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DESIGN AND ANALYSIS OF BIO-INSPIRED CONTROL TECHNIQUES FOR ENERGY FLOW IN A SMART GRID

MSc Thesis for the Partial Fulfillment of
Master of Science in Electrical Automation and Control Technology Management

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A Thesis submitted to
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In partial fulfillment for the Degree
MASTER OF SCIENCE *in* ELECTRICAL AUTOMATION AND CONTROL TECHNOLOGY MANAGEMENT

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DECLARATION

I hereby declare that the work which is being presented in this thesis entitled " Design and Analysis of Bio-Inspired Control Techniques for Energy Flow in a Smart Grid " is the original work of my own, has not been presented for a masters thesis in this or other universities and all sources of materials used for this thesis work have been fully acknowledged.

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Place: Addis Ababa

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This thesis proposal has been submitted for examination with my approval as a TVTI advisor.

Dr. Bisrat Gezahegn	____________________________	
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Thesis on

DESIGN AND ANALYSIS OF BIO-INSPIRED CONTROL TECHNIQUES FOR ENERGY FLOW IN A SMART GRID

By,
Bereket Getahun

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ABSTRACT

The smart grid concept is critical in order to use renewable energy efficiently, which necessitates the integration of renewable energy sources. Rising electricity demand has increased efforts to generate and meet rising demand. As a result, suppliers attempted to reduce consumption with the help of users. Requests to move unnecessary loads outside of peak hours use other generators to supply the grid, and provide incentives to users have all had a significant impact. Automated Home Energy Management System use load scheduling techniques to control house appliances in response to Demand Responce signals. This thesis introduces HEMS, which automatically schedules appliances throughout the house to save money. Thermal loads are prioritized by controllers because they have the greatest impact on the electricity bill. They do, however, take into account many factors that similar models do not, such as the physical properties of the room/medium, the outside temperatures, the comfort levels of the users, and the occupancy of the house. The hourly electricity price, which is typically higher during peak hours, was the Demand Responce signal. The (GWO) algorithm is used to optimize micro-grid energy resource scheduling in relation to power demand. The proposed algorithm is tested in a variety of scenarios, and the numerical simulation results are compared to those of other optimization techniques such as particle swarm optimization (PSO). The proposed method (GWO) achieves outstanding results and out performs other algorithms in terms of solution quality and computational efficiency.

Keywords: *Demand Response, Scheduling, Modelling, Smart grid, Energy storage system, Optimization, grey wolf optimization (GWO)*

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ABBREVATIONS

DR	Demand Response
ESU	Energy Storage Unit
GWO	Grey Wolf Optimizer
HEM	Home Energy Management
PSO	Particle Swarm Optimization
PAR	Peak to Average Ratio
PV	Photovoltaic
RTP	Real Time Pricing
TOU	Time of Use
VPP	Variable Peak Pricing
WoutLSNOP	Without Load Shifting No Photovoltaic
WithLSNOPV	With Load Shifting No Photovoltaic
WoutLSPV	Without Load Shifting and Photovoltaic
WithLSPV	With Load Shifting and Photovoltaic

CHAPTER ONE

INTRODUCTION

1.1 Background

Smart grids enable two-way communication between the consumer and the power supplier with the help of smart meters and other smart tools. With these smart tools, it is ensured that the communication between the producer and the consumer is fast and secure. Considering the advantages of the smart grid, it has been observed that the demand for it has increased [1 - 2].

Recently, with the development of technological studies, changes have occurred in the supply-demand balance. Here, the demand for fast and reliable has also manifested itself in grid applications. It is known that the importance of the smart grid, where classical grid applications are insufficient, is increasing day by day, especially in developed countries. According to reference with the number [3], the importance given to Smart grid applications by developed countries is given.

In [4], the importance of the locations of the grids is mentioned. Accordingly, it was stated that centralized grids cause more environmental pollution than distributed grids. It is also known that centralized grids cause more losses than distributed grids. However, the Smart grid has become even more important to minimize the losses in electrical energy coming to the consumer.

Considering both cases, the idea of smart grids has emerged to distribute electricity and use it optimally. With these ideas, the importance of the smart grid has increased in recent days, as the losses in transmission decrease and it enables consumers to save electricity effectively. With smart grids, the dependency on non-renewable energy sources is reduced, thus minimizing the high carbon emission problem. It also enables the home to have its own Home Energy Management System (HEMS) by connecting to smart homes with micro-grids. The production of solar energy in the places formed by these connections and the management of its relationship with the battery and the grid is done by HEMS [5]. In this study, the possible demand situation of the customers has been determined and constraints have been determined in a way to offer optimum solutions for these demands. The benefit of modeling the methods is that they provide a way of representing real-life applications, and can adjust the parameters of those models to adapt them for the benefit of the customer. With these studies, it is aimed to create the most suitable solution-oriented mathematical model for the consumer and the power supplier, and this aim was achieved at the end of the project [6].

Throughout the future electrical grid to monitor energy in real-time based on demand, sensors and transducers will be crucial components of the future power grid. Using automated power measurement and data processing, smart sensing systems can provide new opportunities for making decisions in real-time. A complex, interconnected system, the electric network, also referred to as the grid. Rising electricity demand need a greater supply of renewable energy that is sustainable.The public electricity grid is currently undergoing a fundamental change. Because distributed generation plants are present, for example, energy flow becomes bidirectional. Based on local demand, electricity is divided across many nodes of the power system, known as microgrids. As a result, both the direction and the flow of energy must change dynamically. Energy flow management has become a very difficult task. Currently, these aspects are not given enough weight in the grid. As a result, the end-user may be forced to accept low-quality energy on occasion. Domestic users bear the brunt of the effects. Today’s transmission and distribution of electricity must meet two fundamental requirements: an uninterrupted energy supply and high quality energy. Implementing a smart grid could be a viable strategy for dealing with rising power demand and smart meter adoption. A range of power monitoring tools and solutions are available to address issues with power usage and control. Numerous utilities are now using smart meters commercially because they offer a wide range of capabilities and services. One of the goals of this thesis is to identify and examine the functions and operations of commercially available smart meters. Smart meters are robust measurement tools that have a digital display, the capacity to track when and how much power is used, and the ability to send data.Such a scenario necessitates the development of new systems that enable the power grid to manage the bi-directional and dynamic flow of energy in a truly intelligent manner. Furthermore, these systems must ensure that new and old equipment can communicate with one another. Renewable energy production, on the other hand, is hampered by supply disruptions. As a result, the possibility of outages and inefficiencies increases. A smart power system should be able to prevent a power outage as soon as possible. Modern sensing systems are required because of these properties. In order to have a precise picture of the state of the power system, sensors must collect data and evaluate it in real time.

1.2 Statement of the problem

The distribution system is the central component of the power system network that provides power to end users. It connects the customer to the generation of electricity. Power delivery reliability is critical to profitability and customer satisfaction. Nowadays, the world is attempting to improve the delivery mechanism and supply quality. However, the power distribution system has remained insufficient to meet customer demand in terms of required reliability and reduced public safety risks. To varying degrees, the power outage impacted poor customer service, and a wide range of critical infrastructure, including industry, business enterprises, and residential users. Low system reliability has resulted in an increase in outages, resulting in additional losses to business sectors. Electricity supply reliability and consistency are critical to many industrial and service activities. Unreliable power supply not only slows or damages production or leads to plant closure, but it also causes equipment damage, and additional maintenance and harms the industry's reputation for product quality. According to the literature, thermal appliances were modelled in various ways depending on their purpose. In several cases, the models failed to account for critical parameters such as the outside temperature, the physical structure of the occupancy building, and user comfort. These parameters will ensure a more accurate load profile, which is critical if the models are to be used in disaster recovery applications. Furthermore, the schedulers discussed in the literature did not take into account changing critical load parameters; the majority of them were designed to turn on/off appliances or shift them away from peak hours, with no control over the individual appliance's settings. Controlling the individual appliance's operation parameters allows for more accurate scheduling results while also maintaining the user's comfort. As a result, the smart grid concept for achieving a smart distribution system is proposed for implementation to address this public issue. They are, in general, an essential component of what industry experts refer to as the smart grid. The smart grid is an updated, modernized version of our country's current infrastructure for transporting electricity from power plants to homes and buildings.

1.3 Objective

1.3.1 General objective

The general objective of the thesis is to design an optimal smart grid for an effective load scheduling model that optimizes appliance settings and schedules loads around the house in response to a DR signal using the grey wolf optimization algorithm..

1.3.2 Specific objective

This research aims to design a system that will address the following issues:

- To create accurate and realistic models of home appliance loads while taking into account more controlling parameters for the demand of response load scheduling and an effective load scheduling model that optimizes appliance settings and schedules loads throughout the house to reduce costs to a bare minimum.
- To investigate the mathematical modeling of solar PV, wind turbines, and storage batteries and create an optimized microgrid system that uses renewable energy and requires the least amount of maintenance.
- To investigate heuristic algorithms used to optimize and schedule the appliances.
- To simulate the smart grid system using matlab-Simulink.

1.4 Significance of the Thesis

To balance energy supply and demand, while meeting environmental and economic objectives, new potential in the smart grid must be investigated. The energy-demand supply imbalance can be reduced by taking into account both sides of the coin, namely generation, and consumption, according to early research into smart grid technologies. The thesis is conceptually divided into four sections: demand side management (DSM), supply side managemnt (SSM), short-term load forecasting (STLF), and electric theft detection (ETD) in the power network.

Until recently, SSM was primarily focused on updating the current generation and transmission facilities. However, modern SSM techniques can find it difficult to replace inefficient power plants, enhance maintenance and management of conventional forms of equipment, and diversify alternate fuel sources. Similar to this, the DSM program needs to involve users for them to make known energy management decisions, managing energy consumption or DSM is more economical than production. Demand Side Management must be given top priority because current distribution issues are the main contributor to system failures. Users in energy management programs are devoted to managing their energy use strategically and effectively. Their loads must be switched between peak and off-peak hours. With little effect on overall usage, this technique successfully reduces energy peak usage.

The immediate benefit of using SSM and DSM approaches is that less money will need to be invested in building new transmission networks and power plant infrastructure to meet the increased demand for electricity. With current technology, extra energy cannot be profitably queued or stored. Additionally, electricity's properties are kept local and time-varying in many ways because of the current power network's restricted ability to transmit power to other locations. A small role is played by electricity load forecasting (ELF) in preserving a power network's equilibrium on both sides.

Non-technical loss (NTL) or Electricity theft is one of the most significant causes of anomalies at the planning and distribution levels of the smart grid. Electricity theft can be identified, which enables utilities to use less energy overall and better control peak demand for electricity. This decreases production and helps in the control of certain abnormalities at the planning and distribution levels. It is essential to have an accurate and efficient method of detecting theft in order to close the supply-demand gap and keep the power management system dependable and efficient. It addresses the problems associated with unpredictable power generation and raises the dependability of readily available energy sources.

These are the primary contributions of this work:

- Cost minimization in total energy generation with optimal power flow (OPF),
- Shaping demand profile with DSM,
- NTL or the reduction of electricity theft through data-driven techniques,
- Load utilizing and reliable forecasting of power prices in the smart grid, and
- Control carbon emission with highly penetrating RES.

SSM, DSM, ELF, and NTL detection are four strategies that can balance rapidly increasing consumption with conventional power plants to build an electricity network with almost zero smart energy creation and consumption.

1.5 Limitations of the thesis

Financial limitations cause a growth bottleneck for the majority of developing technologies. Energy experiments in the real world are expensive. A large time, money, and resource commitment is required for demand-side management, supply-side management, and gathering a sizable amount of consumption data to carry out testing and experimentation in the real world. Second, given the limited computer resources at hand, simulations for distributed energy resource management were not finished quickly. The availability of computer resources will allow for larger time periods study in the future, in accordance with Moore's law. As a result, these domains may integrate a wider variety of dynamic responses to the operation of smart appliances.

1.6 Scope of the Thesis

The goal of the design a system that would assure the greatest penetration of RES to much the anticipated generation pattern while needing the least amount of investment in creating new electricity infrastructure. Solar and wind power producers are combined by an Optimal Power Flow (OPF) model in the study's first phase balances the irregular nature of RES power output. Costs associated with consumption would decrease with this approach, and power peaks would be avoided. ELF, or Non-Technical Losses, has long been a critical part of smart grid systems. It promotes sustainability and helps utilities create budget-friendly plans for the planning and management of power systems. STLF in big data-driven smart grids is the topic of the study's concluding section. In order to reduce energy waste at the building level and the risk of erratic grid dependability, the STLF is crucial. Put a stop to power grid fraud and energy theft. Due to energy loss and poor power quality, electricity theft is often more expensive for utilities than nonpayment. Power theft has been an issue since it first began, and no electric utility is protected from it.This is not only raises end-user costs and necessitates costly government subsidies, but it also causes global utility outages. This study's main goal is to show how SSM, DSM, STLF, and NTL detection work and how they may adapt to grid needs using Matlab/Simulink.

1.7 Methodology

The phases of this thesis' development are broken down into the initial stages of work and the final report of creating and simulating control systems for energy flow in smart grids. To reduce the likelihood that a problem may arise while working, it is crucial to maintain the entire process.

- The first duty is to organize the literature reviews, where all the theoretical data on the house modeling and scheduling optimization strategies to be acquired from and a comparison of prior similar research works have been reviewed.
- Develop mathematical model to operate and adjust household appliances.
- A smart grid controller has been created based on a mathematical model to control energy flow.
- Then,control techniques for energy flow in a smart grid is simulated by MATLAB/Simulink.
- In its final section, the paper reviewed the MATLAB/Simulink findings and suggested possible directions for further research.

1.8 Outline of the Thesis

The thesis is laid out as follows. The first chapter contains an overview of the thesis, objective, and scope of work. Chapter 2 presents a literature review and state of the art for hybrid renewable energy systems. The methodology used to create the loads models and the full house controller is detailed in Chapter 3.The fourth chapter discusses the controller design and methodology used to apply the optimizer, as well as the scheduling system structure. In addition, the results of the entire HEMS, including the controller and optimizer, are discussed in Chapter 5. Finally, the conclusion summarizes the main findings of this study, restates the objectives, and discusses future work opportunities.

CHAPTER TWO

LITERATURE REVIEW

The literature provided a lot of information on house modeling and scheduling optimization techniques. The modeling of appliances will be presented first, followed by optimization or scheduling techniques from the literature. Models of Study Systems (in this case, home appliances) can be classified as Empirical or Non-Empirical based on the need for observation and the study purpose.

2.1 Supply Side Management

Efficient energy production, distribution, and transmission refer to the actions taken to ensure energy supply side management(SSM). The primary factor impacting the effectiveness of SSM intervention is the optimal power flow (OPF) of energy at the generation and transmission levels. Utility companies should experiment with changing their load profiles so that only the most critical generating equipment is employed (compared with high-efficiency equipment that should be used to the maximum). SSM and OPF allow the power provider to postpone large capital investments that would otherwise be required to increase capacity in growing areas. In a smart grid, effective SSM approaches deliver electricity at a lower cost while lowering environmental emissions per unit of provided end-use electricity (allowing for lower consumer prices).SSM can contribute to improving the dependability of a supply system. Given the current trend of supply industry deregulation, it is becoming increasingly important to implement SSM practices that benefit the supplier, the user, and the environment. Utilizing state-of-the-art technologies, SSM in smart grids enables utilities to enhance maintenance procedures, more effectively monitor their equipment, and increase operational capacities. In addition to diversifying their fuel sources, they might also think about on-site generation options like co-generation (such as natural gas, solar, wind, and bio fuels).

Since the inception of OPF, which was roughly 50 years ago, many conventional optimization techniques have been offered for application in this field. Examples include quadratic programming, nonlinear programming, mixed-integer linear programming, and interior-point methods [21–23]. Due to their quick convergence and dependability in choosing the best solution, some of these tactics have been successfully applied in business. However, one of the major problems with such optimization strategies is the requirement of initially linearizing the optimization function.

2.1.1 Application of Heuristic Algorithms

Heuristic optimization algorithms are also recommended as a solution to this problem.These aim to maintain the original cost function while finding the best possible solution for the power system [24]. Single solution-based and population-based heuristic algorithms are the two categories into which they fall. The best single solution-based heuristic algorithms in this field are tabu search and simulated annealing [25, 26]. Some of the genetic algorithms that have been proposed include differentiating evolution (DE), artificial bee colonies (ABC), crow search algorithms (CSA), cuckoo search optimization (CSO), particle swarm optimization (PSO), and success history-based adaptive differential evolution (SHADE) algorithms [27-33].

