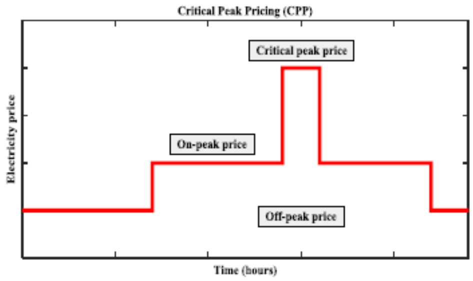

Fig.5. Critical peak pricing.

Demand-side bidding (DSB)

In Demand-side bidding, the costumer is given an opportunity to choose the best time to get-involved and measures required during real-time and upcoming spot markets

Based on [34], DSB allows customer to be refunded at the real-time market price for disconnecting loads, when requested by the market operator, in a same way that power plants are remunerated to supply.

4. DEMAND RESPONSE (DR)

Demand response (DR) is the process of minimizing load at times when either contingency happens which intimidates the balance between supply and demand or market conditions happen that raise production cost.

Three basic categories of DR automation are listed below [35]:

- Manual Demand Response- suggests manually switching OFF appliances.
- Semi-Automated Response- implicates the application of home energy management control systems for load shedding, where facilities staff initiates a preprogrammed load shedding strategy.
- Fully-Automated Demand Response- commence at a building the use of access card (programmable card) which is programmed to switch on or off the appliance the time you need to use or not and within a certain period of time it goes off.

Types of Load of the household and its Characteristics

The residential appliances can be categorized into different types as shown in Table 1.

Base Loads

Base load refers to the appliances that to be operated continuously throughout the day. Examples of this baseload are an air conditioner, electric heater, etc.

Non-shiftable Loads

These are appliances which must be turned ON immediately when it is needed, and their working period cannot be changed.

Shiftable Loads

These refer to the appliances which can complete their tasks within the preferred time intervals, e.g., washing machine, dishwater, etc. They can further be divided into two types namely interruptible and non-interruptible loads [36]-[37].

- Interruptible load-refers to the appliances that can be given a discrete time interval to complete its working cycle. E.g., water heater, refrigerator
- Non-interruptible load-refers to the appliance which is turned ON exactly once to complete its job.

Table 1. Load types and its Characteristics.

No	Category	Types of loads	Home appliance
1	Manageable	Shiftable	Washing Machine, Dish Washer
2	Manageable	Interruptible	Water heater, Refrigerator
3	Manageable	Weather Based	Air Conditioner, Electric Heater
4	Non-manageable	Auxiliary	TV, laptops, lights

Benefits of Load Management

LM and DR require an avoidable effort of costumer's prosperity and home-independence. Nevertheless, the execution of Load Management and Demand Response plan can lead to several benefits in terms of technical, economic, environmental and social benefits. Based on [38]-[40], the chief advantages of an electricity market are given as:

- Increased overall economic efficiency.
- Market power mitigation.
- Improved system reliability.
- Reduced price volatility (risk management).
- Minimization of average energy costs to all customers.
- Consumer service.
- Environmental impact.
- Minimizing the generation margin
- Modifying distribution network investment efficiency

5. OPTIMAL SCHEDULING OF SMART HOME ENERGY CONSUMPTION

Total load demand for appliances depends on how they are scheduled over the certain period of time. For example, if all appliances start at once, the coincident demand should be very high to surpass the maximum limits introduced by the electricity distributors and most of the time adversely affects in-home electrical system. Therefore, the appliance usage should be appropriately used one after another to maintain the peak demand to a minimum level as well as electric bill, yet the comfort is not sacrificed. To minimize the electric bill and make better use of its available generation from the utility, the energy consumption of the smart home environment must be minimized. Also, to reduce electric bill, the concept of in-home energy management system (HEMS) is proposed and implemented through an optimal scheduling of smart home appliances. A scheduled strategy is planned in such a way that energy usage of several appliances is arranged to match low price periods in a day. The main concept is to move the shiftable loads (high resistive and inductive loads) in residential house into off-peak periods with low-price rate. Although the maximum power for selection of appliances is not set, some of the probable appliances with shifted and high consumption nature are shown in Table 2.

Table 2. Appliances and Power Consumption Patterns.

Appliances	Daily Power	Energy Consumption Patterns
Heater 1	1100 W	Preferred hours: 7 a.m-9 a.m: 300 Wh, 10 a.m: 200 Wh
Washing Machine	500 W	Preferred hours: 12 p.m: 500 Wh
Iron	400 W	Preferred hours: 9 a.m: 500 Wh, 1 p.m: 300 Wh
Dish Washer	400 W	Preferred hours: 12 p.m-2 p.m: 400 Wh
Heater 2	800 W	Preferred hours: 9 a.m: 500 Wh, 2 p.m: 300 Wh

Problem Formulation

For this case, the load management problem is considered to be linear. It contains of a linear function subjected by linear constraints. The optimal solution of load management problem depends upon the solution of linear equations, defining optimal and secured operation of the home network. In general, a constrained load management problem can be given as shown below [41-42]:

$$\min = \{f(x) | x \in X\}$$
$$\text{Subject to } g(x) \geq 0$$
$$h(x) = 0$$

where: *f(x)* is the objective function, *g(x)* is the inequality constraint function, *h(x)* is the equality constraint function, *x* is the set of each decision variable.

Formulating Objective Function

The goal of the objective function of load management problem is to reduce the total electric bill by scheduling

the appliance on the basis of one-day ahead of TOU tariffs. The total electric bill is given in (1):

$$\min \sum_{k=1}^{m} C^k \left(\sum_{i=1}^{N} \sum_{j=1}^{ni} P_{ij}^k X_{ij}^k \right) \tag{1}$$

where:

$$X_{ij}^k = \begin{cases} 1 \text{ if appliance is ON} \\ 0 \text{ if appliance is OFF} \end{cases} \tag{2}$$

If smart-grid (SG) is added, then the equation will be as follows:

$$\min \sum_{k=1}^{m} \sum_{i=1}^{N} \sum_{j=1}^{ni} \left(C^k P_{ij}^k X_{ij}^k - g^k G_{ij}^k X_{ij}^k \right) \tag{3}$$

If solar PV modules are added, then the equation will be as follows:

$$\min \sum_{k=1}^{m} \sum_{i=1}^{N} \sum_{j=1}^{ni} \left(C^k P_{ij}^k X_{ij}^k - g^k * r * PR * A * T_{ij}^k \right) \tag{4}$$

where: r is the solar panel efficiency, (0.16 used in simulation). The value of PR is 0.75 (used in simulation). The A variable is the area of the photovoltaic modules which is 4 m^2 and T is the hourly irradiation. g^k is the feed-in tariff.

System Constraints

These define the conditions for solving the objective function of the load management, they include the following constraints:

- Load phases of the appliance should fulfill their energy requirements.

$$\frac{1}{4} \left(\sum_{i=1}^{N} \sum_{j=1}^{ni} P_{ij}^k \right) = E_{ij} \quad \forall \{i,j\} \tag{5}$$

- Load safety factor.

$$\sum_{i=1}^{N} \sum_{j=1}^{ni} P_{ij}^k \le \beta^k \quad \forall \{k\} \tag{6}$$

where: i is the cutback appliance index, k is the slot time over a certain period of time, j is the is the phase load number index correlated within each appliance, ni is the phases load shiftable set of numbers correlated with every appliance i, N is the appliances cutback set numbers, m is the slot time maximum number present in a day, P^k_{ij} is the power consumption of each appliance i having load phase j at time slot k, C^k is the TOU tariff, X^k_{ij} binary decision variable with value 1 if i^{th} appliance is ON otherwise 0.

