Optimization of Electricity Consumption Using Thermal and Battery Energy Storage Systems in Smart Buildings

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Optimisation de la consommation d'électricité utilisant un système de stockage d'énergie thermique et un système de stockage d'énergie par batterie dans les bâtiments intelligents

Zohreh ROSTAMNEZHAD

RÉSUMÉ

En raison de la consommation d'électricité variable dans les bâtiments pendant la journée, les systèmes de stockage d'énergie (SSE) sont utilisés pour stocker l'énergie et la restituer aux heures de pointe pour réaliser l'écrêtage de la charge de pointe, afin d'économiser les coûts, fournir la demande de la charge et augmenter la qualité de l'alimentation ainsi que la stabilité. Cependant, compte tenu de la capacité limitée des SSE et de leurs diverses contraintes, il est difficile de répondre entièrement aux critères d'écrêtement des pointes de charge déterminés par les compagnies d'électricité. La nouveauté de la présente thèse est l'utilisation d'un système de stockage d'énergie thermique (SSET) parallèlement au stockage d'énergie par batterie (SSEB) pour compenser les limitations des SSEB et définir la charge/décharge optimale des SSE par des approches d'optimisation.

L'unité de gestion de l'énergie proposée utilise un système de stockage d'énergie thermique (SSET) et un système de stockage d'énergie par batterie (SSEB) pour stocker l'énergie en période creuse et la décharger en période de pointe. Le programme de charge/décharge optimal de TESS et BESS a une grande importance dans la réalisation d'un écrêtage complet de la charge de pointe. Par conséquent, les horaires de charge/décharge de SSET et SSEB sont formulés comme un problème d'optimisation. Dans un premier temps, l'optimisation par essaims de particules (PSO) est utilisée afin d'obtenir un horaire optimal en raison de son efficacité et de son temps de calcul. L'approche mathématique est également appliquée pour prouver la convexité du problème et l'unicité de la solution. Dans un deuxième temps, pour valider la solution optimale obtenue par PSO, l'apprentissage par renforcement (RL) est employé et les résultats sont comparés. Dans ce contexte, le problème d'optimisation est formulé comme un processus de décision de Markov puis résolu par la méthode d'apprentissage Q. Pour assurer la fiabilité et la stabilité de l'alimentation, tous les types de charges, y compris les charges électriques branchées et thermiques sont considérées et supportées par les SSE pendant les périodes de pointe. De plus, pour modéliser les composants et les charges du bâtiment, la modélisation en boîte grise est adoptée.

L'efficacité des méthodes proposées est démontrée en utilisant la consommation électrique réelle d'un bâtiment du campus. Les résultats montrent que les méthodes sont capables de définir les horaires de charge/décharge des SSE de façon optimale afin de réduire les coûts tout réduisant la capacité du SSEB.

Mots-clés: Gestion de l'énergie, Essaims de particule, apprentissage par renforcement, Système de stockage d'énergie thermique, Système de stockage d'énergie par batterie.

Optimization of Electricity Consumption Using Thermal and Battery Energy Storage Systems in Smart Buildings

Zohreh ROSTAMNEZHAD

ABSTRACT

Due to the variable electricity consumption pattern in buildings during the day, energy storage systems (ESS) are considered to be employed to store the energy and release it in peak hours to achieve peak load shaving, save cost, provide the demand load, and increase the power quality and stability. However, based on the limited capacity of ESSs and their limitations, it is challenging to meet peak load shaving criteria determined by utility companies. The novelty of this thesis is the employment of thermal energy storage system (TESS) alongside battery energy storage system (BESS) to compensate for BESS limitations and define the optimal charging/discharging schedule of TESS and BESS by optimization approaches.

The proposed power management unit uses a thermal energy storage system (TESS) and a battery energy storage system (BESS) to store the energy in off-peak periods and discharge it in high load demands. The optimal charging/discharging schedule of TESS and BESS has an important role in achieving complete peak load shaving. Therefore, the charging/discharging schedules of TESS and BESS are formulated as an optimization problem. In the first framework, particle swarm optimization (PSO) is employed to obtain the optimal schedule due to its computational time efficiency. The mathematical approach is also applied to prove the convexity of the problem and the uniqueness of the solution. In the second framework and to validate the optimal solution by PSO, reinforcement learning (RL) is employed and results are compared. In this context, the optimization problem is formulated as Markov decision process (MDP) and then solved by Q-learning algorithm. To provide power reliability and stability, all types of loads including electrical plugged and thermal loads are considered to be supported by ESS during peak periods. Moreover, to model the building components and loads, grey-box modeling is adopted. The efficacy of the proposed framework is demonstrated by using real electric power consumption data of a campus building. Results show these proposed frameworks are capable of defining optimal charging/discharging of ESSs, saving cost, compensating for BESS limitations, and reducing its capacity.

Keywords: Power management, particle swarm optimization, reinforcement learning, thermal energy storage, battery energy storage.

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LIST OF ABREVIATIONS

HVAC	Heating, Ventilation, and Air Conditioning
KKT	Karush-Kuhn-Tucker
PMU	Power management unit
MDP	Markov decision process
TESS	Thermal energy storage
BESS	Battery energy storage
ESS	Energy storage
SOC	State of charge
PSO	Particle swarm optimization
QL	Q-learning
RL	Reinforcement learning
DRL	Deep reinforcement learning

LIST OF SYMBOLS AND UNITS OF MEASUREMENTS

kg	kilogram
kJ	kilojoule
kWh	kilowatt-hour
kW	kilowatt
°C	degree Celsius

INTRODUCTION

The growing power demand in residential and commercial buildings is a serious issue. Commercial and residential buildings consume a significant amount of 40% and 30% of total energy in the U.S. and Canada, respectively (Energy Information, 2012). The electricity consumption profile in buildings is variable during a day (Rahman, Srikumar & Smith, 2018) and this feature intensifies meeting electricity demand during peak hours. Besides, consuming electricity in peak hours is costly for end-users. Hence, peak load shaving is needed to smooth the consumption pattern and reduce the electric power consumption in peak hours. Energy storage system has an important potential to achieve peak load shaving by the reduction of the electrical energy consumption during peak load demand, compensating the irregular generation patterns of renewable energies, and enhancing the power quality and reliability. In this context, energy storage system is charged during off peak hours and releases the energy in peak times to attain peak load shaving in the smart buildings. Each storage technology has specific limitations and requisites such as low energy density, high investment cost, very high self- discharge, small to medium range of capacity for short time intervals. Battery energy storage as a primary technology to be employed for peak load shaving. It is the practical option in terms of efficiency, capability of charging and discharging in short time intervals and ease of installation. However, battery energy storage system has relatively low life cycling times and high investment costs including expenses related to its capacity which motivate to consider another energy storage in parallel with batteries to gain more benefits.

In this sense, this thesis aims to focuses on achieving peak load shifting through the deployment of TESS in parallel with BESS in the building. The optimal schedules for charging/discharging of TESS and BESS are formulated as an optimization problem and solved through the optimization process to attain peak load shifting and reduce BESS capacity. First, particle swarm optimization is employed to obtain the optimal schedule of energy storage system. Then reinforcement learning is employed to address the optimization problem and derive the optimal operation of energy storage system. To achieve complete peak load shaving, all loads in the building including electrical plugged loads and thermal loads are considered to be supported by ESS during peak periods. Moreover, TESS is allowed to use the waste heat produced in the HVAC system. Therefore, the electrical boiler role, which has a significant electricity consumption, can be reduced. Therefore, employing TESS leads to shave part of peaks and consequently reduce the BESS capacity in the smart building.

CHAPTER 1

RESEARCH PROBLEM

1.1 Research Background

Extensive use of electricity has changed the face of the world, and it has influenced literally every aspect of people's lives in a way that one cannot imagine life without it. The growing need for more electricity is gradually outpacing production, so limited energy sources, generation, management and especially consumption patterns of energy have received more attention.

Buildings play an undeniable role in electric power consumption. It is essential to enhance the energy efficiency of buildings to decrease the amount of consumption by using proper control strategies in heating and conditioning systems. The major energy usage in buildings dedicates to heating, ventilation, and air conditioning (HVAC) systems (almost 50%) (Saloux & Candanedo, 2018) and (Afram, Janabi-Sharifi, Fung & Raahemifar, 2017). Space heating individually, can consume up to 60% of total energy in countries with extreme weather conditions such as Canada (Afram *et al.*, 2017).

Furthermore, a major issue in buildings is the large variation of loads in different hours of day, especially peak times that leads to increase costs and high energy losses among many other detriments. In terms of smoothing the consumption pattern, peak load shaving have been proposed and many investigations have been conducted to address peak load shaving methods including demand response programs, optimization and control strategies, and employing energy storage systems (EESs). Among them, using energy storage system is considered as a feasible solution to meet the specific needs and limitations in peak hours for buildings. There are different methods for energy storage including mechanical, electrochemical, electrical, chemical, and thermal energy storage (Luo, Wang, Dooner & Clarke, 2015). Among all, one of the most extensively used ESS technologies in different domains (industry & domestic) is a rechargeable battery energy storage system (BESS) that takes a relatively short time to be built and the place of installation is much flexible. Another prominent ESS technology is thermal energy storage system (TESS). TESS is designed to keep heat or cold in a storage medium to keep it available for later use, in various temperatures, place, or power conditions (Cabeza, Martorell, Miró, Fernández & Barreneche, 2015). Consumers can reduce their energy consumption during peak hours by shifting their energy usage from highly costed peak times to other times with low price by storing the energy in off peak period and releasing the energy in peak times. Employing energy storage system allows customers to simultaneously shave peak load and perform daily activities as usual. Therefore, future research emphasizes on the proper application of EES for peak shaving purpose.

To minimize the peak consumption (input from the grid) and achieve peak load shaving by using ESS, it is necessary to develop an optimal schedule operation of HVAC system and ESS. The charging and discharging schedule of the ESS are defined by employing optimization approaches to optimize electric power consumption in peak hours and also reduce the cost. However, obtaining the optimal operation of ESSs is challenging and not easy to implement. In this regard, it is important to focus on defining an optimal operating strategy of ESS to gain more cost saving, smooth the peak loads, and reduce the ESS capacity.

1.2 Research Motivation

Energy consumption is growing fast around the globe. Researchers in many fields are trying hard to change the way energy is generated and consumed. Researchers and scientists have tried to come up with new approaches such as renewable energy sources (RES) (Iqbal, Javaid, Iqbal, Aslam, Khan, Abdul, Almogren & Alamri, 2018). To gain more benefits of renewable energy sources and overcome the challenges of electricity transmission, renewable energy sources have been applied in microgrid and buildings as an important source of consuming electricity.

Renewable energy sources have some intrinsic disadvantages such as their unpredictable nature which is highly dependent on the specific season and time of day of generation. The other more challenging problem associated with renewable energy sources is their slow dynamics, which makes them unreliable energy sources to use in times of emergency situations. All these factors lead to a much higher need for flexibility in the power system for balancing the network. Therefore, the implementation of appropriate technology to store the required energy for using in demand times is essential to overcome the aforementioned challenges caused by the presence of renewable energy sources in micro-girds.

As it has been mentioned, one of the significant continuous challenges of services is to maintain a balance between electricity generation and demand. If the electricity generation system fails to match the electricity demand accurately, instability, voltage fluctuation, and total blackouts will possibly follow so that the power system will be influenced (Gajduk, Todorovski & Kocarev, 2014). So it is really important to track the consumption profile and meet the power electricity demand.

Furthermore, the consumption profile is highly variable during a day, and a serious challenge in power system management is to take care of the sudden increase in demand during the peak load. The peak demand challenge is increasingly getting more serious due to the growth in the number of end-users. Some European and North American countries have addressed this problem by peak shaving methods. However, the continuous increase in demand will inevitably lead to more power outages and raises the costs of electricity generation (Rahimi, Zarghami, Vaziri & Vadhva, 2013), (Chua, Lim & Morris, 2016), (Joshi & Pindoriya, 2015).