The effectiveness of search tactics in the context of OPF has also been improved by a number of custom heuristic approaches. In order to improve optimization for a particular problem, the authors presented a modified GA to address the OPF problem [27]. When put to the test on the well-known IEEE RTS 96 and IEEE-30 bus systems, the modified GA surpasses the normal GA in terms of elitism and fitness scaling.Similar to this, a faster PSO algorithm computes an OPF quadratic cost function that accounts for multiple valve-point loading effects faster than the conventional PSO technique [34].

Authors in [35] proposed the population-based heuristic algorithm known as Artificial Bee Colony (ABC), which computes with other proposed approaches in part due to the algorithm's resilience but also perhaps because fewer parameters were regulated. ABC competes with other proposed algorithms for OPF. Exploration and exploitation must be matched for modern heuristic strategies to be effective. When effectively driven, the former highlights the algorithm's ability to investigate in the search domain of uncharted territories. On the other hand, the latter strengthens the algorithm's capacity to locate the overall answer using the data offered by the exploration method.

The scientific community faces a significant challenge as a result of these two polar opposite qualities. Standard Artificial Bee Colony has performed well in terms of discovering due to its randomness,its but its weak exploitation phase may cause substandard convergence [36]. ABC has been suggested to be improved using the DE algorithm [37]. The usage of "onlooker bees," who have a predetermined probability and are aware of the best option currently accessible, is included in this. Gao et al[38] .'s successful usage of a chaotic system allowed them to alter the search process and enhance not just the initialization phase but also the search for the ideal solution. SHADE was a proposed algorithm by Tanabe and Fukunaga [33]. Here, putting up efficient control parameters is used to guide the choice of additional control parameters. To correctly balance the exploration and exploitation processes is the goal. Nonlinear, multimodal, and constrained optimization issues also experience a moderately quick convergence rate. This tactic is predicated on understanding the current best option for upgrading the typical ABC exploitation feature. Tanabe and Fukunaga [33] presented a more advanced DE variant that results in the SHADE algorithm. Future control parameter selection will be guided by the successful control parameter choices made in this case. Achieving the perfect balance between the operations of exploration and extraction is the goal. For optimisation problems that are confined, multimodal, and nonlinear, a moderately quick convergence rate is also reached.

Gao et al. [38] adopted a chaotic system in order to enhance initialization and performance. When SHADE is combined with a strong constraint handling method, such as the superiority of the feasible solution (SF) approach [39], its effectiveness is even further boosted. It can sometimes take a very long time for the resulting SHADE-SF [40] to converge, so this may happen on occasion (i.e., becomes stuck in a local solution). As a result of only having been tested with the IEEE-30 bus system, the techniques described in references [40, 41] cannot be depended upon to perform as intended.

For instance, the author [40] went through 24000 iterations to find the best answers. The large computing load, however, delayed the iterations' convergence to a local solution. Similar to this, the authors of references [41, 42] only succeeded in acquiring the constant convergence curves for other algorithms after 200 iterations of using their advised strategies. When iteration counts are larger (i.e. > 1000), different algorithms are more likely to do better than the suggested methods in terms of finding better solutions more quickly.This indicates how algorithms' potential for exploration and exploitation were neglected. Although network restrictions are important for OPF, economic dispatch (ED) problem constraints were typically ignored. Constraints on the system, particularly those pertaining to network characteristics, were routinely ignored. Reference [43] mentions system limits, but it isn't made obvious how to adhere to them. Although they are crucial in the context of OPF, emission issues and voltage profile are generally ignored in the ED problem. More research on OPF is required in a network that combines thermal power generators (TPGs), solar power generators (SPGs), and wind power generators (WPGs).

2.2 Demand Side Management

Homes consume between 20 and 40 percent of all energy, so energy-efficient construction is essential for the long-term expansion of electric power networks [44]. Buildings have been discovered to be a significant source of energy waste in addition to being one of the major energy consumers. The DSM's engagement is essential in order to decrease energy waste at the building level and to lower the risks related to grid reliability [45]. In order to affect energy demand and produce the necessary modifications to the utility's load shape in terms of size, temporal pattern, and frequency, the Demand Side management supervises, applies, and targets a number of operations in utilities.

One of the ground-breaking methods for home load management is Direct Load Control, one of the DSM ideas whose significance was first understood in the 1970s [46]. The utility company uses DLC software to remotely control how much energy is used at home and how some appliances work. DLC programs are frequently used in thermal comfort equipment like heating, ventilation, and air conditioning (HVAC), freezers, pumps, and light control. When it comes to home automation and residential load control in particular, user comfort is a top consideration and is considered as a barrier to DLC program implementation [47].

High-power appliances should be transferred from peak to off-peak hours in addition to implementing this helpful measure in order to successfully lower the peak-to-average ratio (PAR) in load demand. As plug-in hybrid electric vehicles grow more common, load shifting is predicted to become even more important (PHEVs). For every mile of driving, PHEVs typically require between 0.2 and 0.3 kWh of electricity for charging [48]. The new load on the current distribution system is significantly increased as a result. It more than doubles the normal household demand, especially during charging hours, making the already high PAR worse.In the absence of property reinforcement systems, high penetration of PHEVs can lead to an unbalanced condition that compromises power quality requirements, causes problems with voltage management, and even poses a risk of damaging consumer and utility equipment. DLC program features are no longer used because of dynamic pricing. Users are encouraged via a dynamic pricing structure to control their loads voluntarily, such as shutting down and moving large loads from peak to off-peak hours [49]. Critical-peak pricing (CPP), real-time pricing (RTP), inclination block rate (IBR), time of use pricing (ToUP), and day-ahead pricing are among the most popular and often used dynamic pricing techniques (DAP). These programs encourage users to move their appliances from peak to off-peak hours. As a result, consumer expenses are cut, and the PAR is decreased [50]. In contrast, in response to a pricing signal load scheduling takes the place. For developing a smart grid, having energy efficiency on the supply and demand sides has been made [51].

2.2.1 Applications of heuristic algorithms

Numerous state-of-the-art algorithms have recently been created and implemented in SG by researchers. These algorithms were successful in analyzing the load consumption characteristics of industrial, commercial, and residential structures. In order to lower energy expenditures for utility companies and users, research has concentrated on optimizing energy controllers and schedulers. The supply-demand ratio must be balanced, and consumer expenses must be kept to a bare minimum. To optimize the value for all parties involved, these algorithms take into account a variety of factors, such as appliance ratings, pricing strategies, energy company priorities, and consumer demand. [45] offers a strategy for scheduling energy use in the residential sector based on game theory. Using a distributed algorithm-based optimization, Mohsenian-Rad A. et al. conducted their study. Energy consumption scheduling is comprehensively covered from a variety of unique but connected angles (ECS). To create a pricing system, the convex and growing cost optimization functions are applied. The suggested tactic is viewed as a model for DSM tactics. As a replacement mechanism, the Vickrey-Clarke-Grove (VCG) method, which was put out in [52], is used.

By offering incentives, the proposed VCG strategy persuades customers to switch their load from peak to off-peak hours. The advancement of social welfare and a flattening of the average load shape curve lead to an increase in utility. For a DSM model to be successful, it must use effective pricing techniques. When participating in demand response programs, the price predictor and energy scheduler in HEMS work together. To reduce energy use, the authors developed a comprehensive mathematical model with price prediction capabilities. An experimental setup is used to demonstrate how a little adjustment to unrelated but related performance variables might affect consumption patterns to optimum efficiency. In HEMS, a device's waiting time and its programmable or adaptable control parameters are negatively connected. The authors' suggested paradigm disregards justice despite delivering very strong performance results. In [54] discusses the demand for a heuristic-based optimization model in DSM and the planning of home appliances using evolutionary algorithms (EA). To address the optimization issue, an unique pricing strategy termed day-ahead load shifting price is suggested. Residential, commercial, and industrial end users are all considered while getting the simulation findings. Their top aim was to establish a mechanism that would connect consumer satisfaction or delay to appliance waiting time. The researchers' findings on a reduction in PAR and a reduction in overall energy costs were comparable. The suggested paradigm's difficulties in maintaining fairness and interoperability among smart appliances, however, was a significant drawback.Users in energy management programs are devoted to managing their energy use strategically and effectively.To schedule smart home equipment, refer to RTP [55].The authors' main focus was on reducing the cost of energy in HEMS by eliminating unconventional power use and optimizing the advantages of energy storage systems. The proposed strategy reduced both the total cost and the peak price by 22.6 and 11.7 percent, respectively, in comparison to the conventional pricing structure. They underutilized optimization strategies, which was a significant fault in their study. The suggested DSM architecture addresses difficulties with robustness and scalability by storing energy during off-peak times and utilising it during peak times to keep costs down. An optimal scheduling model based on linear programming was used to reach the authors' subpar results.

According to the author [56], the non-deterministic polynomial (NP) optimal scheduling model is based on time-hardness. The authors use greedy iterative algorithms to achieve their goal of home scheduling.They use techniques from linear programming and artificial intelligence to optimize their work. The traits of lesser peak fluctuation and reduced peak load are also discussed. The formulation of the problem is based on both the consumer's load demand and the cost of generation. References [57] offer an algorithm for fascinatingly scheduling home appliances that is based on mixed-integer linear programming.

Home appliances are scheduled using the real price tariff to save money and lower peak demand. The proposed approach is examined in [58] using a variety of user types. Commercial, industrial, and residential customers are grouped together. It is feasible to draw the conclusion that the suggested algorithm greatly lowers PAR and electricity costs based on the simulation findings. In references [59], the GA-based cost minimization approach is applied. A controller is created to monitor the charging and discharging thresholds particular to the battery bank in order to lengthen battery life and efficiency. Additionally, while electricity is cheap, batteries need to be fully charged. When costs grow, several high-priority appliances are powered by batteries to help consumers save money. It's important to remember that the focus of all earlier studies was on end users with a steady load curve. But while creating a pricing strategy, load unpredictability must be heavily considered [52]. The energy usage profile of the consumer must be used by the DSM model to determine the consumer's load curve. Real-time pricing and inclining block rates must be combined in order to achieve an effective balance. The authors present a multi-stage model that details appliance usage over various time spans. The development of an objective function takes into account the consumption-based classification of appliance load in order to achieve optimization-based scheduling. With regard to the charging system and load synchronization avoidance, their proposed approach outperformed numerous state-of-the-art models, yielding excellent results. The experimental findings point to a decrease in energy expenditures, a total PAR increase, and a successful implementation of fairness.

The suggested approach, however, does not take a crucial feature of HEMS appliance waiting times into account. Fairness and optimality are two of the most potent and related concepts, claim academics [60]. They offered it as a pricing scheme replacement for the work proposed in [62] by merging RTP with an hour-by-hour invoicing system. An optimization problem based on game theory was made to reduce the overall energy cost and PAR to have the outcomes. The proposed method demonstrated a 73 percent increase in fairness efficiency when optimality and fairness were inversely related and residential consumers were taken into account.

Customers were enticed to engage in DR programs and plan their loads in accordance with the utility's price signal by Mohsenian et al[62] .'s use of an incentives-based methodology. Short-term load and price prediction techniques will be challenging to deploy for the majority of utility firms. To improve load control, the energy consumption scheduler must simultaneously forecast the actual price while taking the environment for electricity pricing into account. According to the authors of Ref [63], a three-layered, autonomous DSM architecture with an iteration flow mechanism between layers is preferred.A demand response (DR) manager, a load forecaster, an admission controller, and a load balancer are the three layers that make up the suggested model.Once the user had made a choice and asked that operation begin, various loads were grouped according to their energy consumption characteristics. The AC's job is to assess if there is enough power to switch on a device while taking the entire load limit into account. The AC will permit the appliance to run if both the power peak limit and are reached.

2.3 Electricity load forecasting

In the 1960s, it became clear that accurate short-term load forecasting (STLF) techniques were required, and one of the earliest in-depth investigations on STLF was completed in 1966 by Heinman et al. [64].Regression analysis was used by the authors to look into the connection between summertime energy use and temperature. Since then, several additional strategies and techniques for STLF have been put forth, with varied degrees of success. Classical stastical methods and AI methods make up the two categories of STLF approaches.

2.3.1 Stastical Models

The load pattern is recognized utilizing static methods, and applied the time series analysis method to forecast the value of the data based on the identified pattern. The independent variable's coefficients in the hypothetical model are then determined using regression analysis. As an illustration, in [66], the authors used a multivariate linear regression model with hourly temperature data as independent variables to predict the electric load for Sulawesi Island, Indonesia, up to 24 hours in advance. On the other hand, by linking previous observations, time series models provide accurate forecasts. Using the auto-regressive integrated moving average is a common time series model (ARIMA). These models have demonstrated good performance metrics using Jenkins and Box techniques. Fard et altechnique, .'s which is based on ARIMA, was suggested [68] to capture the linear component of the load time series. Prediction accuracy is unstable, though, because there are many outliers, computing results is challenging, and models need to be created from scratch.

2.3.2 Arthificial Inteligence and Machine Learning

Starting from 1990s, numerous studies on Artificial Inteligence algorithms as prediction tools have been conducted. In AI, neural networks are a common technique (NNs). Artificial neural networks (ANNs) base their predictions on the presumption that past data and outside variables have a nonlinear connection. The NNs prediction models are frequently employed in a number of applications because they yield good prediction results. However, NNs have a number of drawbacks, such as over-fitting, estimating connection weight, model development, and relying on a large amount of data for model training. Utilizing NNs in STLF scenarios is difficult as a result of these considerations [69]. Turkey et al. [70] presented support vector machines (SVM) and support vector regressors (SVR) in 1995 as a cutting-edge AI technique to solve the shortcomings of NNs. STLF research, which largely focuses on selection or classification strategies, is particularly interested in decision tree (DT) algorithms and ANNs [71].

Both approaches have drawbacks. For instance, DT suffers from overfitting difficulties, which results in strong model performance during training but poor performance during prediction. Similar to this, ANN models have poor control over convergence and stability as well as poor generalization and uncertainty handling capabilities. Additionally, the performance evaluation criterion is only based on a small quantity of price and load data, and the learning-based model ignores the idiosyncrasies of vast data. Forecasting accuracy must be further improved by accounting for the characteristics of big data.

2.4 Detection of electricity theft (Non-Technical)

This part examines the most recent findings on the topics brought up as well as the significance of current study. The use of the classifier begins with feature pre-processing. Researchers combined decision DT and SVM algorithms in a study [72] to more effectively detect electricity theft. Despite promising results, the problem of missing data was not addressed in either study. In their extensive review of 34 supervised ML-based research articles on ETD, the authors [73] found that only half of the studies taken into consideration addressed the problem of missing data values. Maddilina et al. employed SVM and the XGBoost boosting classifier. In [74] to identify abnormalities in consumer purchasing trends. Consumers are assessed according to their load profiles while analyzing data from smart meters, and crucial factors are derived from auxiliary data. The SVM used the boosting technique to enhance training and performance by applying the empirical risk minimization principle.The absence of numerous outliers in the primary data can make classification accuracy unstable, and the authors neglected to take data preparation methods into account. Data class unbalancing is a significant problem with labelled data sets from smart meters used in ETD applications. Due to the bias issue, minority samples (theft cases), which are key to identifying, frequently get undetected. The ML model will pick up on important traits and ideas peculiar to the majority class. A balanced sample representation is essential for efficient and objective ML model performance. In a deep learning (DL) model to accurately detect electricity theft, Paulo et al. [75] made notable use of convolutional neural networks (CNNs). The final output of the CNN obtained from a fully linked layer, however, considerably hinders model generalization. To solve this issue, the authors of [76] applied a random forest (RF) method to acquire the classification task results. Synthetic minority oversampling technique (SMOTE) was used in their study to solve the imbalanced class problem [77]. The strategy that was given resolved the problem with model generalization, although using synthetic data in SMOTE can lead to overfitting issues. When a model over fits, it performs poorly on training or observed data but better on test or unseen data. After the data has been properly preprocessed, a classifier that can distinguish between clients who are being honest and dishonest can be chosen. Machine learning and time-series models can both be used to perform ETD. Smart meter data can be used to distinguish between typical and aberrant patterns and footprints of power consumption, with irregular patterns being longer and more intense than normal patterns. The machine learning algorithm is gradually trained to understand how input features (consumption) and related labels relate to one another using supervised learning as a foundation (field inspection results).