6. INTELLIGENT ALGORITHM

Whale Optimization Algorithm (WOA)

Seyedali and Andrew (2006) [43-45], proposed an innovative nature based meta-heuristic optimization technique known as Whale Optimization Algorithm (WOA) that models the general behaviors of humpback whales. Usually, whales are considered as talented animals in movement. The WOA is motivated by the special hunting characteristic of humpback whales [43]. In general, the humpback whales aim to hunt krills or small fishes near the sea area. They use a genuine technique called bubble net feeding. With this technique, they swim around the target and build up a peculiar bubble beside a circle or 9-shaped path [43].

Mathematically, WOA can be expressed into three categories as: *(a) Encircling prey, (b) Bubble net hunting method, and (c) Search the prey.*

Fig.6. Bubble-net feeding behavior of humpback whale [43].

Encircling prey

WOA predicts the existent best candidate solution is the objective prey. Others try to update their positions toward best search agent. The behavior models are shown in (7)-(10) [43]:

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \times \vec{D} \tag{7}$$

$$\vec{D} = \left| \vec{C} \times \vec{X}^*(t) - \vec{X}(t) \right| \tag{8}$$

$$\vec{A} = 2 \times \vec{a} \times \vec{r} - \vec{a} \tag{9}$$

$$\vec{C} = 2 \times \vec{r} \tag{10}$$

where (7) show the best solution position and the position of the vector. The current iteration is expressed by it. $\vec{A}$, $\vec{C}$ are vectors coefficient. $\vec{a}$ decreased from 2 to 0 directly. $\vec{r}$ is a random vector [0, 1].

Bubble net hunting method

This one is classified into two categories as *Shrinking encircling prey* and *Spiral position updating.*

- *Shrinking encircling prey*

Here $\vec{A} \in [-a,a]$ whereby $\vec{A}$ is reduced from 2 to 0. Here the position is set down at random values in between [−1, 1]. The current position of $\vec{A}$ is achieved between original position and position of the current best agent.

- *Spiral position updating*

Helix-shaped movement spiral equation (11) is used to imitates.

$$\vec{X}(t+1)=\vec{D}\times e^{bl}\times\cos(2\pi l)+\vec{X}^* \tag{11}$$

In the two paths above, whales swim around the prey during hunting simultaneously. 50% probability is accounted for above two methods [41] to update whale's positions.

$$\vec{X}(t+1)=\begin{cases}\vec{X}^*(t)-\vec{A}\times\vec{D} & \text{if } p<0.5\\ \vec{D}' \times e^{bl}\times\cos(2\pi l)+\vec{X}^* & \text{if } p<0.5\end{cases} \tag{12}$$

where $D'=\left|\vec{X}^*-\vec{X}(t)\right|$ express the whale and the prey distance known as the best solution. b is constant, $l \in [-1, 1]$. P is random number [0, 1].

Search for prey

Instead of the best agent, randomly selected search agent updating is performed to obtain the global minima.

$$\vec{D}=\left|\ \vec{C}\times\vec{X}_{rand}-\vec{X}\ \right| \tag{13}$$

$$\vec{X}(t+1)=\vec{X}_{rand}-\vec{A}\times\vec{D} \tag{14}$$

$\vec{X}_{rand}$ are the current iteration random whales.

The input data to the proposed WOA is the number of appliances to be scheduled n, the population size of a whale N, and the maximum number of iterations it_{max}. The WOA beginning by producing N solutions from the random population in the search environment [0, 100], for every position the fitness function Fit_i is examined by using the above equation (1). Then the fitness function F_{best} with respect to its best whale position y_{best} are obtained. The values of A and C parameters are evaluated based on a parameter to diminish from 2 to 0, then the position of every whale is updated with respect to parameter p. The preceding procedures continued until the stoping criteria are achieved. The last and final step is to translate values into binary to represent the switching state of the appliances. The implementation of WOA is described by flowchart given in Fig 7.

Algorithm: WOA Algorithm for Appliance Scheduling

```
Input: n: number of appliances, N: population size of
    whales, it_max: maximum number of iterations.
Output: y_best Optimal cost values.
Generate a population of N whales y_i, i = 1, 2, …, N
t = 1
for all y_i do // parallel techniques do
Calculate fitness function Fit_i for y_i from equation (1)
end for
Determine the best fitness function F_best and its
            position whale y_best.
repeat
   for For every Value of a decrease from 2 to 0 do
      for i = 1: N do
          Evaluate C and A using equation (10)
 and equation (9) respectively.
            p = rand
            if p ≥ 0.5 then
              Update the solution using equation (11)
            else
               if |A| ≥ 0.5 then
              Update the solution using equation (14)
               else
              Update the solution using equation (8)
               end if
            end if
         end for
      end for
      t = t + 1
until H < it_max
```

Fig.7. Pseudo-code of the WOA algorithm.

7. SIMULATION RESULTS AND DISCUSSION

Optimization of the Residential Electricity Bill (Cost) without Solar PV integration

The optimization of the appliance scheduling problem for cost reduction of the household for the 24-hours a day based on TOU tariff was performed by using a WOA technique. It was used to schedule five (5) different shiftable appliances (i.e., Heater1, washing machine, Iron, Dishwasher, and Heater2) each with different daily energy consumption as shown from Table 2 above. Preferred working hours for operating an appliance (equipment) was taken into account to ensure total constant power supply from either utility (grid).

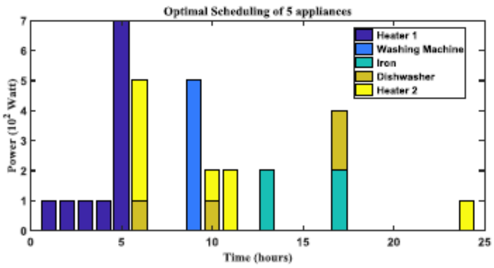

Fig.8. Optimal scheduling of appliances without Solar PV modules penetration.

The effectiveness and the efficiency of the WOA algorithm based on TOU tariff of the appliance scheduling problem for 24-hours a day was tested by comparing the electricity cost (bill) of the homes from the base case (i.e, before optimization) and after optimization. Table 3, give out the comparison of the simulation results of electricity bill (cost) of the household before WOA optimization and after WOA optimization with respect to TOU tariff. The optimization problem was done in MATLAB as seen from Fig 8 above. The simulation results shows that WOA minimizes electricity bill of the household at a large and can be adopted for load management in smart homes.

Table 3. Cost Comparison without PV Integration

TOU Tariff: Hourly Electricity Price Fluctuation		
Appliances	Bill before WOA ($)	Bill after WOA ($)
Heater 1	0.099	0.091
Washing Machine	0.055	0.041
Iron	0.032	0.031
Dish Washer	0.048	0.024
Heater 2	0.064	0.055
Total	0.298	0.242

Optimization of the Residential Electricity Bill (Cost) with Solar PV integration

In this case, the impact of penetrating renewable energy sources (Solar PV) in the smart home for electricity cost reduction was examined. The optimization was carried out in two different cases. First case was the base case (before optimization) and the second case was optimizing by WOA with integrating with renewable energy sources (WOA + solar PV) with respect to TOU tariff. Table 4, shows the comparison of the simulation results of electricity bill (cost) of the household before WOA optimization and after WOA with renewable energy source (solar PV) based on TOU tariff. Fig. 9 indicate the optimal scheduling of appliances with the integration of Solar PV modules.