Therefore, investigations have been conducted to address peak load shaving methods including demand response management (Cichy, Beigelböck, Eder & Judex, 2016), integration of electric vehicle (Wang & Wang, 2013), and using energy storage systems (Kalkhambkar, Kumar & Bhakar, 2016). One of the most effective strategies of peak load shaving is achieved through the process of charging energy storage systems in off-peak periods and discharging in on-peak hours. There are different methods for energy storage. Energy can be stored by different strategies such as mechanical (Abdeltawab & Mohamed, 2016), battery energy storage system (BESS) (Leadbetter & Swan, 2012), electrical (Chen, Cong, Yang, Tan, Li & Ding, 2009), chemical (Niaz, Manzoor & Pandith, 2015), and thermal energy storage system (TESS)(Erdemir & Dincer, 2020). Each storage technology has specific limitations and requisites. For example, flywheels which is one of the important mechanical storage systems, have limitations including high cost, low energy density, and mechanical fatigue (AL Shaqsi, Sopian & Al-Hinai, 2020). On the other hand, pumped hydro energy storage (PHES) and compressed air energy storage (CAES) have demerits related to environmental problems and high installation costs. Moreover, superconducting magnetic energy storage (SMES) as another ESS is used with the battery to store the energy. However, complicated design, expensive cost, and temperature sensitivity are some of its main issues (Enescu, Chicco, Porumb & Seritan, 2020).

Among all, BESS is the practical candidate to achieve peak load shaving due to its efficiency, charging/discharging in short time intervals and ease of installation to be used in buildings. Nonetheless, BESS has relatively low life cycling time, high investment cost, and high maintenance expenses which hinder its large-scale use. The expenses of BESS are mainly related to installation cost, maintenance cost, and replacement cost which are affected by battery capacity, lifetime, and rate of degradation of the battery. Therefore, the size of the battery requires specific attention to prevent extra expenses (Hannan, Wali, Ker, Rahman, Mansor, Ramachandaramurthy, Muttaqi, Mahlia & Dong, 2021). On the other hand, TESS is also a technique well suited for being applied in buildings for energy management and saving the cost. TESS is designed to store heat or cold in a storage medium for later usage at various temperatures and power conditions (Cabeza *et al.*, 2015). It is considered to provide the heating and cooling demand in buildings and shave the peak in peak hours by storing the energy in off-peak hours and releasing it during peak hours. Although, TESS has low environmental impact and greenhouse gas emissions, it cannot satisfy the plugged load in buildings and needs to be in large scale units due to its low heat capacities (Sarbu & Sebarchievici, 2018). Therefore, due to the mentioned advantages and disadvantages of TESS and BESS, they can be considered to be employed alongside each other to complement their mentioned limitations. Moreover, the simultaneous application of TESS and BESS can lead to the reduction in BESS capacity and consequently save investment and maintenance costs. Hence, based on the merits of TESS and BESS, this thesis mainly focuses on achieving peak load shaving and reduction in BESS capacity by utilizing BESS and TESS as the energy storage systems in an institutional building.

Although the peak shaving using ESSs is proposed and achieved through different researches, the limitations of using batteries and TESS to compensate a large amount of peak load are not considered. Peak load shaving is achieved by installing a very large tank or bank of batteries which raises the high cost. In addition, based on limited capacity of ESSs, it is challenging to meet peak load shaving criteria which utility companies determine. Furthermore, most of the studies emphasize on using only one type of energy storage which leads to more cost and expenses of installation and maintenance like employing a large-size of BESS. Moreover, since defining an optimal operation schedule for simultaneous employment of TESS with BESS is a complicated task, the previous works consider only thermal loads related to HVAC system, or only plug loads (receptacle loads) like lights and computers for peak load shaving mechanism. Besides, using rejected heat by building components such as chillers has significant benefits on saving electricity and cost which is most often neglected.

These gaps are considered as motivations for this thesis to focus on achieving peak load shifting through the deployment of TESS and BESS in the building. To achieve complete peak load shaving, all loads in the building including electrical plugged loads and thermal loads are considered to be supported by ESSs during peak periods. The optimal schedules for charging and discharging of TESS and BESS are defined through the optimization process to attain peak load shifting and reduce BESS capacity.

1.3 Research Objectives

The first objective: The main objective of this project is obtaining an appropriate strategy to reduce electricity cost and minimize the peak of electric power consumption of a building in a micro-grid. One way to reduce power demand is to use a procedure called peak load shaving, in which some electrical loads are operated only during off-peak periods-when demand for, and the cost of electricity are relatively low. As it is mentioned, one of the undeniable challenges in micro-grid is to maintain a balance between electricity generation and demand. Several problems such as instability and voltage fluctuation will occur if the balance between generation and demand fails. Therefore, the objective has dedicated using the peak shaving approach in the system that can overcome some of the significant ongoing challenges mentioned in the previous section. It has direct effects on benefits for the grid operator, the end-user and carbon emission reduction.

The second objective: Integrating energy storage system to the grid is the potential strategy of peak shaving. Among all ESSs, BESS is the practical candidate to achieve peak load shaving due to its efficiency, charging/discharging in short time intervals, and ease of installation to be used in buildings. However, the size of the battery should be determined accurately since a major portion of BESS expenses is related to costs of installation, maintenance, and replacement, which are proportional to battery capacity, lifetime, and rate of degradation of the battery. In this regards, TESS is deployed in cooperation with BESS to reduce the capacity of the BESS, gain significant cost benefit, and reduction in capital expenses. However, defining the charging/discharging schedule of thermal energy storage and battery energy storage is considered as one of the main challenges. Therefore, another objective is going to obtain the charging/discharging schedule of ESSs with respect to threshold values of power electric consumption set by the main grid to reduce the BESS capacity and shave the peak.

The third objective: Presence of chillers and boilers in the building makes it possible to take advantage of the waste heat from one system to feed the other or store the energy to be used in a proper time in order to minimize the electricity to produce the required heat. TESS is supplied by the waste heat produced in the HVAC system. Benefiting from this approach, the electrical boiler's role in producing heat, which has a significant electricity consumption in peak hours, is eliminated from the total electric power demand, leading to a reduction in BESS capacity. Moreover, the solution of the optimization problem (charging/discharging operation of ESSs) will then dictate a working schedule for the heat production system in the building. So the next objective is allocated to optimize the operation of the system in order to minimize cost, eliminate the boiler role, and produced required heat to store in energy storage system.

1.4 Research Methodology

In this section, our methodologies to achieve the aforementioned objectives are presented.

Addressing the first objective: In buildings, peaks are mainly based on electrical devices such as lights and computers (fixed loads) and thermal devices (shiftable loads) such as a boiler and chillers supplied by the power grid. Peak load shaving mechanism should investigate different scenarios to cover peaks in buildings due to using different types of ESSs. In this context, the peak load shifting mechanism contains two main states: charging the ESS in off-peak hours and discharging the ESS to supply load demand in peak periods. Discharging happens during peak hours to minimize the electricity load demand from the power grid. The peak load shaving mechanism for discharging TESS and BESS is investigated through three scenarios:

- In the first scenario, the great portion of the peak load is related to the shiftable load. Hence, the priority is to use the TESS and discharge it to support the shiftable load.

- The second scenario happens when the peak load is corresponding to fixed load in the building. In this scenario, BESS is deployed to fulfill the fixable load requirements.

- The third scenario which is the main focus of this thesis, indicates the peak load as the combination of both fixable load and shiftable load. In this plan, TESS and BESS are used to meet the demand and shave the peak.

Addressing the second objective: To achieve peak shaving, the load shifting should be attained by optimization approach through deployment of TESS and BESS. The considered building includes both shiftable load such as thermal load and fixed load like lighting and electronic devices that are collected in each time interval. Both TESS and BESS have limited capacities with the prespecified maximum value of charging and discharging rates, which are the cases in practice. Utility companies penalize the building when the electricity usage passes the predefined threshold. Bringing all together, the optimal rate of charging and discharging of ESS is obtained maximum peak load shifting. Thus, the charging and discharging schedule, namely operating schedule, of TESS and BESS is formulated by an optimization problem with respect to the constraints and limited capacity of ESS. Hence, firstly particle swarm optimization (PSO) is employed to obtain the optimal schedule due to its computational time efficiency. Furthermore, we formulate the problem as Markov decision process (MDP) and define the reward function, environment state, and action. Then the model-free based reinforcement learning (RL) is employed to achieve optimal charging/discharging rate of ESSs. The results of PSO and RL are compared to show the effectiveness of proposed method to reduce the BESS capacity and attain peak load shaving.

Addressing the third objective: It is necessary to obtain a reliable model to analyze and take more benefits of using waste heat produced by the building components. Buildings contain several mechanical, hydraulic and electrical components such as heat and mass transfer devices, air handling equipment, air and liquid distributed systems, chillers, and boilers. Most of the time the exact model of all the components of building cannot be obtained easily. Gray-box modeling is an effective method for modeling when some HVAC processes are not clearly defined by thermodynamic equations. This method is a combination of physics models (i.e., white-box modeling) and data-driven models (i.e., black-box modeling). The relationship between inputs and outputs of all the components of heating and cooling systems such as chillers, boilers, and existing tanks is derived based on historical data and thermodynamic principles. Based on thermodynamic principles, the rejected heat by chillers is calculated and considered to find the demand load. Then, the mathematical models will be used to find the correlations between produced heat and electrical consumption. Moreover, based on the recorded data of total electricity consumption and calculated load demand of buildings, the system behavior during peak hours and off peak hours will be defined and modeled. Therefore, an optimized working schedule will be realized by considering all the interconnections and interactions among chillers, storage tanks, and the electricity grid into our optimization problem.

1.5 Thesis Outline

The thesis is organized as follows: Chapter 1 outlines the research problem including the research background, motivations, objectives, an overview of methodologies. Subsequently, in Chapter

2, the state-of-the-art of the existing literature in this area of research is taken into account. Chapter 3 introduces the modeling of the smart building including HVAC system, TESS, BESS, and demand loads. Chapter 4 characterizes the optimization problem and address the optimal solutions by using PSO. Following this, Chapter 5 presents the model free reinforcement learning approach to solve the optimization problem. The optimization problem is modeled as MDP and solved by Q-learning. The conclusion, and future work are illustrated in the final chapter.

CHAPTER 2

LITERATURE REVIEW

In recent years, one of the major issue in power systems is the increasing demand for electricity in peak hours that leads to higher costs. This issue can be solved if consumers reduce their energy consumption during peak hours by shifting their energy usage from costly peak hours to other times with low price through peak load shaving mechanism. One of the most effective strategies of the peak load shaving is the integration of energy storage systems into the grid. In this technique, peak load shaving is achieved through the process of charging energy storage system specifically thermal energy storage and battery energy storage when demand is low (off-peak period) and discharging when demand is high. In this context, a bundle of parameters such as technical constraints of the systems have to be considered. Achieving an optimal trade-off among all parameters (e.g. charging and discharging schedule) of both energy storage systems is a complicated task. Furthermore, various variables such as weather, instantaneous energy price, and the irregular demand may affect the charging and discharging schedule of TESS and BESS. Therefore, We aim to propose a promising optimization strategy to obtain an optimized operation of ESSs to achieve the peak load shaving.

This chapter is dedicated to the literature review about modeling of the system, energy storage systems, peak load shaving mechanism in microgrid and necessary tools that will be required in future to pursue our research objectives.

2.1 Modeling of smart buildings

It is necessary to obtain a reliable model of the HVAC system to analyze and improve its control system properly and obtain peak load shaving. HVAC systems contain complex structures which consist of heat and mass transfer devices, thermal energy storage, air handling equipment and air and liquid distributed systems. The existence of several mechanical, hydraulic and electrical components makes the dynamics of HVAC plants nonlinear. HVAC modeling is dynamic, nonlinear and very high order because of the physical features such as high-thermal-inertia, real lag time, uncertain disturbance factors, etc. of the system (Homod, 2013). HVAC and building modeling is divided into three groups: physics-based (or white box/mathematical), data-driven (or black box/inverse), and gray box (or hybrid) (Afroz, Shafiullah, Urmee & Higgins, 2018b).