In order to observe normal and abnormal power consumption, the study presented in [78, 79] used supervised machine learning. These methods don't need specialized equipment or an understanding of network topology and have low computing costs because they employ pre-generated data. The limitations of existing classification-based algorithms include a high falsepositive rate (FPR), the need for time-consuming expert input, and a slow rate of adaptation to new types of electrical fraud [80]. Because of the importance of boosting and deep learning (DL) techniques, a small but growing body of research [81-84] has successfully implemented NTL detection in smart grids with the SGCC (State Grid Cooperation of China) dataset. The proposed model's area under the curve (AUC) scores were positive in 92% of cases. However, increasing the accuracy of boosting algorithms is extremely difficult because each estimate in the techniques must rectify the inaccuracy of the predecessors.This is a result of the large number of outliers, noise, and sparse data. [82] used an LSTM model with a CNN architecture for ETD. The proposed hybrid model uses LSTM to solve a classification issue and CNN to automate the feature extraction procedure. In order to prevent class disparity, the authors also used the synthetic minority oversampling approach (SMOTE). This results in incorrect prediction model outputs for unobserved/test data, leading to generalization and overfitting issues. One significant problem is that CNN and MLP networks are incapable of analyzing large amounts of time series data. Because the input is limited to a fixed-size window, the prediction model is unable to detect a drop in the EC data that occurred prior to the analysis period. [84] employed a deep siamese network to discern between dishonest and honest clients using EC data (DSN). Two drawbacks were sacrificed in order to get decent prediction results in the proposed model when compared to previous successful DL approaches [85].

First of all, since DSNs learn in quadratic pairs, training takes some time. Second, because paired learning is incorporated into the DSN output, it is not generalizable and is sensitive to some input variables [86]. Electrical theft is frequently detected using time-series data analysis techniques, and in secure power markets, statistical techniques like autoregressive moving average (ARIMA) have been successful. In order to account for changes in probability distributions generated by various clients, Singhet al. [87] established the idea of relative entropy. Similarly, Joker et al. [88] projected that with enhanced metering infrastructure, normal and abnormal consumption patterns will be predictable by using energy consumption patterns as the foundation of a recognition system (AMI). Statistical techniques, on the other hand, can be particularly useful for ETD since they allow the capture of partial nonstationary data in SM data.The classification accuracy of the model may vary because discrete outliers are present and raw data were used in its creation. To connect to the phenomena of energy theft, it is vital to distinguish the outliers from the norm and to emphasize the characteristics of typical energy consumers. Several families in small towns should have their energy usage statistics combined, Jindal et al. [72] stated in a recent article. The authors first trained an SVM classifier on a range of features using a decision tree to anticipate the value of home energy usage in order to find consumers with atypical consumption habits. In order to study the correlations between socioeconomic indices and losses for energy theft detection in various circumstances, Pulz et al. [89] constructed social indicators using census data. Aggregated data-based techniques have their uses. Prior research, which has mostly concentrated on classifier construction or feature engineering algorithms, has used traditional classifiers like SVM and decision trees (DT) extensively [90, 91]. SVM must be employed to improve classification outcomes, but doing so is difficult and costly computationally. Although DT does well during training (on known data), overfitting issues prevent it from doing well during prediction (on unknown data) [92].The experiments are only applicable to loads or prices with insufficiently large data, and present machine and deep learning algorithms rarely take into consideration vast amounts of data. Therefore, by using large data, theft detection precision might still be raised.

2.5 Summary of Literature Review

The challenges and important topics pertaining to OPF, DSM, ELF, and NTL are covered in this chapter. The traditional OPF is a very non-linear, non-convex optimization problem because of non-linear constraints. Because of its swift convergence and durability, the literature proposes employing interior-point approaches,quadratic programming, mixed integer linear programming, non-linear programming, and mixed integer linear programming to resolve OPF difficulties. However, such optimization approachs linearize first the optimization function, which affects the non-convex, non-smooth and non-differntiable features of the optimization.To increase the efficiency of the search techniques in the context of OPF, a variety of customized heuristic methods have been suggested. A review of clever energy management techniques is provided, together with the benefits and drawbacks of the offered procedures. Because there is a fluctuating and diverse demand for power, the grid user uses Demand Side Management (DSM) techniques to alter the load profile and reduce total end-user costs. This chapter also includes recent research on demand response and requirement management techniques.All DSM methods to date have been successful in shifting load from peak to off-peak times. In-home energy management systems optimize the objective demand profile by using algorithms for scheduling household appliances in response to the utility pricing signal. Either a more direct approach that considers the requirements of all user types should be created, or end-user participation in DR operations should be given priority. One of the most important challenges the current system faces is preserving the stability of the power network as the penetration of distributed energy resources rises. The majority of recent literature is devoted to classifier design. Recent advancements in communication technologies have increased the demand for bigdata based load and price forecasting models for the smart grid. It is challenging to correct the demand-supply imbalance.

CHAPTER THREE

MATHEMATICAL MODELS FOR SMART GRID

3.1. Introduction

With the help of smart meters and other smart tools, smart grids enable two-way communication between the consumer and the power supplier. These intelligent tools ensure that communication between the producer and the consumer is quick and secure. Given the benefits of smart grids, it has been observed that demand for them has increased. Changes in the supply-demand balance have recently occurred as a result of technological studies. The demand for fast and dependable service has also manifested itself in grid applications. In this section, division of two different cases for the design of smart energy home systems using a mathematical model and a PV system. The tools used in these models differ from those used in non-smart energy home systems; using the mathematical model will be developed, and attempted to shift the adjustable household appliances from times when electricity prices were high to times when they were low. Furthermore, aimed to benefit from solar energy, reduce energy costs, and use the energy storage system to store the energy obtained from the sun for later use to power household appliances.

3.2. Design Parameters

The mathematical model has been done by considering all the needs and demands, especially for HEMS. As can be seen in the explanations were given in detail in the following section, the developed a mathematical model with applicable, changeable parameters as a result of the thesis.

$P_a(h)$ how much power an appliance consumes each time interval

p_{ij}^{k} energy assihned to energy phase (j)of appliance (i) during the whole period of time slot (k).

E_{ij} energy requirement for energy phase (j) for appliance (i).

B_a working hours array of an appliance a day.

$B_a(h)$ working or not each time interval.

$B_a l$ number of ones there are in $B_a(h)$

$E_a(h)$ how much energy an appliance consumes each time interval

$E_{SI}(h)$ total energy consumption of shiftable and interruptible appliances each time interval.

$E_{SNI}(h)$ total energy consumption of shiftable and non-interruptible appliances each time interval.

$E_R(h)$ total energy consumption of regular appliances each time interval.

$E_{final}(h)$ total energy consumption of all appliances of home each time interval.

$S_n(h)$ solar power generation capacity.

$E_{solar}(h)$ energy generated by photovoltaic cell each time interval.

$E_{battery}(h)$ stored energy in battery each time interval.

$E_{grid}(h)$ total energy consumed from grid.

$E_{gridmax}(h)$ maximum energy capacity of time slot (h).

$E_{load}(h)$ total energy consumed by user in each time interval.

$E_{battery}^{Cap}$ battery capacity or total energy in battery

$C_a(h)$ how much money an appliance makes each time interval.

CSI cost of shiftable and interruptible appliance.

CSNI cost of shiftable and non-interruptible appliances.

CR cost of regular appliances.

M array of average sunbathing time in hours.

S_p array of different cells with different power capacities (kW)

n- number of solar panels.

T_{app} how many hours an appliance works.

$P_{battery}$ power supplied by the battery.

P_{solar} power produced by solar panels.

P_{invAC} power on the inverter's AC bus.

$\mu dc2ac$ performance of inverter.

P_{grid} power supplied from the grid.

P_{loads} power consumed by appliances.

SOC_{gel} state of charge for Gel Battery

SOC_{li} state of charge for Li-Ion battery.

SOC_{pb} state of charge for lead acid battery.

f_{diss} total dissatisfaction level caused by all appliances.

f_{diss}^{SI} dissatisfaction level caused by shiftable and interruptable devices.

f_{diss}^{SNI} dissatisfaction level caused by shiftable and non-interruptible devices.

$S_a(h)$ score evaluating the dissatisfaction level caused by operating shiftable appliance "a" at time slot "h" (0-5)

Pr_a user preference array for ath appliance.

(Final) scalar multiplication array of user preference array and "working hours of an appliance'

β_{ch} battery charge efficiency.

β_{dch} batter's discharge efficiency.

$P_{battery}^{ch}(h)$ battery charging power.

$P_{battery}^{dch}(h)$ battery discharge power.

$P_{ch,min}$ minimum battery charging power,

$P_{ch,max}$ maximum battery charging ower.

$P_{dch,min}$ minimum battery discharge power.

$P_{dch,max}$ maximum battery discharging power.

3.3. Mathematical Models Utility

In the first case, aimed to shift the electricity consumed by users from times when electricity demand is high, i.e. when electricity prices are high, to times when electricity demand is low, i.e. when electricity prices are low. It is intended to use the proposed mathematical model to operate the adjustable household appliances in accordance with the three-time electricity tariff. As a result, it has been studied how to reduce the cost that will be reflected on the electricity bill [4].

Types of appliances will be categorized

- Shiftable and Interruptible (SI)
- Shiftable and Uninterruptible (SNI)
- Regular Appliances (R)

3.3.1. Mathematical Models of Load Shifting, Minimization of Dissatisfaction

The objective function:

$$\begin{aligned} &Min\,\mathrm{Cos}\,t = Min[CSI + CSNI + CR] = \min \sum_{h=0}^{23} (E_{final}(h)c(h) \\ &\min f_{diss} = \min(f_{diss}^{SI} + f_{diss}^{SNI} \end{aligned} \tag{3.1}$$

The constraints:

Electrical demand –supply balance

Considering load shifting,

$$E_{final}(h) \le E_{grid}(h) \quad \text{(Load always met by the grid)} \tag{3.2}$$

$$E_{final}(h) = E_{SI}(h) + E_{SNI}(h) + E_R(h) \tag{3.3}$$

$$CSI = \sum_{h=0}^{23} E_{SI}(h)xc(h) \tag{3.4}$$

$$CSNI = \sum_{h=0}^{23} E_{SNI}(h)xc(h) \tag{3.5}$$

$$CR = \sum_{h=0}^{23} E_R(h)xc(h) \tag{3.6}$$

$$E_{SI}(h) = \sum_{a=1}^{a=a\max} (P_a(h)xB_a(h)) \tag{3.7}$$

$$E_{SNI}(h) = \sum_{a=1}^{a=a\max} (P_a(h)xB_a(h) \tag{3.8}$$

$$E_R = \sum_{a=1}^{a=a\max} (P_a(h)xB_a(h) \tag{3.9}$$

$$E_{load}(h) = E_{final}(h) \quad \text{(Illegal electric usage)} \tag{3.10}$$

Grid constraints

$$0 \le E_{grid}(h) < E_{grid\max}(h) \quad \text{(Supplied energy amount)} \tag{3.11}$$

$$0 \le \sum_{a}^{allappliances} E_a(h)xB_a(h) \le E_{grid\max}(h) \quad \text{(Supplied energy amount)} \tag{3.12}$$

$$ceil(T_{app}) = Bal \tag{3.13}$$

Phase wise energy requirement of appliances,
Appliance operation cycle energy:

$$\sum\nolimits_{k=1}^{m} p_{ij}^{k} = E_{ij}, \forall i, j \tag{3.14}$$

Power safety
Total required energy:

$$\sum\nolimits_{h=0}^{23} E_{final}(h) \le E_{grid,\max}(h) \tag{3.15}$$

User dissatisfaction:
Here the aim is to minimize the dissatisfaction level of the users caused by shifting the devices.

$$f_{diss} = f_{diss}^{SI} + f_{diss}^{SNI} \tag{3.16}$$

Where f_{diss}^{SI} represents the dissatisfaction level caused by shiftable –interruptible devices and f_{diss}^{SNI} the dissatisfaction level caused by shiftable-uninterruptible devices

$$f_{diss}^{SI} = \sum_{a=1}^{tota1ofSIdevices} \sum_{h=1}^{h=24} S_a(h)xB_a(h) \tag{3.17}$$

$$f_{diss}^{SNI} = \sum_{a=1}^{tota1ofSNIdevice} \sum_{h=1}^{h=24} S_a(h)xB_a(h) \tag{3.18}$$

Appliances work or not

$B_a(h) = [b_a^1, b_a^2, ...b_a^{24}]$ Every shiftable appliance has this binary array.

$B_a(h)$ if the appliance works 1, if not 0 between (0AM -1AM)

Dissatisfaction score

$S_a(h)$ This is a score evaluating the dissatisfaction level caused by operating shiftable appliance “a” at time slot “h”, which is determined by customers according to their living arrangements.

$S_a(h)$ Ranges from 0 to 5 (integer values). A large value of $S_a(h)$ means a higher dissatisfaction level [5].
In summary, the objective function of this mathematical model equation (3.16) is to minimize the summation of the two equations that lie above (3.17) and (3.18).

$$\Pr_a xB_a = Final \quad \text{(User preference arrayed)} \tag{3.19}$$

3.4. Mathematical Models of Utility, PV Panels and Storage (Battery)

3.4.1. Solar Package System

In today's world, the term "prosumer" refers to a consumer who is also a producer. In other words, each consumer who consumes electricity can generate its own energy by incorporating photovoltaic (PV) cells and so on. Furthermore, the electricity generated by PV panels can be stored in batteries and used at convenient time intervals to reduce the day's electricity bill. The primary goal of the second case is to reduce the daily cost of electricity by utilizing PV panels and their corresponding solar batteries. We dubbed the system, which consisted of PV panels and a solar battery, a "solar package system." To actualize the second case, there will be some models and concepts. The mathematical model of the system will be the same to the model described in section 3.2 by considering appliance operation cycle energy will be given by:

$$\sum_{k=1}^{m} p_{ij}^{k} = E_{ij}, \forall i, j 3.21 \tag{3.20}$$

To begin with, it is well understood that a PV panel requires solar energy to convert it into electrical energy; thus, the sunbathing time of a solar cell is critical. Knowing that an array is made up of 12 elements that represent the daily solar power capability for the entire year. The daily average of sunbathing time in hours is used to calculate the solar power capability index.

$$\begin{aligned} &M_{1x12} = [2.4, 3.2, 4.4.6.1, 8.3.10.2, 10.9, 10.1, 8.1.5.5, 3.6, 2.5] \\ &hours(average)(country) \end{aligned} \tag{3.21}$$

For example, the m1 value is the daily average of sunbath hours in January. As a result, m1 = 2.4 hours denotes the daily average of Ethiopia's sunbath in January. Following that, solar cell manufacturers create various cells with varying power capacities. As a result, the power generation capacity of various PV cells must be expressed using the following array:

$S_{p4x1} = [0.3, 0.5, 1, 2]$ kilo-watts (different panels)

The energy produced by the solar cell can be modelled using the energy-power equation as follows assuming the same types of panels are used in terms of efficiency:

Energy (kWh) = Number of Panels (n units) x Solar Panel Power (kilo-watts) x Time (hours)

$$(E_{solar})_{4x12} = nx(S_p)_{4x1}x(M)_{1x12}$$

For instance, let the number of panels be 4. Then, the energy matrix produced by these panels can be calculated as:

$(E_{solar})_{4x12} = 4x[0.3, 0.5, 1, 2]x[2.4, 3.2, 4.4, 6.1, 8.3, 10.2, 10.9, 10.1, 8.1, 5.5, 3.6, 2.5]$

$(E_{solar})_{4x12} =$

Table 3.1 Energy matrix produced by panels

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
1	2.88	3.84	5.28	7.32	9.96	12.24	13.08	12.12	9.72	6.6	4.32	3
2	4.8	6.4	8.8	12.2	16.6	20.4	21.8	20.2	16.2	11	7.2	5
3	9.6	12.8	17.6	24.4	33.2	40.8	43.6	40.4	32.4	22	14.4	10
4	19.2	25.6	35.2	48.8	66.4	81.6	87.2	80.8	64.8	44	28.8	20

In the matrix given above each row represents the energy production using the related solar panel(s) in the Sp vector. For example, the first row shows us the monthly energy production of 4 units of 0.3-kilo-watt solar panels and so on. Then, we can summarize the PV model as:

$$PV\ \mathrm{mod}el : (E_{solar})_{ixj} = nx(S_p)_{ix1}x(M)_{1xj} \tag{3.22}$$

The authorized power limit of solar panels in Turkey is limited to 10 kW power per apartment. Thereby, this constraint can be shown as:

Solar panels authorized power limit $n.S_{p_{ix1}} \leq 10kW$

As mentioned above, the solar system is a package of PV panels, solar battery and maybe an AC inverter. As a result of this, the solar energy provided by PV panels cannot exceed its corresponding solar battery capacity.