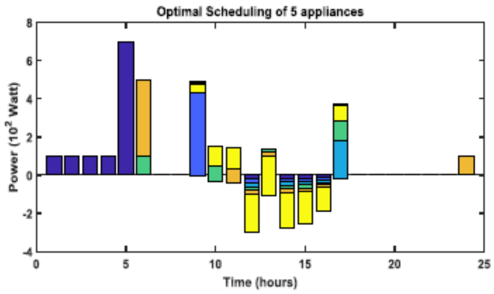

Fig.9. Optimal scheduling of appliances with the integration of Solar PV modules.

Table 4. Cost Comparison with PV Integration

TOU Tariff: Hourly Electricity Price Fluctuation		
Appliances	Before WOA ($)	WOA with solar PV ($)
Heater 1	0.099	0.073
Washing Machine	0.055	0.039
Iron	0.032	0.024
Dish Washer	0.048	0.021
Heater 2	0.064	0.039
Total	0.298	0.196

It can be shown from Table 4, that optimizing by WOA with solar PV (i.e., WOA + Solar PV) has major impact in case of minimizing the electricity cost than optimizing only with WOA. The extra energy from the solar PV that sold back to the grid in times when the PV generate more energy than the demand of the home was taken into consideration. The assumption made during simulation was that feed-in tariff (price of the energy sold back to the grid) equals to TOU tariff. A summary of the comparison of the Scheduling optimization of different cases is given from Table 5 below.

Table 5. Comparison of the Scheduling Optimization.

24-Hours Electricity Bill of the Appliances ($)	
Pricing	TOU tariff
Base Case ($)	0.298
WOA without PV ($)	0.243
WOA with PV ($)	0.196
WOA with PV and energy selling ($)	0.18

For validation, the results of WOA algorithm was compared with those of Mixed Integer Linear Programming (MILP). The procedures for performing MILP were described in [46] and results are shown in Table 6.

Table 6. Comparison of electric bills from MILP and WOA

24-Hours Electricity Bill of the Appliances ($)		
Pricing	TOU tariff	
	MILP	WOA
Base Case ($)	0.298	0.298
Optimization without PV ($)	0.263	0.243
Optimization with PV ($)	0.24	0.196
Optimization with PV and energy selling ($)	0.2	0.18

From Table 6, the results of electric bills from MILP and WOA in base case are seen to be the same. But for the case of optimization with and without PV, WOA gives better savings in electric bills compared to MILP. As seen in Table 6, the remained electric bill after optimization with PV and energy selling, WOA performs better than MILP in both cases.

8. CONCLUSION

Reducing the environmental impact such as increased Greenhouse Gases (GHG) emissions that greatly affect the earth's temperature, changes in weather, sea level, land use patterns and responding effectively and efficiently to the energy demand (cost and peak load reduction) is crucial towards achieving sustainability. WOA method was used to optimize and reduce the daily electricity cost through appliance scheduling. The scheduling optimization was implemented respectively with respect to Time-of-Use (TOU) billing method depending on the type of electricity price fluctuation. Moreover, the optimization was done in two different ways, i.e., optimization without solar PV and optimization integrating with solar PV. Simulation results depicted that optimizing the cutback of the electric appliances through WOA minimizes the cost up to 40% when no renewable energy is placed and by up to 53% when renewable energy is taken into account with respect to TOU pricing. Also, in terms of scheduling, WOA showed that it can be adopted for scheduling appliances in households for both electric bill and peak load reduction. The reduction in electric bill indicates the cutback of load demand from the specific user which can serve during severe peak demand. Moreover, the great saving of electric bills indicates a better performance of WOA.

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System Reconfiguration for Technical Power Loss Reduction in the Distribution Network by Using Genetic Algorithm

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***Abstract*—Power loss in the transmission network are not as effective as those on the distribution network. Hence, this paper focuses only on the reduction of technical power losses in distribution networks. System reconfiguration is used to reduce technical power losses, increase system security, enhance power quality and relieve the overloading in the distribution network. In this proposed method, the change in the system is accomplished by opening the sectionalizing switches and closing tie switches of the system so that radiality of the system is achieved and all of the loads are energized. The optimization problem in 20 nodes test feeder is solved by using genetic algorithms technique established in MATLAB software. It can be shown from the simulated result that system reconfiguration not only reduces power losses but also maintain voltage profiles within permissible limits in the distribution network.**

Keywords—Distribution network; System reconfiguration; Power flow; Genetic Algorithm; Optimization.

I. INTRODUCTION

Distribution system furnishes power to provide for our heating, lighting, and equipment needs. Several considerations are important for efficient operation of electrical distribution systems. Economic measures are used to increase the efficiency of electrical power systems for reducing power losses. These measures include electrical load management, computerized monitoring, demand factor control and load factor planning. For the case of load management, power losses in distribution network can be minimized by introducing capacitor installment, reconductoring, transformer load monitoring, voltage modification and network reconfiguration. Network reconfiguration is the process of altering the topological structure of the network by closing the open/close status of sectionalizing and tie switches to reach a network that optimizes the desired objectives. Distribution feeders have a number of switches that are usually closed (sectionalizing switches) and switches that are normally open (tie switches) [1]. Mostly, electric distribution feeders are configured radially for effective coordination of their protective systems [2]. Distribution feeders contain switches some of which are normally open. During a fault, some of the normally closed switches are opened to isolate the faulted network branch [1]. At the same time, some of the normally open switches are closed to transfer part or all the isolated branches to other feeders. In their standard positions, All switches are restored after the clearance of the fault [3-4].

Distribution engineers have periodically reconfigured the feeders by opening and closing switches (switching operation) in order to increase the network reliability and reduce line losses [5]. The resulting feeders must remain radial and satisfy all load requirements and voltage constraints. Coordination of the protective scheme of the newly configured system is also necessary to ensure that the reliability is maintained at the required level. Distribution networks are built as meshed networks, while they are operated radially. Their configurations may be changed with manual or automatic switching operations so that all the loads are injected and reduce power loss, increase system security, and enhance power quality [4,6]. Reconfiguration also mitigates the overloading of the system components. The change in network configuration is done by opening the sectionalizing switches and closing tie switches of the network respectively. These switching are done in such a way that loops of the system are not required, and all loads are energized. Clearly, the greater the number of switches is, the greater the possibilities are for reconfiguration, and better the effects are [4,7].

II. PROBLEM FORMULATION

The optimal reconfiguration problem is a nonlinear optimization problem. It consists of a nonlinear objective function defined with nonlinear constraints. The optimal reconfiguration problem requires the solution of nonlinear equations, describing the optimal and secure operation of the distribution network. The general optimal reconfiguration problem can be expressed as a constrained optimization problem as follows.

Minimize	$f(x)$
Subject to	$g(x)=0$, equality constraints
	$h(x)\leq 0$, inequality constraints

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A. Objective Function

The objective function of the optimal feeder reconfiguration to minimize the total power loss can be given as;

Minimize

$$\sum_{i=1}^{n} R_i \frac{(P_i^2+Q_i^2)}{V_i^2} X_i \tag{1}$$

Where the variables are defined as follows:

R_i is the resistance of the line section i

P_i is the real power of the line section i

Q_i is the reactive power of the line section i

X_i is the state value of switch i

n is the number of buses or node

Where

$$X_i = \begin{cases} 1, & \text{if switch is closed} \\ 0, & \text{if switch is open} \end{cases}$$

B. System Constraints

In the following constraints, the objective function is subjected.

