People's Democratic Republic of Algeria
Ministry of Higher Education and Scientific Research

University M'Hamed BOUGARA – Boumerdes

Institute of Electrical and Electronic Engineering
Department of Electronics

Final Year Project Report Presented in Partial Fulfilment of
the Requirements for the Degree of

MASTER

In **Electronics**

Option: **Power Engineering**

Title:

Load balancing in smart grids using multi-objective evolutionary optimization technique

Presented by:

- **Abdi Lina Amel**

Supervisor:

Mr.A.Recioui

Registration Number: 2019/2020

ABSTRACT:

The work concerns the balance between the supplied and consumed power in a residential area. An optimization task is formulated and solved. The re-formulation of the optimization task to include renewables is also provided. It was revealed in the results that with the proposed optimization technique, a significant reduction in the energy usage cost and the waiting time of the appliances (delay) for residential consumers can be achieved.This work can be used in smart home and smart cities applications.

TABLE OF CONTENTS:

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

p_s	peak-hour start time
p_e	peak-hour end time
m_s	mid-peak hour start time
m_e	mid-peak hour end time
o_s	off-peak hour start time
o_e	off-peak hour end time
c_p	peak hour cost
C_m	mid-peak hour cost
c_o	off-peak hour cost
X_p	population for off-peak hour
Y_p	population for mid-peak hour
Z_p	population for peak-hour
A_a	transition delay time between waiting state and running state for appliance a
ϵ_a	deferred time of appliance a
ω_a	running state end time or waiting state start time of appliance a
Th	Off-peak hour energy usage threshold value
Ip	Individual appliances, power consumption array
AE	Available energy
S_q	Scheduling queue
W_q	Waiting queue
Pr	Presently required power for the request
AppRun	Home appliances running state
defCnt	counter for interrupt
maxDef	maximum number of interrupts

D_p	Device priority to set of appliances
Toff	Off-peak hour time in a day
High	Home appliances priority level

DEDICATION

I dedicate this work to my parents and brother. Your unconditional and endless love and support is always what made me persevere in all of my endeavors. I am the most lucky to have you three in my life and words can't suffice to describe how much you mean to me. I promise to continue to strive to make all of you proud of my achievements. I also dedicate it to all my family members and friends, for their words of encouragement and valuable advice.

Acknowledgements

First and Foremost, i thank Allah the almighty for all his blessings and for granting me the patience and strength to complete this work.

Next, I would like to thank my supervisor professor A.Recioui for providing guidance and feedback throughout this project. I would also like to thank Professor Mohamed Adda for his valuable suggestions and for taking time out of his busy schedule to guide me in my simulation. I would also like to recognize the assistance of the website matlab project helper in fixing my programs to get the results of my simulation. Special thanks to Lounis Hadjer for her practical suggestions and helpful advice. Thanks should also go to Mrs Zohra Lounis, the executive director of the nuclear research center of the Atomic Energy Commission of Algiers for her help. Finally, I would like to thank all the teachers that taught me and shared their precious knowledge and the staff of the INELEC for assisting us with all our study related concerns throughout these five years.

GENERAL INTRODUCTION:

Utility companies are required to generate enough supply to meet the electrical demand at any given moment **[1]**.However, it is a known fact that traditional resources are limited and according to International Energy Agency (IEA), electricity demand is expected to increase by 2% per year until 2040. In the future, utility companies may not be able to match supply with demand **[2]**. To remedy to this issue, one solution is to implement demand side management or demand response programs to be more precise in the residential sector. demand response is defined as "the changes in electric usage by end-use consumers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale prices or when system reliability is jeopardized" **[4]**. The reason why we are focusing on the residential sector to solve this problem is that the latter accounts for 30-40% of the global energy use **[3]**.In addition to maintaining the balance between the supply and demand of electricity, another issue that we need to address at present is the global concern over green-house emissions from traditional energy resources. There is now a need to integrate clean and renewable energy resources into the grid **[3]**.

Unfortunately, the current electric grid does not properly accommodate renewable energy sources and the main challenge in the implementation of a DSM program is the quest for knowledge of the daily behavior of loads in the electrical system, which is generally not available from the systems based on conventional electrical meter **[1, 5]**.Mainly for these two reasons, the need for a smart grid has emerged.

To make a grid smart, a communication between the customer and the utility generating the electricity is required. A smart grid has controls, automation, and new technologies all working together to respond to changes in electric demand. The smart grid simplifies the integration of renewable energy sources into the grid and is ready to respond to changes in the electricity demand and quickly and efficiently implement demand response programs **[6]**.

Nature inspired or evolutionary algorithms (EAs) are efficient candidates for solving scheduling problems such as the problem scheduling of electrical appliances in a home under a demand-response program **[7]**. Scheduling problems may have more than one objective. In the electrical appliances scheduling problem, for example, the energy usage cost and the comfort of the user can be considered simultaneously. The two objectives in this case involve a trade-off (increase in one objective will lead to a decrease in the other and vice versa).Emulating the biological evolution mechanism and Darwin's principle on the "survival of the fittest", EAs are a robust tool for solving multi-objective (MO) optimization problems such as the electrical appliances scheduling problem involving more than one objective that conflict with each other **[8]**.

In this report, a multi-objective optimization technique for demand side management with load balancing approach is implemented in MATLAB.

The work is divided into three chapters. In chapter 1, we give some generalities about smart grid, the challenges encountered in the integration of renewables in the grid, solutions that exist in smart grid to enable the integration of renewables and a definition for demand side-management and its benefits. In chapter 2, a description for our home energy management system is provided. Finally, In Chapter 3, the simulation results in MATLAB are presented and discussed.

Chapter 1

Introduction:

The existing electricity utility grid, also called the conventional, traditional or legacy grid, is a hierarchical system in which power supply to the consumers at the bottom of the chain is ensured by the main power plants (that use fossil fuels) at the top of the chain through transmission and distribution networks as shown in figure 1.1. The source has no real-time information about the termination point's service parameters and the grid is built on the principle of unidirectional power flow, system is one way pipeline **[2, 9]**. Due to the growing concern over climate change caused by greenhouse gases emissions and the brisk increase in electricity demand (2% per year until 2040) which exceeds the demand for any other form of final energy globally, there is a tendency to replace fossil fuels by renewables such as wind and solar **[10, 9]**.However, In addition to being a consumer of fossil fuels, the current grid is not well suited to distributed energy resources (DER's) **[2]**. The infrastructure of the current grid was designed to utilize existing technology and handle the requirements defined during the ninetieth and twentieth century **[1]**. It suffers from lack of automated analysis, slow response to rapid change in loading, limited control and poor coordination between generated and consumed energy which resulted in a great number of severe outages in the past decades **[9]**. About 90% of all these power outages have their roots in the distribution network; from bottom of the chain, i.e. from distribution system **[2]**.

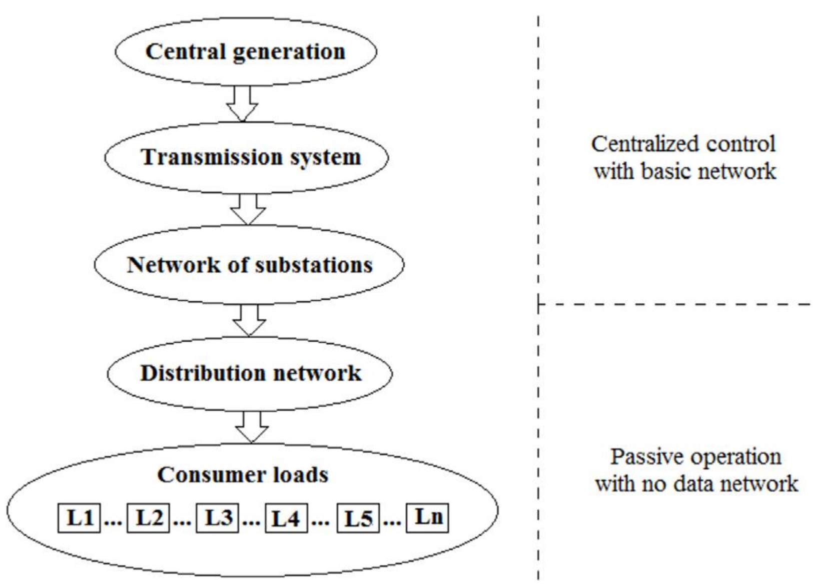

Figure 1.1: The existing electricity utility grid (**[2]**)

1 Generalities

The smart grid (SG) is the next generation of the power distribution grid that aims to utilize the new digital information and communication technologies (ICT's) to revolutionize and overcome the problems of the existing grid **[2, 9]**. It incorporates the benefits of ICT to deliver real-time information and enable the near instantaneous balance of supply and demand in the electrical grid **[2]**. As opposed to the existing grid, it offers a bi-directional flow of power and information **[11]**. Smart grid delivers electricity from suppliers to consumers using digital technology through control automation, continuous monitoring and optimization of distribution system, in order to save energy, reduce consumer cost and improve reliability **[12]**.

Smart grid enables to fill the gap between supply and demand through the integration of renewables (RE's) and demand side management (DSM) also called demand-response (DR) programs. Although, the intermittent and stochastic nature of renewables results in significant challenges in their integration in the grid such as voltage and frequency fluctuations, SG enables it through DSM programs and energy storage systems(ESS) **[13]**.

In this chapter, we will go through the generalities about smart grid, the challenges of integration of RE's in power system, how smart grid enables this integration. Finally, we will conclude with a definition of demand side management.

1. Generalities about Smart Grid:

1.1. Definitions:

The concept of Smart Grid combines a number of technologies, consumer solutions and responds to various policy and regulatory drivers. There is no universally accepted definition of what constitutes a smart grid.

The definition of Smart Grid by European technology platform is,
"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."

In smarter grids the Smart Grid is defined as,

1 *Generalities*

“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 manipulated 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).”

Definition of Smart Grid by U.S. department of energy (DOE) is,

“A Smart Grid uses digital technology to improve reliability, security and efficiency (both economic and energy) of the electrical system from large generation, through the delivery systems to electricity consumers and a growing number of distributed generation and storage resources.”

[2].

Or,

“A grid that is "Intelligent, efficient, accommodating, motivating, opportunistic, quality-focused, resilient and Green."

[11].

IEC definition for Smart Grid is,

“The Smart Grid is a developing network of transmission lines, equipment, controls and new technologies working together to respond immediately to our 21st Century demand for electricity.”

IEEE definition for Smart Grid is,

“The smart grid is a revolutionary undertaking-entailing new communications-and control capabilities, energy sources, generation models and adherence to cross jurisdictional regulatory structures.”

[2].

The definition adapted from the European Technology Platform Smart Grid (ETPSG) is,

“Smart Grid is a concept and vision that captures a range of advanced information, sensing, communications, control, and energy technologies. Taken together, these result in an electric power system that can intelligently integrate the actions of all connected users—from power generators to electricity consumers to those that both produce and consume electricity (“prosumers”)—to efficiently deliver sustainable, economic, and secure electricity supplies.” **[14]**.

The previous US Energy Secretary Steven Chu writes that “the Smart Grid is the key enabler for: integration of renewable energy sources into the grid, management and deployment of energy storage, load management, system transparency, and cyber and physical security of the electric energy system”. **[15]**.

All the definitions, however, have in common that smart grid results from the convergence of three industries:

a) Electrical power (energy)
b) Telecommunication infrastructure
c) Information technology (IT)

[11].

Or, smart grid utilizes communication technology and information to optimally transmit and distribute electricity from suppliers to consumers **[1]**.

Also, based on the several definitions provided above, smart grid can be nicely defined through its features as follows:

→ Fully automated power delivery network that monitors and controls electricity flows.
→ Two-way flows of electricity and information between the power plant and the appliance, and all points in between.
→ Lowered carbon footprint and reduced emissions, increased access to renewable energy resources (like solar and wind).
→ Use of digital technology to save energy, reduce cost and increase reliability.
→ Improved power quality for needs of 21st century economy.
→ Reduced disruptions, improved efficiency and better asset utilization.