2.1.1 Physics-based (white box) model

The white box model is based on the mathematical equations of the laws of energy and mass balance, heat transfer, flow balance and momentum. The physics-based model requires a specific assumption to be gained. This model is mainly used for prediction and analyzing the performance of HVAC system components through simulation. It is usually applied into systems with slow-moving temperature and humidity processes while it is better to use static models for the fast dynamics of systems such as mixed air temperature and energy consumption (Afram & Janabi-Sharifi, 2014a).

2.1.2 Data-driven (black box) model

Data-driven models can be obtained by collecting the data of system performance in different situations. These models are established by defining a relationship between the input and output variables using the mathematical techniques such as neural network and fuzzy logic systems. The capability of black box models in HVAC systems has been investigated in different studies. It has been proved that the most benefits of models can be achieved by using sufficient training data (Zeng, Zhang & Kusiak, 2015). Black-box modeling technique consists of different types of strategies to model the HVAC system which is given in Figure 2.1 (Afroz *et al.*, 2018b).

2.1.3 Gray-box (hybrid) model

Gray box modeling is considered as the combination of physics models and data-driven models. The primary structure of the model is designed by white box modeling, however, the parameters of the model are driven by applying parameter estimation algorithms on the measured data of the systems. Gray box is an effective method for modeling when some HVAC processes are not

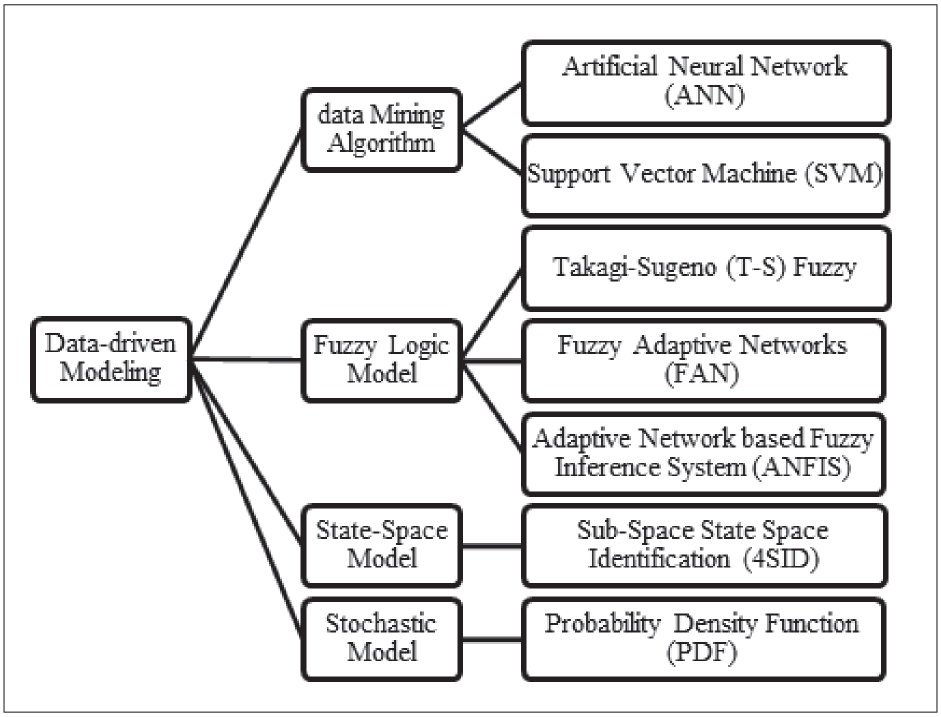

Figure 2.1 Classification of black box modeling technique

clearly defined by thermodynamic equations. Furthermore, the beneficial aspect of the gray-box model is regarded for control and optimization applications when is expressed in a form of transfer function or state space (Ghiaus, Chicinas & Inard, 2007).

The authors in (Ghiaus *et al.*, 2007) established a hybrid model in a linear form to represent a constant air volume which is able to improve the control function. To avoid coupling between humidity and temperature, they developed the model based on the assumption that each element changes only one variable. Therefore, they established separated elemental transfer functions. A gray box modeling was developed in (Afram & Janabi-Sharifi, 2015a) for the residential HVAC system. They investigated the effects of the existence of on/off controllers on the energy consumption. One of the main drawbacks of their work is lack of thermal energy storage in their modeling and more advance controllers such as MPC and PID.

The authors in (Vaghefi, Jafari, Zhu, Brouwer & Lu, 2016) developed a hybrid forecast model from the physics-based and the data-driven model. Their model is capable of forecasting the optimal heating and cooling set point values. The combined forecast model was then applied to an MPC framework to control heating and cooling set points that eventually reduced the total energy and electricity cost and thermal discomfort penalty simultaneously. The weakness and strength of three approaches of modeling is given in Table 2.1.

Table 2.1 The weakness and strength of three approaches of modeling

Modeling Technique	**Weakness**	**Strength**	**Research Studies**
White-box model	- Complex - Consideration of assumptions that they are not realistic - Requires some physical parameters - Poor accuracy	- Requires less data - Easy to generalize - Easy to control and optimize	(Ghiaus & Hazyuk, 2010) (Scotton, Huang, Ahmadi & Wahlberg, 2018) (Afram & Janabi-Sharifi, 2014a)
Black-box model	- Less flexible - Requires a significant data - Depends on measurement data of input and output variables	- Simple - No need to understand the physics of the systems - Obtains undeniable prediction accuracy	(Chen, Wang & Srebric, 2015) (Kusiak, Li & Tang, 2010) (Afram & Janabi-Sharifi, 2015c) (Hou, Liu & Tian, 2017)
Gray-box model	- Accuracy depends on data using to train the model	- High accuracy - Easy to generalize - Comparatively less complex - Appropriate for control and optimization	(Afram & Janabi-Sharifi, 2015b) (Ghiaus *et al.*, 2007) (Vaghefi *et al.*, 2016)

2.2 Energy storage system

Converting energy from one form (mostly electrical energy) to another form which is able to be stored in different ways, and then converting the stored energy back into electrical energy, lies in the heart of the processes of energy storage system. Positive implications of ESS for the power network, are:

(i) being useful in peak demand, (ii) enabling real-time energy management protocols, (iii) compensating the irregular generation patterns of renewable energies, enhancing the power quality and reliability, (iv) providing energy to remote and vehicle loads, (v) helping the implementation of smart grids, (vi) being useful in the management of distributed/standby power generation, (vii) diminishing the import of electrical energy during peak load demand (Nelson, Balakrishnan & Murthy, 1999).

Grasping the details of energy supplies and the specific considerations of the end-user, is a prerequisite of proper evaluation of ESS, which is a complicated subject matter. Altogether, many actions should be coordinated in different domains of the energy system to make way for a maximum extraction of the potential benefits of ESS.

Therefore, the criteria for an appropriate choice of method and technique of storing energy should be emphasized. Based on the ideas of different experts, different criteria have been classified and the principal issues that should be considered are: 1) energy resources at hand, 2) specific need for energy and its respective application, 3) efficiency of the energy storage, 4) foundation for energy storage, and other matters of importance. To categorize the numerous technologies for energy storage, different methods have been proposed based on their functions, response times, and suitable storage duration. ESS technologies based on the form of stored energy are divided into mechanical, electrochemical, electrical, chemical and thermal energy storage.

Battery energy storage systems and thermal energy storage systems have gained fame and importance recently and are also easily applied in practice. In Table 2.2 the drawbacks of some common ESS for commercial building is given:

Table 2.2 Weakness of some ESS technologies

Technology	**Weaknesses**
Pumped hydro power	- Low energy density - Geographical restriction - High investment cost
Compressed air energy storage system	- Certain geological restriction necessary - High investment costs - Low efficiency for adiabatic CAES (< 55%)
Flywheel	- Low energy density - Very high self-discharge - Safety reasons; crack, bearing failure, external shocks

2.2.1 Thermal energy storage System (TESS)

The most desirable form of energy storage is the direct storage of electrical energy, but using capacitors is only suited for capacity levels of small to medium range and for short time intervals. The same limitation also applies to flywheels. There are specific limitations and requisites associated with each storage technology discussed so far. For example, a pumped hydroelectric energy storage requires two separate reservoirs with a desired difference in elevation between the two. Furthermore, taking advantage of compressed air energy storage is only possible when there is access to a very large cave to store high pressure air. Using fuel cells is also troublesome because of the need to store hydrogen and there are many complications associated with this technique that need more research and investigation. Altogether, one can conclude that thermal energy storage is a technique with the least requirements and limitations regarding the location or other factors that greatly limit the use of other methods (Li & Chan, 2017).

TESS offers a very high potential for maximizing the efficiency of thermal equipment and replacing many other energy storage techniques because of its economical advantages. The main important factors to consider, when choosing a TESS system are: required storage period (e.g. diurnal, seasonal), economic feasibility, and conditions of operation. Considering the research trend about energy efficiency and conservation, TESS turns out to be a success among other thermal technologies so far (Dincer, 2002).

- **Advantages of TESS:**

  The advantageous performance offered by TESS is expressed in one or more of the following ways:

  - Increasing generation capacity:

    The variability in demand allows for short time planning (e.g. diurnal) and producing energy when less needed and using it when most needed. This enables smaller production units to be able to respond to bigger consumers.

  - Shift energy purchases to low-cost periods:

    A TES system allows for an economically optimized purchase plan in which the consumer buys electricity with the lowest cost and uses the energy when the prices are high.

  - Increase system reliability:

    By adding a storage system the consumer can reach a stable and continuous access to power, so the reliability is increased (Dincer, 2002).

- **TES Technologies:**

  - **Water tank:**

Tank systems make use of heat transfer fluids as the main heat storage medium and store the fluid medium in either one or two insulated tanks. The use of TES tanks in heating, air-conditioning, and other applications have, in general, received increasing attention in recent years and thermally stratified storage tanks have been used more, recently. The important designs of tanks are two tank indirect system which require two heat transfer fluids, two tank direct system with a single HTF that can perform with both solar field HTF and for TESS and single tank thermocline systems that have a liquid heat transfer fluid to be used in both solar field HTF and TESS. Investigation in this area has found out that a single tank TESS can save up to 35% of capital cost. Tanks are usually made up of stainless steel or reinforced concrete and covered by a thick insulation layer. They can either be above ground or underground.

- **Stratified Water Tank:**

  thermally stratified water tanks has been known as the prominent strategies to store energy on daily scale. It is fully developed and has significant efficiency with low price. By means of complex optimal control with stratified water tank, peak shaving, and load leveling will be achieved as well as thermal comfort and reducing energy consumption (Yu, Huang, Haghighat, Li & Zhang, 2015), (Saloux & Candanedo, 2018), (Saloux & Candanedo, 2019).

2.2.2 Battery Energy Storage system (BESS)

Batteries rely on different chemical systems to store electrochemical energy to make them suitable for different applications (Afram & Janabi-Sharifi, 2015a). One of the most extensively used ESS technologies in different domains (industy & domestic) is rechargeable battery. Electrochemical cells are connected in series or parallel in a BES system, and provide electricity and deliver a specific voltage as a consequence of an electrochemical reaction. Each cell has two electrodes (an anode and a cathode) with an electrolyte which can be at solid, liquid or ropy/viscous states (Vaghefi *et al.*, 2016), (Ghiaus & Hazyuk, 2010). Electrochemical reactions happen at the anode and cathode at the same time during discharge and when the battery is being charged the reverse reactions happen by applying an external voltage to the two electrodes. Power quality, energy management, ride-through power and transportation systems are just some among the many applications of batteries. It takes a relatively short time to build a BES system (approximately 12 months) (Scotton *et al.*, 2018). and the place of installation is very much flexible may it be inside a building or in the vicinity of the place where such system is needed. The main drawbacks associated with such systems are the relatively low cycling times and the high costs of maintenance which hinder its extensive large-scale use (Mishra & Palanisamy, 2018).