- Operating voltage at each node must be in safety range

$$V_{i\,min} \leq V_i \leq V_{i\,max} \tag{2}$$

- Feeder capacity limit

$$|I_i| \leq I_{i\,max} \tag{3}$$

- Power flow equations

$$\sum P_{Gen} = P_{loss} + \sum P_{load} \tag{4}$$

$$\sum Q_{Gen} = Q_{loss} + \sum Q_{load} \tag{5}$$

- Radiality of the network must be maintained after reconfiguration

$$\sum_{i=1}^{(a+t)} X_i = n - 1 \tag{6}$$

where: $V_{i\,min}$ is the minimum voltage limit of *ith* node

$V_{i\,max}$ is the maximum voltage limit of *ith* node

V_i is the voltage at *ith* node

n is the number of buses

a is the number of branches

t is the number of tie switches

$I_{i\,max}$ is the maximum current capacity of *ith* branch

I_i is the current in the *ith* branch

$\sum P_{Gen}$ is the total real power generation

$\sum Q_{Gen}$ is the total reactive power generation

P_{loss} is the total real power losses

Q_{loss} is the total reactive power losses

$\sum P_{load}$ is the total real power load

$\sum Q_{load}$ is the total reactive power load

III. The Proposed Genetic Algorithms

Based on the propositions of genetics and natural selection, the search technique was recently used by the genetic algorithm (GA) for an optimization. For minimizes the cost function. GA enables a population to compose many individuals in the evolvement of underspecified selection rules up to a state that maximizes the which is called fitness function. John Holland redeveloped the method in 1975 and at the end publicized by David Goldberg for solving difficult problems involving the control of gas-pipeline transmission for his dissertation. Holland's actual work was summarized in his book. In schema theorem, a theoretical basis for GAs was the firstly redeveloped. The work of De Jong was stated the effectiveness function of the GA optimization and decided to find optimized GA parameters for the first concerted effort in 1975. Goldberg has incorporated the most fuel to the GA showing successful applications and excellent book. Up to now, different evolutionary in programming version have been tried with varying degrees of success.

The genetic algorithm utilizes main types of procedures at each step to create the next generation from the current population [8]:

- *Selection rules* select the individuals, called parents that contribute to the population to the next generation.
- *Crossover rules* combine two parents to form children for the next generation.
- *Mutation rules* apply random changes to individual parents to create children.

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TABLE I. SWITCH STATUS CHROMOSOME FOR BEST RECONFIGURATION.

s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15	s16	s17	s18	s19	s20
1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	0	1	1	1	0

IV. EXPLANATION OF THE PROPOSED METHOD.

In the sample, the radial distribution system is shown below in Fig. 1, full branches represent lines that are in operation (sectionalizing switches) and dotted branches i.e. s5, s15 and s20 represents the line with open switches (tie switches). The base network can be reconfigured by closing an open branch (tie switch) say s15. Therefore, this switching will create a loop with a total number of branches including tie-branch in this loop will be 7, composed of branches 2-10, 10-12, 12-17, 17-18, 18-16, 16-15 and 15-3. A branch of the circuit containing a switch should be opened, say branch s16, to restore the radial structure of the network. Due to this switching, the load between branches s17-s13 to be transferred from one feeder to another.

A. Algorithms of the proposed system.

Step 1: Read the system data.

Step 2: Create the number of random variables in 1 and 0's of 20-bit size as per the population size and initialize maximum number of iterations for GA.

Step 3: Check the criteria whether the test system is radial or not; if the test system network has no closed loops and all the loads were connected, otherwise go to step 2.

Step 4: Select the initial population that obeys the radiality and check the sending end and receiving end connection for the branches in the network.

Step 5: Calculate the fitness of the population.

Step 6: Perform crossover operation by taking two chromosomes at a time from the population. create a random number for the crossover point. perform crossover operation by interchanging the bits in the left side of the crossover point.

Step 7: Perform the mutation operation (after crossover operation) by generating two random numbers mutating the chromosomes and change the bit 0 to 1 or 1 to 0 for the two chromosomes.

Step 8: If the offspring does not obey the radiality, replace it with 1's.

Step 9: Sort the population and off springs.

Step 10: Choose the best individuals of population size according to their fitness.

Step11: Steps 6 to 10 are repeated until maximum iteration is reached.

Step12: The switch status for the minimum loss Configuration is also displayed.

Step 13: Stop the process.

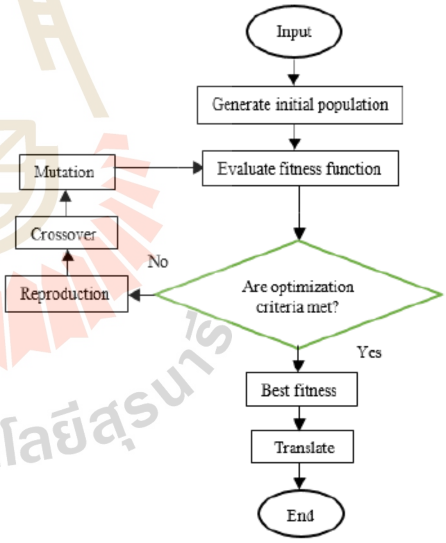

Fig. 1. Flowchart of the reconfiguration for loss reduction.

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V. RESULTS AND DISCUSSION OF THE PROPOSED SYSTEM.

Both Genetic algorithm (GA) and Power flow method are used to calculate the optimal active power losses and voltages of the network as shown in Table II.

TABLE II. SYSTEM RESULTS USING A GENETIC ALGORITHM (GA)

System	Power Loss (p.u.)	Voltage (p.u.)	Tie Switches
Before reconfiguration	0.0084281341	0.8674962662	(7-13), (12-17), (9-20)
After reconfiguration	0.0065947383	0.8809854127	(7-13), (17-18), (16-15)

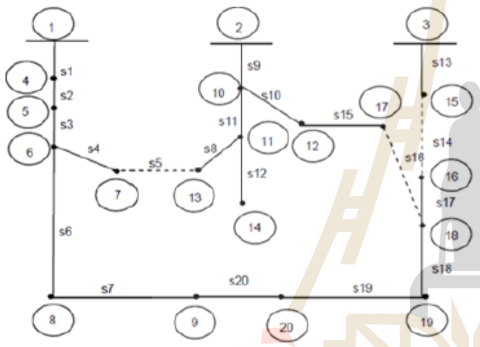

Fig. 2. Sample radial distribution system with the best reconfiguration.

It showed that from Fig. 3. by closing both tie-switch s15 and s20 and opening sectionalizing switch s14 and s16, not only we can obtain the best reconfiguration of the distribution network but also, can keep the radiality (loops are not allowed) of the network. Hence, power losses can be reduced from 0.0084281341 p.u to 0.0065947383 p.u near the global optima and maintain voltage profiles within the permissible limits of the distribution network from 0.8674962662 p.u to 0.8809854127 p.u.

VI. CONCLUSION.

In this paper, genetic algorithm method has been employed to solve optimal distribution network reconfiguration problems for loss reduction. The components of the proposed genetic algorithm based method including population, reproduction, crossover, mutation were recited. The proposed algorithm produce a near optimal solution by searching over different radial configuration with branch exchange type switching and by adopting the nature of essential genes. Results from Table. II shows that the proposed algorithm based method is validity, feasible, efficient and effectiveness for distribution system reconfiguration.

Genetic algorithms used successfully to reduce power loss considering linear and non-linear characteristics.

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APPENDIX

TABLE III. SWITCH STATUS CHROMOSOME FOR BASIC RECONFIGURATION.

s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15	s16	s17	s18	s19	s20
1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0

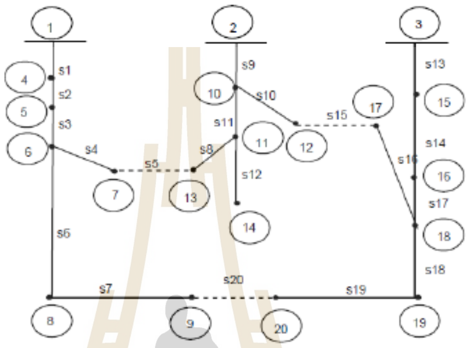

Fig. 3. Sample distribution network with three tie branches.