[11].

1.2. Components of smart grid:

Previously, we mentioned that the smart grid concept combines a number of technologies. This combination of different technologies is employed in order to achieve the desired goals of reliable efficient, efficient and clean energy distribution. According to DOE, the following technologies are taking into account:

- Integrated two-way communication
- Advanced components
- Advances control methods
- Sensing and measurement technologies
- Improved interfaces and decision support
- Application of smart grid technology

Integrated two-way communication:

It enables operator's real-time monitoring and interaction with smart grid components and improves his ability to manage grid operation. In SG, operator can detect and manage the problem without any notification from customers, leading to faster problem resolution and decreased operational costs. To have this capability, SG components require two-way communication ability.

Advanced components:

They include the areas of superconductivity, fault tolerance, excess electricity storage, smart devices, smart devices, and diagnostics equipment. This technology actively determines the electrical behavior of the grid. So-called smart devices can provide useful consumption feedback to both the consumers and energy suppliers to enable better energy management. These advanced components will provide unique advantages over technology of the current grid.

Advanced control methods:

Utilizing the two-way communication component described in the "Integrated Two-Way Communication" part, the advanced control methods allow operators (human or machines) to manage the various smart grid components. Specifically, they enable advanced data collection, as well as diagnostics and appropriate maintenance.

Sensing and measurement technologies:

New sensing and measurement technologies support smart grid stability, health, and security functionality. The most common of these technologies is the smart meter. Figure 1.2 displays a current smart meter. A smart meter monitors usage statistics and reports the usage details to the utility company, consumers, and third party service providers. Depending on the smart meter and supporting infrastructure, the smart meter can be used for other administrative functions, such as power outage notification and remotely disabling service.

Figure 1.2: Example smart meter(**[1]**)

Improved interfaces and decision support:

Humans and machines use different languages and, as a result, important information can be lost in translation. Due to its nature, a smart grid will collect data too immense and complex for a human to comprehend in a short time frame. The human machine interface (HMI) must be able to simplify the data and resulting analysis in an efficient manner to enable operators and managers to make decision quickly. HMI can be described as how users interact with a machine. According to the international engineering consortium (IEC-www.iec.org), the success of a system often relies on how effective the HMI is in gaining the user's acceptance of the system.

Application of Smart Grid technology:

An informed consumer is an intelligent consumer. This is the theoretical reason behind the drive to provide consumers with real-time usage data. Applications will provide consumers with real-time usage statistics and pricing, as well as recommendations for reducing their utility bill. The application seek to provide this information in a ubiquitous manner ensuring the consumer always know exactly how much electricity they are using and how much that electricity costs.

[1].

1.3. Justification for smart grid:

The objectives of smart grid as defined by the United States Department of Energy (DOE) are:

→ Guaranteeing the reliability of the grid to degrees never before possible.

→ Keeping its affordability

→ Strengthening worldwide competitiveness

→ Completely accommodating renewable and traditional energy sources

→ Possibly lowering our carbon footprint

→ Introducing improvements and efficiencies that we cannot yet envision.

[1].

1.4. Comparison between existing utility grid and smart grid:

A comparison between the characteristics of conventional utility grid and smart grid is made in the table that follows:

Table 1.1. Comparison of conventional utility grid and Smart Grid (**[2]**).

Characteristics	Conventional utility grid	Smart Grid
-Active consumer participation.	-Consumers are uninformed and they do not participate.	-Consumers are involved, informed and participate actively.
-Provision of power quality for the digital economy.	-Response to power quality issues is slow.	-Rapid resolution of power quality issues with priority.
-Accommodation of all generation.	-Many obstacles exist for	-Many distributed energy resources

	integration of distribution energy resources.	with plug-and-play option can be integrated at any time.
-Optimization of assets	-Little incorporation of operational data with asset management-business process silos.	-Greatly expanded data acquisition of grid parameters; focus on prevention, minimizing impact to consumers.
-New products, services and markets.	-Limited and poorly integrated wholesale markets; limited opportunities for consumers.	-Mature and well-integrated wholesale markets; growth of new electricity markets for consumers.
-Resiliency against cyber-attacks and disasters.	-Vulnerable to malicious acts of terror and natural disasters; slow response.	-Resilient to cyber-attack and natural disasters; rapid restoration capabilities.
-Anticipating responses to system disturbances (self-healing).	-Responds to prevent further damage; focus on protecting assets following a fault.	-Automatically detects and responds to problems; focus on prevention, minimizing impact to consumers.
-Topology.	-Mainly radial	-Network
-Restoration.	-Manual	-Decentralized control
-Reliability	-Based on static, offline models and simulations.	-Proactive, real-time predictions, more actual system data.
-Power flow control	-Limited	-More extensive
-generation	-Centralized	-Centralized and distributed substantial RES and energy storage.
-Operation and maintenance	-Manual and dispatching	-Distributed monitoring, diagnostics and predictive.
-Interaction with energy users	-Limited to large energy users	-Extensive two-way communications
-System communications.	-Limited to power companies	-Expanded and real-time
-Reaction time.	-Slow reaction time	-Extremely quick reaction time

2. Challenges of integration of renewables to the grid and smart solutions:

The deep penetration of renewable energy sources is on the cutting edge of smart grid vision **[16]**. This topic is still being researched up to this day and many ways to integrate the different types of renewable sources have been developed **[17]**. The reason for the growing interest in better integration of renewables with the grid is because renewable energy offers alternative sources of energy which is in general pollution free, climate friendly, sustainable and unlimited **[18]**. Renewable energy sources such as wind and solar, however, are fundamentally different from conventional generation such as coal, nuclear, natural gas. The energy production from these renewable sources is *not dis-patchable* [cannot be controlled on demand], *intermittent* [exhibits large fluctuations], and *uncertain* [random or not known in advance]. We will use the term *variability* to encompass these three characteristics of renewable generation. The variable nature of RE's poses significant challenges in their integration to the electric energy systems at deep penetration levels **[15].**

We can distinguish two types of challenges:

- **Technical challenges:** Guaranteeing the reliability of the power system with the increase in variability.
- **Economic, policy, and regulatory Challenges:** effectively managing the cost of RE integration and the grid investments that support it, designing policies to harness maximum value from RE, and guaranteeing that appropriate incentives are in place to encourage appropriate grid investments.

Fortunately, smart solutions exist to mitigate these challenges. The specific challenges related to the two types and the solutions that smart grid provides for their mitigation are given in the next subsection.

2.1. Technical challenges and smart solutions:

2.1.1. **Technical Challenges:**

With a deeper penetration of RE's, we can identify two dominant technical challenges, these are:

- Managing variability during the continuous balancing of the system:

The grid integration of DG systems brings some issues such as voltage and frequency fluctuation. The power production from RESs such as wind or solar energy oscillates largely owing to variations in meteorological conditions, which may result in surplus fluctuations in voltage as well as the frequency of the grid. The appropriate functioning of several consumer appliances is prone to such fluctuations and may consist of changes in the peak and RMS voltage on the distribution line. Such output power fluctuations needs surplus energy to maintain the balance between supply and required demand of grid on a continuous basis.

- Balancing supply and demand during generation scarcity and surplus situations.

It is system operators' need to balance supply and demand in situations of high RE production and low demand or low RE production and high demand. Supply of wind and solar may not coincide closely with demand, introducing challenges at the bulk power system level and—if there is significant distributed PV generation—at the local distribution system level.

2.1.2. **Smart solutions:**

Smart grid solutions emerging to manage the challenges that arise with the variability of renewable energy sources include:

• *Better forecasting.* Widespread instrumentation and advanced computer models allow system operators to better predict and manage RE variability and uncertainty.

• *Smart inverters.* Inverters and other power electronics can provide control to system operators, as well as to automatically provide some level of grid support.

• *Demand response.* Smart meters, coupled with intelligent appliances and even industrial-scale loads, can allow demand-side contributions to balancing.

• *Integrated storage.* Storage can help to smooth short-term variations in RE output, as well as to manage mismatches in supply and demand.

• *Real-time system awareness and management.* Instrumentation and control equipment across transmission and distributions networks allows system operators to have real-time awareness of system conditions, and increasingly, the ability to actively manage grid behavior.

2.2. economic, policy, and regulatory Challenges and smart solutions:

2.2.1. **economic, policy, and regulatory challenges:**

In addition to technical challenges, institutional challenges also arise with increasing shares of variable RE. Broadly these relate to the unique economics of variable RE, which give rise to various policy and regulatory issues. Two specific challenges are identified here: capital-intensive grid upgrades, and uncertain project costs and cash flows.

- ***Capital-intensive grid upgrades:*** Grid upgrades may be required to accommodate wind and solar power. For example, to the extent high quality wind and solar resources are located far from demand centers, new transmission lines or upgrades to existing lines may be required. At the distribution level, rooftop PV may accelerate the fatigue of distribution components, such as low-voltage transformers, system reliability, translates to greater value from RE investments.
- ***Uncertain RE project costs and cash flows:*** Smart grid solutions are emerging to two specific issues that historically have negatively impacted RE project economics: grid upgrade costs allocated to RE project developers and energy curtailment when full RE production cannot be readily integrated into the power system. Both issues may cause cash flows of the project to diverge further from expectation. To the extent upgrades become costly or curtailments increase, the investment landscape for variable RE becomes more uncertain and can slow overall deployment.

In cases where policy measures and subsidies insulate project investors from these risks—for example to further enhance the investment environment for RE—costs and risks may be socialized. Smart grid investments can also play an important role in reducing those costs and risks.

Cost-effective methods of reducing curtailment and minimizing new transmission or grid upgrades can therefore capture more value from RE sources, improve the viability of individual RE projects, and maximize value to the system, enhancing the overall investment climate.

2.2.2. **Smart solutions:**

Smart grid solutions emerging to address the economic, policy, and regulatory challenges of variable RE include:

• *Dynamic line rating.* Real-time information about transmission line capacity can allow grid operators to extract more value from existing lines, reducing the need for costly upgrades.

• *Demand response.* Enabled by smart meters and intelligent loads, customer demand response solutions can help absorb excess RE generation, reducing the need for distribution upgrades.

• *Smart inverters and other advanced power controls.* Smart inverters and other power controls can reduce the need for significant grid transmission and distribution upgrades, thus reducing costs that may otherwise be levied on RE projects or socialized.

• *Grid-scale storage.* Large-scale storage of various types can help to reduce the need for additional transmission capacity.

• *Behind-the-meter storage.* Customer storage solutions can help absorb excess PV generation, reducing the need for distribution upgrades.

• *Advanced energy management systems.* Advanced energy management systems that provide real-time, high-resolution visibility and control of power systems, can allow grid operators to defer more costly capital expenditures.

• *Better forecasting.* System-level forecasting can help system operators operate their grids more flexibly, allowing more production to be accepted.

[14, 19].

3. Demand side management:

3.1. Definition:

DSM is an initiative implemented by electricity utilities to encourage consumers to adopt procedures and practices that are advantageous to both parties. These practices include any activity that aims to change load shapes by influencing the electricity consumption behavior of consumers. Notably, the implementation of DSM increases the complexity of existing power systems because the adequate performance of DSM requires monitoring power system loads and generators. Consequently, the deployment of sensors, the provision of incentives to participants of DSM programs and the performance of the general activities of DSM will incur additional expenditures. However, the benefits of DSM far outweigh its drawback of increased power system cost.

Figure 1.3. shows that DSM consists of energy efficiency, demand response and strategic load growth. Demand response is normally performed through peak clipping, valley filling or load-shifting activities or any combination of these techniques. Demand response is also known as flexible load shape because of the flexibility exhibited by the activities.