- **Lead–acid batteries:**

  The most extensively used rechargeable battery is the lead–acid battery. Lead–acid batteries have a rapid response times, a small daily self-discharge rates (<0.3%), a relatively high cycle efficiencies (63-90%) and low capital costs (50–600 $/kW h). However, there are still limited installations around the world as large-scale EES, mainly due to their relatively low cycling times (up to 2000), energy density (50–90Wh/L) and specific energy (25–50 Wh/kg). In addition, they may perform poorly at low temperatures so a thermal management system is normally needed, which naturally increases the associated costs (Ghiaus & Hazyuk, 2010), (Mishra & Palanisamy, 2018).

- **Lithium-ion (Li-ion) batteries:**

  The Li-ion battery is considered as a desirable option where the response time, small dimension and/or weight of equipment are critical. Li-ion batteries also have high cycle efficiencies, up to 97% . The main downsides are that the cycle DoD can influence the Li-ion battery's lifetime and the battery pack usually needs an on-board computer to control its operation, which rises its net cost.

- **Sodium–sulfur (NaS) batteries:**

  The NaS battery is considered as one of the most favorable options for high power ESS designs. The main advantages of NaS batteries include relatively high energy densities, almost zero daily self-discharge, higher rated capacity than other types of batteries (up to 244.8MWh) and high pulse power capability. The battery utilizes inexpensive, non-toxic materials resulting in high recyclability (99%). However, the limitations are high annual operating costs (80 $/kW/year) and an extra system needed to manage its operating temperature.

2.3 Optimization and control techniques in smart buildings

Due to the substantial increase in energy consumption in buildings, energy saving strategies have got more attention in many countries. Statistical survey cleared that building energy consumption in the EU was 37% of the final energy totals in 2004 and this number for the USA is 41% in 2010. The major energy usage dedicates to heating, ventilation, and air conditioning (HVAC) systems (almost 50%) (Pérez-Lombard, Ortiz & Pout, 2008). Therefore, the development and implementation of complex control techniques for HVAC systems have become a priority in building energy management.

HVAC systems consist of many processes which is slow moving with time delays, and time-varying internal and external disturbances act on the system. HVAC systems usually work under varied operating condition. Besides, the price of energy is different and variable associated with different areas. Hence, it is necessary to implement an appropriate control strategy to overcome the mentioned challenges (Afram & Janabi-Sharifi, 2014b).

Due to the importance of control and optimization in HVAC systems, significant investigation has been done. A cost-optimal solution based on demand response (DR) actions for a thermal energy storage system with a ground source heat pump is defined for residential houses in a cold climate by (Alimohammadisagvand, Jokisalo, Kilpeläinen, Ali & Sirén, 2016). They minimized life cycle cost (LCC) of thermal energy storage joined with a ground source heat pump. They defined the cost optimal size of thermal energy storage as well as its temperature set point. Then, they evaluated the changing setpoint temperature of space heating and storage tank by three control algorithms including a control algorithm based on real-time hourly electricity price (HEP), a control algorithm based on previous HEP and a control algorithm based on future HEP.

The authors in (Bianchini, Casini, Vicino & Zarrilli, 2016) developed a predictive control algorithm based on price–volume signals to have effects on their consumption pattern. They sent signals once or twice a day to identify a price of power consumption in case of being below or above a specified maximum amount of energy to be consumed during hours.

Optimal operating strategy and cost optimization scheme for a micro grid has been presented by using differential evolution algorithm (Vahedi, Noroozian & Hosseini, 2010). At the first modeling based on some real manufactural data are conducted then the proposed cost function takes into consideration the costs of the emissions CO_2 as well as the operation and maintenance costs. The battery storage is used for storing excess energy. The optimization is designed to minimize the cost function of the system while constraining it to attain the customer demand and safety of the system.

The authors in (Iqbal *et al.*, 2018) proposed optimization schemes for reducing electricity cost and minimizing peak to average ratio (PAR) with maximum user comfort (UC) in a smart home. Firstly, the problem was mathematically formulated then optimized by grey wolf optimization (GWO), binary particle swarm optimization (BPSO), genetic algorithm (GA) and wind-driven optimization (WDO). Finally, three hybrid strategies for reducing electric price and peak to average ratio were proposed. In addition, to achieve more reliable, efficient and stable operation, a battery storage system was integrated.

The work in (Wu, Tazvinga & Xia, 2015) presented an optimal energy management model for a grid-connected residential PV system and battery hybrid system. Their model optimized the electricity cost by considering constraints such as power balance, solar output and battery capacity limits. Their methods attained great cost saving and robust control performance. One main drawback of their work is related to not considering users comfort. The authors in (Wang, Huang, Wang, Li, Zhang & Tian, 2018) proposed operation optimization modeling for microgrid considering distributed generation, environmental factors and demand response. One of the main strengthens of their work is related to consideration of users comfort as well as reducing the cost in demand response program. To solve this operational optimization problem, a genetic algorithm is used to implement an objective function and DR scheduling strategy.

The development and implementation of complex control techniques for HVAC systems are important. To control the HVAC systems, there are three main groups including classical control (On/Off, Rule-based controllers and PID), hard control (Robust Control, Optimal Control, Model Predictive Control) and soft control (Fuzzy logic control, Neural network control). Figure 2.2 shows the three different categories of HVAC Control methods. Following, each strategy will be explained in details.

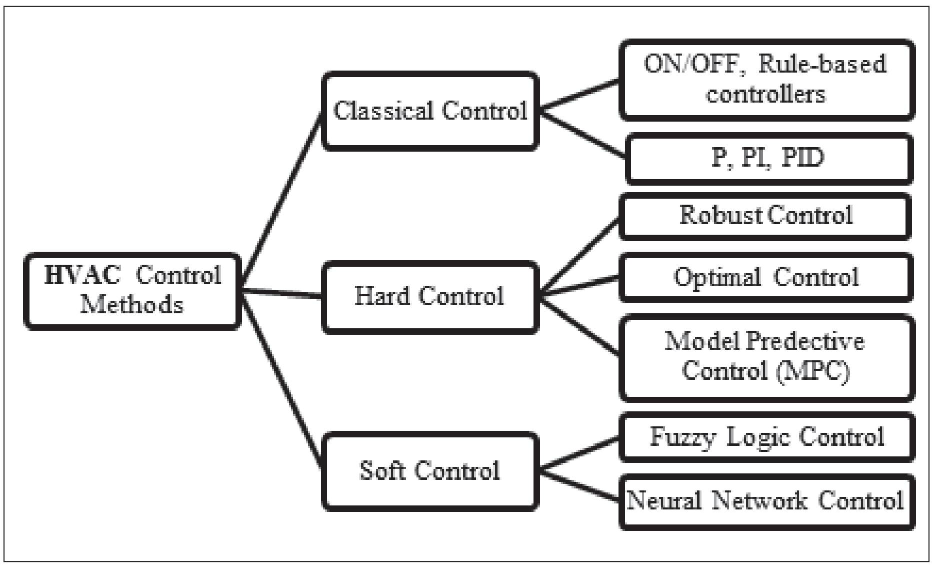

Figure 2.2 Classification of control strategies in HVAC

2.3.1 Classical control

Classical controllers contain the most common control strategies including on/off control and P, PI, and PID control. The on/ off controller uses an upper and lower threshold to adjust the process within the given limits. The P, PI, and PID controllers use error dynamics and regulate the controlled variable to achieve accurate control of the process (Taylor, House, Street, Wt, Hvac, Systems, Lim, Rasmussen & Swaroop, 2011).

- **Drawbacks:**

  Although the on/off controller is the most instinctive and easiest to implement, it is a challenge to control HVAC processes with time delays. Because of the high thermal inertia of many HVAC processes, a process that is controlled using an on/off controller and rule-based controllers displays large swings from the setpoints. Although the results of the PID application is acceptable, but tuning the controller parameters is a major issue. The performance of the controller reduces if the operating conditions vary from the tuning conditions. Retuning or auto-tuning approaches for the PID controller can be time-consuming and unacceptable (Salsbury, 2005).

2.3.2 Soft control

Soft control uses data to obtain the controllers. Two important controllers in this area are the fuzzy logic controller and artificial neural network. Example of using FL is (Yu & Dexter, 2010) investigation that the three levels hierarchical supervisory FL controller is designed to determine the set point for lower level controllers. The defined operation modes are used for the water and air subsystems. The artificial neural network is a feed-forward controller. It is mainly used for modeling and prediction. It can be trained based on controller inputs and outputs to be used instead of a conventional controller. The work in (Lee, Yeo & Kim, 2010) introduce a predictive controller for a radiant floor heating system base on a neural network. They used multi-layer perception to train the data.

- **Drawbacks:**

  The implementation of FL control requires comprehensive knowledge of the plant operation and its different states. ANN-based control design needs training data on a wide range of operating conditions. These requirements may not be available for many systems.

2.3.3 Hard control

Hard control consists of gain scheduling control, nonlinear control, robust control, optimal control and MPC. The robust controller works under time-varying disturbances and variation in parameters. The work in (Anderson, Buehner, Young, Hittle, Anderson, Tu & Hodgson, 2008) used MIMO robust control for HVAC systems including supply air temperature and zone temperature control. Despise of robust control, the optimal control focuses on solving an optimization problem to minimize a certain cost function. The main objectives of HVAC systems are generally minimization of energy consumption and electric cost and maximization of thermal comfort. Some prominent investigation has been done to gain the objectives. The authors in (Greensfeldera, Henzea & Felsmannb, 2011) studied the optimal control of passive building thermal storage with real time pricing program. They used active thermal storage control coupled with passive thermal energy storage control to achieve the reduction in cost and consumption.

- **Drawbacks:**

  The implementation of optimal control and robust control require complex computational burden. Moreover, they need the specification of additional parameters, which could be difficult and impractical for integration in HVAC systems. Due to these challenges, MPC is one of the most promising techniques because of its ability to constraint handling, and slow-moving dynamic control, disturbance elimination, and integrate energy conservation strategies into controller formulation.

2.4 Machine learning approaches in smart buildings

Due to challenges in developing a dynamic and mathematical model of the building and considering all effective parameters on the behavior of heat and cooling systems, model-free energy management systems are developed. In this context, machine learning approaches are recently used in energy management field to predict the power consumption and optimize the operation of the components of the micro-grid and smart grid. Machine learning focuses on the use of historical data and algorithms to simulate and mimic the way of human learning process and finally improves the accuracy to generate the exact model. Basically, the learning part of the machine learning algorithm has three primary sections: a decision process, an error function and a model optimization process.

- **Decision Process:**

Machine learning algorithms use historical data as input to predict new output values and estimate the pattern of the data.

- **An error function:**

The error function is needed to evaluate the prediction of the model and estimation of the pattern of the data.

- **A model optimization process:**

In training process, the wight of the model are adjusted to increase the accuracy of the prediction model and estimations. The optimization process and error function is repeated until the desired accuracy is met.

Machine learning models are divided into three main categories:

- **Supervised machine learning:**

In supervised machine learning, labeled data-sets are used to train the algorithms for prediction, estimation and classification of the data. Linear regression, logistic regression, random forest, and support vector machine (SVM) are some models that used in supervised machine learning.

- **Unsupervised machine learning:**

The error function is needed to evaluate the prediction of the model and estimation of the pattern of the data. Neural networks, k-means clustering, and probabilistic clustering methods are some algorithms that used in unsupervised machine learning.

- **Semi-supervised learning:**

Semi-supervised machine learning is combination of supervised machine learning and unsupervised machine learning approaches.

- **Drawbacks:**

The quality and quantity of data utilised for training heavily influences how well a machine learning algorithm performs. The resulting model could be erroneous and biassed if the data is biassed or incomplete. Moreover, machine learning models can sometimes be too complex and may overfit the training data, meaning they perform well on the training data but poorly on new, unseen data. Besides, some machine learning algorithms can require a lot of computational resources, making them difficult to run on less powerful devices or in real-time applications.