TABLE IV. LINE DATA FOR 20-BUS SYSTEM

Bus	Section Resistance (p.u.)	Section Reactance (p.u.)	Bus Load MW	MVAR Q	End Bus Capacitance
1-4	0.77266	0.510989	0.01294	0.009708	0.00315
4-5	0.9646	0.359645	0.010032	0.007524	0.00153
5-6	0.4331311	0.16155	0.006016	0.004512	0.00108
6-8	0.86638	0.32312	0.001408	0.001056	0.00027
8-9	0.30132	0.11229	0.000904	0.000678	0.00018
2-10	0.953585	0.53552	0.00591	0.004434	0.00108
10-11	0.3377042	0.205746	0.0084	0.0063	0.00135
11-14	0.29568	0.180097	0.0116	0.0087	0.00171
3-15	0.683307	0.560993	0.013008	0.009756	0.00262
15-16	0.58239	0.422629	0.00372	0.00279	0.00072
16-18	0.791048	0.295024	0.027352	0.002178	0.00063
18-19	0.94171	0.351231	0.01704	0.001578	0.00045
19-20	0.678018	0.252868	0.008632	0.002106	0.00054
6-7	0.33756	0.1748	0.005671	0.002145	0.00078
17-18	0.76816	0.28661	0.004578	0.00452	0.000417
10-12	0.1474	0.1605	0.004592	0.004672	0.005671
11-13	0.1216	0.23499	0.004621	0.004685	0.005774
7-13	0.8663	0.3231	0	0	0
9-20	0.6833	0.5609	0	0	0
12-17	0.7681	0.2866	0	0	0

Intelligent Algorithm for Optimal Load Management in Smart Home Appliance Scheduling in Distribution System

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***Abstract*— One of the essential factor for the better operation of an electrical power system is load demand. Normally, higher load demand leads to instability and insufficient power supply. To make an electrical power system stable and sufficient, a good correlation between demand and supply should exist. A survey conducted during 2011 indicated that residential sector is consuming 18% of total energy. Also, the demand was seen to increase rapidly close to and sometimes beyond the supply. Hence, this paper focuses on appliance scheduling for cost reduction and peak load reduction by increasing demand-side response in the smart home. A load management algorithm is developed in MATLAB which reduces both cost and peak load consumption by managing the operation according to utility controls and consumer preferences. The optimization problem was solved by using Genetic Algorithm (GA) technique. The simulation results depicted that GA can be adopted for appliance scheduling in the household, reduction of electric bill as well as cutback of peak demand from the demand side.**

Keywords— Demand-Side Management; Demand response; Smart home; Genetic Algorithm

I. Introduction

In the electrical power system, load demand plays an important role of maintaining the stability of the system. A good proportionality between demand (consumption) and supply (generation) should hold in order to avoid generation disturbances which later introduces negative effects in technical, economic and social areas [1]. The rapid rise of energy needs has made electric utility companies to expand generation plants with respects to peak demand rather than average power in order to meet the consumer's demand [2]. This approach, unfortunately, renders power systems highly underutilized and customers' consumption patterns increasingly irresponsible. Additionally, it has driven utility companies to make huge long-term investments in new generation power plants which are mostly and typically based on traditional (conventional) energy sources. Such power plants – in addition to being capital intensive – lead to increased Greenhouse Gases (GHG) emissions that greatly affect the earth's temperature, changes in weather, sea level, and land use patterns [3]. Efficient utilization and special consideration of the optimal plant generation capabilities must be employed in order to improve the under-perfoming available generating plants without building new power plants [4] - [5]. Nowadays, load management has been accepted worldwide as the simplest, safest and cheapest technique that provide a better correlation between generation and load by performing load management practices on demand side loads through demand reduction or reshaping the load profile.

Usually, load management practice aims to shift the load from on-peak period to off-peak period so as to reshape the load profile which in-turn reduces the total cost of electricity. Through energy management-based researches, an electrical engineer can cut costs of power system operation through utilization of optimal available generation capacity. A survey conducted during 2011 indicated that 18% of total energy is being consumed by residential sector [6]. Due to this reason, this paper target on scheduling home appliances (HAs) in the smart home integrated with renewable energy. Smart home (SH) appliances are connected to home area network (HAN) to coordinate power usage demanded the home under control. Load management is an essential key factor in smart grid (SG) for scheduling home appliances (HAs) in the smart home. A modern technology, with sophisticated metering infrastructure, can allow a two-way transmission of information between the utility company and the consumer through metering unit to enable a smooth aggressive load deviation. Regarding this direction, demand-response (DR) programs give incentives to significant costumers, generally in terms of money, to minimize their energy use during on-peak periods [6]. Demand Response appear at a very fast timescale, approximately real-time, it results to a stable and sufficient power grid system and importantly minimizes electric cost and CO2 emissions [7]. In this paper, Time-Of-Use (TOU) tariff was used.

Smart grid, in the growing power system technology, is currently considered as an upcoming solution to the most of the existing power systems. It comes in different names such as smart power grid or intelligent grid [2] to take over an old, disorganized and defenseless existing power system. An efficient performance of smart grid depends on the advanced technologies in electrical power, control, communication, information theory, bi-directional flows of electrical power and information which promotes an advanced and modern power system with cost-effective, safety and security. In smart grid, advanced energy-metering infrastructure (AMI) and energy monitoring are performed over a number of smart meters and sensors equipped all the way in smart homes. The part of communication as well as networking technologies ensure real time data collection and transmission to and from both sides. In smart grid (SG) system, the load management is an essential factor to control energy management system. Through load management strategies in smart grid (SG), reduction of peak load during the peak period and control pricing of electricity unity can be achieved through customer participation in the smart home [8]-[14].

II. Strategies for Load Management on Demand Side

There exist several strategies applicable for load management on demand side such as valley filling, peak clipping, and load shifting. Others are strategic conservation, strategic load growth, and flexible load shape. The operation of these strategies are shown on Fig. 1.

The descriptions of the above-mentioned strategies are given below:

- Peak clipping- minimizes system peak loads during on-peak period
- Valley filling- building loads during off-peak period
- Load shifting- transferring of loads from on-peak period to off-peak periods and vice versa
- Strategic load growth- increase customer usage resulting in sales increment beyond valley filling
- Flexible load shape- incentive contracts and tariffs (i.e, RTP, TOU, etc) with possibilities to shift consumer's equipment from on-peak period to off-peak period

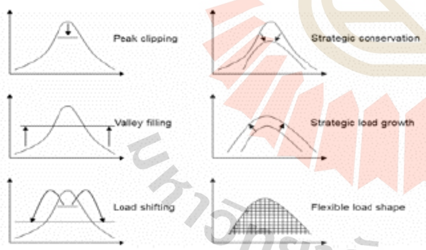

Fig. 1. The Load control strategies.

III. Problem Formulation

A. Forulating Objective Function

The goal of the objective function of load management problem is to reduce the total electric bill by scheduling the appliance on the basis of one-day ahead of TOU tariffs. The total electric bill is given in (1) [6]:

$$\min \sum_{k=1}^{m} C^k \left(\sum_{i=1}^{N} \sum_{j=1}^{ni} P_{ij}^k X_{ij}^k \right) \tag{1}$$

Where: $$X_{ij}^k = \begin{cases} 1 \; if \; appliance \; is \; ON \\ 0 \; if \; appliance \; is \; OFF \end{cases} \tag{2}$$

Where: k is the slot time over a certain period of time, j is the is the phase load number index correlated within each appliance, ni is the phases load shiftable set of numbers correlated with every appliance i, N is the appliances cutback set numbers, m is the slot time maximum number present in a day, C^k is the TOU tariff, P_{ij}^k is the power consumption of an appliance i.