$0 \leq E_{solar}(h) \leq E_{battery}(h)$ (Battery capacity solar energy matching)

Solar Battery Storage

Every solar battery has a charge capacity that restrains the maximum storage from PV cell energy.

$$\text{Battery capacity: } SOC(h) = \frac{E^{h}_{battery}}{E^{cap}_{battery}} \tag{3.23}$$

In case of overcharging and undercharging, the lifespan of the batteries decreases. Therefore, in this research, the authors avoided overcharging and undercharging by keeping the energy stored in the battery within a certain range. The interval values determined in equation in (3.24).

$$\text{Battery level: } \begin{array}{l} \%40 \le SOC_{pb}(h) \le \%75 \\ \%40 \le SOC_{gel}(h) \le \%75 \\ \%20 \le SOC_{li}(h) \le \%80 \end{array} \tag{3.24}$$

These values Eqn (3.25) and (3.26) were adjusted based on the appliances that are constantly in use at home. The refrigerator and deep freezer, which are constantly used, have been used to calculate the lowest power value that should be in the batteries. The highest value was calculated by taking into account the power consumed by most household appliances when they are in use [7].

Battery maximum Charging power limit:

$$P_{ch,\min} = 0.04kW < P^{ch}_{battery}(h) / B_{ch} < 0.35kW = P_{ch,\max} \tag{3.25}$$

Battery maximum discharging power limit:

$$P_{dch,\min} = 0.04kW < P^{ch}_{battery}(h).B_{dch} < 0.35kW = P_{dch,\max} \tag{3.26}$$

If it is assumed that the "solar package system" (solar panels, solar battery, AC inverter) includes an inverter, the calculation must be performed.

Battery with AC inverter

$$P_{invAC} = P_{invDC} x \mu_{ac2dc} \quad \text{(Power lost in inverter when energy moving battery to loads)} \tag{3.27}$$

$$P_{battery} + P_{solar} + P_{invDc} = 0 \quad \text{(In case of inverter power loss)} \tag{3.28}$$

3.5. Load Optimization and Scheduling

As previously stated in section 3.4, prosumers generate electricity while consuming it. Many of them would rather store extra energy in solar battery storage systems. Solar photovoltaic panel systems are made up of photovoltaic panels, solar charge controllers, and batteries. These solar batteries are an important part of renewable energy systems. To be connected to the electricity grid, solar batteries require energy storage produced by a wind turbine, solar panel, or hydroelectric system. Solar batteries are extremely useful if you want to use a separate power grid or if there is a power outage.

Figure 3.1 HEMS with PV Cell and Storage [7]

The general structure of HEMS with photovoltaic cells and a battery is depicted in Figure 3.1. In this system, PV cells charge the batteries which store electrical energy to use later. When prices are high and the house does not require electricity, it will be able to supply electricity from the battery to the grid. The use of pre-generated electricity at intervals when the cost of electricity is higher than at other intervals reduces bills more efficiently. As a result, in our model, PV panels charge the batteries, and the stored energy ($E_{battery}$) is used at high-cost intervals.

As previously stated, the goal function here is to minimize energy consumption from the grid (E_{grid}) and electricity dependency.

$$E_{grid} = \left\{ \begin{array}{l} E_{load} - E_{battery}, E_{battery} > 0kWh\, and\, E_{grid} > 0kWh\, and\, h_{22} \geq h \geq h_{17} \\ E_{load}, E_{grid} > 0kWh\, and \left(E_{battery} = 0kWh\, or h_{17(nextday)} > h > h_{22} \right) \\ 0, E_{battery} > 0kWh\, and\, E_{grid} = 0kWh \end{array} \right\} \tag{3.29}$$

User Dissatisfaction:

The goal here is to reduce the level of dissatisfaction among users caused by device switching.

$$f_{diss} = f_{diss}^{SI} + f_{diss}^{SNI} \tag{3.30}$$

Where f_{diss}^{SI} represents the dissatisfaction level caused by shiftable-interruptible devices and f_{diss}^{SNI} represents the dissatisfaction level caused by shiftable-uninterruptible devices.

$$f_{diss}^{SI} = \sum_{a=1}^{total\ \#of\ SI\ devices} \sum_{h=1}^{h=24} S_a\left(h\right) x B_a\left(h\right) \tag{3.31}$$

$$f_{diss}^{SNI} = \sum_{a=1}^{total\ \#of\ SNI\ devices} \sum_{h=1}^{h=24} S_a\left(h\right) x B_a\left(h\right) \tag{3.32}$$

Appliances work or not

$B_a(h) = [b_a^1, b_a^2, ...b_a^{24}]$ Every shiftable appliance has this binary array.

$B_a(h)$ = if the appliance works 1, if not 0 between (0 AM - 1 AM)

Dissatisfaction score

$S_a(h)$ = This is a score evaluating the dissatisfaction level caused by operating shiftable appliance “a” at time slot “h”, which is determined by customers according to their living arrangements.

$S_a(h)$ = Ranges from 0 to 5 (integer values). A large value of $S_a(h)$ means a higher dissatisfaction level [5].

In summary, the objective function of this mathematical model eqn. (3.33) is to minimize the summation of the two equations that lies above (3.31) and (3.32).

$$\mathrm{Pr}_a * B_a = Final \quad \text{(User preference arrayed).} \tag{3.33}$$

CHAPTER FOUR

CONTROLLER DESIGN

4.1 Smart Grid Optimization

Optimization of the smart grid is designing the optimal micro grid with minimum social and economic impact. To design a smart grid with minimum cost and highly efficiency the concentration should be focused on determining the size of the system components with an intelligent energy management system. The combination of generation sources and using high-quality components also has a considerable influence on the life time of the system. And can decrease the cost of electricity for end-users in rural areas.

4.1.1 Mathematical problem formulation

The mathematical problem formulation smart grid optimization with the objective function of cost minimization can be expressed as:

$$\min f(x) = \sum_{t=1}^{T} (Ft + oMdg + TCPDbesb) \tag{4.1}$$

$$Ft = \sum_{t=1}^{T} (\cos td.t + \mathrm{Cos}\, tbest.t) \tag{4.2}$$

$$\mathrm{Cos}\, tdg.t = cstPV, tBPV, t + \cos tPWT, tBWT, t \tag{4.3}$$

$$OMdg = (OMPV + OMWT)XT \tag{4.4}$$

The cost of the smart grid is the entire cost of all grid components, which includes the daily operating costs for the storage batteries, wind turbines, solar PV, and storage batteries. The one-time initial fixed cost (Fcbes) and total annual maintenance cost (Mcbes) of the battery, both of which are proportional to the size of the battery, determine the price of the battery. The cost of the storage battery can be stated as follows when the battery size is at its maximum.

$$\mathrm{Cos}\, tbes = (Fcbes + Mcbes) * Cbes \tag{4.5}$$

This study's operational time is assumed to be within 24 hours. In this study, TCPD is calculated by taking into account the interest rate (IR) of the financing installation and the lifetime (LT) of the BES, as shown below.

4.1.2 Constraints

The optimization of the micro grid is primarily intended to reduce the cost of electricity; however, the reduction of the micro grid's operational costs is subject to different constraints.

- Balance electrical load requirements

The electrical power generated by the micro grid components, which include solar power, wind power, and electrical power injected from energy storage batteries, should be equal to and satisfy the required demand. This is expressed mathematically as [41].

$$pPV + pWT + pBes = Pd \tag{4.6}$$

- Renewable energy's boundaries

Because of their weather dependence, solar power and wind power are two renewable energy resources considered in this study. As a result, each unit should have its own maximum and minimum power generation boundaries.

$$pPVmim, t \leq pPV \leq pPV\,\mathrm{max}, t = 1..........T \tag{4.7}$$

$$tpWTmim, t \leq pWT \leq pWT\,\mathrm{max}, t = 1........T \tag{4.8}$$

- Battery constraints in energy storage

Because of their advantages over other batteries, lithium batteries were chosen for this study. The battery constraints are classified as charging and discharging constraints.

Charging mode

$$\begin{aligned}
&Cbes,t+1 = \min\left\{Cbes,t-\Delta tPbes,t\eta c, Cbes\min\right\}\\
&Pbes,\min \le Pbes,t \le Pbes,\max\\
&Pbes,t\max = \min(Pbes,\max,\frac{(Cbes,t-Cbes,\min)\eta d}{\Delta t}\\
&Pbes,t\min = \min(Pbes,\max,\frac{Cbes,t-CBEs,\min)\eta d}{\Delta t}
\end{aligned} \tag{4.9}$$

Discharge mode

$$\begin{aligned}
&Cbes,t+1 = \max(\frac{(Cbes,t-\Delta tPbes,t)}{\eta d}), Cbes,\min\\
&Pbes,\min \le Pbes,t \le Pbes,\max, t = 1,2,3......T
\end{aligned} \tag{4.10}$$

The equations above are used to express the boundaries of energy storage batteries. The proposed energy storage batteries should then meet the required demand under the aforementioned constraints.

Constraints on Operating Reserve (OR)

The generation capacity available to the system operator within a short time interval to meet demand in the event that a generator fails or there is another disruption in supply is referred to as the operating reserve in electricity. Most power systems are designed so that the operating reserve is always at least the capacity of the largest supplier plus a fraction of the peak load under normal conditions. An idealized representation of the four types of reserve power and the time intervals in which they are used following an unexpected failure. The non-spinning or supplemental reserve and the spinning reserve both make up the operating reserve. By raising the power output of already-connected generators, extra generating capacity known as the spinning reserve is made possible. The majority of generators accomplish this increase in output power by increasing the torque supplied to the turbine's rotor. The supplemental reserve, sometimes referred to as the non-spinning reserve, is an additional generating capacity that is not immediately linked to the system but can be swiftly brought online.

This typically equates to the power available from fast-start generators in isolated power systems. However, in interconnected power systems, this may include power that can be made available quickly by importing power from other systems or retracting power that is currently being exported to other systems. Generators designed to provide both spinning and non-spinning reserve should be able to reach their promised capacity in less than ten minutes. Most power system guidelines require that a significant portion of operating reserve come from the spinning reserve. This is due to the spinning reserve generator being slightly more reliable (it does not have start-up issues and can respond immediately, whereas non-spinning reserve generators have a delay as the generator starts-up offline). Excess energy from power demand is generated by electrical power generation from renewable energy resources. The energy storage battery is reserved for power. The reserved power can then be pumped into the micro grid system in less than a minute by turning on the energy storage system, and when the national grid becomes available, the utility grid is turned on. This can be expressed mathematically as follows.

$$P_{pv,t}+P_{WT,t}+P_{BES,t}=P_{Demand,t}+OR,t,t=1,2,3,4,,,,,T \tag{4.11}$$

When the utility is once available then the

$$P_{PV,t}+P_{WT,t}+P_{BES,t}+P_{grid,t}=P_{demand,t}+OR,t,t=1,2,3,4,5,,,,,T \tag{4.12}$$

When OR,t is 5 minute.

4.1.3 Grey wolf optimizer (GWO)

The Grey Wolf Optimizer (GWO) is a powerful meta-heuristic algorithm. As a newly developed algorithm, it can compete with algorithms such as PSO, GA, and many others in terms of solution accuracy, computational effort and avoidance of premature convergence. GWO was inspired by grey wolves, which are members of the Candia family and top predators on the food chain. This species of wolf lives in groups of 5 to 12 individuals. The alpha wolf is the pack's leader and is in charge of everything. While the beta is the second level after the alpha, it is responsible for reinforcing the alpha's instructions throughout the pack and providing feedback to the alpha. The lower level of the grey wolf hierarchy is known as omega, and it is frequently used as a scapegoat. Furthermore, if the wolf is not alpha, beta, or omega, he or she is referred to as delta. Delta wolves serve as scouts, sentinels, elders, hunters, and caregivers. Finding the best prey location as computed by alpha in collaboration with a beta, delta, and omegas is the goal of mathematically modeling GWO for ESU Scheduling. The best prey location represents the optimal ESU schedule, resulting in the greatest cost savings. The wolf with the lowest daily power consumption cost among the 'n' wolves becomes the alpha.

The position of alpha in the search space is represented by the symbol x_{α}. The wolf in the location with a lower cost saving than alpha but a higher cost saving than the remaining wolves becomes beta. Its location is denoted by the symbol X. Similarly, the wolf in a location with a lower cost saving than beta but a higher cost saving than the remaining solutions becomes delta, and its location is represented as x_{β}. The remaining wolves become omega. Omegas' positions in the search space are updated based on their relative positions to alpha, beta, and delta. Omegas may encircle the prey whose location is estimated based on alpha, beta, and delta positions, or they may diverge from the estimated location of the prey to find a better prey. If the omega comes across a prey that is more fit than the prey surrounded by alpha, beta, and delta, it becomes the alpha. The wolves in second and third place in relation to the prey become beta and delta, respectively. Omega is the new name for the remaining wolves. Using the coordinates of alpha, beta, and delta as a starting point, Figure 4.1 shows how the omega updates its location inside a 2D search space after each cycle.

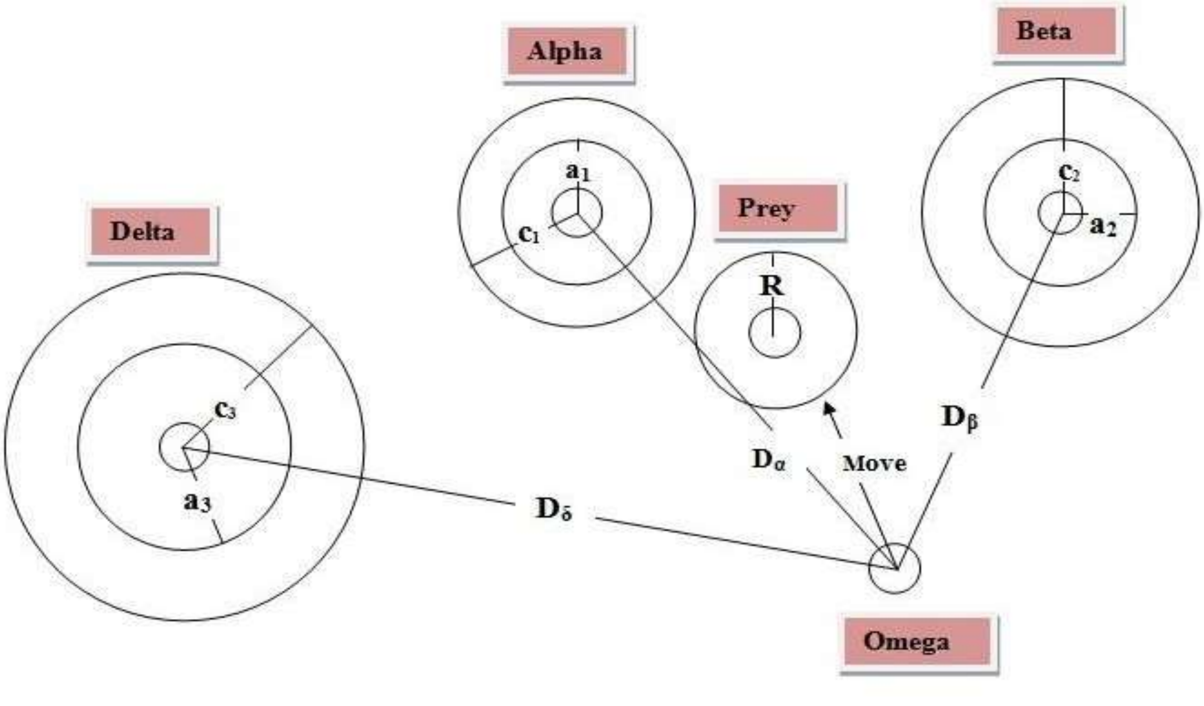


Figure 4.1 Omega's position in the 2D search space is updated.

The location of each omega wolf is updated using the following equation:

$$X_{ij(t+1)} = \frac{X_{\omega\alpha_{ij}} + X_{\omega\beta_{ij}} + X_{\omega\delta_{ij}}}{3} \tag{4.13}$$

Where

$X_{ij(t+1)}$ is the new location of jth elements of ith omega location

$X_{\omega\alpha_{ij}}$ is the new location of j^{th} elements of omegas location vector X_i on the j^{th} elements of alphas location vector X_α.