2.4.1 Reinforcement Learning

Reinforcement learning (RL) is the subsection of machine learning to make a sequence of decisions to optimize and predict. RL mainly has five elements: agent, action, state, reward function, environment as shown in Figure 2.3. At each time step, an agent takes an action a_t on an environment where the agent operates. The environment responses to the agent and provides the feedback related to the action made by the agent in the form of a reward signal r_{t+1} and moves from the current state s_t to the next state s_{t+1}. The main goal of the agent is to collect the largest amount of the reward (R_t) as follow (Sanchez Gorostiza & Gonzalez-Longatt, 2020):

$$R_t = \sum_{i=t}^{N} \gamma^i r_i, \tag{2.1}$$

where γ is the discount factor. To maximize the reward, the agent needs an optimal policy π which is an optimal strategy for the agent to map the current situation of the agent, state (S_t), to a probability distribution over the action. Therefore, in RL, the main goal is to define the agent with an optimal policy that maximizes the total future rewards in the environment.

The problems in RL, are formulated as a Markov decision process (MDP). A MDP provides the dynamics of the environment to observe the reactions of the environment to the action taken by the agent at a given state. A MDP contains a transition function that given the current state of the environment and an action, defines a probability of moving to any of the next states and a reward function. Due to difficulties in defining the transition function for the environment,

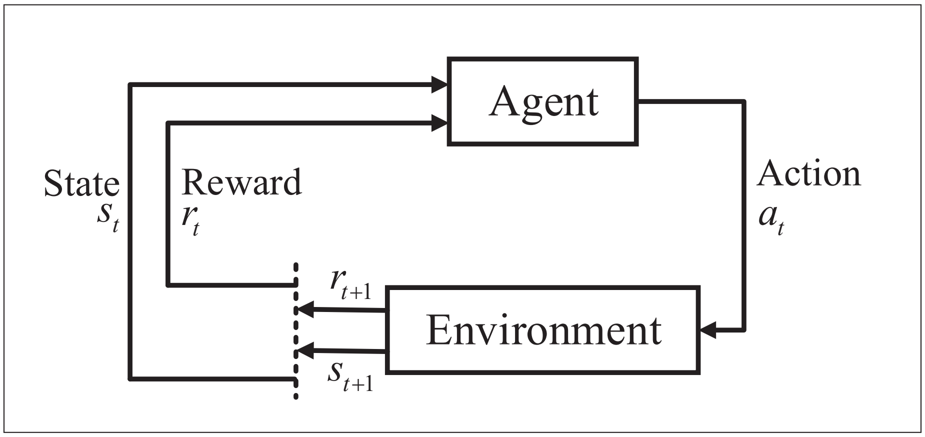

Figure 2.3 Illustration of reinforcement learning framework

model-free reinforcement learning is considered to estimate the optimal policy without using the dynamics of the environment. The optimal policy is derived by considering a value function as a function which evaluates a state (or an action taken in a state), for all states (Andrew, 1998).

2.5 Peak load shaving with energy storage systems in smart buildings

The electricity consumption profile in buildings is variable during a day (Rahman *et al.*, 2018) and this feature intensifies meeting electricity demand during peak hours. Besides, consuming electricity in peak hours is costly for end-users. Hence, peak load shifting is needed to smooth the consumption pattern and reduce the electric power consumption in peak hours.

Numerous methods have been proposed to perform peak load shifting including demand response management (Alvarez, Agbossou, Cardenas, Kelouwani & Boulon, 2020; Cichy *et al.*, 2016; Lu, Hong & Yu, 2019; Shao, Ding, Siano & Lin, 2019) integration of electric vehicle (Zhang, Tan & Gary Wang, 2018), and (Mahmud, Hossain & Ravishankar, 2019) optimization and control strategies (Mehrizi-Sani, 2014; Morstyn, Hredzak & Agelidis, 2018; Zhai, Liu, Zhang & Zhang, 2018), and using energy storage systems (Chen, Wang, Wang, Qian & Peng, 2020; Klein, Herkel, Henning & Felsmann, 2017; Kodaira, Jung & Han, 2020). Energy storage system (ESS) has a significant potential to achieve peak load shaving due to the decrease of the electrical energy consumption during peak load demand, compensating the irregular generation patterns of renewable energies, and enhancing the power quality and reliability. There are different strategies to store energy such as mechanical (Abdeltawab & Mohamed, 2016), battery Energy Storage (Leadbetter & Swan, 2012), electrical (Chen *et al.*, 2009), chemical (Niaz *et al.*, 2015), and thermal energy storage (Erdemir & Dincer, 2020). Each storage technology has specific limitations and requisites such as low energy density, high investment cost, very high self-discharge, small to medium range of capacity for short time intervals. Among all, BESS is the practical option in terms of efficiency, capability of charging and discharging in short time intervals and ease of installation. However, battery energy storage system (BESS) has relatively low life cycling times and high investment costs which hinder its large-scale use. A thermal energy storage system (TESS) can be employed alongside BESS to compensate limitations of BESS. TESS is designed to maintain heat or cold in a storage medium for later use, in various temperatures, places, or power conditions (Cabeza *et al.*, 2015).

2.5.1 Peak load shaving with battery energy storage system

The work in (Kodaira *et al.*, 2020) derives the optimal operation schedule of battery energy storage system to smooth peak by using prediction intervals. The optimal schedule of charging and discharging of BESS is derived to reduce the probability of the highest future peak. In (Leadbetter & Swan, 2012), the authors develop a model and define the optimal characteristic of BESS to minimize the electricity consumption. BESS size for a typical house in different regions of Canada is investigated and defined. The result shows how installing BESS can lead to have peak load shaving and consequently reduce the expenses.

(Reihani, Motalleb, Ghorbani & Saad Saoud, 2016) study the efficacy of BESS to achieve peak load shaving and load smoothing by the real-time control strategy and nonlinear programming method. In this work, a rooftop Photo-Voltaic (PV) is considered to meet the building power demand. Two approaches to forecast the demand load to have peak load shaving and smoothing the demand profile are used including nonlinear programming methods (complex-valued neural networks) and a real time control strategy (series-parallel forecasting). In (Ke, Ku, Ke, Chung & Chen, 2015), the authors develop the charging and discharging strategy for BESS to balance the electricity consumption for peak and off-peak periods by using a probabilistic neural network to predict the campus load and photovoltaic-generating capacity. Different sizes of BESS are examined to define the feasible BESS size regarding the different size of PV to gain more peak load shaving and benefits of PV. The authors in (Vedullapalli, Hadidi & Schroeder, 2019) propose a demand management algorithm by optimizing the operation of BESS and heating ventilation air conditioning (HVAC) to minimize the electricity consumption in peak hours. The thermal mass building and BESS are applied to store the energy in peak hours and release the energy on off peak hours. In order to get more cost saving and shaving the peak, the operation of HVAC is considered to be optimized to minimize the electric power consumption in peak hours. All the HVAC modeling is done in EnergyPlus as one of the powerful modeling software. The work in (Chua, Lim & Morris, 2017) proposed an approach to obtaining the optimum size of BESS for commercial and industrial building is proposed to optimal peak reduction. In their method, the historical load profiles of the customers are studied based on the desired peak to be shaved. This approach let the customers select the optimized size of energy storage regarding the cost saving of the peak shaving process at different tariff schemes. A genetic algorithm-based ESS sizing for microgrids is presented in (Fossati, Galarza, Martín-Villate & Fontán, 2015). They used energy management strategy based on fuzzy logic system and genetic algorithm to shave the peak and define the optimal size of the BESS. The authors in (Prasatsap, Kiravittaya & Polprasert, 2017) presents a strategy to obtain the optimal capacity of BESS to have peak load shaving in university. They used the consumed electricity data for both daily and annual scales. Based on the highest recorded demand, they define the optimal energy capacity. Furthermore, two different approaches for managing the operating of the energy storage system are considered which are time based and differentiated power criteria. They demonstrated that both management strategies reduce the cost for both consumers and utilities.

2.5.2 Peak load shaving with thermal energy storage system

As it is described before, the main feature of thermal energy storage system (TESS) is shifting load from peak time to off-peak hours. Implementation of TESS has significant economic effects on electricity market structures. For all applications of TESS, there is the same basic principle: charging (supply the energy to TESS), storing, and discharging (getting the energy back from TESS. TES applications have many potential benefits for both customers and utilities. From customers' side, having a more efficient system and saving money are achievable. For utilities, the demand can be spread through the whole day. So TESS is considered to reduce the peak of electrical demand and high costs of electricity. This technology attracts more interest if cooling and heating are also produced electrically like hot water, cooling and air-conditioning. One of the remarkable applications of TESS is when it is combined with air conditioning reduction in peak load and change in energy consumption for residential air conditioning is obtained based on the model presented by (Upshaw, Rhodes & Webber, 2015). Here, TESS extracts heat from a storage medium and provides a cooling capacity. This will reduce the refrigeration plant capacity and leads to an optimized and efficient operation for most of its working time. TESS application in Australian climate was analyzed for peak load shaving by (Rahman, Rasul & Khan, 2011). The results show that up to 61% and 50% of the electricity cost can be cut by using full and partial chilled storage systems.

In (Powell, Kim, Cole, Kapoor, Mojica, Hedengren & Edgar, 2016), a university campus is considered and the dynamic optimization is applied to determine optimal time schedule of TESS in peak hours to store and extract excess energy in order to reduce the fuel consumption and energy cost. The energy systems in this study includes combine heat and power (CHP), district heating, district cooling, and TESS. the work in (Rongxin, Douglas, Mary Ann & Klaus, 2015) analyzed the two main types of TESSs: Full storage TESSs and partial storage TESSs, which are designed to shift the entire cooling system load to the off-peak period and only a portion of the cooling load off-peak, respectively. The plant supplies the ice tank in off-peak and stores the energy, then it discharges over peak times. The important feature of the plant is its operation during summer and also the rest of the year. During summer it works as a partial storage system and for the rest of the months, it operates as a full storage system.

Meanwhile, To balance the electrical energy supply and demand, the authors in (Erdemir & Dincer, 2020) study the effectiveness of employing TESS for shifting cooling and heating loads to off-peak hours. In this study, it is considered that heating and cooling loads from HVAC system are shifted from the electricity peak load periods to off-peak hours by thermal energy storage systems. The authors in (Baniasadi, Habibi, Bass & Masoum, 2018) develop an optimal real-time thermal energy management system (TEMS) to minimize energy consumption and achieve peak load shifting while maintaining user comfort in the building. The proposed TEMS consists of two TESSs including a water tank storage system and building thermal mass, and two online closed-loop model predictive control (MPC) systems. The work in (Gholamibozanjani & Farid, 2020) employs phase change materials as TESS and price-based control systems to store the solar energy during off-peak times and use it in a high demand period. the performance of an office-size building in the presence of active air-PCM heat storage in combination with a price-based control (using ON/OFF controller) for shifting both heating and cooling loads from peak hours to off peak hours.

In (Verrilli, Srinivasan, Gambino, Canelli, Himanka, Del Vecchio, Sasso & Glielmo, 2017), the authors propose a MPC system to define the operating schedule of a district heating power plant, specifically TESS, to provide the demand load in peak hours. To handle the fluctuating demand, the MPC uses forecasts and combines it with a constrained optimization problem. The objective function reflects the cost, whereas the generator limits, TES dynamics, thermal loads, including supply temperature, power plant layout, and reliability, are the constraints. The optimization problem is modeled as a mixed-integer linear program with both continuous and logic variables.

2.5.3 Peak load shaving with TESS and BESS

A number of works consider both TESS and BESS to achieve peak load shaving. The work in (Klein *et al.*, 2017) compares BESS, water tank as TESS, fuel switch, and building thermal mass in terms of their improvements in handling the fluctuation in load, peak load shifting, efficiency and implementation.

In (Bagheri Sanjareh, Nazari, Gharehpetian & Hosseinian, 2021), the authors present an energy management scheme utilizing TESS and BESS to minimize the energy consumption and required capacity of BESS. In this study, the optimal sizing of TESS and BESS is obtained. The work in (Niu, Tian, Lu & Zhao, 2019) studies the flexibility potential of TESS and BESS in terms of minimizing the operational cost.The cooling demand is forecast by an autoregressive model with exogenous inputs, then a mixed integer linear model is formulated to optimize the dispatch of building energy systems with minimal operating costs.