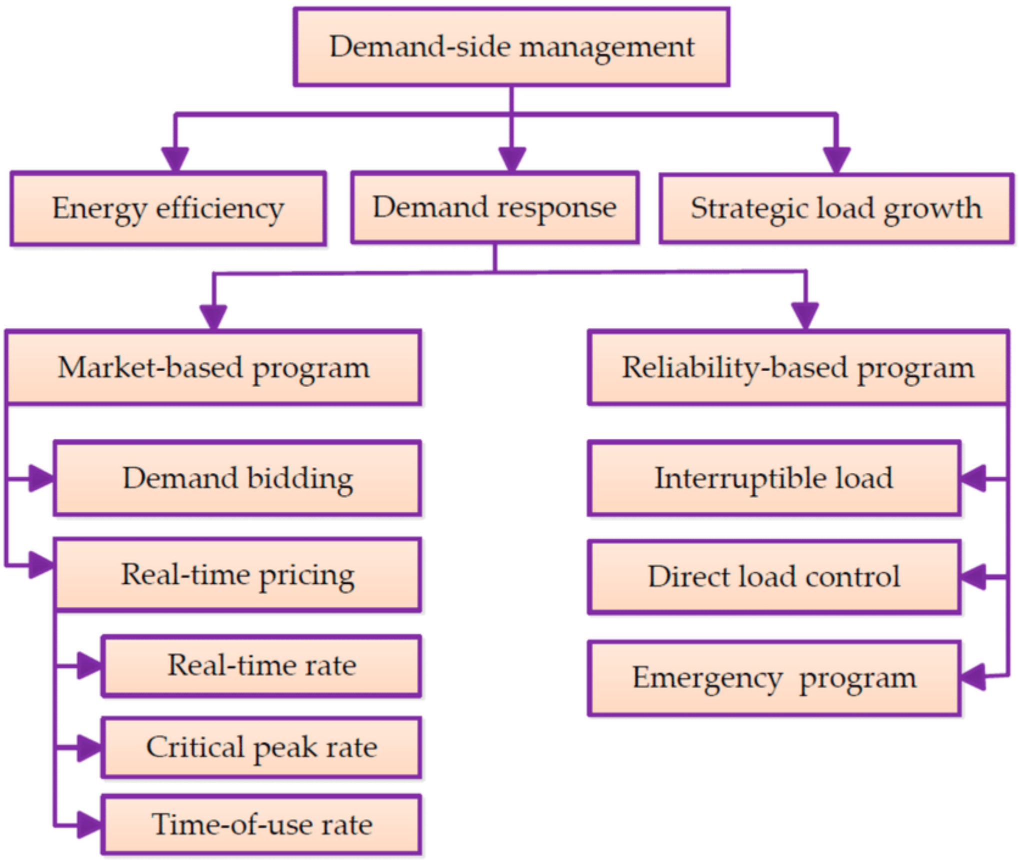

Figure 1.3: Various DSM (Demand-side management) techniques (**[4]**)

3. 1.1. Energy efficiency:

Energy efficiency is defined as a long-term conservation strategy that aims to save energy and reduce demand through energy-efficient processes. Examples of energy-efficiency programs include house-appliance efficiency enhancement and weatherization. Weatherization involves protecting a building from external elements, such as wind and sunlight and upgrading buildings to decrease energy consumption and losses. The implementation of energy-efficiency programs can decrease demands during on-peak times and average power system costs, as well as postpones the need to expand power system capacity. Energy-efficient strategies include:

1. Adopting energy-efficient buildings and appliances to optimize energy consumption and encouraging the energy-conscious behavior of users.

2. Improving and conducting the regular maintenance of electrical equipment by recovering heat waste, enhancing maintenance procedures, using modern equipment with optimized designs and practicing cogeneration.

3. Improving the efficiency of power transmission and distribution networks by using (1) distributed generation; (2) advanced control systems for voltage regulation, three-phase balancing, power factor correction and data acquisition and analysis in supervisory control and data acquisition systems; (3) modern technologies, such as low-loss transformers, gas installation substations, smart metering and fiber-optics for data acquisition and (4) high-transmission voltages.

3. 1.2. Demand Response:

Demand response (DR) involves a short-term load manipulation program that aims to influence energy consumption behavior. DR is defined as “the changes in electric usage by end-use consumers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale prices or when system reliability is jeopardized”. Given that one of the advantages of DR is that it affects load directly, other DSM techniques are gradually being replaced by DR programs in the new electricity market environment.

DR is performed using either valley filling to build loads during off-peak periods; peak clipping to reduce loads during on-peak periods or load shifting, which combines valley-filling and peak-clipping activities. As shown in Figure 1, DR programs are further divided into either reliability-based or market-based. In reliability-based DR programs, consumers decrease their loads and/or voluntarily or involuntarily participate in controlled appliance use. In turn, consumers derive economic incentives by enrolling in this program. By providing real-time electricity market prices, market-based DR programs provide consumers with the options to adjust electricity consumption. Reliability-based DR programs consist of the following:

1. Interruptible load program. This program is usually applied by large industrial and commercial consumers who can shut down their load for a short duration. In this program,

consumers receive discounted electricity rates as compensation for accepting service interruptions. However, they can also be penalized if they do not participate in the program when required.

2. Direct load control program. In this program, the utility is allowed to directly interrupt or reduce consumer power supply during peak demand times after consumers are notified. In return, interrupted consumers receive compensation.

3. Emergency program. Consumers are given incentives to reduce their demand during system contingencies. In contrast to the interruptible load program, this program does not impose any penalties if consumers cannot participate.

Market-based DR programs consist of the following:

1. Demand bidding program: This program allows major consumers to bid for specific load curtailments. Consumers stay at a fixed rate and they receive high payments when wholesale electricity prices are high.

2. Real-time pricing program: Electricity production costs fluctuate over time and average system costs are fixed without considering its undesirability, particularly for large commercial and industrial consumers. To address these issues, the real-time pricing program is introduced and implemented through the following:

a. Time-of-use rate. This rate is a predefined electricity price offered over a wide range of time periods, that is, seasonal, monthly, weekly or daily. The rate is voluntary and reflects basic production costs to decrease consumer demands during periods of high prices.

b. Critical peak rate. This rate offers consumers dynamic pricing that reflects actual market costs during critical peaks. This rate is usually offered a day ahead of the expected peak and is predefined but may be dynamic when necessary. Critical peak pricing rates can be used to improve power system reliability because they reflect the system state. Hence, if appropriate critical peak pricing signals are sent out, consumers may participate by decreasing load during system-stress events.

c. Real-time rate. In this program, consumers pay rates that are a function of actual market rates. Prices are usually supplied hourly or a day ahead to enable preplanning. Thus, rates will vary depending on the fluctuations in electricity supply.

3. 1.3. Strategic Load Growth:

Strategic load growth is defined as increased electrical energy load and is normally induced by utilities through dual fuel heating, heat pumps, thermal storage (thermal energy is stored during off-peak times for use during on-peak periods) and promotional rates. Strategic load growth is sometimes unavoidable because of the general increase in electricity demands, especially with the advent of electric vehicles of modern power systems or air conditioning in warm countries.

[4].

3.2. Benefits of demand side management:

The economic, environmental, market performance and overall technical benefits provided by DSM include (1) maintaining voltage stability; (2) relieving transmission congestion; (3) increasing the flexibility of preventive maintenance scheduling; (4) postponing the required upgrading of electrical power system facilities; (5) balancing energy resource; (6) mitigating the drawbacks posed by the intermittency of renewable energy sources; (7) increasing the flexibility of electrical power system operation; (8) reinforcing integrated resource planning; (9) increasing the utilization of renewable energy sources; (10) reducing the startup and shutdown of thermal units that require excessive starting costs; (11) maintaining the reliability of electrical power systems and reducing the risk of being out of service; (12) avoiding capital costs; (13) increasing efficiency; (14) reducing running costs; (15) enhancing power quality, security and power factor (16) increasing consumer satisfaction (17) improving the market performance of electricity power systems; and finally (18) mitigating environmental damage. These improvements can yield significant secondary benefits, such as reductions in losses and premature ageing and leads to the adoption of efficient residential appliances and industrial equipment.

These benefits are summarized in Figure 1.4.

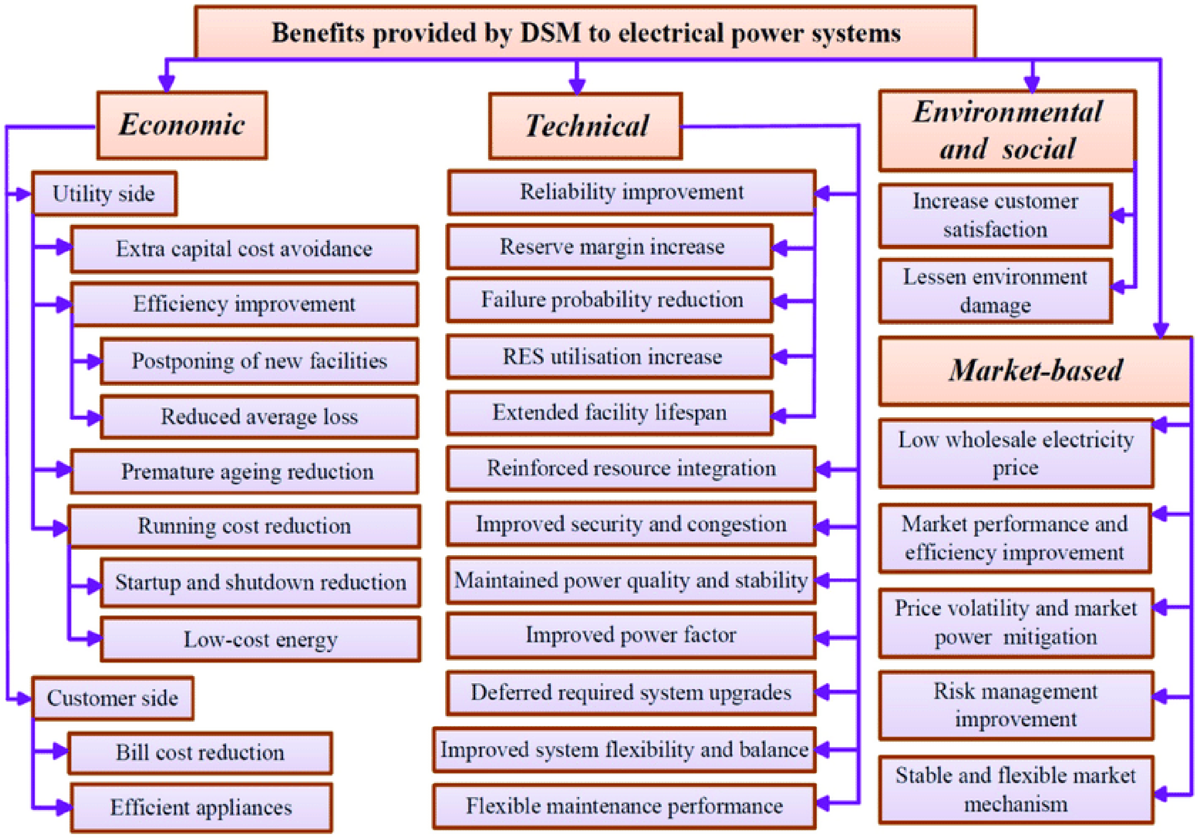

Figure 1.4: Benefits achieved by the DSM program (**[4]**)

Conclusion:

Now that we've defined Smart grid and Demand side management and saw how both ease the integration of Renewable Energy sources into the grid, we'll move to the theoretical part of the implementation of a multi-objective evolutionary algorithm which enables to implement demand response program in a smart home connected to smart grid and equipped with a renewable energy source, this will result in cost reduction for energy usage and minimum waiting time for appliance execution.