B. System Constraints

The objective function of the cost reduction of the electricity bill is subjected to the following constraints:

- Load phases of the appliance should fulfill their energy requirements as in (3).

$$\frac{1}{4}\left(\sum_{i=1}^{N} \sum_{j=1}^{ni} P_{ij}^k \right) = E_{ij} \qquad \forall \{i, j\} \tag{3}$$

- Load safety factor is given as in (4).

$$\sum_{i=1}^{N} \sum_{j=1}^{ni} P_{ij}^k \le \beta^k \qquad \forall \{k\} \tag{4}$$

- Timing constraints in (5)

$$X_{ij}^k + S_{ij}^k \le 1 \qquad \forall \{i, j, k\} \tag{5}$$

IV. Intelligent Algorithms

A. Mixed Integer Linear Programming (MILP)

MILP (Mixed Integer Programming) is a generalization of LP in which the variables of the linear model are an integer. The variables could also be binary in some cases, as in [14].

B. Genetic Algorithms (GA)

Genetic Algorithms (GA) described by Charles Darwin [15], are direct, parallel, stochastic technique for global search and optimization which imitates the evolution of the living organism. GA is among the group of Evolutionary Algorithms (EA). The EA use the three primary principles of the natural evolution: reproduction, natural selection, and mutation as in [15], [16], [17].

TABLE I. PARAMETERS OF THE GA

Generation	Population	Crossover	Mutation	Elitism rate
5000	10	0.9	0.1	0.5

V. SIMULATION RESULTS AND DISCUSSION

Both MILP and GA were used during simulation for appliance scheduling of customers 24-hours energy consumption for electricity cost (bill) minimization and peak load reduction. The energy boundary of the household provided by the grid operator (utility) is shown from Table II. Fig. 2 shows shiftable (non-interruptible) load energy consumption magnitudes.

From Fig. 3 to Fig. 8 indicate appliance scheduled in 24-hours for optimal electricity consumption for end-users by both MILP and GA. As depicted from the Fig. 3 to Fig. 8 below, it can be noted that during the peak period, i.e., hour 14, the customer consumes lower energy in that period; and during the off-peak periods, such as hour 7, the end-user uses higher energy in that period.

Due to incentive contract capacity constraint from the utility company has been brought into attentions in this paper. Hence customer's total electrical energy usage in every hour won't exceed the incentive capacity contract in order to avoid extra electricity bill to be refunded, and during buzzy peak period should be balanced to the utility contract measure. As indicted from Fig. 5 and Fig. 8 at hour 6, the customer's energy cost was 3073, 3189, 3943 for MILP and 3069, 3181, 3937 for GA, respectively.

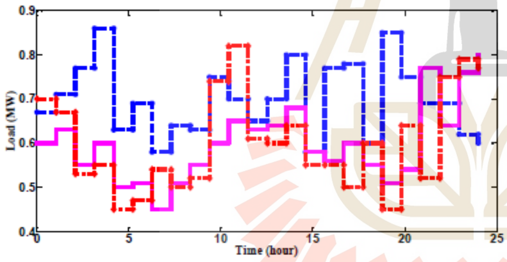

Fig. 2. Non-interruptible load of three customers.

TABLE II. CONSUMER ELECTRICITY SCHEDULE DATA

Number of consumers	Lower boundary of shiftable load (MW)	Upper boundary of shiftable load (MW)	Total shiftable load (MW)	Grid contract load
1	0	0.6	6	1.22
2	0	0.5	6.5	1.22
3	0	0.55	7	1.22

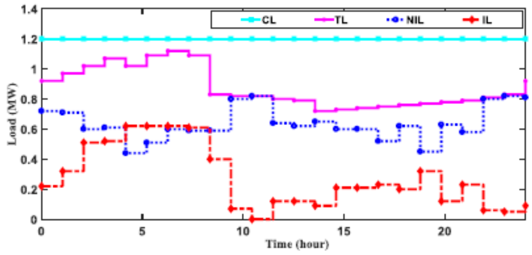

Fig. 3. Electricity scheduling of consumer 1 by MILP.

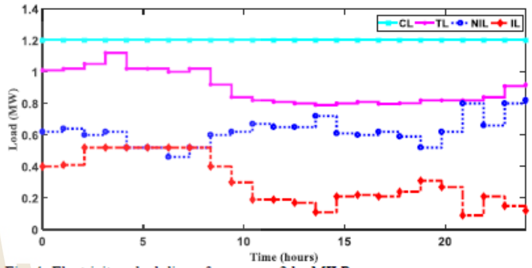

Fig. 4. Electricity scheduling of consumer 2 by MILP.

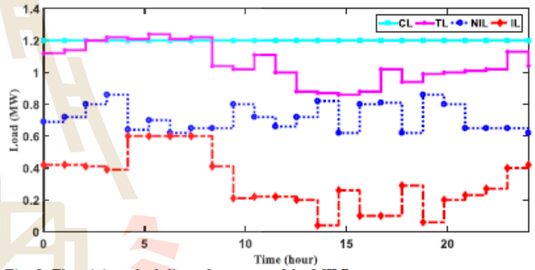

Fig. 5. Electricity scheduling of consumer 3 by MILP.

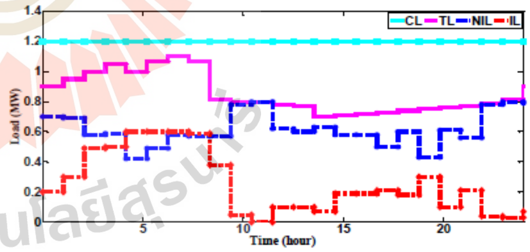

Fig. 6. Electricity scheduling of consumer 1 by GA.

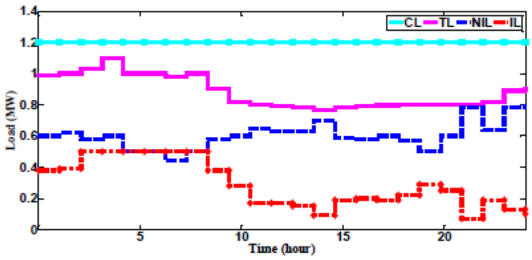

Fig. 7. Electricity scheduling of consumer 2 by GA.

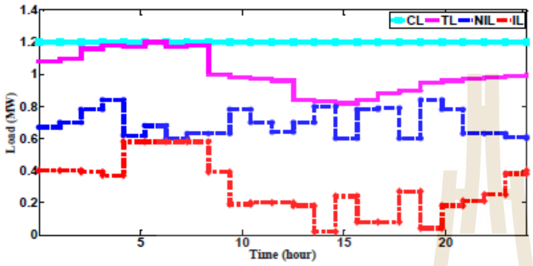

Fig. 8. Electricity scheduling of consumer 3 by GA.

Where: CL is the contract load from the utility company to the customers, TL is the total load, NIL is the non-interruptible load, and IL is the interruptible load.

VI. CONCLUSION

The paper aims to minimize customers electricity cost (bill) by optimizing one-day (24-hours) customer's energy consumption problem. The new and modern energy rate charging scheme was presented in this paper, end-users will be able to find out energy rate with respect to energy usage based on hourly energy rate curve announced by the utility, which is sufficient and efficient approach whereby both two parties (utility company and consumer) can benefit. Not only a consumer can benefit monetary reward from the contract he/she signed from the utility company to undergo appliance scheduling during peak-period but also utility company may escape from grid outages (power failure) resulted from peak-period problems.