The authors in (Mohandes, Acharya, Moursi, Al-Sumaiti, Doukas & Sgouridis, 2020) present an optimal sizing scheme of TESS, BESS and a photovoltaic system to provide the balance between generation and demand, minimize the operational cost of microgrid components, and achieve peak load shifting with respect to user comfort. The authors in (Nousdilis, Kontis, Kryonidis, Christoforidis & Papagiannis, 2018), analyze the economic benefits of using BESS in coordination with TESS in the nearly zero energy building environment.The proposed model modeled the combined operation of photovoltaics, solar thermal generators, heat pump generators, electrical and thermal storage devices. An optimization approach is applied to define optimal size of the lithium-ion battery energy storage system.

Although in these papers, peak load shaving is achieved, the limitations of using batteries and TESS to compensate a large amount of peak load are not considered (Ke *et al.*, 2015; Reihani *et al.*, 2016; Vedullapalli *et al.*, 2019). In addition, based on the limited capacity of ESSs, it is challenging to meet peak load shaving criteria determined by utility companies (Niu *et al.*, 2019). Furthermore, most of the studies emphasize on using only one type of energy storage (Verrilli *et al.*, 2017), and considering only shiftable loads like thermal loads related to HVAC system (Erdemir & Dincer, 2020), or fixed loads such as lights and computers (Ke *et al.*, 2015) since defining an optimal load shifting mechanism using TESS with BESS is a complicated task. Besides, using waste heat produced by building components such as chillers has significant benefits on saving electricity and cost which is most often neglected (Mohandes *et al.*, 2020) and (Klein *et al.*, 2017).

Table 2.3 summarizes the comparison of related works focusing on different applications of TESS and BESS in buildings to achieve peak load shaving and reduce the BESS capacity.

Table 2.3 Discussion on related works in using BESS and TESS in buildings

Ref.	TESS	BESS	Shiftable load	Fixed load	Prediction of load	BESS size Reduction	Highlighted topic	Research gap
(Erdemir & Dincer, 2020)	✓		✓				Investigation on effectiveness of employing TESS for shifting cooling and heating loads.	The share of fixed load demand in peak hours has been neglected .
(Ke *et al.*, 2015)		✓		✓	✓		Development of the charging, discharging strategy for BESS.	The shiftable load demand in peak hours has not been discussed and the approach to define the BESS capacity has been generalized for a special case study.
(Vedullapalli *et al.*, 2019)		✓	✓	✓	✓		Optimizing the operation of BESS and HVAC	The constraints of BESS have been not considered including its size which causes the high costs.
(Baniasadi *et al.*, 2018)	✓		✓		✓		Employment of two online closed-loop MPC systems with different types of TESS.	The constrains of TESS have not been clarified and the peaks caused by fixed load has not been addressed.
(Gholamibozanjani & Farid, 2020)	✓		✓		✓		Employment of phase change materials as TESS and price-based control systems.	The optimization approach to obtain the optimal amount of PCM was not discussed due to the high cost of PCM.
(Verrilli *et al.*, 2017)	✓		✓		✓		Defining the operation schedule of TESS through MPC system.	Two types of load including curtailable and shiftable loads were considered and the effects of plugged loads in the building were missed.
(Niu *et al.*, 2019)	✓	✓	✓	✓	✓		Minimizing the operational cost through the flexibility potential of TESS and BESS.	The reduction of the BESS capacity has not been investigated while TESS was implemented in the building.
(Mohandes *et al.*, 2020)	✓	✓		✓	✓	✓	Presenting a sizing scheme of EESs and a photovoltaic system and minimizing the operational cost of microgrid components.	The waste heating and cooling energy produced by HVAC system to save more cost and energy has been neglected.
(Nousdilis *et al.*, 2018)	✓	✓	✓	✓			Analyzed the economic benefits of using BESS in coordination with TESS in the nearly zero energy building environment	The optimization approach has not been discussed and described extensively. The optimal charging/discharging schedule for EESs was not presented.
(Bagheri Sanjareh *et al.*, 2021)	✓	✓	✓	✓		✓	Reduction in BESS capacity by adding TESS in isolated microgrid.	The obtained sizing for EESs was constrained to a specific case study and the optimization approach has not been discussed.

2.5.4 Peak Load Shaving Using Machine Learning Approaches

Recent works in (Ahrarinouri, Rastegar & Seifi, 2021; Lu *et al.*, 2019; Venayagamoorthy, Sharma, Gautam & Ahmadi, 2016; Wang, Li, Ming & Wang, 2020; Yu, Xie, Xie, Zou, Zhang, Sun, Zhang, Zhang & Jiang, 2020) have focused on using model-free approaches for energy management systems.recent works in (Ahrarinouri *et al.*, 2021; Lu *et al.*, 2019; Venayagamoorthy *et al.*, 2016; Wang *et al.*, 2020; Yu *et al.*, 2020) have focused on using model-free approaches for energy management systems. The authors in (Lu *et al.*, 2019) proposed an energy management scheme based on multi-agent reinforcement learning and artificial neural network to minimize the electricity cost while the users comfort has been maintained. The authors in (Yu *et al.*, 2020) proposed an optimal algorithm for scheduling HVAC systems in presence of ESS in the smart home by using deep reinforcement learning (DRL). The work in (Ahrarinouri *et al.*, 2021) used multi-agent reinforcement learning (MARL) to optimize the operation schedule of smart home components such as combined heat and power unit, a plug-in electric vehicle, solar panels, and controllable electrical loads. This work reduced the energy consumption costs and increase the calculation speed by using MARL. In (Venayagamoorthy *et al.*, 2016), the authors developed an intelligent dynamic energy management system (I-DEMS) to maximize reliability and extend the battery life used in the building and maximize the users satisfaction. The authors in (Wang *et al.*, 2020) proposed an energy management system based on RL to demand response management under the time of use tariff and reduce the total operating costs of the distribution system operators.

Although all aforementioned studies tried to control and optimize the operations of components of the smart building to obtain peak load shaving and saving costs, they have not considered the simultaneous application of different types of energy storage systems in the building and limitations of each EESs. Energy can be stored by different strategies such as mechanical (Abdeltawab & Mohamed, 2016), battery energy storage system (BESS) (Leadbetter & Swan, 2012), electrical (Chen *et al.*, 2009), chemical (Niaz *et al.*, 2015), and thermal energy storage system (TESS) (Erdemir & Dincer, 2020). Each storage technology has specific limitations and requisites such as high installation costs, environmental problems, low energy density, mechanical fatigue, and short discharge time. Among all, BESS has been considered as the main ESS in most aforementioned papers due to its efficiency, charging/discharging in short time intervals and ease of installation. However, it is worth to mention that BESS has relatively low life cycling times and high investment costs which hinder its large-scale use and are neglected in mentioned studies. Furthermore, the main issue in using ESSs in buildings is related to defining the optimal schedule of charging/discharging when different electrical, heating and cooling systems exist in the building to meet the demand and shave the peaks. Moreover, in the above-mentioned papers, only one type of load mainly plug load in the building has been considered while the effects of other type of loads such as HVAC systems loads on defining the optimal operation schedule of buildings components have been neglected.

In light of these gaps, this thesis focuses on achieving peak load shifting through the deployment of TESS and BESS in the building. To achieve complete peak load shaving, all loads in the building including electrical plugged loads and thermal loads are considered to be supported by ESS during peak periods. To save cost and energy, TESS stores the waste heat produced by chillers and deliver it to the building on peak hours. The optimal schedules for charging and discharging of TESS and BESS are defined through the optimization process to attain peak load shifting and reduce BESS capacity.

CHAPTER 3

SYSTEM MODELING

3.1 Power management unit modeling

The introduced framework of power management unit (PMU) is illustrated in Figure 3.1, which consists of an HVAC system coupled with a TESS, BESS, loads and peak load shaving mechanism. Components and loads are modeled using historical data and thermodynamic principles known as grey-box modeling.

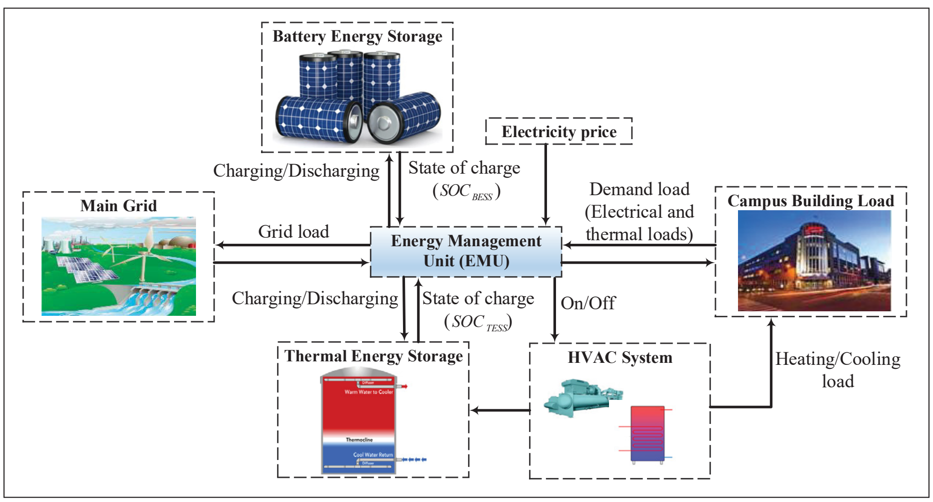

Figure 3.1 Scheme of the campus in presence of PMU and ESSs

Campus buildings generally contain mechanical, hydraulic and electrical components such as heat and mass transfer devices, air handling equipment, air and liquid distributed systems, chillers, and boilers. Developing a reliable model of the building components and loads is necessary to analyze and implement a peak load shaving mechanism. In this context, physics-based (white-box) model, grey-box model, and data-driven (black-box) model can be used to characterize a reliable model. White-box and black-box models are established based on the accurate physical knowledge and historical database of the system, respectively. White-box modeling needs a comprehensive understanding of all details and physics of building's components, which are not primarily available. On the other hand, the black-box model requires high data quality.

Grey-box modeling approach is an effective method for modeling complex systems that are sophisticated to be described by thermodynamic equations (Afram, Fung, Janabi-Sharifi & Raahemifar, 2018). This method is a combination of white-box and black-box models, which inherits the advantages of both white-box and black-box models. The advantages of the grey-box model are high capacity, easy to establish, comparatively less complex and suitable for control and optimization applications (Vaghefi *et al.*, 2016) rather than white-box modeling and black-box modeling which are complex, less accurate and less flexible. The limitations and challenges of using grey-box model are: lack of a unified software solution to obtain the model, the presence of some approximations in the model, and its vague creation (Li, O'Neill, Zhang, Chen, Im & DeGraw, 2021). Given that HVAC processes cannot be clearly modeled by thermodynamic equations and are hard to be described by only data-modeling. Therefore, a method should be adopted that can model the system by historical data and thermodynamic principles. Hence, this thesis employs grey-box modeling due to its above-mentioned advantages to address the challenges of modeling the sophisticated systems such as HVAC system. In this context, the operational data of building components is recorded and arranged. Then, the relations between inputs and outputs of heating and cooling systems such as chillers, boilers, and ESSs are derived based on historical data and thermodynamic principles to establish a novel grey-box model of the system. The considered building is a campus of a university located in Canada, which includes an electric boiler with 98% efficiency, and a chiller with a cooling capacity of 703.3 kW, efficiency 0.447 kW/ton and COP 5 as shown in Figure 3.2. It is assumed that the HVAC system of the building works properly. A water tank storage and a Lithium-Ion battery bank are considered for TESS and BESS, respectively. The sample time to record the data is corresponding to 15 minutes. The total building electricity consumption for each sample of the time interval is measured by an electricity usage monitor and presented in Figure 3.3. The pattern of total electric power consumption in building consists of fixed and shiftable loads. Fixed load accounts for 79.8% of total electric power demand on average. Fixed load is related to electric devices such as lights, computers, and laboratories in building and measured by the metering devices in the campus building. In contrast, shiftable load is associated with the electric power consumption of the chiller and the electric boiler.