Chapter 2

1. Introduction:

Currently, the energy consumption of the residential sector accounts for around 30–40% of the total energy use all over the world. The residential loads often contribute significantly to seasonal and daily peak demand **[3]**.

Thus, there is a need for practical solutions to shift the high-power household appliances to off-peak hours to reduce the peak-to-average ratio (PAR) in load demand from utility's side which will also give cost benefit to consumers as the energy usage cost is significantly lower at off-peak hours compared peak hours. Appropriate load-shifting is foreseen to become even more crucial as plug-in hybrid electric vehicles (PHEVs) become popular. Most PHEVs need 0.2–0.3 KWh of charging power for one mile of driving. This will represent a significant new load on the existing distribution system. In particular, during the charging time, the PHEVs can almost double the average household load and drastically exacerbate the already high PAR **[20]**.

When scheduling comes to play a major role in the smart energy in power grid system, the highest priority devices are executed first than the normal appliances. Nature inspired algorithms are the efficient candidates for solving the scheduling problems **[7]**.

The system proposed in this chapter can schedule the home appliances on a priority based approach using a multi-objective evolutionary algorithm to reduce both the energy usage cost and the waiting time of appliances, reducing the waiting time of appliances is necessary to maintain the user comfort.

2. State of the art work about load balancing:

In **[29]**, the main concept of the approach proposed to schedule the usage of home appliances is the aggregation of home appliances into priority classes and the definition of a maximum power consumption limit, which is not allowed to be exceeded during peak hours. The purpose is two analyze how a power consumption limit and priorities for home appliances will affect the demand peak and the user's everyday life. Reversible share (RFS) algorithm originally developed for telecommunication network is applied to verify the effectiveness of the proposed algorithm. The results have shown that the defined maximum power limit of 750 and 1000 was not exceeded and the trade-off was an average delay of 36, 1 (increment of 30% in task time) and 12, 36 (increment of 10 % in their task time).

In **[28]**, a multi-objective mixed integer linear programming model (MOMILP) is proposed to minimize simultaneously the peak load and cost of a residential area. Constraints, including daily energy requirements and consumer preferences are considered. Its effectiveness in reducing electricity cost and electrical peak-load was verified through the simulation of the results obtained for different scenarios with different objectives. The results have shown a significant reduction in both functions.

In **[7]**, scheduling of appliances is achieved using a genetic algorithm (GA) in order to efficiently utilize the energy available. In the proposed work, it is employed to optimize the electrical appliances energy usage cost. A comparison against the conventional approach is made. Simulation results show that the proposed genetic algorithm consistently produces better results in real time pricing (RTP) when compared to the conventional method. User comfort was not considered in the optimization.

Similarly, in **[26]**, GA is used to schedule the electricity usage in the home for the purpose of reducing of reducing the electricity cost and peak average rate (PAR) under RTP combined with inclined block rate model (IBR).The approach was proven to be effective in the reduction of the two parameters however as in **[17]**, it did not consider the comfort of the user.

Finally, in **[21]**, the paper which we based our work on used GA for the optimization of energy usage cost and waiting time of appliances to reduce the discomfort of the user. The optimization yielded improvement in the two functions.

In our work, we'll re-use the algorithms used in **[21]** in MATLAB to get the results of energy usage cost and waiting time of appliances optimization and see how they compare to the paper and we'll see how we can bring modifications to these two algorithms to integrate renewables.

3. Communication architecture for a residential home:

A communication infrastructure is the foundation for the success of the developing smart grid DR **[3]**. Various communication infrastructures are available in the smart grid domain. For a public domain like the internet, selection of a suitable architecture among the available ones is critical.it should satisfy the features of the smart grid and it has to be easy to adapt in the real time environment with active consumer participation. The complete conceptual model conceptual model of the smart grid system with residential area network and renewable energy sources is shown in figure 2.1. It consists of conventional electrical system components (generation, transmission and distribution), the latest smart grid component (smart meter), active home appliances and renewable energy sources. Power grid, smart meter with home PC (personal computer), Internet, consumer and renewable energy sources are integrated with residential home.

The home computer runs the load balancing algorithm for electrical appliances to reduce the power usage cost and waiting time. Home PC acts as a centralized server which support to communicate the consumer and service provider through Internet like a web server. In addition to that, home PC is responsible for store and retrieval of the information. Also, supports for scheduling activity with the algorithm support.

The smart meter is employed for the exchange of information between consumers and service provides with the internet acting as a medium.

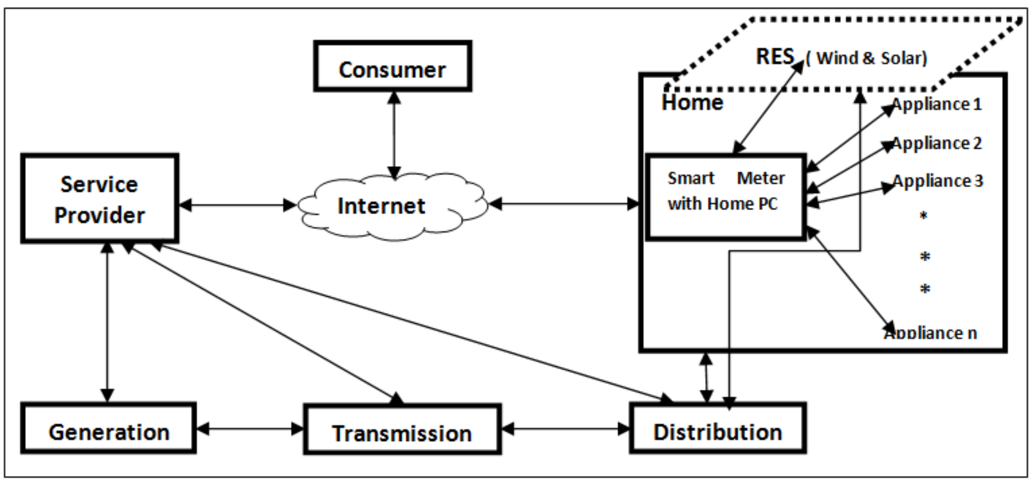

Figure 2.1: conceptual model of smart grid system (**[21]**)

Iot and its technologies have made it possible for the consumer to communicate with the home network and its home appliances from any places with the use of smart devices. With the internet acting as a medium, the consumer has the ability to communicate with service provider by using the home computer which also supports to communicate the home appliances. All the electrical appliances are equipped with sensors to monitor and transmit the data to centralized server. It also supports the electrical appliances scheduling in home area network.

Service providers collect the data from smart meter to understand the user requirements like demand and setting up the pricing details for the ToU pricing models. Smart meter also helps to collect the electrical appliance usage details under different climate conditions, for example, an individual appliance energy usage for per hour, per day, per week and per month. Among these information service provider can identify the saturation level of consumers' electrical appliances then these gathered information is interpreted by utility companies based on the automation requirement, forecast of energy and real time pricing models.

At present, the major problem of the power grid is unable to satisfy the consumer energy demand in the DSM during peak hours. The consumer always depends on the service provider or electricity board. There arises a need for consumer to find other energy sources like wind and solar so called renewable energy sources. Smart grid supports integration of renewable energy sources into the existing power grid to benefit the consumer and reduce the peak to average ratio. Consider a residential home is equipped with local renewable energy sources like wind and solar. These renewable energy sources can communicate with smart meter and consumer. To analyze the electrical energy usage pattern, the home acts as a consumer and service provider. The consumer when uses the renewable energy sources can reduce the usage of power grid and the surplus energy is sold back to the power grid.

Communication between the home appliances and the smart meter uses the existing communication technologies such as wired or wireless. However, the residential home can send short control messages for performing the switching, status and other operations.The wireless technologies like Wi-Fi and ZigBee are sufficient to manage the home area network communication. **ZigBee is a wireless communication protocol for DSM in smart grid, which operates low power, and low data rate for the home networks. It provides several advantages for building an automated home networks in smart grid. Also, ZigBee operate within the ISM 2.4 GHz frequency band.** Further, the suggested architecture ensures benefits for both consumer and service provider. It provides active participation in the DSM domain to the consumer. In addition to that it reduces the energy usage cost for power consumption and helps service providers to indirectly derive the consumer to use the power in different ToU pricing models. So that service provider can manage their peak load demands by using the attractive tariff to end users with incentives.

[21].

4. Multi-objective evolutionary algorithm for demand side management:

The optimization of energy usage cost and waiting time of appliances during the day in a smart home is what we call a multi-objective optimization problem (MOOP). Before, beginning to describe the system used for our optimization task, it is useful present some basic knowledge about multi-objective optimization, why evolutionary algorithms are preferred over mathematical programming techniques for MOOP's and which evolutionary algorithm is most suitable for us.

3.1. Generalities about Multi-objective optimization:

Multi-objective optimization caters to achieving multiple goals, subject to a set of constraints, with a likelihood that the objectives will conflict with each other. It can also be explained as a multi-criteria decision-making process, in which multiple objective functions have to be optimized simultaneously. In many cases, optimal decisions may require tradeoffs between conflicting objectives. Examples of it can be found in economics (setting monetary policy), finance (risk–return analysis), engineering (process control, design tradeoff analysis), and many other applications in which conflicting objectives must be obtained. One of the prerequisites of multi-objective optimization is to determine whether one solution is better than another. However, no simple method exists for reaching such a conclusion. Instead, multi-objective optimization methods commonly adopt a set of Pareto optimal solutions (also called non-dominated solutions), which are alternatives with different tradeoffs between the various objectives. In the solution defined by a Pareto optimal set, one objective cannot be improved without degrading at least one other objective in the set **[22]** and the image of this set (i.e., the corresponding objective function values) form the so-called *Pareto front* **[23]**.

3. 1.1. Multi-objective optimization problem statement:

A general multi-objective optimization problem (MOOP) consists of a number of objectives and is associated with a number of equality and inequality constraints. Without loss of generality, it can be formulated in mathematical terms as follows:

$$minimize\ f(X) \tag{2.1}$$

Subject to:

$$g_i(X) \leq 0, i = 1,2, \ldots, m \tag{2.2}$$

$$h_j(X)=0, j=1,2,\ldots,l \tag{2.3}$$

$$X^{(L)} \leq X \leq X^{(U)} \tag{2.4}$$

Where:

- $X = [x_1, x_2, \ldots, x_n]^T$: is the vector of design variables, defined in the design space $\mathbb{R}^n$ and $X^{(L)}$ and $X^{(U)}$ are respectively the lower bounds and upper bounds of the design variables.
- $f(X) = [f_1(X), f_2(X), \ldots, f_k(X)]^T$, $X \in \mathbb{R}^n$: is the vector of objective functions to be minimized.
- $g_i(X)$ and $h_j(X)$ are the i^{th} and j^{th} inequality and equality constraint functions of the problem respectively.

The three equations (2.2)-(2.4), define the region of feasible solutions, $\mathbb{S}$, in the design space $\mathbb{R}^n$. The constraints $g_i(X)$ are of types "less than or equal" functions in view of the fact that "greater or equal" functions may be converted to the first type if they are multiplied by -1.Similarly, the problem is the "minimization" of the functions $f_i(X)$, given that functions "maximization" can be transformed to the former by multiplying them by -1.

A few additional definitions are required to introduce the notion of optimality used in multi-objective optimization:

Definition 1: Given two vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^k$, we say that $\mathbf{x} \leq \mathbf{y}$ if $x_i \leq y_i$ for i=1, 2,…,k, and that **x** *dominates* **y** (denoted by $X \prec Y$) if $\mathbf{x} \leq \mathbf{y}$ and $\mathbf{x} \neq \mathbf{y}$.

Definition 2: we say that a vector of decision variables $x \in \mathcal{X} \subset \mathbb{R}^n$ is non-dominated with respect to $\mathcal{X}$, if there does not exist another $x' \in \mathcal{X}$.