Finally, extra electricity cost by the consumer can be avoided as shown from the simulation results due to the energy constraints which prevents customers electricity use not to exceed the contract capacity. Also, for comparison and effectiveness of the algorithms, GA showed better results compared to MILP. Therefore, GA showed that can be adopted for appliance scheduling in household for electricity cost minimization.

ACKNOWLEDGMENT

This work was backed by the Laboratory of High Voltage Insulation Technology of Suranaree University of Technology, Thailand.

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APPENDIX B

MATLAB SOURCE CODE

- **MATLAB Source Code for Optimal Appliance Scheduling in Smart Home without Renewable Energy Integration**

```
% Programme Name : Smart Home Energy Management
% Author         : Mr Hussein Swalehe
% Version        : First Step
% Last Update    : 15/12/2017
% Software       : Matlab R2017b
%Scheduling Optimization
%Minimization of the Residential Electricity Bill
%i=5 & j=24
%Electric Price Rate f ($/kWh):
f=[0.09;0.08;0.08;0.08;0.09;0.1;0.1;0.8;0.1;0.11;0.11;0.11;0.11;0.11;
0.11;0.11;0.09;0.1;0.12;0.12;0.11;0.12;0.12;0.11];
intcon = 1:24;
Aeq=[5,3,4,6,1,1,1,1,5*0.05,3*0.04,4*0.05,6*0.03,0.08,0.07,0.06,0.03,
5*0.03,3*0.03,4*0.04,6*0.04,0.06,0.07,0.08,0.09];
beq = [25];
%Maximum working power ub /%Standby power lb
lb = zeros(24,1);
ub = 1.2*ones(24,1);
ub(5:end) = Inf; % No upper bound on noninteger variables
[x,fval,exitflag,output] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
x
fval
bar(x);
%%
t=[1:1:24];
plot(t,x)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
%%
%Appliance 2
%f=p
intcon = 1:24;
Aeq =
[5*0.03,3*0.03,4*0.04,6*0.04,0.06,0.07,0.08,0.09,5,3,4,6,1,1,1,1,5*0.
05,3*0.04,4*0.05,6*0.03,0.08,0.07,0.06,0.03];
beq = [25];
lb = zeros(24,1);
ub = 3*ones(24,1);
ub(5:end) = Inf;
[y,fval,exitflag,output] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
y
fval
```

MATLAB SOURCE CODE (Continued)

```
bar(y);
%%
%Appliance 3
intcon = 1:24;
Aeq =
[25*0.03,3*0.03,4*0.04,6*0.04,0.06,3.7,7.08,1.09,4.5,0.3,0.4,6,1,1,0,
1,5*0.05,3*0.04,4*6.05,6*0.03,0.08,8.07,1.06,0.03];
beq = [2.5];
lb = zeros(24,1);
ub = 0.5*ones(24,1);
ub(5:end) = Inf;
[z,fval,exitflag,output] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
z
fval
bar(z);
%%
%%Appliance 4
intcon = 1:24;
Aeq =
[2.5*0.03,7*0.03,4*0.04,6*0.04,0.06,3.7,2.08,0,4.5,8.3,9.4,0,1.5,1,0,
1,5*0.05,3*0.04,4*6.05,5*0.03,0.08,8.07,1.06,8.03];
beq = [12.5];
lb = zeros(24,1);
ub = 5.5*ones(24,1);
ub(5:end) = Inf;
[v,fval,exitflag,output] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
v
fval
bar(v);
%%
%Appliance 5
%f=p
intcon = 1:24;
Aeq =
[8*0.03,3*0.03,4*0.04,6*0.04,0.46,10.07,0.08,9.09,5,3.69,4,6,1.56,0,1
.9,.89,5*0.05,30*0.004,4*1.05,6*0.03,0.08,0,0.06,8.03];
beq = [60];
lb = zeros(24,1);
ub = 7*ones(24,1);
ub(5:end) = Inf;
[w,fval,exitflag,output] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
w
fval
bar(w);
%% Optimal Scheduling of 5 appliances
t=[1:1:24];
plot(t,x,'r-*',t,y,'b-*',t,z,'g-*',t,v,'k-*',t,w,'c-*','LineWidth',2)
title('Optimal Scheduling of 5 appliances');
xlabel('Time (hours)');
ylabel('Power (10^2 Watt)');
grid on;
legend('Heater', 'Washing Machine', 'Fridge', 'Dishwasher', 'Iron')
%% Optimal Scheduling of 5 appliances
GU=[x,y,z,v,w];
```

MATLAB SOURCE CODE (Continued)

```
bar(GU,'stacked')
title('Optimal Scheduling of 5 appliances');
xlabel('Time (hours)');
ylabel('Power (10^2 Watt)');
grid on;
legend('Heater 1', 'Washing Machine', 'Iron', 'Dishwasher', 'Heater
2')
```

- **MATLAB Source Code for Optimal Appliance Scheduling in Smart Home with Renewable Energy Integration**

```
% Programme Name : Smart Home Energy Management
% Author         : Mr Hussein Swalehe
% Version        : First Step
% Last Update    : 15/12/2017
% Software       : Matlab R2017b
%% Electricity Generated Output of the PV system:
%Irradiation
H=[0,0,0,0,0,0,0,0,97,211,228,418,424,381,351,257,156,0,0,0,0,0,0,0];
%Performance Ratio
PR=0.75;
%Solar Panel Yieldgx
r=0.16;
%Total Solar Panel Area in m^2
Area=4;
gE=Area*r*PR.*H;
%i=5 & j=24
%Electric Price Rate f ($/kWh):
f=[0.09;0.08;0.08;0.08;0.09;0.1;0.1;0.8;0.1;0.11;0.11;0.11;
0.11;0.11;0.11;0.11;0.09;0.1;0.12;0.12;0.11;0.12;0.12;0.11];
intcon = 1:24;
Aeq=[5,3,4,6,1,1,1,1,5*0.05,3*0.04,4*0.05,6*0.03,0.08,0.07,0.06,0.03,
5*0.03,3*0.03,4*0.04,6*0.04,0.06,0.07,0.08,0.09];
beq = [25];
%Maximum working power ub /%Standby power lb
lb = zeros(24,1);
ub = 1.2*ones(24,1);
ub(5:end) = Inf; % No upper bound on noninteger variables
[x,fval] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
x
fval
bar(x);
%%
t=[1:1:24];
plot(t,x)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
intcon = 1:24;
```

MATLAB SOURCE CODE (Continued)

```
Aeq =
[5*0.03,3*0.03,4*0.04,6*0.04,0.06,0.07,0.08,0.09,5,3,4,6,1,1,1,1,5*0.
05,3*0.04,4*0.05,6*0.03,0.08,0.07,0.06,0.03];
beq = [25];
lb = zeros(24,1);
ub = 3*ones(24,1);
ub(5:end) = Inf;
[y,fval] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
y
fval
bar(y);
%%
t=[1:1:24];
plot(t,y)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
intcon = 1:24;
Aeq =
[25*0.03,3*0.03,4*0.04,6*0.04,0.06,3.7,7.08,1.09,4.5,0.3,0.4,6,1,1,0,
1,5*0.05,3*0.04,4*6.05,6*0.03,0.08,8.07,1.06,0.03];
beq = [2.5];
lb = zeros(24,1);
ub = 0.5*ones(24,1);
ub(5:end) = Inf;
[z,fval] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
z
fval
bar(z);
%%
t=[1:1:24];
plot(t,z)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
intcon = 1:24;
Aeq =
[2.5*0.03,7*0.03,4*0.04,6*0.04,0.06,3.7,2.08,0,4.5,8.3,9.4,0,1.5,1,0,
1,5*0.05,3*0.04,4*6.05,5*0.03,0.08,8.07,1.06,8.03];
beq = [12.5];
lb = zeros(24,1);
ub = 5.5*ones(24,1);
ub(5:end) = Inf;
[v,fval] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
v
fval
bar(v);
%%
t=[1:1:24];
plot(t,v)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
intcon = 1:24;
```