$X_{\omega\beta_{ij}}$ is the new location of j^{th} elements of omegas location vector X_i on the j^{th} elements of beta's location vector X_β.

$X_{\omega\delta_{ij}}$ is the new location of j^{th} elements of omegas location vector X_i on the j^{th} elements of delta's location vector X_δ.

$X_{\omega\alpha_{ij}}, X_{\omega\beta_{ij}}, X_{\omega\delta_{ij}}$ will derive using the following equations:

$$\begin{aligned} X_{\omega\alpha_{ij}} &= X_{\alpha i} - A_{\omega\alpha_{ij}}.(D_{\omega\alpha_{ij}}) \\ X_{\omega\beta_{ij}} &= X_{\beta j} - A_{\omega\beta_{ij}}.(D_{\omega\beta_{ij}}) \\ X_{\omega\delta_{ij}} &= X_{\delta j} - A_{\omega\delta_{ij}}.(D_{\omega\delta_{ij}}) \end{aligned} \tag{4.14}$$

Where

$X_{\alpha i}$ is j^{th} element of the alpha location vector X_α

$X_{\beta j}$ is j^{th} element of the betas location vector X_β

$X_{\delta j}$ is j^{th} element of the deltas location vector X_δ

$A_{\omega\alpha_{ij}}$, $A_{\omega\beta_{ij}}$, $A_{\omega\delta_{ij}}$ are the jth elements of ith omega's randomization coefficient vector's $A_{\omega\alpha}$, $A_{\omega\beta}$, $A_{\omega\delta}$. $A_{\omega\alpha}$ simulates the random movement of omega wolf around alpha's location by assuming that alpha is close to the prey. $A_{\omega\beta}$ simulates the random movement of omega around beta's location by assuming that beta is close to the prey. $A_{\omega\delta}$ simulates omega's random movement around the location of delta by assuming delta is close to the prey.

So that $A_{\omega\alpha}$, $A_{\omega\beta}$, $A_{\omega\delta}$ will be given as:

$$\begin{aligned} A_{\omega\alpha_{ij}} &= 2*a*rand[0,1]-a \\ A_{\omega\beta_{ij}} &= 2*a*rand[0,1]-a \\ A_{\omega\delta_{ij}} &= 2*a*rand[0,1]-a \end{aligned} \tag{4.15}$$

Where

$rand[0,1]$ is a random numberin the interval [*0,1*].

$'a'$ is decision variable and it is uniformly decreased from2 to 0 during iteration.

Each iteration, $A_{\omega\alpha}$, $A_{\omega\beta}$, $A_{\omega\delta}$ are assigned a random value in the interval [-*a, a*].

- *'a'* is greater than 1 for the first half of iterations. Omegas diverge from the estimated prey location they made based on the locations of dominant wolves during these iterations in order to find better prey.
- *'a'* is less than 1 for the second half of iterations. The omegas encircle the prey in a smart location calculated based on dominant wolf positions to trap and attack it.

When 'a' becomes zero during the final iteration, all elements of the randomization coefficient vectors $A_{\omega\alpha}$, $A_{\omega\beta}$, $A_{\omega\delta}$ become zero. The entire pack charges at the prey. All of the wolves' coordinates become the same as the coordinate of the fittest prey. The following equation is used to calculate the value of 'a' for each iteration:

$$a = 2 - (\frac{2*t}{t_{total}}) \tag{4.16}$$

Where

t is the current iteration and t_{total} is the total number of iterations.

$D_{\omega\alpha_{ij}}$ is the distance of j^{th} elements of omegas location vector X_i on the j^{th} elements of alphas location vector X_α.

$D_{\omega\beta_{ij}}$ is the distance of j^{th} elements of omegas location vector X_i on the j^{th} elements of beta's location vector X_β.

$D_{\omega\delta_{ij}}$ is the distance of j^{th} elements of omegas location vector X_i on the j^{th} elements of delta's location vector X_δ.

$D_{\omega\alpha_{ij}}$, $D_{\omega\beta_{ij}}$ and $D_{\omega\delta_{ij}}$ given as :

$$\begin{aligned} D_{\omega\alpha_{ij}} &= \left| C_{\omega\alpha_{ij}} . X_{\alpha_j} - X_{ij}(t) \right| \\ D_{\omega\beta_{ij}} &= \left| C_{\omega\beta_{ij}} . X_{\beta_j} - X_{ij}(t) \right| \\ D_{\omega\delta_{ij}} &= \left| C_{\omega\delta_{ij}} . X_{\delta_j} - X_{ij}(t) \right| \end{aligned} \tag{4.17}$$

Where

X_{ij} is the jth elemen of ith omega's location vector.

Natural barriers prevent the omega from pinpointing the precise locations of alpha, beta, and delta. The position of the dominating wolf can never be accurately predicted by the omega. This is represented by obstacle vectors $C_{\omega\alpha}$, $C_{\omega\beta}$ and $C_{\omega\delta}$.

Elements of $C_{\omega\alpha}$, $C_{\omega\beta}$ and $C_{\omega\delta}$ are all random numbers in the range [0 2].

$C_{\omega\alpha_{ij}} . X_{\alpha_j}$ is the approximate location of the jth element of alpha's location vector.

$C_{\omega\beta_{ij}} . X_{\beta_j}$ is approximate location of jth element of beta's location vector.

$C_{\omega\delta_{ij}} . X_{\delta_j}$ is the approximate location of the the jth element of delta's location vector.

GWO algorithm for optimal ESU scheduling is summarized in the following steps:

1. Generate a pack of 100 grey wolves initially in the interval [-15, 15] using the equation

   $$\text{Position} = \text{P}_{\text{min}} + \text{rand}(\times (\text{P}_{\text{min}} = \text{P}_{\text{min}})$$

   Increase the maximum number of iterations to 50.
2. Use the objective function for cost reduction to determine each wolf's fitness.
3. Using the fitness value with the lowest cost, order the complete pack. Place the wolves in order of fitness. Use alpha, beta, and delta as your three lowest daily power consumption charges to save the wolves.
4. Change the decision-variable 'a' to 2.
5. Use equations to update Omega Wolf's locations (4.13)-(4.17).
6. Using the equation, uniformly reduce "a" (4.16). Return to step 2 if the terminal count is greater than the iteration. In all other cases, the optimal ESU schedule for cost savings is the alpha.
7. Using the equation, uniformly reduce "a" (4.16). Return to step 2 if the terminal count is greater than the iteration. If not, the alpha is given back as the best ESU schedule for cost savings.

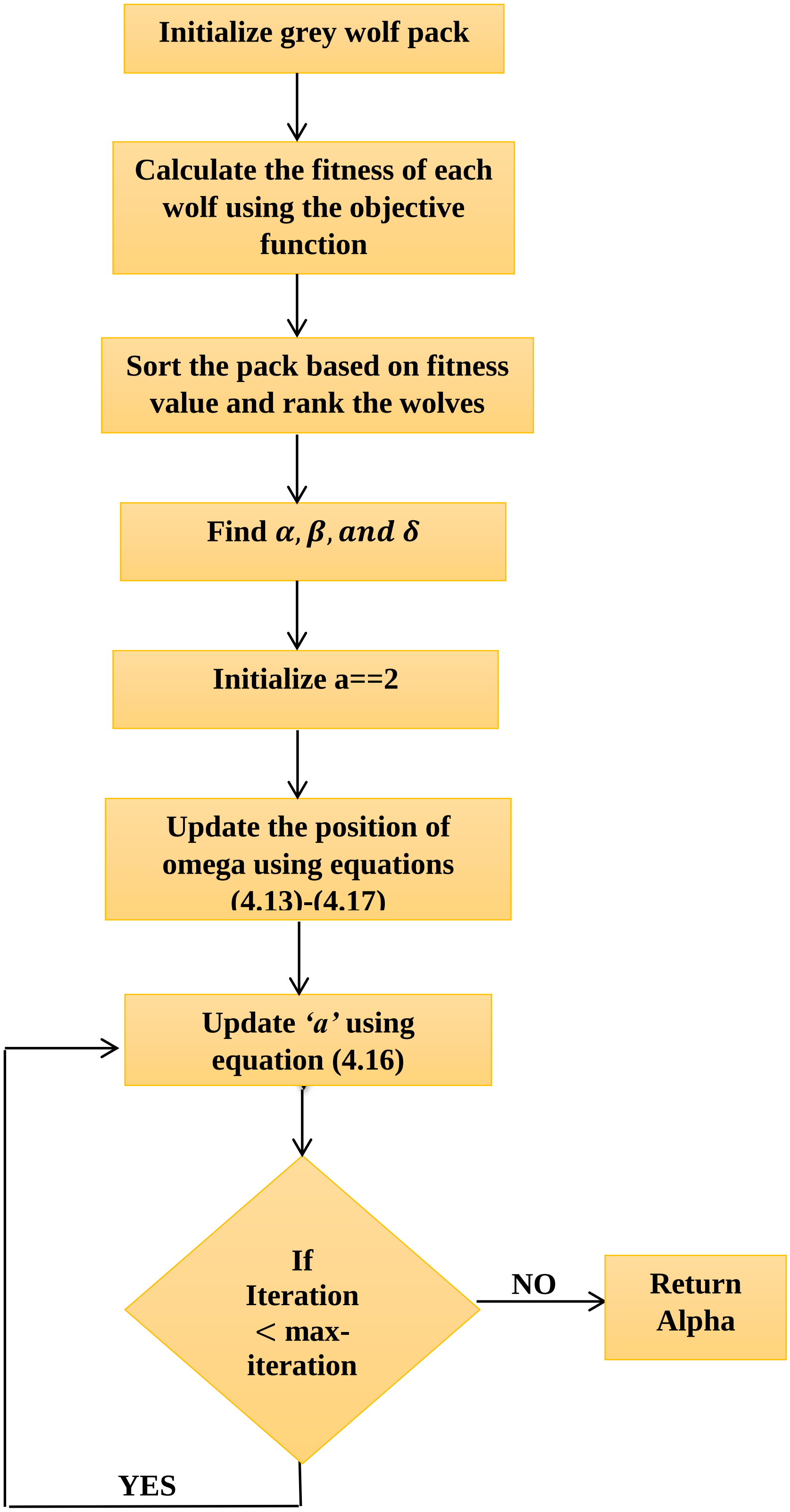


Figure 4.2 Flow Chart of GWO Algorithms

4.1.4 Particle Swarm Optimization

Figure 4.3 illustrates the steps involved in applying the Particle Swarm Optimization algorithm to a problem of optimization. They are as follows for each block:

Step 1: is to enter all of the crucial factors pertaining to the design challenge and Particle Swarm Optimization (PSO) characteristics. The population size, the number of algorithm iterations, the maximum particle velocity, the constant values of social acceleration and cognitive acceleration, the range of inertia weight, the number of design parameters (20) chosen (7), the upper and lower bounds of these design parameters as shown in Appendix A Table A1.1, and the restrictions that the smart grid is subject to are among these parameters.

Step 2: is to establish a population that is randomly chosen and has the same size as that decided in Step 1. For each candidate in the population, each design parameter has a random value. The population could be thought of as a swarm of particles.

Step 3: Since the issue is a minimization problem, the fittest particle is the one with the lowest fitness value, which is saved as gbest. Find the objective function value of the entire population (or particles). This value, known as "The fitness value," is kept as pbest (personal best) for each particle and serves as its own objective function value that satisfies all constraint requirements (global best).

Step 4: Using equation, all particle velocities are modified (4.13 - 4.17). After the update, the particle's velocity is checked to determine if it exceeds the maximum velocity; if so, it lowers to that value.

Step 5: Using equation, this step updates the locations of all particlesof (4.16). The placements must fulfill the constraint constraints as well as the upper and lower bounds of the design parameters when they are modified.

Step 6: The goal function value for each individual particle in the swarm is calculated at this stage. If the new fittest solution for a particle is superior to its current pbest, it replaces the gbest and becomes the new global best. The fittest solution is the least significant value as the problem is subject to reduction (gbest).

Step 7: The best solutions, or "the fittest," are included in saved particles (solutions), which aren't updated until better particles (solutions) are found.

Step 8: Up until the algorithm termination criterion is satisfied, steps 4 through 7 are cycled (specific computation time or number of iterations).

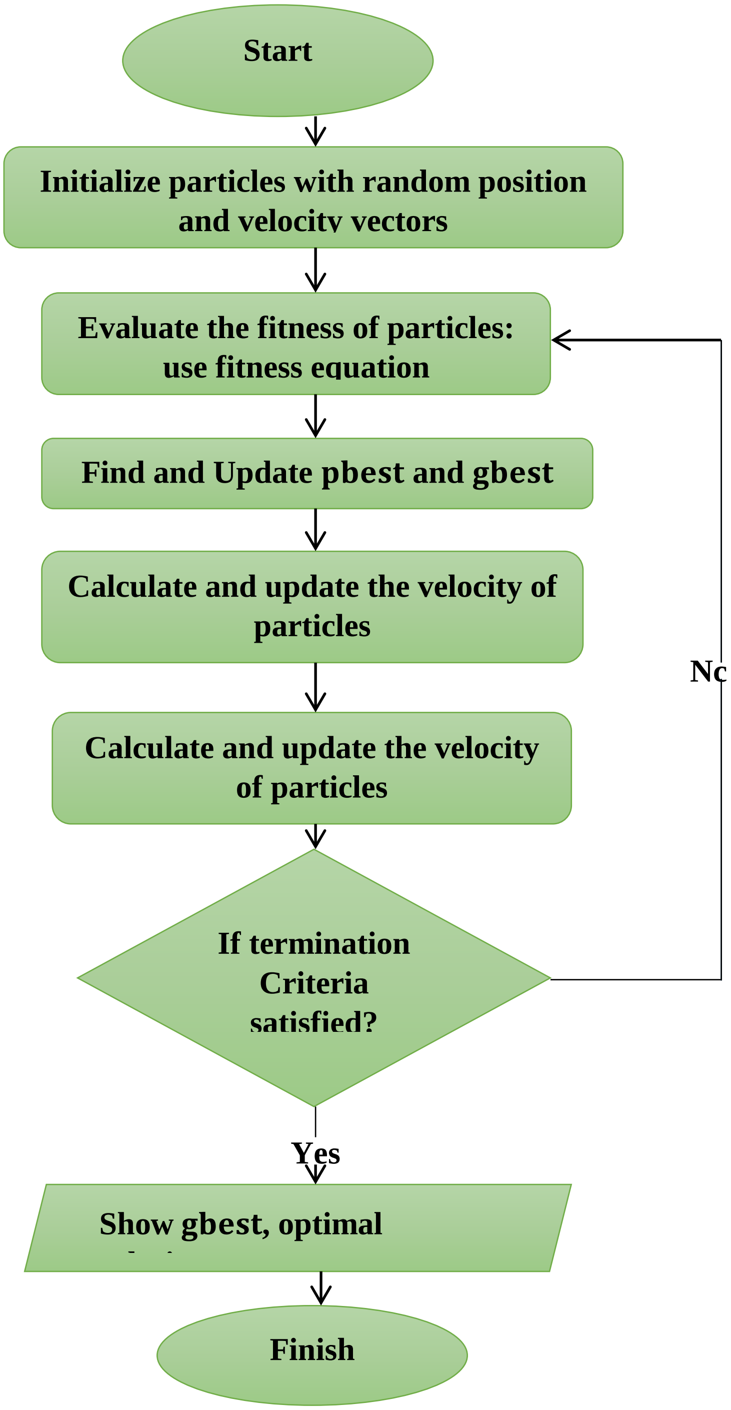


Figure 4.3 PSO Flow Chart

4.2 Optimization of GWO and PSO algorithms

Because the population size and maximum iteration number of an algorithm can affect the answers it produces, these parameters must be tuned for the algorithms to produce the "Best solutions feasible." Determining the ideal population size for each algorithm is crucial because the solutions of optimization algorithms are highly dependent on population size; some algorithms perform well and obtain better solutions when the population size is small, while others perform well and obtain better solutions when the population size is large.

The best population size for the method can be found by running the algorithm ten times on various population sizes and comparing the results obtained by each population size; the population size at which the algorithm obtained the best solution is then deemed the optimal population size. The optimal iteration number can be defined as the point at which the convergence line in a convergence graph reaches a steady state and stops converging in order to prevent excessive computation time and unnecessary iterations because computation time is directly proportional to the maximum iteration number.

CHAPTER FIVE

RESULTS AND DISCUSSION

5.1 Introduction

Verification of the system requires a variation of test scenarios. The optimizers were run using these different price and occupacy schemes and the outputs were compared to their correspondinr output.