Definition 3: we say that a vector of decision variables $x^* \in \mathcal{F} \subset \mathbb{R}^n$ ($\mathcal{F}$ is the feasible region) is *pareto-optimal* if it is non-dominated with respect to $\mathcal{F}$.

Definition 4: the *pareto-optimal* set $\mathcal{P}^*$ is defined by:

$\mathcal{P}^* = \{x \in \mathcal{F} | x \in \mathcal{X}\}$

Definition 5: The pareto-front $\mathcal{PF}^* = \{ f(x) \in \mathbb{R}^k | x \in \mathcal{P}^* \}$.

Therefore, our aim is to obtain the Pareto optimal set from the set *F* of all the decision variable vectors that satisfy the three equations (2.2)-(2.4). However, in practice, not all the Pareto optimal set is normally desirable or achievable, and certain types of solutions or regions of the Pareto front tend to be preferred **[23]**.

3. 1.2. Multi-objective optimization using evolutionary approach:

In spite of the fact that a wide variety of mathematical programming techniques have been developed to tackle MOPs since the 1970s, such techniques present a number of limitations, from which the most remarkable are that these algorithms are quite susceptible to the shape and/or continuity of the pareto front and that they usually generate one element of the Pareto optimal set per algorithmic execution. Additionally, some mathematical programming techniques require that the objective functions and the constraints are provided in algebraic form and in many real-world problems we can only obtain such values from a simulator. These limitations have motivated the use of alternative approaches, from which meta-heuristics have been a very popular choice, mainly because of their flexibility (i.e., they require little domain specific information) and their ease of use. From the many meta-heuristics currently available, evolutionary algorithms have certainly been the most popular in the last few years in this area, giving rise to a field now known as evolutionary multi-objective optimization (EMO). The first Multi-Objective Evolutionary Algorithm (MOEA) was called Vector Evaluated Genetic Algorithm (VEGA) and was proposed by Schaffer in 1985.Something interesting is that there was not much interest in EMO research for almost a decade. However, in the mid-1990s, this area started to attract a lot of attention from several research groups around the world, and has maintained a high research activity since then **[23]**. In order to find multiple Pareto-optimal solutions, evolutionary algorithms are the best, because it deals with a population of solutions.it allows for finding an entire set of pareto-optimal solutions in a single run of the algorithm. In addition to this, evolutionary algorithms are less susceptible to the shape or continuity of the pareto-front **[24]**.

There are two main goals in every multi-objective evolutionary algorithm:

i. Convergence towards optimal Pareto front: how to guide the population towards the optimal Pareto front?

ii. Diversity: how to maintain diverse solutions in Pareto set? .A good diversity mechanism gives well distributed solutions in optimal Pareto front and also truncates the size of Pareto set.

Evolutionary based techniques use the concept of genetic algorithm and solve the multi-objective optimization problem. Following are the steps of multi- objective evolutionary algorithms:

Step1 Initialization: Initialize a random population based on the population size.

Step2 Fitness assignment: Assign a rank by considering each individual of the population for generating a mating pool.

Step3 Variation: Apply variation operator (crossover, mutation) on the mating pool to generate new solutions.

Step4 Environmental selection: Select best solutions according to the size of mating pool for next generation.

Step5 Repeat above procedure until termination criterion meets or maximum number of generations reach.

[25].

3.2. Problem solving:

To solve our problem, we'll use the Non-Dominated Sorting Genetic Algorithm-2 (NGSA-2), an elitist multi-objective evolutionary algorithm, introduced by Deb and Argarwal. It is the improved version of NGSA proposed by Deb and Srivinas. The rank of every solution is computed based on how many number of solutions it dominates. In order to maintain the diversity of a population the algorithm finds average distance of two neighbors on either side of a solution. Along each of the objectives (as shown in figure 2.2). The distance is called crowding distance of that solution. For generating mating pool for next generation, selection of solutions is performed based on rank and crowding distance. When two solutions have the same rank then a solution that has higher crowding distance is selected for mating pool. To implement elitism, the best parents are combined with the best offspring obtained and then select best solutions (according to fitness and spread), so it does not require extra memory (archive) to preserve elite solutions.

[25].

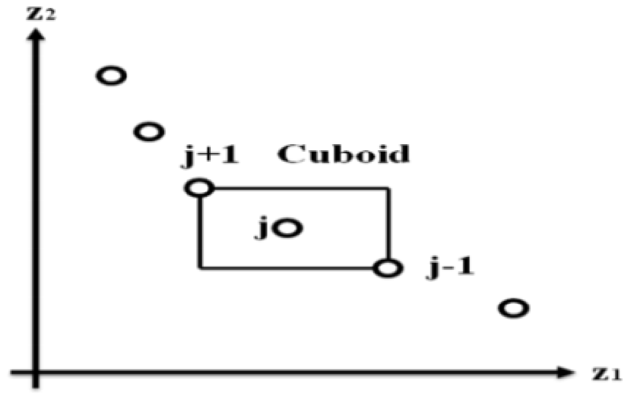

Figure 2.2: Crowding distance calculation points in circles are solutions of the non-dominated front (**[25]**)

Our problem consists of the two objective functions:

a. $T(C)$:total cost of power

b. D_{avg} :average delay time of the appliances(average waiting time for electrical appliances execution)

The optimization using NGSA-2 produces the set of solutions to minimize both the objective functions.

Generally, electrical appliances fall under one of two categories: schedulable and non-schedulable appliances. A schedulable device can stop running and resume later while a non-schedulable device is always connected or involves only non-preemptive operations. Contrary to non-schedulable devices, schedulable devices are preemptive in nature. Thus, only schedulable devices can participate in the DSM mechanism.

[21].

3.2.1. Tariff details:

Real time pricing program with ToU rate is applied as follows:

Table 2.1: Tariff details (**[21]**)

S. no.	Time period	Cost in cents
1	12 AM to 7 PM (Off-peak hours)	3
2	7 AM to 11 AM (Peak hours)	7
3	11 AM to 17 PM(Mid-peak hours)	5
4	17 PM to 9 PM (Peak hours)	7
5	9 PM to 12 AM (Off-peak hours)	3

3.2.2. MOEA algorithm:

The steps of the MOEA algorithm for our problem are given as follows:

→ Set values: set the parameter values (p), (m), (o), (Cp), (Cm), and (Co).

Where: p: peak hour, m: mid-peak hour, o: off-peak hour, Cp: peak-hour cost, Cm: mid-peak hour cost, and Co: off-peak hour cost.

→ Initialize: set all the initial parameters (Xp), (Yp), (Zp), and (Aa).

Where: Xp: the population for peak power usage values, Yp: the population for mid-peak power usage values, Zp: population for off-peak power usage values, and Aa: starting time of appliance.

→ Evaluate the fitness function T(C) and Davg (cost and delay).

→ Build the pareto-front based on the dominance.

→ Apply G.A:-Apply genetic algorithm operations like selection, crossover and mutation.

→ Stop:-check counter values to perform the stop operation. If the counter value has reached maximum number of iterations then print the solution otherwise calculates the fitness function for a new set of input population.

[21].

3.2.3. Problem formulation:

The energy consumed by an individual home appliance A_p:

$$A_p = P \times T/M \tag{2.5}$$

Where: P: power consumed by the appliance, T: operating time of the appliance in hour, and M: energy measurement units in terms of kWh.

The cost of the energy consumed by the appliance is computed using the formula:

$$A_c = C \times A_p \tag{2.6}$$

Where, C: power usage cost per unit

The total consumed power of a home for a day is computed using the formula:

$$T_p = X_p + Y_p + Z_p \tag{2.7}$$

Where, $X_p, Y_p,$ and Z_p represent the power consumed by a set of appliances during peak, mid-peak and off-peak hours respectively.

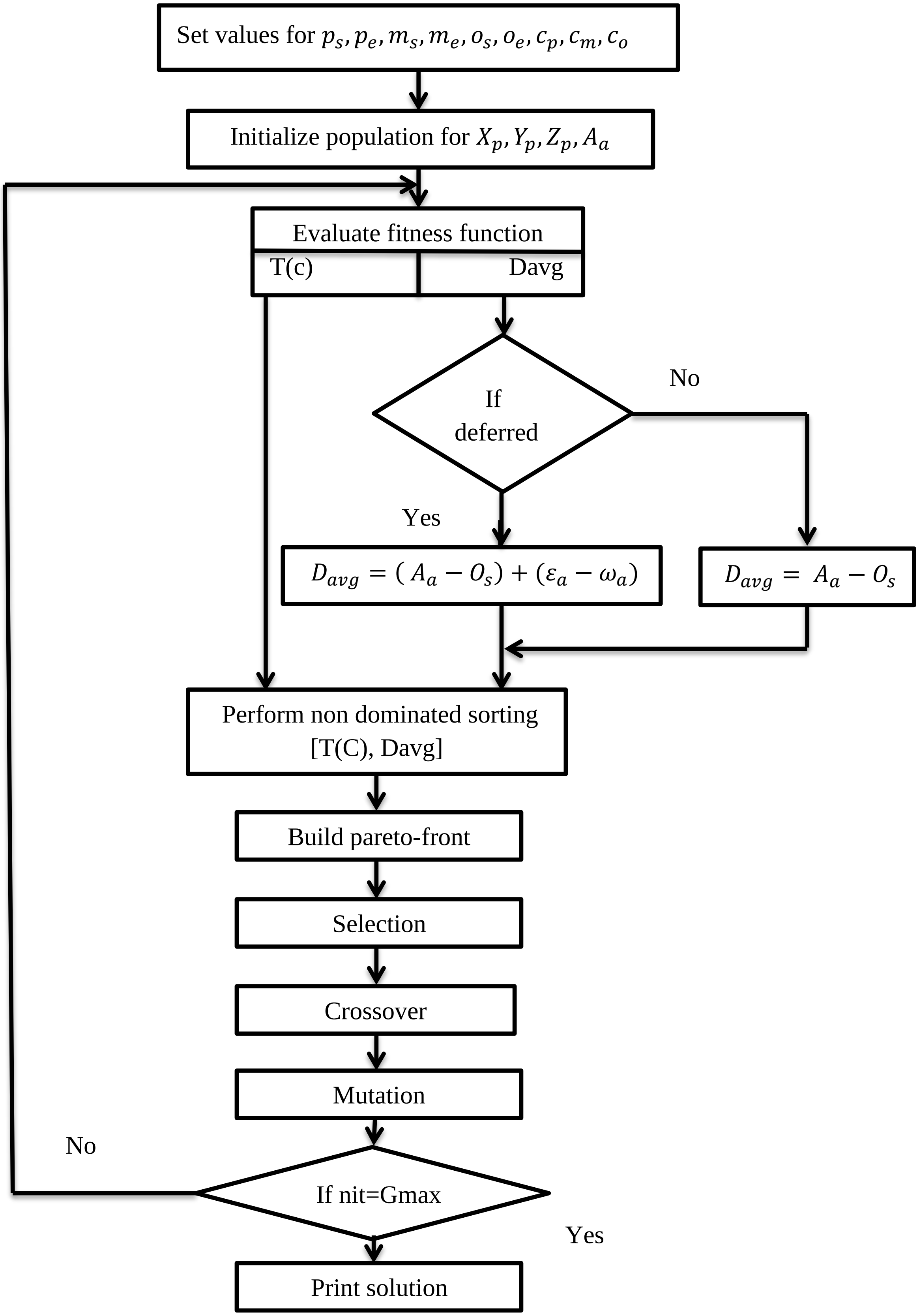

Figure 2.3: Flowchart for MOEA optimization approach (**[21]**)

The same way the time of a day can fall under one of three categories (peak, mid-peak, and off-peak). A device priority can be one of three: high (H), medium (M), or low (L). If $D_p = H$ and the request to execute is received at peak hour then the cost of energy usage at the time is computed using the formula:

$$X_c = C_p \times X_p, \qquad p_s \leq t \leq p_e \tag{2.8}$$

Where, C_p: energy cost at peak hour, p_s: peak hour start time period, and p_e:peak hour end time period.