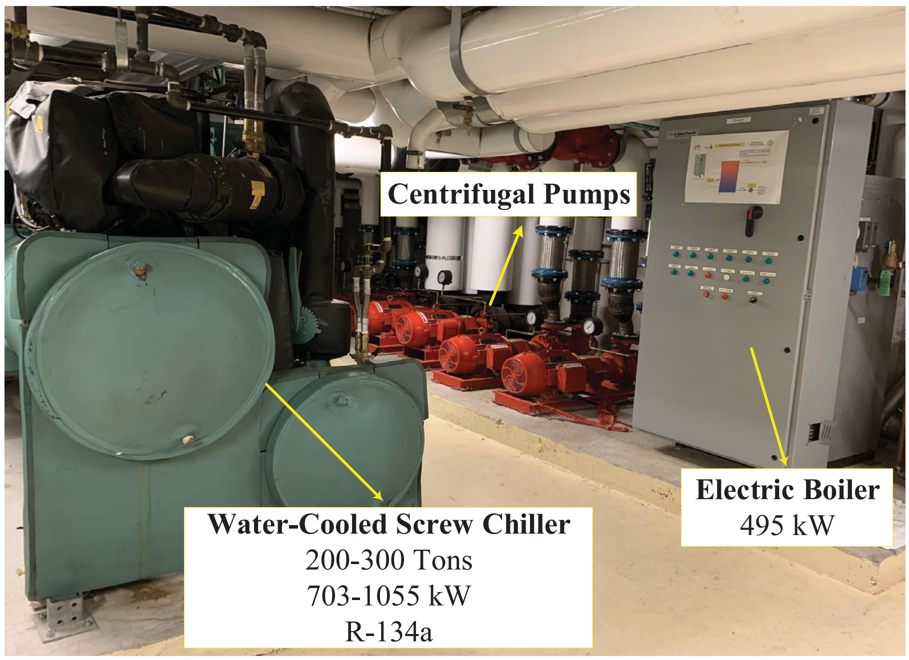

Figure 3.2 The electric boiler, chiller, and connected pumps installed in the campus building

3.2 HVAC system

The considered HVAC system consists of a chiller, an electric boiler, a cooling tower, and water pumps, as shown in Figure 3.4. The chiller, which consists of an evaporator, a compressor, a thermal expansion valve, and a condenser, is responsible for providing cooling load in the building. Two pumps are considered to supply cold water provided by the evaporator into the building. The waste heat produced in the condenser, Q_{CND}, is considered to feed TESS and calculated as follow (Afroz, Shafiullah, Urmee & Higgins, 2018a):

$$\dot{Q}_{CND} = \dot{m}_{CND} C_p (T_{CNDOW} - T_{CNDIW}) \tag{3.1}$$

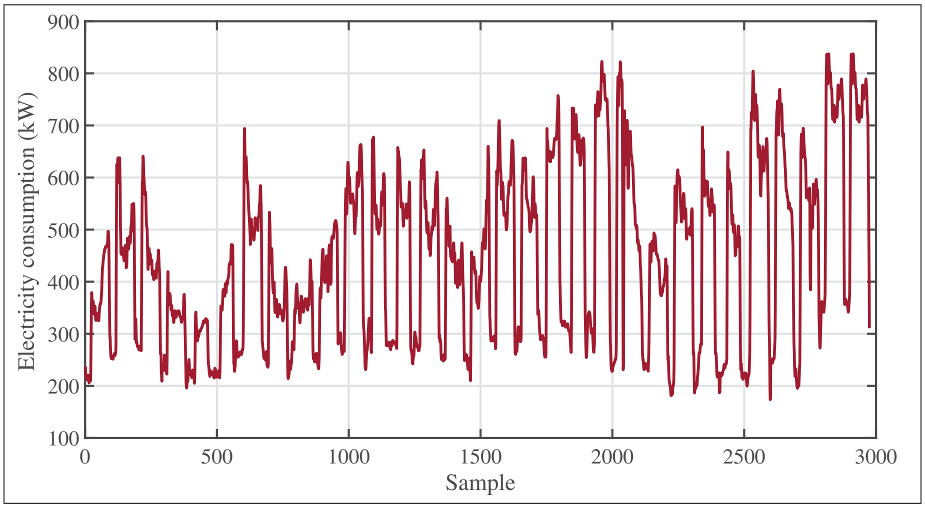

Figure 3.3 Total electric power load of the building for January of 2019

where $\dot{m}_{CND}$ is the water flow rate in the condenser, C_p is the water specific heat, T_{CNDOW} and T_{CNDIW} are the outlet and inlet water temperature from the condenser, respectively. The relation between produced heat and electricity consumption of the chiller is interpolated by a second-order function to obtain a grey-box model of electric power consumption by the chiller.

A cooling tower is generally considered to reject the waste heat produced by the condenser and reduce the temperature of the water. In this work, we propose integrating the TESS into the building to use the waste heat in the cooling tower to fill the water tank requirement in winter time as shown in Figure 3.4. In this context, the valve of cooling tower is closed and produced hot water in condenser moves toward water tank storage. Consequently, the energy is saved and the electricity consumption related to the cooling tower and connected pumps is eliminated.

The electric boiler is considered as another major electricity consumer in the building, especially in peak hours. The electricity cost to run the electric boiler with 98% efficiency is remarkable. The heat provided by the boiler is calculated based on the thermodynamics principle as follow (Farooq, Afram, Schulz & Janabi-Sharifi, 2015):

$$\dot{Q}_B = \dot{m}_{BW} C_p (T_{BO} - T_{BI}) \tag{3.2}$$

where Q_B is the heat produced by boiler, $\dot{m}_{BW}$ represents the mass flow rate through the boiler, T_{BO} and T_{BI} are outlet temperature and inlet temperature in the boiler. Moreover, the electric power consumption is obtained by historical measured data from previous years. Then the relation between produced heat and consumed electricity is extracted by the grey-box model to define the power consumption by boiler corresponding to required heat demand.

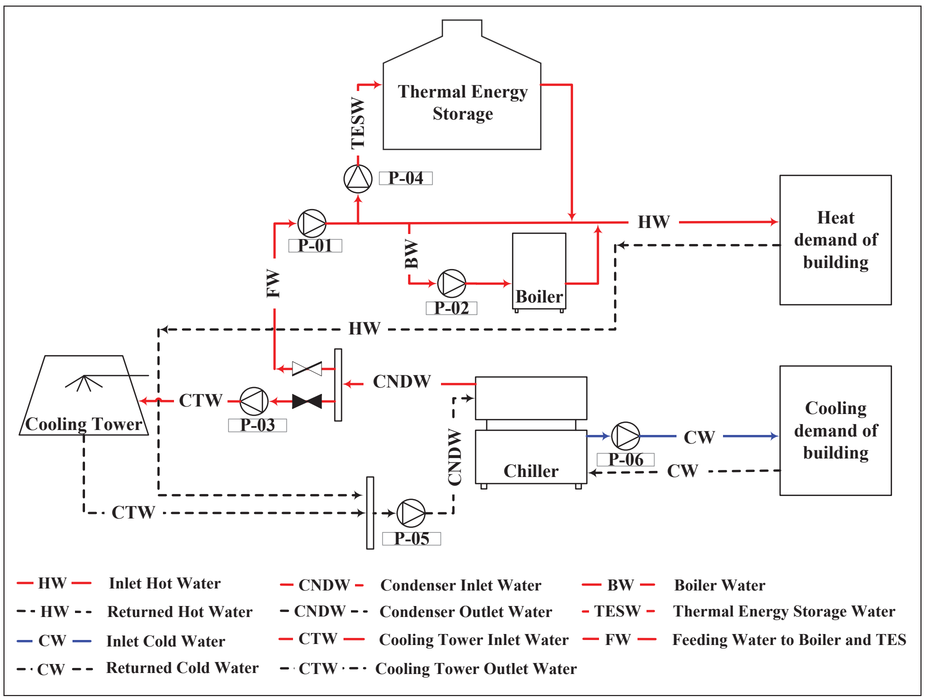

Figure 3.4 Schematic of heating and cooling systems of the campus

3.3 Thermal energy storage system

Water tanks are mainly used as TESS due to their high capacity to store energy in campus buildings. In this study, the water tank is connected to the chiller and supplied by the produced heat in the condenser of the chiller. The fully mixed water is assumed in the tank. Based on the heat produced by chillers, the average inlet temperature of water in the insulated tank is 37°C after passing the pump. The characteristics of the proposed TESS are given in Table 3.1. The heat stored in TESS by assuming the constant rates of mass water flow is presented as follow

(Dincer & Rosen, 2002):

$$\dot{Q}_{TESS} = \dot{m}_{TESS} C_p \Delta T_{TESS} \tag{3.3}$$

where $\dot{Q}_{TESS}$ is heat energy transferred to the TESS, $\dot{m}_{TESS}$ is the mass flow rate of the hot water provided by the condenser, and ΔT_{TESS} is the difference of temperature in condenser. The tank operates in two modes, charging and discharging. The water tank is charged by the heat produced in the condenser and discharged in peak hours to eliminate electricity consumption of the electric boiler and their pumps.

3.4 Battery energy storage system

Li-ion battery in comparison with other types of batteries has high energy density, high efficiency, and long cycle life. A bank of Li-ion batteries is considered to shave the peaks of fixed loads. The characteristics of the BESS are given in Table 3.1. The following equation describes the dynamics of the stored energy in battery (Dagdougui, Mary, Beraud-Sudreau & Dessaint, 2016):

$$E_{BESS}(t) = (1 - \sigma) E_{BSS}(t - 1) + \kappa x(t) \tau \eta \tag{3.4}$$

where $E_{BSS}(t)$ is the stored energy at time t, $\kappa x(t)$ is charging/discharging power, σ is the self-discharge rate of the battery, τ is the time interval, and η is the efficiency of discharging/charging in BESS. If $\kappa x(t) < 0$, the battery bank discharges the required load and if $\kappa x(t) > 0$, the battery is charged by the grid. The capacity of BESS is limited and is considered as one of the constraints for the optimization problem.

3.5 Electric power consumption model and load profile

Buildings have different components that cause different types of loads including fixed and shiftable loads (Ruzbahani, Rahimnejad & Karimipour, 2019). Fixed loads are related to electricity consumption that cannot be shifted such as lights, computers, and electrical devices. On the other hand, shiftable loads can be transferred from peak hours to another time. For instance, electric boilers and chillers can be considered as shiftable loads. Dividing the total load

Table 3.1 Characteristics of each ESSs

ESS description		Value	Unit
BESS	Battery capacity without TESS	825	kWh
	Battery capacity with TESS	475	kWh
	Minimum State of Charge (SoC)	10	%
	Maximum State of Charge (SoC)	95	%
	Maximum charge/discharge of power	200	kW
	Efficiency	90	%
TESS	TESS capacity	2000	kWh
	TESS temperature	37	°C
	Heat loss per hour	0.002	°C
	Efficiency	87.6	%

into these two categories simplifies the complexity of the problem. Hence, in this thesis, this approach is employed. The total building electric power load consisting of fixed and shiftable loads is acquired from an educational campus building. The framework of campus building loads is given in Figure 3.5 which indicates the shiftable load, fixed load and total electric power load.