5.1.1 Load Shifting Algorithm Explanation

Set up constraints, tariffs, and an appliance list. Determine the hourly load array using only fixed devices. This array will be used to determine whether it has exceeded the hourly maximum load. Iterate over dissatisfaction and shiftable devices. First, determine how many hours a device works per day, and then assign this device an empty array of 24 elements (each element corresponding an hour). This array will be filled with ones. Iterate through the tariff array that has been sorted. It tells here which hours are the cheapest, and can start putting ones into a temporary array from the first element of the sorted array. If an appliance works three hours a day, place three of the appliance next to each other. Then multiply this temp array by the device's power and add it to the power array to see if any hour exceeds the maximum hourly load. If not, it needs to change the device's hourly array; if it does, need to try to find another hour when the tariff is less expensive and repeat the process.

Table 5.1 Work hour of shiftable appliances

Appliance name	Old work hours	New work hours
Vacuum Cleaner	1 p.m.	1 a.m.
Water Heater	3 p.m. – 6 p.m.	3 a.m. – 6 a.m.
Water Pump	1 p.m. – 3 p.m.	1 a.m. – 3 a.m.
Dish Washer	7 p.m. – 9 p.m.	9 p.m. – 11 p.m.
Hair Dryer	9 p.m.	11 p.m.
Washing Machine	4 p.m. – 6 p.m.	6 a.m. – 8 a.m.
Clothes Dryer	7 p.m. – 9 p.m.	7 a.m. – 9 a.m.
Desktop Computer	7 p.m. – 10 p.m.	5 p.m. – 7 p.m.
Iron	8 p.m. – 9 p.m.	2 p.m. – 3 p.m.
Electrical Shaver	8 a.m.	1 p.m.
Phone Charger	6 p.m. – 7 p.m.	3 p.m. – 4 p.m.

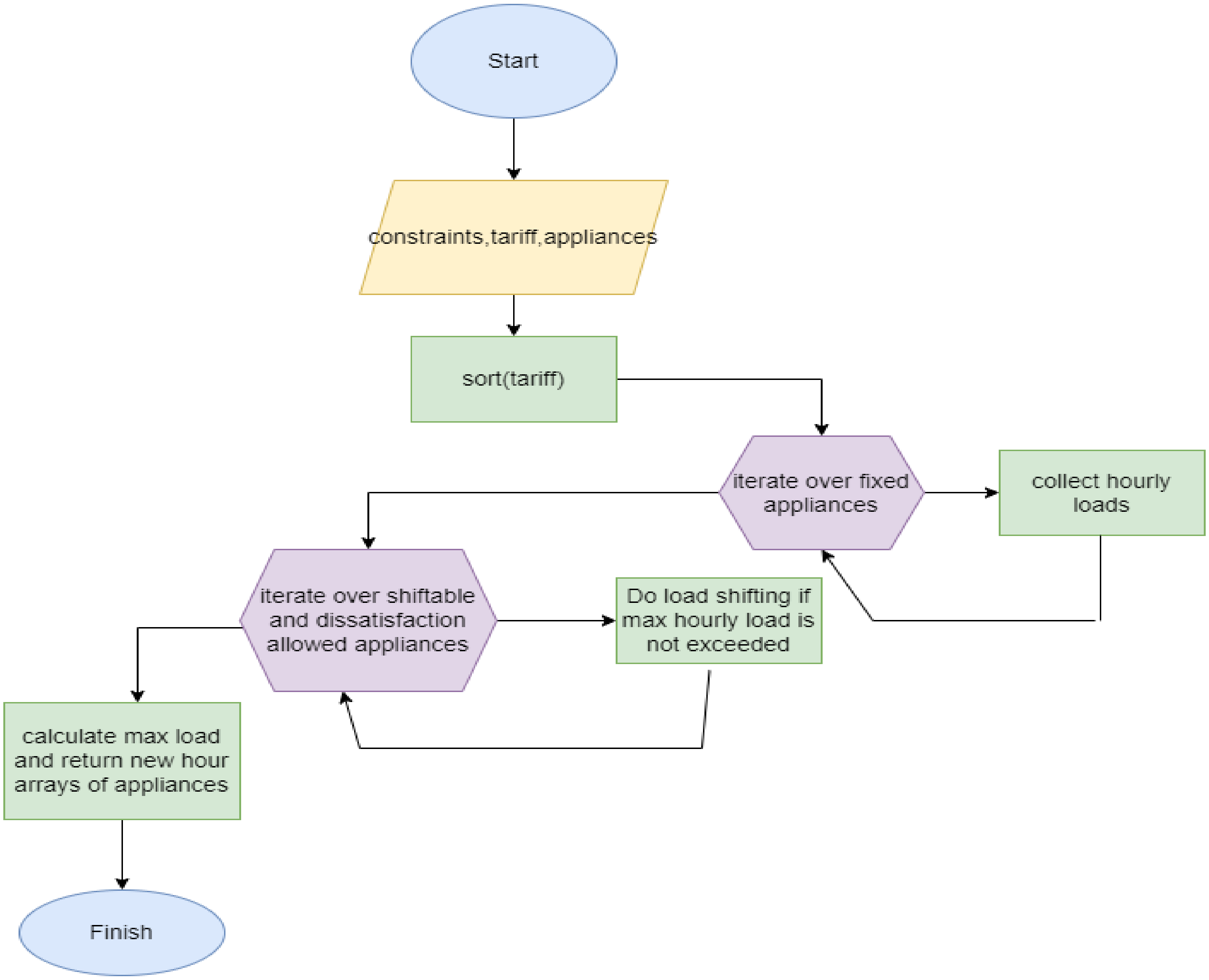


Figure 5.1 Flowchart of Load Shifting Algorithm

Table 5.1 shows the differences in how an appliance works before and after load shift after we applied our load shifting algorithm.

5.2 Result and Analysis

There are two cases, as stated in the model section. In Case one, it is only considered load shifting and excluded PV. PV and home-to-grid scenarios are included in Case-two.

5.2.1 Electricity Tariff

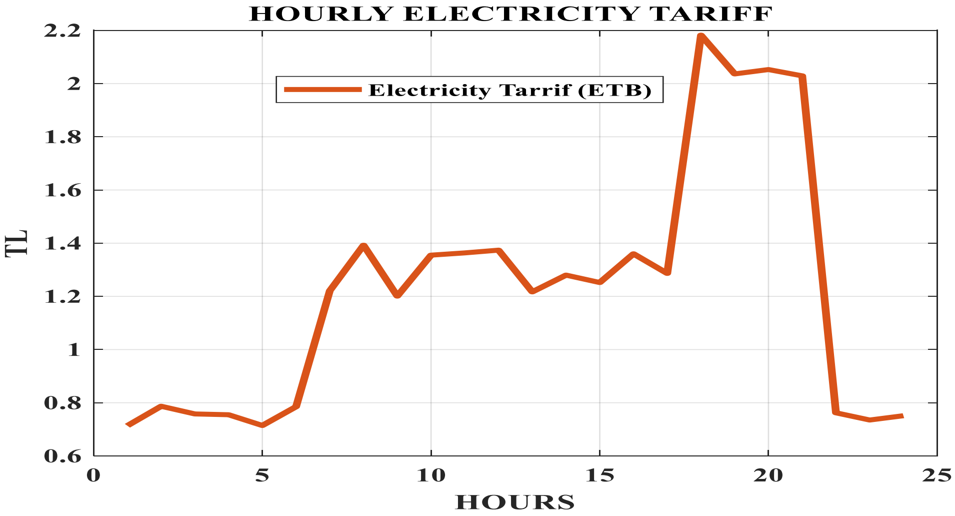
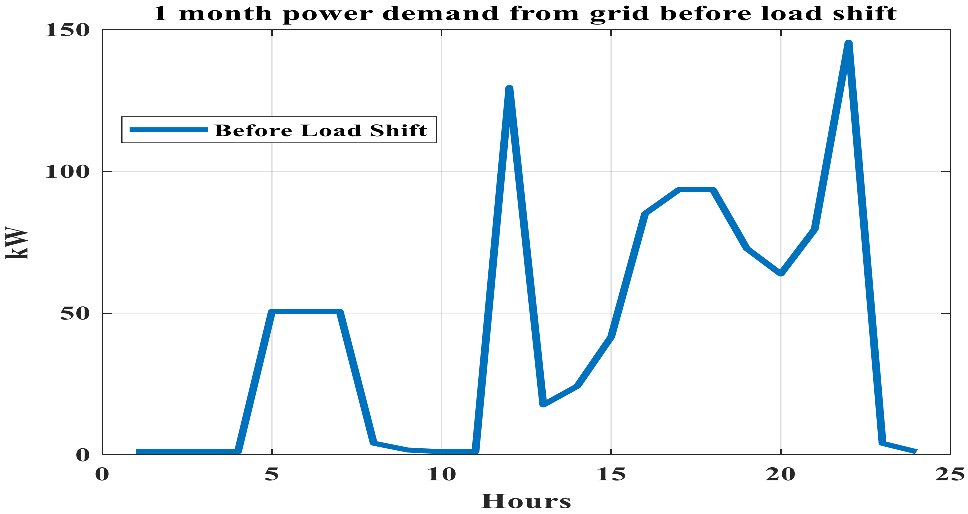


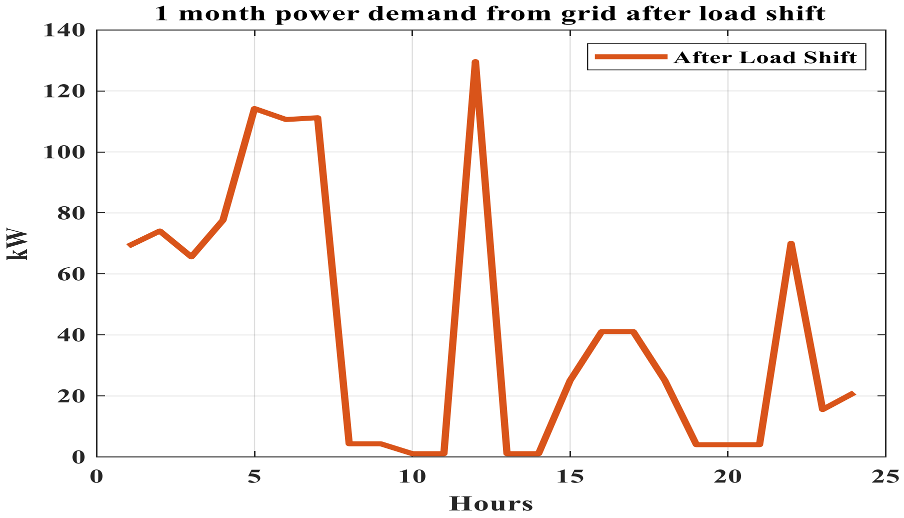
Figure 5.2 Electricity Tariff

Figure 5.2 illustrates a typical electricity tariff. It is much more expensive when there is a higher load demand between 5 and 10 p.m.

5.2.2 Case-1



(a)



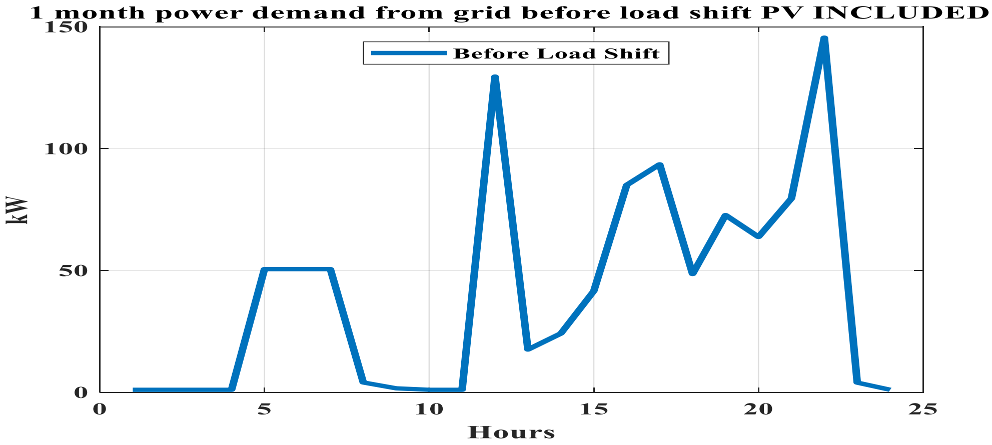
(b)

Figure 5.3 A Typical Load Demand

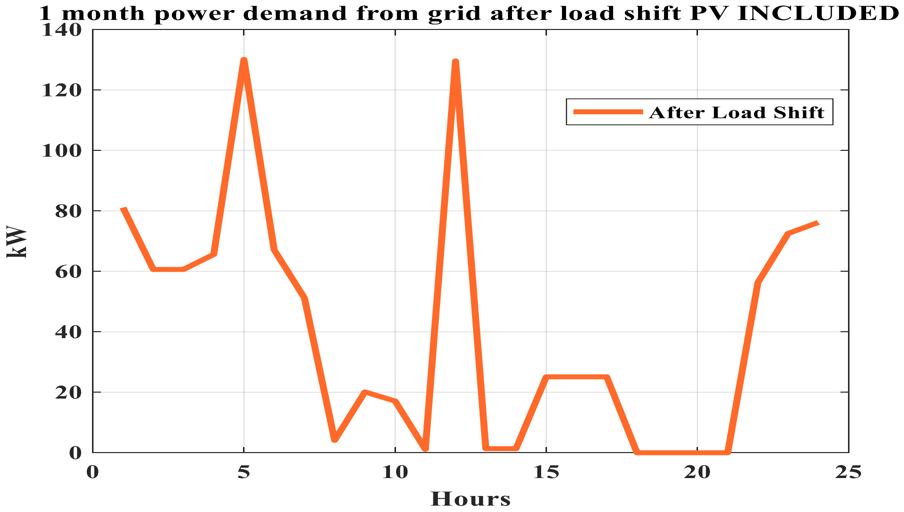
Figure 5.3's blue curve represents a typical household load demand. The load demand peaks between 5 and 10 p.m., as seen in Figure 5.3. The cost of power is negatively impacted by this load demand. Here, shifting the loads will be done while keeping the inhabitants' complaints in mind, in order to lower their electricity bill. The red curve in Figure 5.3 illustrates how the load demand curve changes as a result of the load shifting algorithm. The total cost is reduced as load needs shift to times when the power rate is cheaper. Figure 5.5 illustrates how the overall cost dropped.

5.2.3 Case-2

After obtaining the expected results in the case1, here now PV is added to the model. It should have a positive impact on the total bill. Furthermore, load demand from the grid should decrease when it supplies energy to the system.



(a)



(b)

Figure 5.4 Load demand of a home before load shift and PV included

Figure 5.4 illustrates the load demand before load shift as a blue curve. When comparing the blue curves in Figures 5.3 (a) and 5.4 (a), the load curves are almost identical, but at 5 p.m, the decrease in kW is visible thanks to PV. Total cost is lower here if there is no PV and load shifting. The red line in Figure 5.4 illustrates the load demand when there is load shifting and PV effect. PVs,as is well known, operate and produce electricity effectively between the hours of 1 p.m. and 6 p.m. However, using storage devices to store PV energy and use it when the electricity tariff is higher, which is around 8 p.m. When the red lines in Figures 5.4 and 5.3 is compared, there is a kW difference around 8 p.m. when the storage devices supply energy and the reliance on the grid decreases.

5.2.4 Total Cost

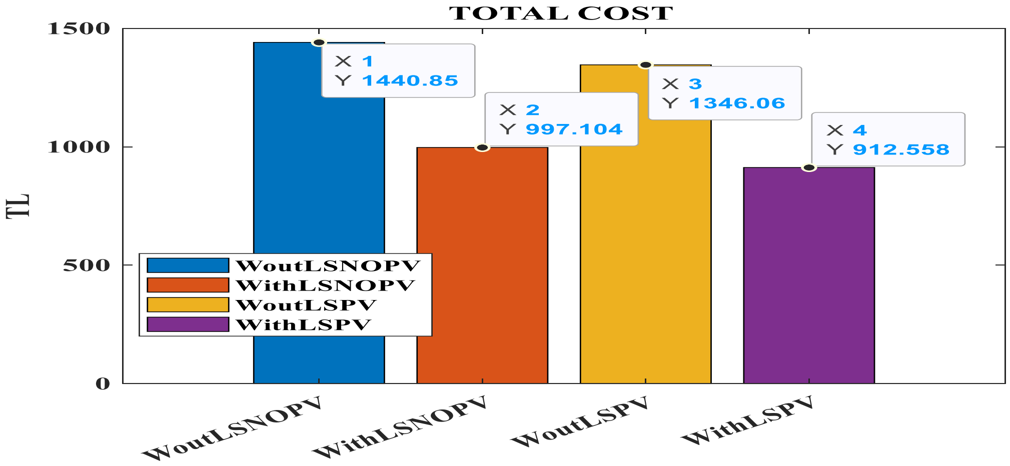


Figure 5.5 Total Cost

As shown in Figure 5.5 Total Cost, the most efficient way to reduce electricity costs is to add PV and load shifting. Because in that case, the amount of energy provided by the grid will be reduce. That means less money is spent on energy. This has a direct impact on the electricity bill.