If D_p=M and the delay time parameter of the device, $D_t = 0$ then the request to execute arrives at mid-peak hours. Thus, cost of energy usage at the time is computed using the formula:

$$Y_c = C_m \times Y_p, \qquad m_s \leq t \leq m_e \tag{2.9}$$

Where, C_m: energy cost at mid-peak hour, m_s: mid-peak hour start time period, and m_e: mid-peak hour end time period.

Finally, if $D_p = L$ and $D_t = 1$ then the request to execute is received at off-peak hour. Thus, cost of energy sage at the time is computed using the formula:

$$Z_c = C_o \times Z_p, \qquad o_s \leq t \leq o_e \tag{2.10}$$

Where, C_O: energy cost at off-peak hour, o_s: off-peak hour start time period, and o_e: off-peak hour end time period.

Combining the three equations (2.8)-(2.10), we obtain the total energy consumption cost usage cost per day. The formula is given below:

$$T(C) = X_c + Y_c + Z_c \tag{2.11}$$

[21].

3.2.4. Objective function:

From equation (2.11), the objective function to minimize the energy usage cost per day is given by:

$$minimize\ T(C) = X_c + Y_c + Z_c \tag{2.12}$$

At off-peak time, priority based approach is applied by the load-balancing mechanism for the appliances execution arrival time. The delay or average waiting time of an appliance in a queue can be calculated using a delay function. The delay function results from subtracting the active state start time from the off-peak hour start time. If a critical or high priority appliance interrupts the execution of a running appliance, the appliance is admitted in the waiting queue and the waiting time of the latter is added to the calculated delay time. D_{avg} is the average delay time for n appliances, A_a is the transition delay time between waiting state and running state for appliance a, w_a is running state end time or waiting state start time of appliance a and ϵ_a is the deferred time of appliance a.

$$minimize\ D_{avg} = \begin{cases} \sum_{a=1}^{n} (A_a - p), o_s \le t \le o_e \\ \quad if\ not\ deferred \\ \sum_{a=1}^{n} (A_a - p) + (\epsilon_a - \omega_a), \\ \quad o_s \le A_a \le \omega_a < o_e \end{cases} \tag{2.13}$$

Using the two equations (2.12) and (2.14), we can optimize the cost and delay time respectively by using the multi-objective evolutionary algorithm.

[21].

3.2.5. Admission control states:

Under the assumption that threshold based power usage pattern is adopted by a residential home. Additional charges are applied in the electricity bill if the consumer's energy usage exceeds the threshold. To prevent the occurrence of this scenario, the algorithm that we propose keeps the energy usage under this threshold. Anytime the service provider implements a power budget scheme in TOU pricing model for peak and off-peak hours and to smoothly achieve the load balancing mechanism, we introduce some states in the proposed system. They are: Wait, Power ON, Running, Power OFF, Interrupt, Deferred and Update. Similarly, the three queues (scheduling, waiting and processing) are maintained by the system.

We refer to the execution state of an electrical appliance as running or active state. If a high priority appliance has to execute while a schedulable appliance is in running state, the latter is deferred until the critical appliances completes the execution. when this is achieved, the deferred appliance resumes its execution. Finally, the appliance is turned off and the power allocated to it is released. The presently available power is calculated by the system and it is allocated to the next waiting home appliances in the scheduling queue.

The admission control mechanism (i.e.) selection of the running process to interrupt can be based on the following categories: i) Random selection of the currently running process, ii) Least recently entered appliance in the running state and iii) the appliances in running state which takes longest running time. If the available power is less than the total required power for the present request, then the suggested system may involve any of the following admission control mechanisms:

1) Random selection: The software based system randomly selects appliance among the presently running state from the set. The state changes from running to deferred.

2) Least recently entered: The system finds the least recently entered appliance in running state and it removes from the list.

3) Longest running time: This method searches for the longest execution time of appliance and it is involved in the admission control mechanism.

The suggested method gives an admission control mechanism with the help of the values collected from smart meter. A random selection admission control mechanism is tested.

[21].

3.2.6. Algorithm for Home appliance scheduling and load balancing:

The algorithm begins by requesting the power consumption values of the appliances and saves it for future use. In case, one or more appliance is in the running state, the available energy is computed as follows:

$$A_e = Th - \sum_{a=1}^{n} \Pr(a) \tag{2.14}$$

Where,

$P_r(a)$: is the power consumed by appliance a, a=1, 2, … ,n.

T_h: is the threshold value of power.

If an appliance requests to operate, the algorithm will check the request time of appliance, level of priority and compare its power consumption with the available energy. If the appliance is requesting to operate during off-peak time, has high priority and its power consumption is less than available energy, request is granted directly and appliance executes its operation. Available energy is updated as follows:

$$A_e = A_e - P_r(a) \tag{2.15}$$

If available energy is not enough to operate the appliance, the appliances that are running at the time are stopped one by one until there is sufficient energy to run the high priority appliance. The interrupted appliances enter into deferred state. After the deferral of an appliance a, available energy is updated as follows:

$$A_e = A_e + P_r(a) \tag{2.16}$$

When the operation of the high priority application is completed, the operation of the deferred appliances is resumed. Here, the system compares available energy at the time with power consumption of deferred. If available energy is greater, the appliance resumes its operation and on its successful completion, available energy is updated as follows:

$$A_e = A_e + W_q(a) \tag{2.17}$$

Where,

$W_q(a)$: is the power consumption value of appliance in the waiting/ deferred queue.

Waiting state appliances are processed the same way as deferred appliances. At last, the power consumption of appliance in scheduling queue is compared with available energy. If available energy is sufficient to run the appliance, request is granted directly else the algorithm periodically checks the available energy and grants the request when there is enough energy at hand.

$$A_e = A_e + S_q(a) \tag{2.18}$$

Where,

$S_q(a)$: is the power consumption value of appliance in the scheduling queue.

[21].

3.2.7. Admission control mechanism:

For home appliances with high level of priority, energy is required during the peak or off-peak time. The request of these appliances is handled by the algorithm using the admission control states mentioned above. The appliance waits in the scheduling queue until it gets response for its power requirement. After the controller checks the feasibility of execution, it sends a signal to the appliance and it enters into powerON state followed by Running state.

The proposed algorithm sets a maximum deferred count for the appliances so that the delay time doesn’t become too high which on certain situations may cause the appliance to enter into starvation state. If an appliance reaches maximum deferred count, it becomes a high priority appliance and in the next allocation, it will be granted power immediately;

Algorithm Load Balancing Algorithm for Electrical Appliances

{Th: Off-peak hour energy usage threshold value}
{Ip: Individual appliances, power consumption array}
{AE: Available energy }
{Sq,Wq:Scheduling queue and waiting queue}
{Pr: presently required power for the request}
{AppRun:Home appliances running state}
{maxDef, defCnt: Counters for interrupts}
{Dp: device priority to set of appliances}
{Toff:off-peak hour time in a day}
{high:Home appliances priority level}
loop $i := 1\ to\ n$
    $Ip[i] \leftarrow Individual\ appliances\ power\ consumption$
end loop
if (AppRun) **then**

$$AE = Th - \sum_{a=1}^{n} Ip[a1] + Ip[a2] + \cdots + Ip[an]$$

end if
loop $s \coloneqq 1\ to\ n$
    if (($Req.T = Toff$)and ($D_p = high$)and($R_p \leq AE$)) **then**
        Process the request
    else if (($Req.T = Toff$)and ($D_p = high$)and($R_p \geq AE$)) **then**
            loop $d \coloneqq 1{:}n$
                State change running to waiting
                $defCnt = defCnt + 1$
                $AE = AE + x.pr$
                    if $R_p \leq AE$ **then**
                        Process the request
                    end if
                    if ($defCnt \leq maxDef$) **then**
                        Change priority
                    end if
            end loop
    else
        loop $w \coloneqq 1{:}n$
            if $W_q[a].Pr \leq AE$ **then**
                Process waiting queue appliance
                    $AE = AE + W_q[a].Pr$
            end if
        end loop
        if ($S_q(a).Pr \leq AE$) **then**
            process scheduling queue appliance
                $AE = AE + S_q[a].Pr$
        else
            loop $z \coloneqq 1{:}n$
                If (($AE \geq S_q[a].Pr$) **then**
                    Calculate available energy
                    Process Schedule queue appliance
                end if

```
                        end loop
                end if
        end if
end loop
```

[21].

5. Conclusion:

Now that we've finished presenting the algorithms used by our home energy management system (HEM), we'll see in the next chapter the results of the optimization of energy usage cost and waiting time of appliances by simulating the algorithms in MATLAB.

Chapter 3

1. Introduction:

MATLAB is a very popular high level language for computation. It is used extensively both in industry and in universities worldwide. It is much easier to use than other popular programming languages such as FORTRAN or C. It takes a very short time to start becoming productive with MATLAB. Mathematical expressions are evaluated much the same way as they would be written in text form. MATLAB is used for a wide variety of activities, including computation, algorithm development, modeling, simulation, prototyping, data analysis, visualization, engineering graphics, and graphical user interface building.

Even though MATLAB is not unique in its ability to perform computational optimization, it is chosen here because it is highly effective software that is user-friendly and widely used. Using MATLAB enables the user to optimize both simple and complex systems and designs with effectiveness and efficiency.

[27].

In this chapter, MATLAB is used to optimize the energy usage cost and waiting time of appliances in a smart home using NGSA-2 multi-objective evolutionary algorithm and the load balancing algorithm discussed in the previous chapter.

2. Simulation:

The appliances used in the simulation along with their power usage are shown in the table below:

Table 3.1: Electrical Appliances Details(**[21])**

S.No	Appliance Name	Power Rating(w)
1	Heater	750
2	Television	200
3	Clothes Dryer	1000
4	Heat pump	500
5	Toaster	750
6	Washing machine	700
7	Pump motor	740
8	Kettle	750
9	Oven	1500
10	Coffee maker	1000

The settings for NGSA-2 are also provided in the table below:

Table 3.2: parameter settings for NGSA-2

Parameter	Value

Population size	100
Distribution index for crossover (etac)	20
Distribution index for mutation (etam)	20
Mutation probability(pm)	1/problem dimension