MATLAB SOURCE CODE (Continued)

```
Aeq =
[8*0.03,3*0.03,4*0.04,6*0.04,0.46,10.07,0.08,9.09,5,3.69,4,6,1.56,0,1
.9,.89,5*0.05,30*0.004,4*1.05,6*0.03,0.08,0,0.06,8.03];
beq = [60];
lb = zeros(24,1);
ub = 7*ones(24,1);
ub(5:end) = Inf;
[w,fval] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
w
fval
bar(w);
%%
t=[1:1:24];
plot(t,w)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
gx=(x-0.001*(gE)');
gy=(y-0.001*(gE)');
gz=(z-0.001*(gE)');
gv=(v-0.001*(gE)');
gw=(w-0.001*(gE)');
gE2=-0.01*gE;
%% Optimal Scheduling of 5 appliances
t=[1:1:24];
plot(t,x,'r-*',t,y,'b-*',t,z,'g-*',t,v,'k-*',t,w,'c-*','LineWidth',
2)
title('Optimal Scheduling of 5 appliances');
xlabel('Time (hours)');
ylabel('Power (10^2 Watt)');
grid on;
legend('Heater', 'Washing Machine', 'Fridge', 'Dishwasher', 'Iron')
%% Optimal Scheduling of 5 appliances
GU=[gx,gy,gz,gv,gw,gE2'];
bar(GU,'stacked')
title('Optimal Scheduling of 5 appliances');
xlabel('Time (hours)');
ylabel('Power (10^2 Watt)');
grid on;
```

MATLAB SOURCE CODE (Continued)

- **MATLAB Source Code for Optimal Appliance Scheduling in Smart Home with Renewable Energy and Battery Energy Storage**

```
% Programme Name : Smart Home Energy Management
% Author         : Mr Hussein Swalehe
% Version        : First Step
% Last Update    : 15/12/2017
% Software       : Matlab R2017b
%% Electricity Generated Output of the PV system:
%Irradiation
H=[0,0,0,0,0,0,0,0,97,211,228,418,424,381,351,257,156,0,0,0,0,0,0,0];
%Performance Ratio
PR=0.75;
%Solar Panel Yield
r=0.16;
%Total Solar Panel Area in m^2
Area=4;
gE=Area*r*PR.*H;
%i=5 & j=24
%Electric Price Rate f ($/kWh):
f=[0.09;0.08;0.08;0.08;0.09;0.1;0.1;0.8;0.1;0.11;0.11;0.11;
0.11;0.11;0.11;0.11;0.09;0.1;0.12;0.12;0.11;0.12;0.12;0.11];
intcon = 1:24;
Aeq=[5,3,4,6,1,1,1,1,5*0.05,3*0.04,4*0.05,6*0.03,0.08,0.07,0.06,0.03,
5*0.03,3*0.03,4*0.04,6*0.04,0.06,0.07,0.08,0.09];
beq = [25];
%Maximum working power ub /%Standby power lb
lb = zeros(24,1);
ub = 1.2*ones(24,1);
ub(5:end) = Inf; % No upper bound on noninteger variables
[x,fval] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
x
fval
bar(x);
%%
t=[1:1:24];
plot(t,x)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
intcon = 1:24;
Aeq =
[5*0.03,3*0.03,4*0.04,6*0.04,0.06,0.07,0.08,0.09,5,3,4,6,1,1,1,1,5*0.
05,3*0.04,4*0.05,6*0.03,0.08,0.07,0.06,0.03];
beq = [25];
lb = zeros(24,1);
ub = 3*ones(24,1);
ub(5:end) = Inf;
[y,fval] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
y
fval
```

MATLAB SOURCE CODE (Continued)

```
bar(y);
%%
t=[1:1:24];
plot(t,y)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
intcon = 1:24;
Aeq =
[25*0.03,3*0.03,4*0.04,6*0.04,0.06,3.7,7.08,1.09,4.5,0.3,0.4,6,1,1,0,
1,5*0.05,3*0.04,4*6.05,6*0.03,0.08,8.07,1.06,0.03];
beq = [2.5];
lb = zeros(24,1);
ub = 0.5*ones(24,1);
ub(5:end) = Inf;
[z,fval] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
z
fval
bar(z);
%%
t=[1:1:24];
plot(t,z)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
intcon = 1:24;
Aeq =
[2.5*0.03,7*0.03,4*0.04,6*0.04,0.06,3.7,2.08,0,4.5,8.3,9.4,0,1.5,1,0,
1,5*0.05,3*0.04,4*6.05,5*0.03,0.08,8.07,1.06,8.03];
beq = [12.5];
lb = zeros(24,1);
ub = 5.5*ones(24,1);
ub(5:end) = Inf;
[v,fval] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
v
fval
bar(v);
%%
t=[1:1:24];
plot(t,v)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
intcon = 1:24;
Aeq =
[8*0.03,3*0.03,4*0.04,6*0.04,0.46,10.07,0.08,9.09,5,3.69,4,6,1.56,0,1
.9,.89,5*0.05,30*0.004,4*1.05,6*0.03,0.08,0,0.06,8.03];
beq = [60];
lb = zeros(24,1);
ub = 7*ones(24,1);
ub(5:end) = Inf;
[w,fval] = intlinprog(f,intcon,[],[],Aeq,beq,lb,ub);
w
fval
bar(w);
```

MATLAB SOURCE CODE (Continued)

```
%%
t=[1:1:24];
plot(t,w)
title('Optimal Scheduling');
xlabel('hours');
ylabel('Power');
gx=(x-0.001*(gE)-0.001*(gBt)');
gy=(y-0.001*(gE)-0.001*(gBt)');
gz=(z-0.001*(gE)-0.001*(gBt)');
gv=(v-0.001*(gE)-0.001*(gBt)');
gw=(w-0.001*(gE)-0.001*(gBt)');
gE=-0.1*gE-0.1*(gBt);
gE2=-0.1*(gBt)';
%% Optimal Scheduling of 5 appliances
t=[1:1:24];
plot(t,x,'r-*',t,y,'b-*',t,z,'g-*',t,v,'k-*',t,w,'c-*','LineWidth',
2)
title('Optimal Scheduling of 5 appliances');
xlabel('Time (hours)');
ylabel('Power (10^2 Watt)');
grid on;
legend('Heater', 'Washing Machine', 'Fridge', 'Dishwasher', 'Iron')
GU=[gx,gy,gz,gv,gw,gE2];
bar(GU,'stacked')
title('Optimal Scheduling of 5 appliances');
xlabel('Time (hours)');
ylabel('Power (10^2 Watt)');
grid on;
```

BIOGRAPHY

Hussein Swalehe was born on, 20 June 1988 in Kahama district, Shinyanga region, Tanzania. He completed his Bachelor Degree in Electrical Engineering in January 2015 from Dar es Salaam Institute of Technology. He later continued a master's degree in Electrical Engineering since November 2016 at the School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima, Thailand. His area of interest in research include smart grid and battery energy storage technology in electrical power system. Additionally, he is now likely focusing on smart modern public transportation and EV charging stations due to the revolution going on the power-system domain.