5.2.5 Before Load Shift NO PV

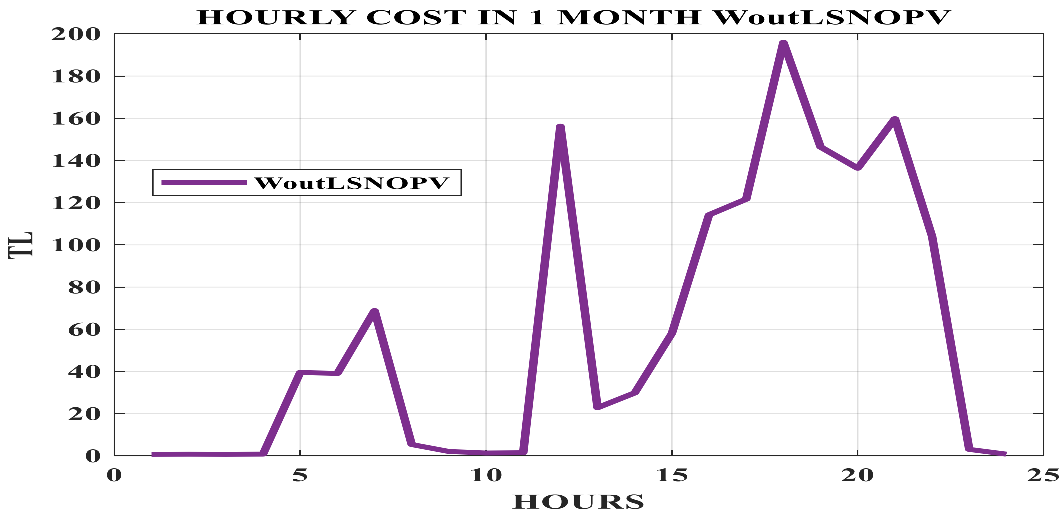


Figure 5.6 Hourly cost in 1 Month Without Load Shifting No PV

The most efficient hours in the electricity bill, as shown in Figure 5.6, are 5 p.m.-9 p.m. Because power demand is at its peak during those time intervals. People return from work to their homes.

5.2.6 After load shift no PV

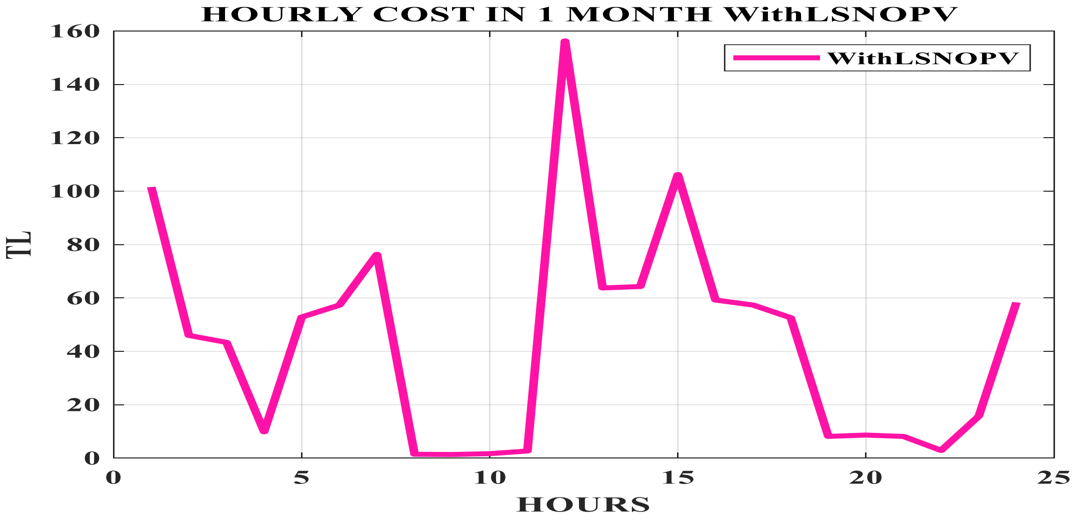


Figure 5.7 Hourly cost in 1 Month with Load Shifting No PV

Figure 5.7 illustrates how power demand is distributed. As it is seen in Figure 5.3, the cost of each time interval is multiplied by each time interval. As shown in the graph, the majority of the electricity bill is attributed to the noon hour.

5.2.7 PV included before load shift

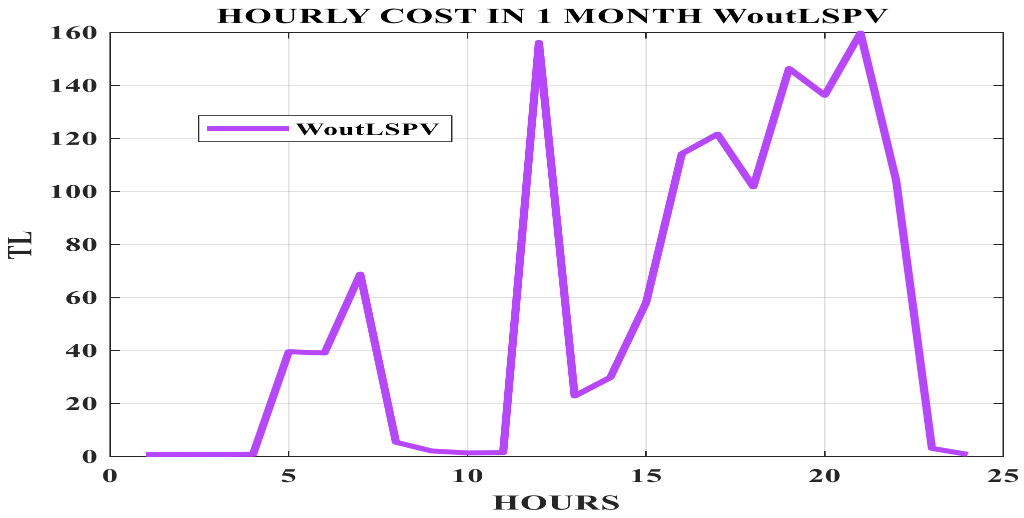


Figure 5.8 Hourly cost in 1 Month without Load Shifting PV

As illustrated in Figure 5.8, the most expensive hours have a significant impact on the bill. Because Load Shifting Algorithm is not yet implemented. However, when compared to figure 5.6, PV has an impact on the cost.

5.2.8 After load shift PV included

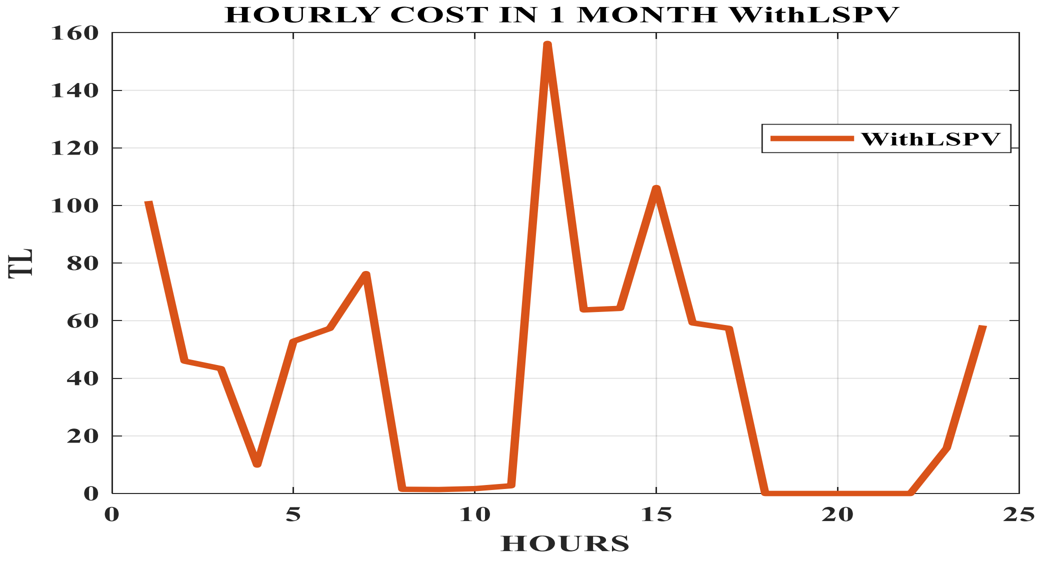


Figure 5.9 Hourly cost in 1 Month with Load Shifting and PV

Figure 5.9 depicts the most efficient curve for the electricity bill. Because in that case, the Load Shifting Algorithm is used. As it is seen, the cost of those time intervals in the evening is zero. Because the electricity generated by the PV is stored in storage devices, the storage acts as a generator at times and supplies power to the system. As a result, there does not have any demand from the grid.

5.2.9 PAR

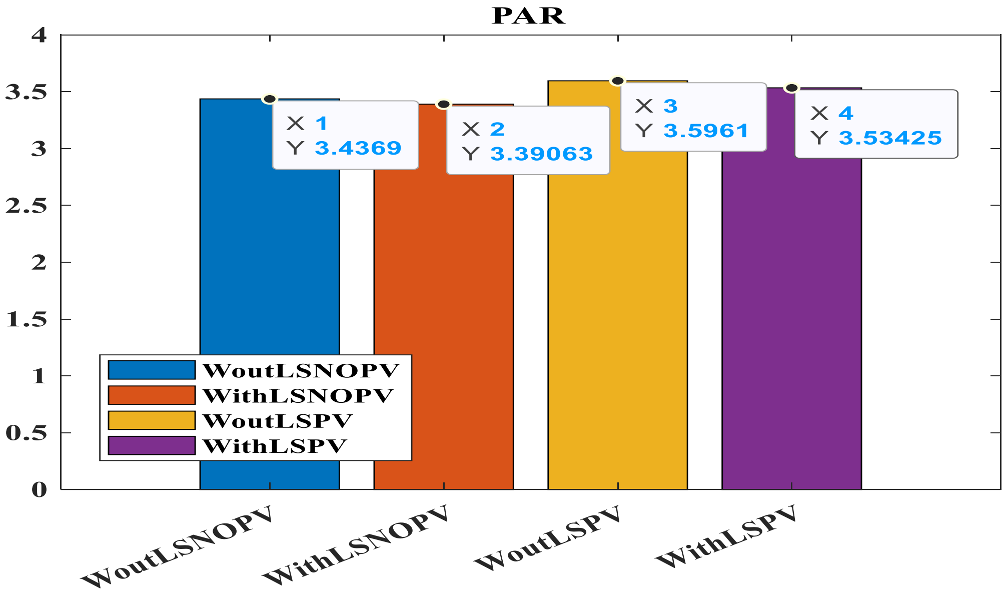


Figure 5.10 PAR for Each Case

Figure 5.10 shows the PAR ratio. There is a slight difference in the PAR ratios. Because the primary goal was to reduce costs, it did not fully consider lowering the par ratio.

5.3 Grey Wolf Optimization (GWO) algorithm Performance, Properties and Best Solution

The Grey Wolf Optimization (GWO) algorithm was tested in a variety of population sizes, starting with one of “10” and increasing in increments of 10 to one of “100”. During each test, the algorithm was used ten times to produce ten different solutions; this is essential for assessing the method's stability by computing the standard deviation. The optimal outcome of the Grey Wolf Optimization (GWO) approach for a population size of 40 is 919.6868 ETB/year, as illustrated in Figure 5.11.

Table 5.2 10 GWO Solutionsfor a populations of 40

TAC	Vacuum cleaner	Water heater	Water pump	Dish washer	Hair dryer	Washing machine	Close dryer
923.9433	0.73551	0.972637	0.009998	0.000196	238.7829	0.008483	73.07992
924.6908	0.756369	0.961408	0.01	0.000182	241.3236	0.009438	73.17185
923.7008	0.757201	0.998404	0.01	0.0002	231.94	0.008801	72.98237
920.2634	0.804759	1	0.01	0.000195	211.6428	0.006077	73.09565
919.6868	0.803492	1	0.01	0.000195	204.8749	0.004914	73.07694
923.0636	0.782745	0.998331	0.01	0.000189	225.6353	0.008122	73.08565
924.4711	0.752612	0.993772	0.009984	0.000195	235.8709	0.009398	73.20713
921.3626	0.771023	0.97575	0.01	0.000189	224.1754	0.006654	73.12857
922.5267	0.775703	0.980198	0.009998	0.000178	227.391	0.007384	73.10508
925.4105	0.722319	0.932043	0.009994	0.000182	251.3099	0.009102	73.22994
Standard Deviation = 1.93							

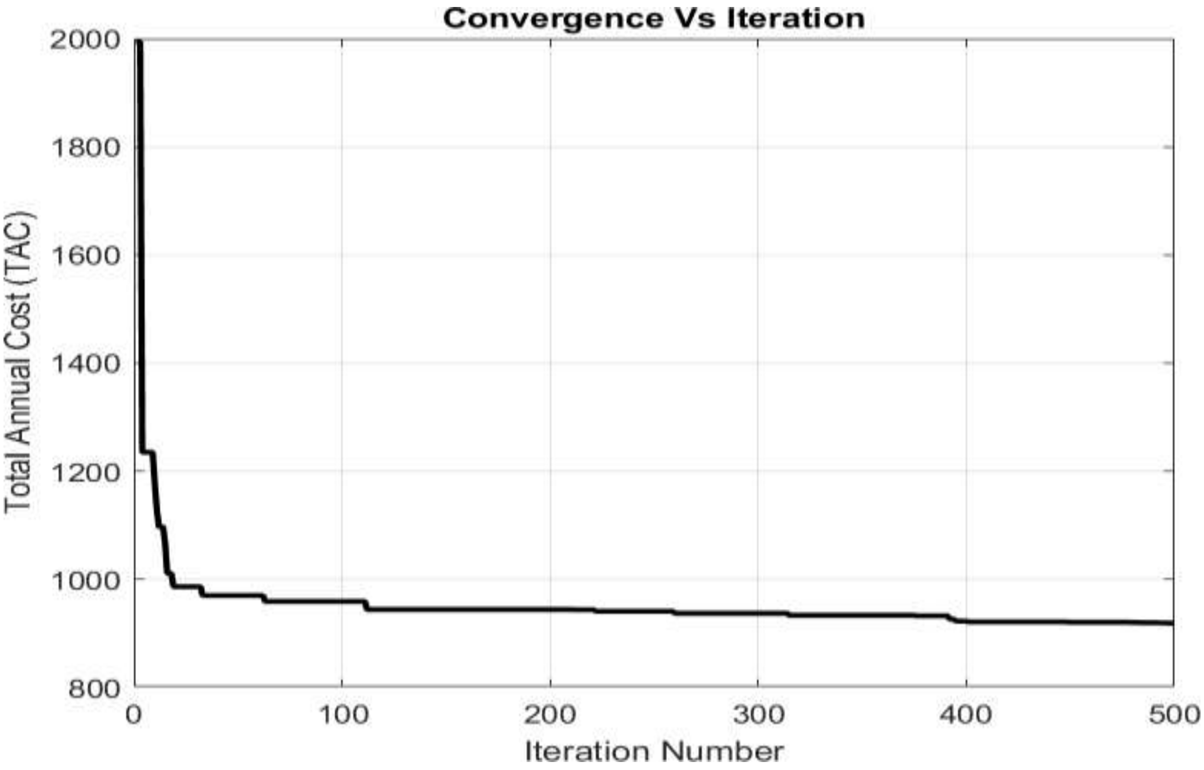


Figure 5.11 Best solution convergence of GWO

5.4 Particle swarm optimization (PSO) algorithm Performance, Properties and Best Solution

The particle Swarm Optimization (PSO) algorithm was assessed with various population sizes, with a step size of 10 and increasing from "10" to "200." During each test, the algorithm was executed ten times to provide ten distinct results. According to Table 5.3, the PSO algorithm calculated the best answer at a population size of 150. The best result was 919.4412 ETB/year, as illustrated in Figure 5.12.