2.1. Cost:

2.1.1. **Results:**

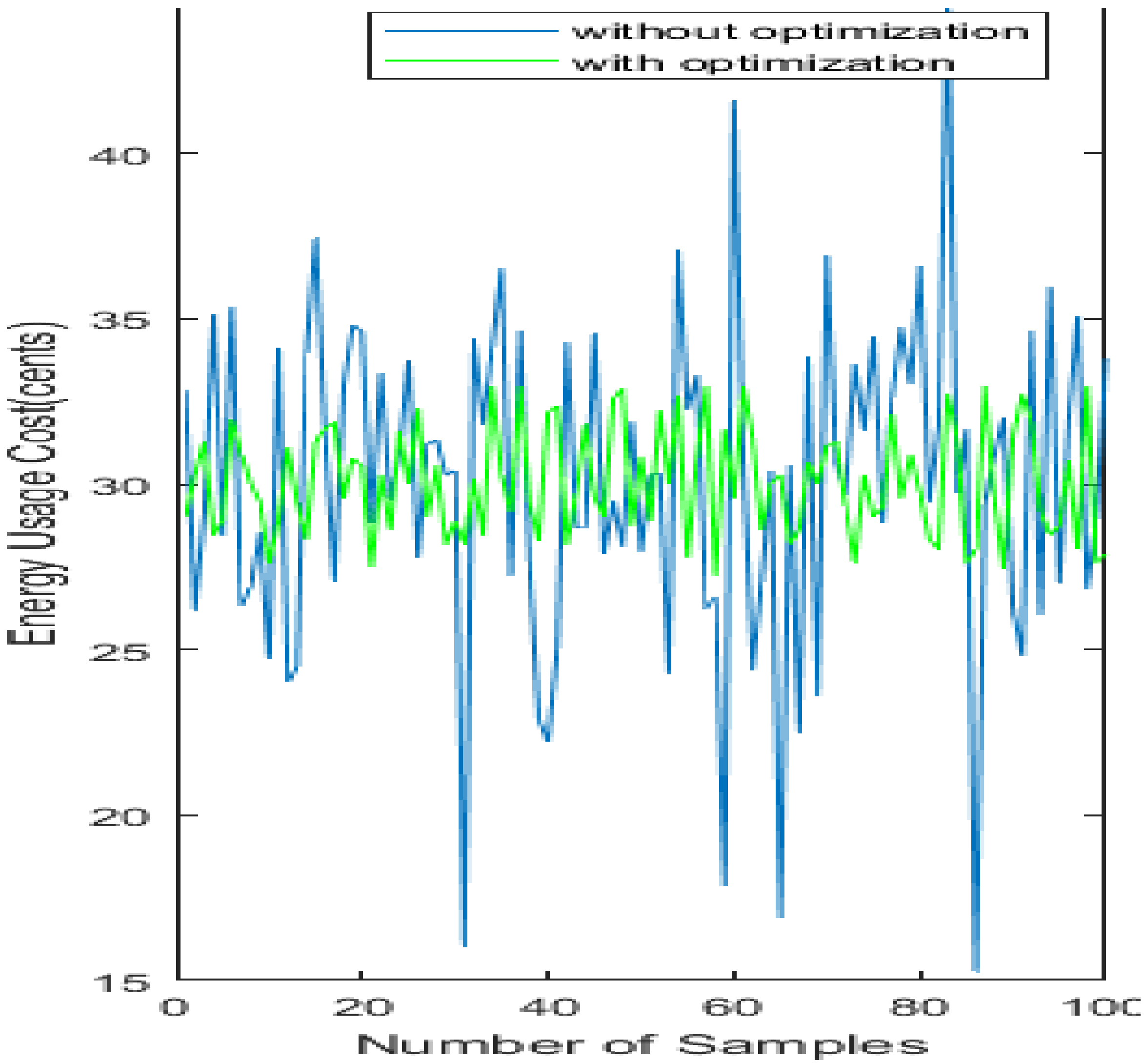

Figure 3.1: Energy usage pattern for cost

2.1.2. **Discussion:**

The result shows that the proposed optimization technique reduces the energy usage cost up to a certain level when compared to normal execution. Without the proposed optimization, the energy usage cost can reach as far as 45 cents and is generally in the range [26.5, 37.5] while with it, energy usage cost is in the range [26.5, 32.5].

2.2. Delay:

2.2.1. Results:

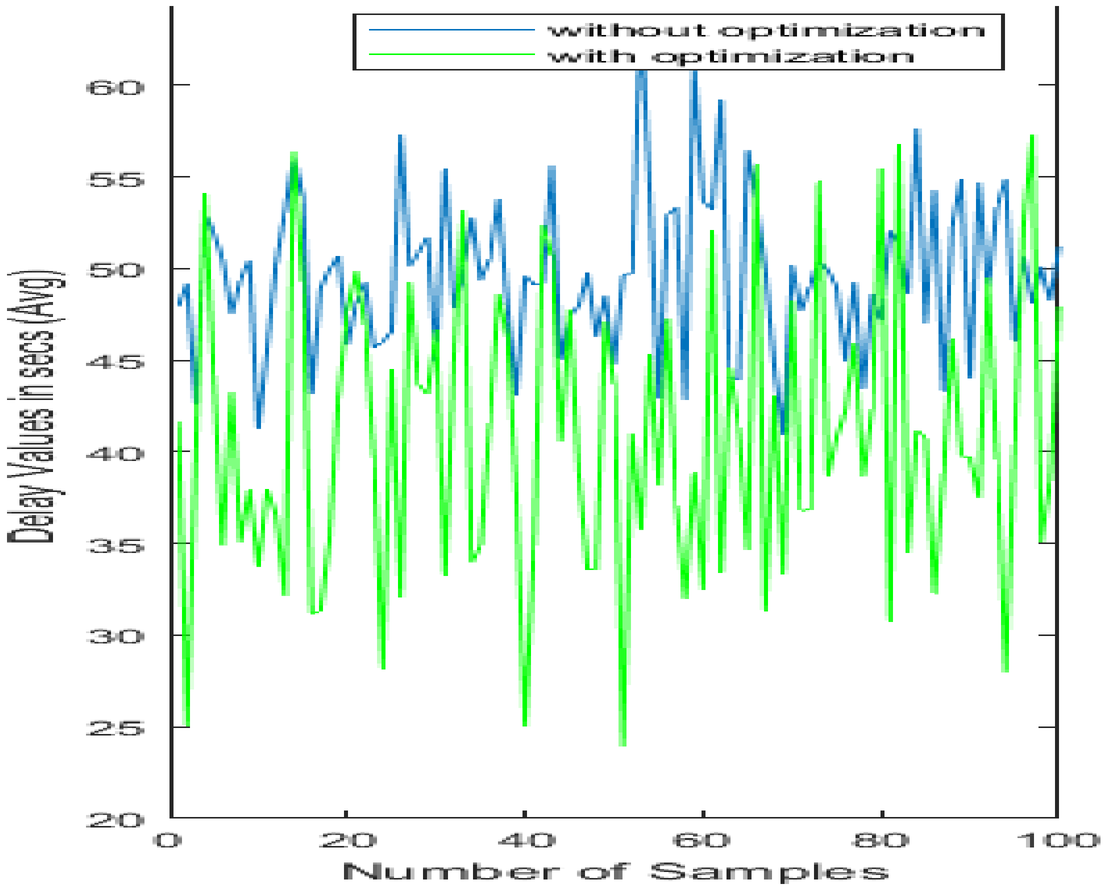

Figure 3.2: Effect of waiting time

2.2.2. Discussion:

It can be seen clearly that the delay values without optimization exceed those with the optimization. Without the proposed optimization, delay is in the range [40, 60] while with the optimization, the delay is in the range [20, 57.5].

2.3. Cost vs Delay:

2.4.1 **Results:**

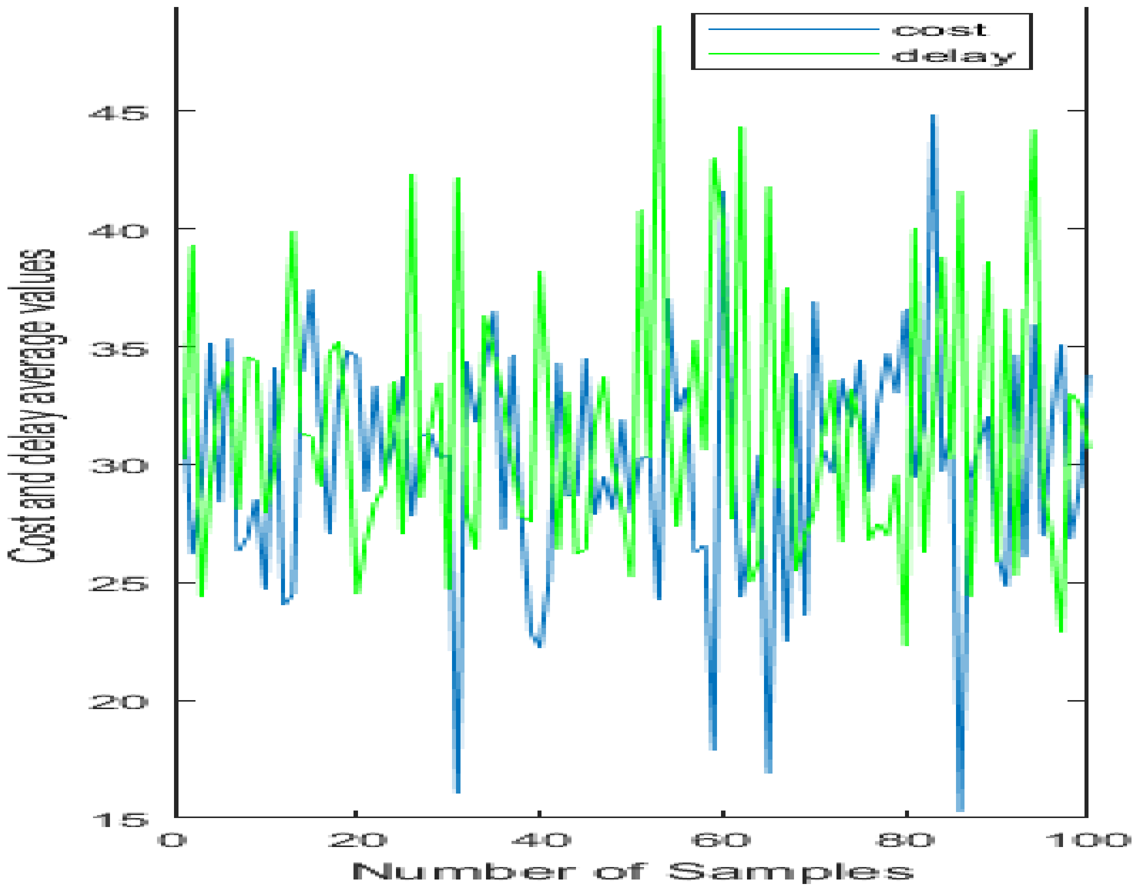

Figure 3.3: Tradeoff between cost vs delay

2.4.2 **Discussion:**

It can be clearly seen that there is a tradeoff between cost and delay, i.e., reducing the cost will lead to higher delay and vice versa. The two objective functions are inversely related.

2.4. Impact of proposed algorithm for Deferred State:

2.5.1 **Results:**

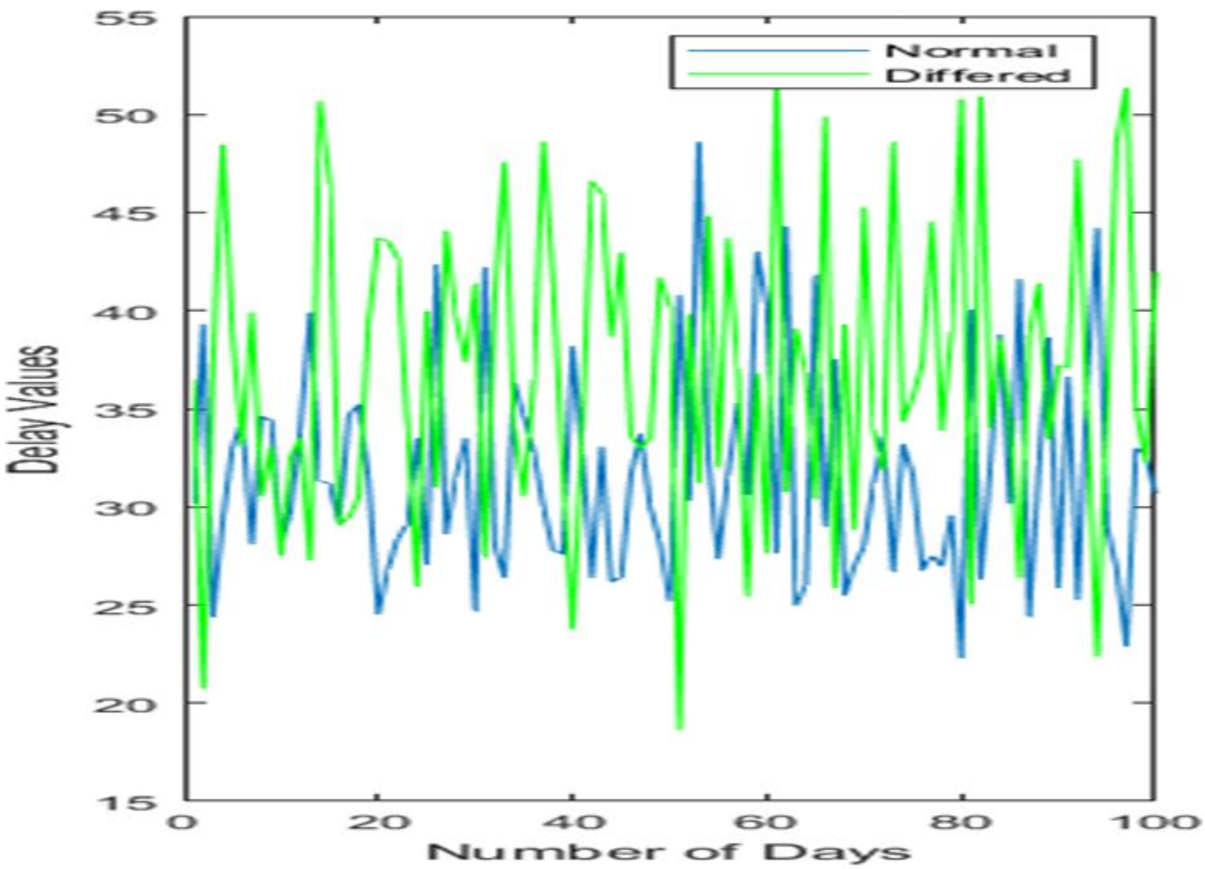

Figure 3.4: Comparison of Delay time

2.5.2 **Discussion:**

Figure 3.4. shows clearly that if the appliances are deferred, the waiting time will increase automatically and can get as high as 52.5 while if the appliances work normally, the delay didn't reach 50. Further, by setting a maximum deferred count, the occurrence of high peaks can be controlled.