Table 5.3 10 PSO Solutionsat population size of 150

TAC	Vacuum cleaner	Water heater	Water pump	Dish washer	Hair dryer	Washing machine	Clothes dryer
926.3136	0.712955	0.906435	0.009999	0.000155	254.1044	0.007584	73.38261
931.3964	0.709565	0.900655	0.00937	0.000153	258.3591	0.008587	78.27794
919.4412	0.8094	1	0.009999	0.000191	206.7299	0.005294	73.09711
923.5367	0.74308	0.937818	0.01	0.000164	240.0878	0.007201	73.3115
925.7124	0.730939	0.916627	0.009999	0.000158	252.1319	0.008452	73.36586
925.8827	0.73329	0.934492	0.01	0.000161	252.0292	0.009379	73.33249
925.0483	0.732934	0.955732	0.009814	0.000168	240.5759	0.007682	74.65727
920.5033	0.776581	0.977112	0.009999	0.000189	215.9411	0.005376	73.1363
924.9139	0.721083	0.932875	0.01	0.000159	247.5974	0.007567	73.34856
925.3109	0.729543	0.931352	0.009987	0.000158	249.0672	0.008219	73.43259
Standard Deviation = 3.282							

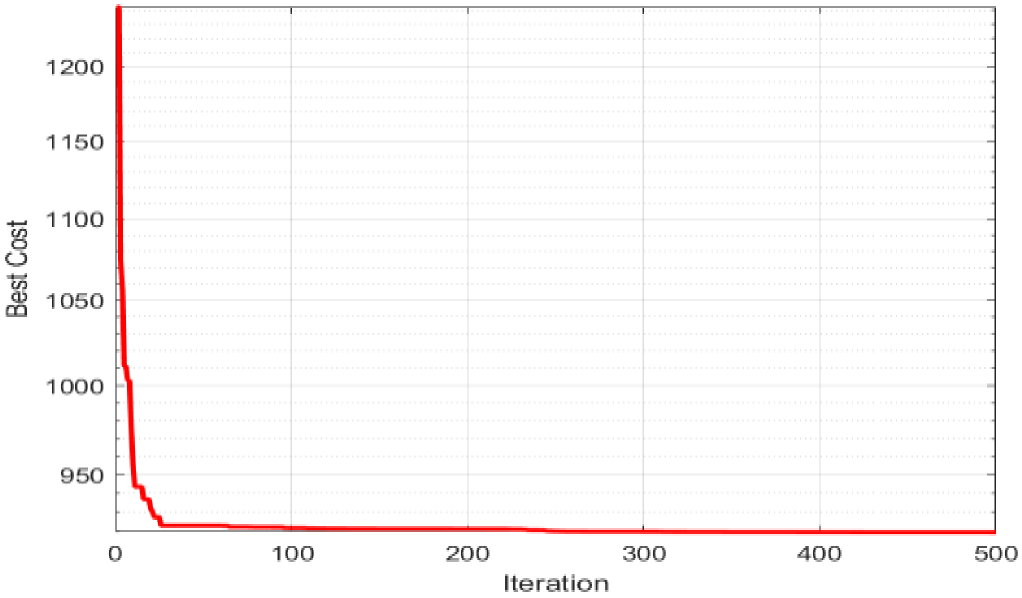


Figure 5.12 Best solution convergence of PSO

5.5 Discussion and Analysis

Table 5.4 Comparison between GWO and PSO algorithms

		Preliminary	GWO	PSO
Design Parameter	Vacuum Cleaner	0.55	0.8035	0.8094
	Water Heater	2.0	1	1
	Water Pump	0.55	0.01	0.009999
	Dish Washer	0.72	0.000195	0.000191
	Hair Dryer	782	204.875	206.73
	Washing Machine	0.53	0.00491	0.0053
	Clothes Dryer	167	73.1	73.1
Objective Function	TAC	6780.7	919.687	919.441
Constraints	α	0.4928	0.4783	0.4737
	δ	0.0321	0.0381	0.0361
	γ	0.0867	0.0411	0.0411
	P_{WT}	577.35	369.41	367.90
	P_{OR}	825.22	652.14	644.76
	P_{PV}	9.34	0.28	0.28
	P_{Batt}	6.90	0.34	0.33
	P_D	1071	1069.8	1069.8
Standard Deviation			1.93	3.282
Computation Time (s)			24.3	1.2

Table 5.4 compares the best outcomes produced by the Grey Wolf Optimization (GWO) and standard deviation,computation time, and outcomes for particle swarm optimization (PSO) algorithms at 70 population size and 200 maximum iteration.

The optimization algorithms were put into action, resulting in a roughly 86 percent reduction in the preliminary smart grid's total annual cost (TAC), and as can be seen in Table 5.4, no constraints (equations 4.13 to 4.17) were broken. This ensures that the optimized design parameters will produce the necessary load scheduling performance. The best answer (919.441 ETB/year) across all algorithms was computed by PSO algorithm, as shown in Table 5.4. (4.13 - 4.17). Using equations 4.13 to 4.17, the GWO algorithm calculated the second-best answer, which is quite similar to the one the PSO algorithm produced (919.687 ETB/year). The algorithm's standard deviation is calculated in order to better examine the performance of the algorithms. The GWO algorithm is the most stable, with the lowest standard deviation value, followed by PSO, as shown in Table 5.4. By outperforming the most well-known and widely-used algorithm, the answer obtained by the GWO method in this thesis illustrates its efficacy and efficiency.

However, a drawback of the GWO algorithm was found when the calculation times of several algorithms were compared. When the GWO and PSO algorithms were evaluated with the identical algorithm parameters (Population size: 70, Maximum iteration: 200), it was found that the GWO algorithm computed the optimum solution in 24.3527 seconds as opposed to 1.27 seconds for the PSO algorithm. The lengthy computing time can be attributed to the math's intricacy.

The simulation result included two cases, or scenarios: one that only considered load shifting and the other that considered both load shifting and PV panels. In the first case, grid power demand is compared before and after load shifting scenarios. Prior to the implementation of the load shifting algorithm, a resident's power demand peaked around evening time, which is also when the electricity price peaked. However, by employing the load shifting algorithm, to shift loads from high-priced intervals to low-priced intervals. As a result, the algorithm is capable of reducing a household's monthly electricity bill by approximately 25%. After that, the PV panels and energy storage devices were added to the second case.

In the first case, the PV panels were tested without load shifting, then with load shifting, and the results were recorded. When compared to no load shifting and no PV cases, these operations that the case with PV and storage included reduced monthly electricity costs by around 30%. Unfortunately, no change in the PAR level was observed because that was not the primary goal. As a result of the research were able to reduce electricity costs by incorporating the necessary constraints into the implementations.

5.6 Demand response

Demand response provides an opportunity for users to play a significant role in the operation of the electric grid by reducing or shifting their electricity usage during peak periods in response to time-based rates or other forms of financial incentives. Demand response programs are being used by some electric system planners and operators as resource options for balancing supply and demand. Such programs can lower the cost of electricity in wholesale markets, and in turn, lead to lower retail rates. Methods of engaging customers in demand response efforts include offering time-based rates such as time-of-use pricing, critical peak pricing, variable peak pricing, real time pricing, and critical peak rebates.

The electric power industry considers demand response programs as an increasingly valuable resource option whose capabilities and potential impacts are expanded by grid modernization efforts. For example, sensors can perceive peak load problems and utilize automatic switching to divert or reduce power in strategic places, removing the chance of overload and the resulting power failure. Advanced metering infrastructure expands the range of time-based rate programs that can be offered to consumers. Smart customer systems such as in-home displays or home-area-networks can make it easier for consumers to changes their behavior and reduce peak period consumption from information on their power consumption and costs. These programs also have the potential to help electricity providers save money through reductions in peak demand and the ability to defer construction of new power plants and power delivery systems specifically, those reserved for use during peak times.

One of the goals of the Smart Grid Program is to develop grid modernization technologies, tools, and techniques to utilize demand response and help the power industry design, test, and demonstrate integrated, national electric/communication/information infrastructures with the ability to dynamically optimize grid operations and resources and incorporate demand response and consumer participation.

CHAPTER SIX

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

To fully implement a HEMS for load scheduling in DR applications was the study's objective. The main objectives were, firstly, to construct accurate empirical models for home appliances, mainly thermal loads, in order to produce correct minutely load profiles of appliances while accounting for many input parameters. Second, develop a full-house controller that takes into account both shiftable and thermal loads and enables the user to view the load profile of the house as well as the estimated cost for the day depending on input choices. Lastly, a straightforward interactive HEMS can be developed that can plan loads away from peak times by modifying their settings in response to a particular ToU DR signal, hence minimizing power usage.Multiple metaheuristic algorithms will be used for scheduling.

All objectives were met, the house appliance models were accurately created, and their responses when operating thermal loads agreed with basic logic. In a single day, the house controller created a full house load profile and calculated the total cost for that house. Different metaheuristic algorithms were used to implement the scheduling, and their performance was compared. Despite the fact that all of the algorithms agreed on the minimum cost and input parameters, the PSO and GWO produced the most consistent results, scoring the lowest value at each iteration.

In order to lower the cost of energy consumption, the GWO algorithm was applied in this thesis to schedule an energy storage unit in a home with and without renewable energy sources. It has been demonstrated that the suggested strategy maximizes cost savings for households, whether they employ renewable energy sources or not. Cost reductions are bigger on days with high hourly price variation when compared to days with low hourly price variation. The performance of the GWO algorithm and the conventional PSO method were contrasted. The GWO performed better than the PSO, which led to substantial cost savings. This argument has gained important as households increasingly employ renewable energy sources like wind and solar. The proposed task was carried out for the home that receives the hourly rates for the next day befoure midnight.

The main contributions of this research are in the full house controller, where each appliance is modelled to take many significant factors into account, such as set-points, outer temperatures, and the physical structure of the medium, user comfort, and room occupancy. All of these factors will have an impact on the accuracy of the load profile produced by the house model, resulting in better cost reduction once the scheduler is used. Furthermore, the developed full house controller can provide the user with a clear understanding of how his/her settings for each appliance affect the load profile of the house and total power consumption. The scheduler developed in this study is very accurate in determining the optimal input parameters to give the lowest daily power consumption. Many similar systems optimize consumption by controlling the status of the appliances, turning them on and off as needed to reduce consumption, whereas the proposed HEMS controls every appliance's settings to achieve the lowest cost. Furthermore, most schedulers use hourly data to calculate load profiles and costs, whereas this system optimizes the load for each minute, achieving high accuracy and greater control over shiftable loads.

6.2 Future Work

The proposed system can be improved in two ways. First, the list of appliances that can be included can be expanded to include more appliances, such as renewable energy sources. This will assist the user in further lowering costs and possibly receiving an incentive when renewable sources contribute to the grid. Another limitation of the proposed system was the lengthy simulation run time. Because of the nature of the input parameters and the minutely sampling time, the scheduler may be slightly slow when generating the final schedule. The trade-off, of course, is accuracy, as a minutely schedule can achieve more accurate and immediate responses than an hourly schedule.

Smaller time periods would significantly speed up processing and produce a more dynamic result for future work. More DR signal alternatives will also increase the system's adaptability, enabling users to take part in any preferred plan depending on their household appliances and daily habits. Lastly, by allowing consumers to contribute to the grid while earning incentives, expanding the models to include more categories of appliances would further cut expenses.

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APPENDIX – A

LOAD SHIFTING ALGORITHM

In response to user dissatisfaction, a load shifting algorithm was implemented.

```
function [new_apps,max_load] = loadShifting()
%
constraints = constraint();
%get the reasonable hours to shift the appliances
[~,indexes] = sort(electricityTariff());

%
old_apps = initializeAppliances();
num_of_apps = size(old_apps,1); %app
type=3; %
work_hour=4; %work hour
dissatisfaction=6; %dissatisfaction
workOrNotHour=5; %work or not array
count=1;
powerIndex = 2;    %appleance
%fixed
powerOfCurrentApps = zeros(1,24);
for ii = 1:num_of_apps
    if strcmp(old_apps{ii,type},'fixed')
        powerOfCurrentApps = powerOfCurrentApps +
old_apps{ii,powerIndex} * old_apps{ii,workOrNotHour};
    end
end
for jj=1:num_of_apps
    if strcmp(old_apps{jj,type},constraints.ALLOWED_TYPE)
        if old_apps{jj,dissatisfaction} ==
constraints.ALLOWED_DISS_LEVEL
            work_hour_temp = ceil(old_apps{jj,work_hour});
            old_apps{jj,workOrNotHour}=zeros(1,24);
            while count <= length(indexes)
                tempPower = zeros(1,24);
                realIndexes =
indexes(count):(indexes(count) + work_hour_temp - 1);
                realIndexes(realIndexes > 24) =
realIndexes(realIndexes > 24) - 24;
                tempPower(realIndexes) =
powerOfCurrentApps(realIndexes);
```

```
                tempPower(realIndexes) =
tempPower(realIndexes) + old_apps{jj,powerIndex};
                if all(tempPower(realIndexes) <
constraints.MAX_LOAD)
                    powerOfCurrentApps(realIndexes) =
powerOfCurrentApps(realIndexes) + old_apps{jj,powerIndex};
                    %powerOfCurrentApps

old_apps{jj,workOrNotHour}(realIndexes)=1;

%disp([old_apps{jj,workOrNotHour},old_apps{jj,1}])
                    count = count + 1;
                    break;
                end
                count = count + 1;
            end
        end
    end
end
 max_load = max(powerOfCurrentApps);
 new_apps=old_apps;
end
```

APPENDIX – B

THE PRELIMINARY DESIGN

Name	Power	Type	Work Hour a day	Work Hour Array	Diss. level	Work Day Array
TV	0.098	fixed	5.0	[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,1,1,1,0]	3	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Vacuum Cleaner	0.55	shiftable	0.8	[0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0]	1	[1,0,0,1,0,0,0,1,0,1,1,0,1,0,1,1,0,1,0,1,0,1,0,0,1,0,0,0,0,0]
Water Heater	2.0	shiftable	4.0	[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,1,1,0,0,0,0,0]	1	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Water Pump	0.55	shiftable	2.5	[0,0,0,0,0,0,0,0,0,0,0,0,1,1,1,0,0,0,0,0,0,0,0,0]	1	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Dish Washer	0.72	shiftable	2.16	[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,1,0,0]	1	[1,0,0,1,0,1,0,1,1,0,1,0,1,0,1,1,0,1,0,1,0,1,0,0,1,1,0,1,0,1]
Hair Dryer	2.2	shiftable	0.2	[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0]	1	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Washing Machine	0.53	shiftable	2.9	[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,1,0,0,0,0,0]	1	[1,0,0,1,0,1,1,1,0,0,1,0,1,0,1,1,0,1,0,1,0,1,0,0,1,0,0,1,1,1]
Clothes Dryer	3.0	shiftable	2.7	[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,1,0,0]	1	[0,1,0,1,0,1,0,1,0,1,1,0,1,0,0,1,1,1,0,1,0,1,0,0,1,1,0,1,0,1]
Air Conditioner	0.75	fixed	3.0	[0,0,0,0,1,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]	3	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Refrigirator	0.021	fixed	24.0	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]	3	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Oven	0.8	fixed	7.0	[0,0,0,0,1,1,1,0,0,0,0,0,0,0,1,1,1,1,0,0,0,0,0,0]	3	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Desktop Computer	0.1	shiftable	4.0	[0,0,0,0,1,1,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]	1	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Iron	2.0	shiftable	2.0	[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0]	1	[1,0,0,1,0,0,0,0,0,1,0,0,1,0,1,0,0,1,0,0,0,1,0,0,1,0,0,0,0,0]
Toast Machine	2.0	fixed	0.25	[0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0]	3	[1,0,0,1,0,0,0,0,0,1,0,0,1,0,1,0,0,1,0,0,0,1,0,0,1,0,0,0,0,0]
Freezer	0.016	fixed	24.0	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]	3	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]

Microwave	0.8	fixed	0.25	[0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0]	3	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Coffee Maker	0.75	fixed	0.5	[0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0]	3	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Kettle	2.2	fixed	0.5	[0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0]	3	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Electrical Shaver	0.02	shiftable	0.08	[0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]	1	[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Phone Charger	0.02	shiftable	2.0	[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0]	1	[1,0,0,1,0,0,0,1,0,1,1,0,1,0,1,1,0,1,0,1,0,1,0,0,1,0,0,0,0,0]