2.5. Energy Usage Pattern for Day:

2.5.1 Results:

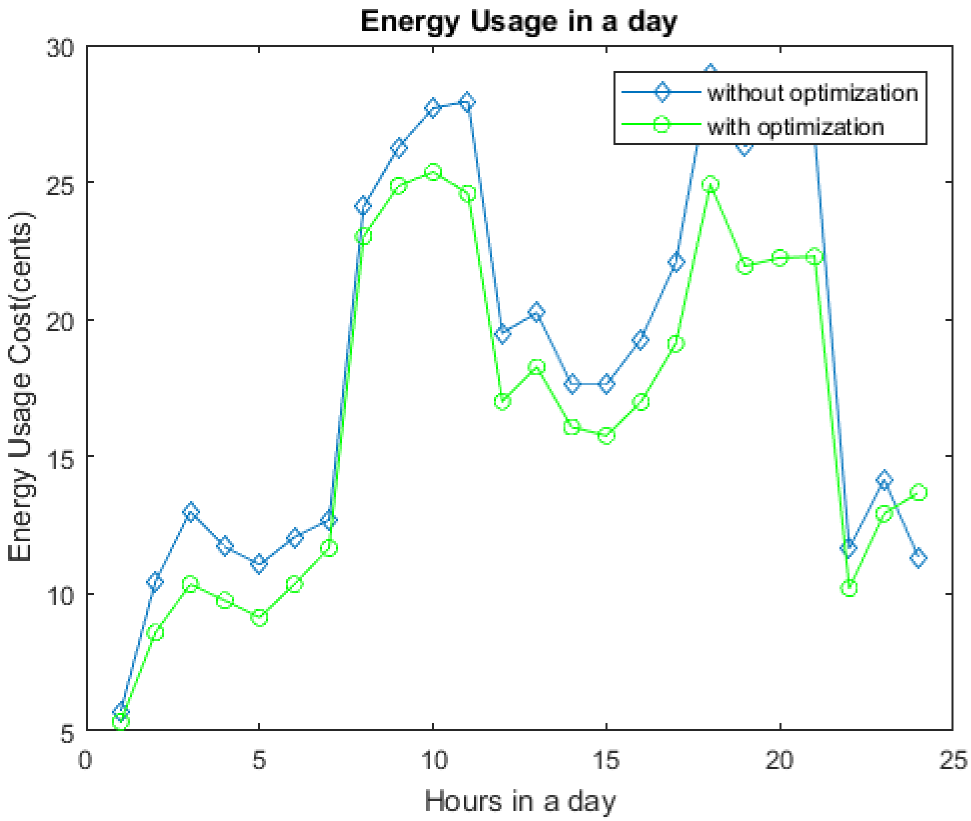

Figure 3.5: Energy Usage in a Day

2.5.2 Discussion:

The values of energy usage cost in a day with the proposed optimization are less than without the proposed optimization for all hours of the day except at the last hour of the day but as it corresponds to off-peak hours, it does not have much influence and the mean value of mean energy usage cost after optimization is still less than its value without it.

Remarks about the simulation:

A certain choice of appliances in the testing of the code did not lead to an optimization. It is unknown whether the algorithm itself has some missing information or our code was not an accurate representation of the algorithm as some of the variables and instructions used were somewhat ambiguous and left to our interpretation. For example:

- Deferal and waiting queue are sometimes described as two different queues in the paper and it appears in other parts that they are the same thing. We considered them as one queue.
- The implementation of the queues in the program is not described and was left to our interpretation.
- The variables X_p, Y_p and Z_p are not described mathematically and this resulted in difficulty in knowing how they were implemented.
- How the two algorithm work together is not mentioned and we had to figure how to link between them to obtain the results.

3. Integration of renewables:

To integrate renewables in our DR response mechanism, the following modifications to the initial algorithm are suggested:

Algorithm Load Balancing Algorithm for Electrical Appliances

{Th: Off-peak hour energy usage threshold value}
{Ip: Individual appliances, power consumption array}
{Ae_g: Available energy from the grid}
{Ae_r:Available energy from renewables}
{Sq,Wq:Scheduling queue and waiting queue}
{Pr: presently required power for the request}
{AppRun:Home appliances running state}
{maxDef, defCnt: Counters for interrupts}
{Dp: device priority to set of appliances}
{Toff:off-peak hour time in a day}
{high:Home appliances priority level}
loop $i := 1\ to\ n$
    $Ip[i] \leftarrow Individual\ appliances\ power\ consumption$
end loop
if (AppRun) **then**

$$AE = Th - \sum_{a=1}^{n} Ip[a1] + Ip[a2] + \cdots + Ip[an]$$

end if
loop $s \coloneqq 1\ to\ n$
    if (($Req.T = Toff$)and ($D_p = high$)and($R_p \leq AE_g$)) **then**
        Process the request
    else if (($Req.T = Toff$)and ($D_p = high$)and($R_p \geq AE_g$)) **then**
        if $R_p \leq AE_r + AE_g$ **then**
            Process the request
        Else
            loop $d \coloneqq 1{:}n$

```
                    State change running to waiting
                    defCnt = defCnt + 1
                    AE_g = AE_g + x.pr
                        if R_p ≤ AE_r + AE_g then
                            Process the request
                        end if
                        if ( defCnt ≤ maxDef ) then
                            Change priority
                        end if
        Else
            loop w := 1:n
                if W_q[a].Pr ≤ AE_g then
                    Process waiting queue appliance
                      AE_g = AE_g + W_q[a].Pr
                else if W_q[a].Pr ≤ AE_r + AE_g then
                    Process waiting queue appliance
                end if
            end loop
            if (S_q(a).Pr ≤ AE_g) then
                process scheduling queue appliance
            else if (S_q(a).Pr ≤ AE_r + AE_g) then
                Process scheduling queue appliance
            Else
                loop z := 1:n
                    If ((AE_g ≥ S_q[a].Pr) or( AE_g + AE_r ≥ S_q[a].Pr)) then
                        Calculate available energy
                        Process Schedule queue appliance
                    end if
                end loop
            end if
        end if
    end loop
```

The algorithm begins by requesting the power consumption values of the appliances and saves it for future use. In case, one or more appliance is in the running state, the available energy from the grid is computed as follows:

$$AE_g = Th - \sum_{a=1}^{n} \Pr(a) \tag{3.1}$$

Where,

$P_r(a)$: is the power consumed by appliance a, a=1, 2, …, n.

T_h: is the threshold value of power.

If an appliance requests to operate, the algorithm will check the request time of appliance, level of priority and compare its power consumption with the available energy from the grid. If the appliance is requesting to operate during off-peak time, has high priority and its power consumption is less than available energy from the grid, request is granted directly and appliance executes its operation. Available energy from the grid is updated as follows:

$$AE_g = AE_g - P_r(a) \tag{3.2}$$

If the available grid energy is not enough, the algorithm adds to it the stored energy from renewables and verifies if the sum of the two is greater than the power consumed by the appliance. If condition is satisfied, the appliance enters in running mode.

If the sum of the two energies is not enough to operate the appliance, the appliances that are running at the time are stopped one by one until this sum is sufficient to run the high priority appliance. The interrupted appliances enter into deferred state. After the deferral of an appliance a, available energy from the grid is updated as follows:

$$AE_g = AE_g + P_r(a) - BE_r \tag{3.3}$$

BE_r: Borrowed energy from renewables

When the operation of the high priority application is completed, the operation of the deferred appliances is resumed. Here, the system compares available energy at the time with power consumption of deferred. If available energy is greater, the appliance resumes its operation and on its successful completion, available energy is updated as follows:

$$AE_g = AE_g + W_q(a) \tag{3.4}$$

Where,

$W_q(a)$: is the power consumption value of appliance in the waiting/ deferred queue.

Waiting state appliances are processed the same way as deferred appliances. At last, the power consumption of appliance in scheduling queue is compared with available energy from the grid. If available energy is sufficient to run the appliance, request is granted directly else it adds the stored energy from renewables and if the sum of the two is enough, request is granted. If the sum is still less than the power consumed by the appliance, the algorithm periodically checks the available energy from the grid and renewables and grants the request when there is enough energy at hand $(AE_g \ or \ AE_g + AE_r \geq S_q(a))$.

$$AE_g = AE_g + S_q(a) \tag{3.5}$$

Where,

$S_q(a)$: is the power consumption value of appliance in the scheduling queue.

3 *Simulation results and discussion*

Our main work concerned the previously obtained results without including renewables. The results of simulation obtained by adding a fixed stored energy from renewables will give results similar but better to the ones that we presented.

4. Conclusion:

In general, the results obtained are satisfactorily and are a good enough approximation to the results we tried to reproduce. The modifications that can be made to the algorithm to include renewables were also presented. The expected results are given for a constant value of stored energy. For realistic results, one should consider the variable nature of renewables.

GENERAL CONCLUSION:

In our work, we reproduced the results of the paper [21] where the proposed optimization method together with MOEA is implemented to optimize the energy usage cost of the consumer and performs the load balancing mechanism so as to minimize the delay for the execution of the electrical appliances. The proposed algorithm also gives an idea to select the admission control method to manage home appliance load. It also suggests the service provider to manage the load requirement during off-peak hour. At the end as an addition to the work done in the paper, we have seen how the algorithm could be rewritten in order to integrate renewable energy sources.

The obtained result reveals that the consumer can use the power within the threshold level to avoid additional pay to the service provider, which also helps to consume more power with minimum cost effectively and feasibly. Further, it is used to analyze the electricity usage cost and waiting time in different conditions. The output shows that the proposed method minimizes both electricity cost and delay time of execution of electrical appliances for consumer.

The results hold a significant importance in smart grid as the efficient energy use is a very important research area. This can be seen through the considerable number of algorithms have been developed so that the utility can provide the same level of energy service while using less energy.

In future work, we can simulate the integration of renewable energy to the model including their variability. It might also be of particular interest for us to consider different scenarios to the optimization to see if the results will be similar for those scenarios. Finally, we may implement the proposed model with different optimization techniques and consider more parameters in demand side management as proposed by the paper this work is based on.

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