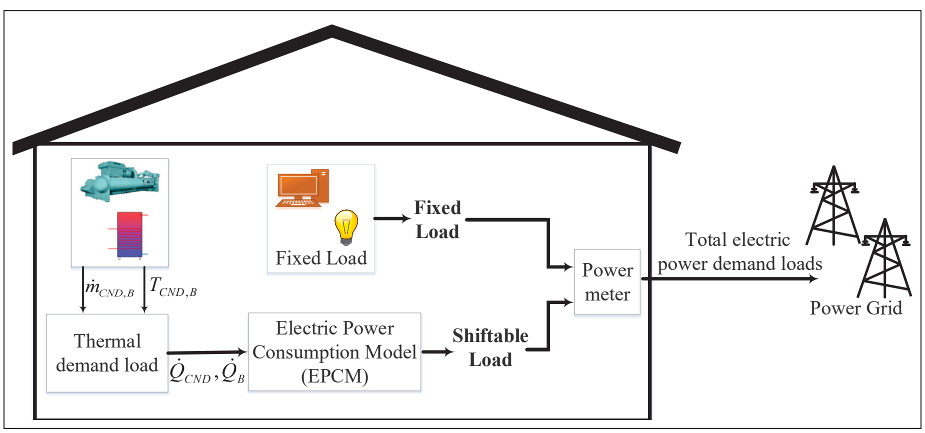

Figure 3.5 An overview of different types of the electric power loads in building

In addition to the main power meter that monitors the total electricity consumption of the building containing shiftable and fixed loads, the submeter devices are also provided to measure the electricity consumption of each component related to fixed load in the building. Hence, the summation of electricity consumption of the components measured by connected metering devices determines the fixed load in the building. While the shiftable load is calculated by using historical data and the thermodynamics principle. EPCM is considered for shiftable load to estimate the electrical consumption based on the heat produced by the HVAC system as shown in Figure 3.5. EPCM is also modeled based on the correlation between the heat rejected by HVAC devices, $\dot{Q}_{CND}$ calculated in (3.1) for chiller's condenser and $\dot{Q}_B$ in (3.2) for boiler, and historical electricity usage. Besides, the water flow rate in the HVAC system, chiller electricity consumption, water temperatures in the chiller, the boiler electricity consumption, and water temperatures in the boiler are all considered as required data to obtain shiftable load in EPCM.

3.5.0.1 Grey-box model

The grey-box model is employed to establish shiftable load and accomplish the EPCM as shown in Figure 3.5. The grey-box modeling is mainly used due to lack of details and exact information of the building's components. As it is discussed, the grey-box modeling develops the flexible model of complicated systems and loads such as chiller, boiler, and shiftable load in the building. In this thesis, the mathematical and thermodynamics principles are used to accomplish a white-box model and then the historical data is adopted to develop a black-box model to create a grey-box model of the system. In this context, the applied thermodynamic principles given in (3.1) and (3.2) are used to define the required heat rejected in the condenser and boiler, respectively. To obtain this part of the model, the historical data of the water flow rate in the HVAC system, water temperatures in the chiller, and water temperatures in the boiler are collected and measured using Metasys® software with a time resolution 15 minutes. Furthermore, the chiller and the boiler electricity consumption is measured by metering devices in the building in 2018 and 2019 to develop the EPCM. It is worth mentioning that missing values in our dataset is retrieved by replacing mean value when there are not outliers and using linear interpolation in Matlab. To establish the grey-box model, the heat demand is calculated through (3.1) and (3.2) and the relation between produced heat and required electricity load for chiller and boiler is defined based on a polynomial curve fitting. The schematic of the grey-box model is presented in Figure 3.6. To execute the grey-box model, 80% of data is considered for training and the rest is used for validation based on the Pareto principle. A second-order polynomial function of required electric power for providing heat demand is adopted in EPCM. The R-squared is 92.25%, which indicates the accuracy of the developed model.

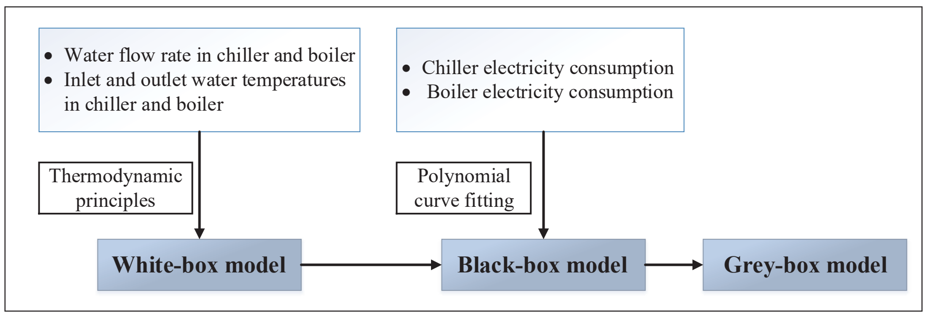

Figure 3.6 The schematic of grey-box model

Table 3.2 The share of fixed and shiftable loads in total electric power consumption related to the second scenario

Loads		Power consumption	Power consumption in peak hours
		%*	%*
Scenario	Fixed load	77.67	81.41
	Shiftable load	22.33	18.6

* Percentage of power consumption by shiftable and fixed loads with respect to total electric power consumption

Fixed load is related to electric devices for January as shown in Figure 3.7. Shiftable load is obtained based on EPCM which is presented in Figure 3.8. The total power consumption, fixed load and shiftable load for one day are demonstrated in Figure 3.9 to clarify the the share of each type of loads.

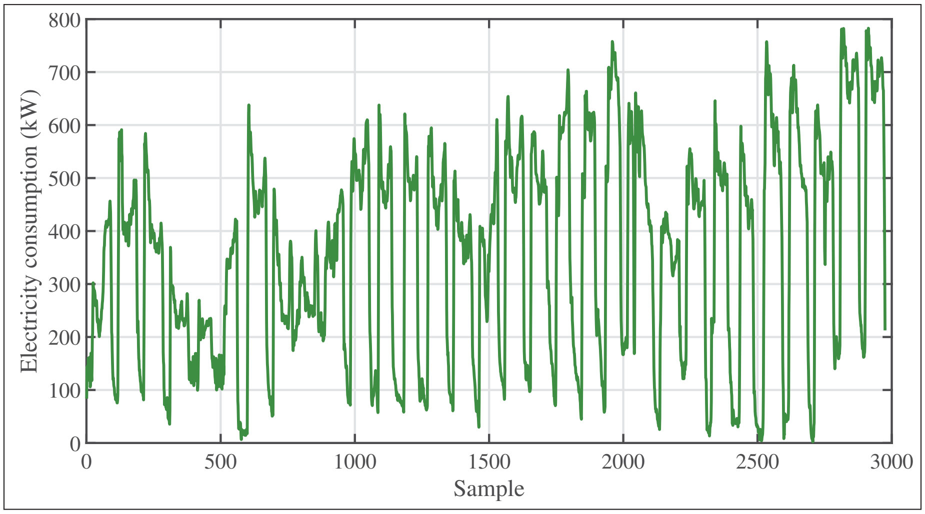

Figure 3.7 Electrical fixed load for January of 2019

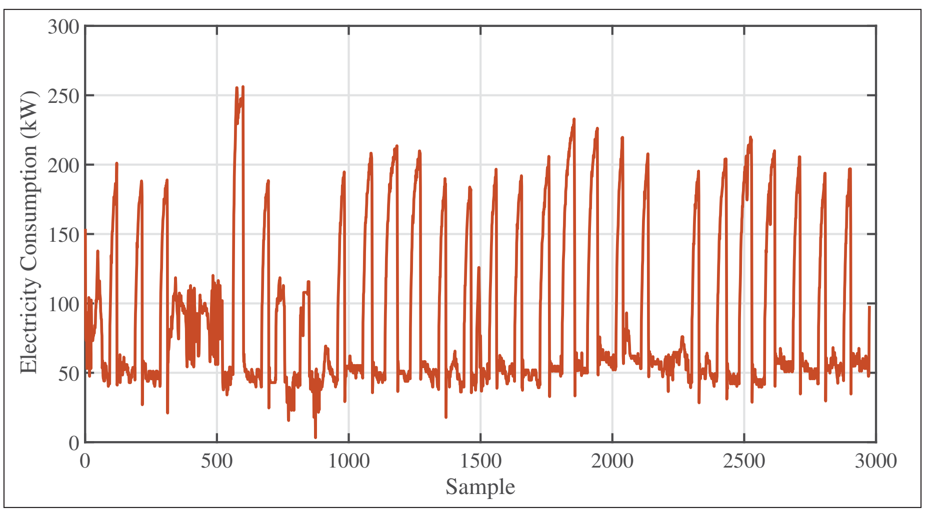

Figure 3.8 Electricity consumption related to shiftable load for January of 2019

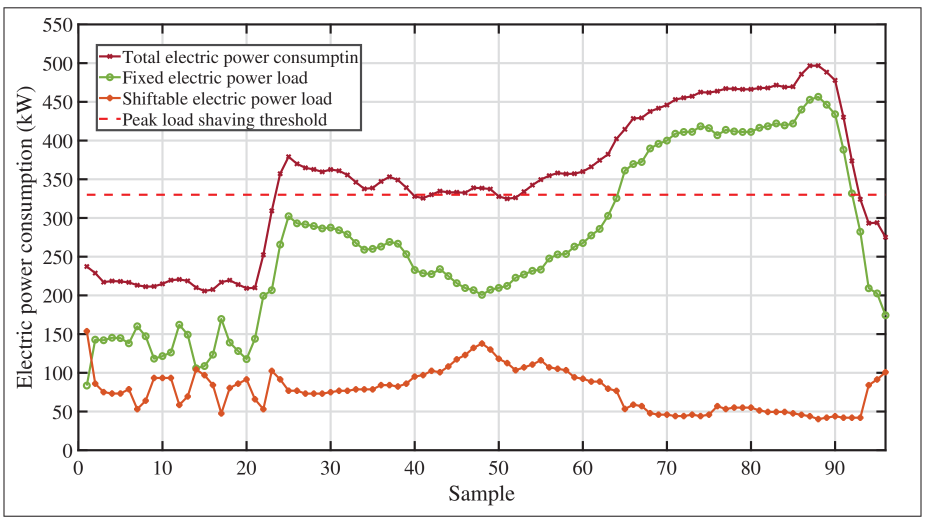

Figure 3.9 Total, fixed and shiftable electric power loads in a day of January 2019

CHAPTER 4

PEAK LOAD SHAVING MECHANISM USING PARTICLE SWARM OPTIMIZATION

4.1 Peak Load Shaving Mechanism

In buildings, peaks are mainly caused by electrical devices such as lights, computers and thermal devices. Since different types of ESSs are used in buildings, the peak load shaving mechanism should be designed considering different scenarios to cover electricity consumption peaks. In this context, the peak load shaving mechanism contains two main states: charging and discharging the ESS. In charging, the produced waste heat in the chiller's condenser charges TESS during the day. Moreover, the chiller is run and consumes electricity to produce heat in the condenser for charging the TESS until its maximum capacity during off-peak hours. Furthermore, BESS is supplied by the power grid during off-peak hours. Charging in ESSs is performed considering their maximum capacities and constraints.

The peak load shaving mechanism for discharging TESS and BESS is investigated through different scenarios in PMU. One of these scenarios is when a significant portion of the peak load is caused by the shiftable load. Hence, the priority is to use the TESS and discharge it to serve the shiftable load. If the peak load exceeds the stored energy in TESS, then BESS is engaged to shave the peak load. Another scenario happens when the peak load corresponds to the fixed load in the building. In this scenario, BESS is employed to fulfill the fixed load requirements. The final scenario, which is the main focus of this thesis, is when the peak load is caused by both fixed and shiftable loads. In this case, TESS and BESS are used to meet the demand and shave the peak. In this context, TESS and BESS are charged in off-peak hours by provided heat in the condenser and main grid, respectively. Therefore, the total electric power consumption in the off-peak period is increased to charge the EES with respect to the electric power consumption threshold. Then, on peak times, TESS and BESS discharge the heat and electric power, respectively, to satisfy the demand in the building. Therefore, by using the optimization approach, PMU defines the optimal operating schedule of TESS and BESS to manage the shiftable and fixed loads, respectively.

4.2 Optimization Problem Formulation

A new PMU, which includes optimization and peak load shaving mechanisms, is proposed. The considered campus building, which is equipped with TESS, BESS, and HVAC systems, includes both shiftable and fixed loads that are collected for each time interval. Both TESS and BESS have limited capacities ($\mathbf{c}$), $0 \leq \mathbf{c} \leq \mathbf{c}_{max}$, with the prespecified maximum values of charging/discharging rates as given in Table 5.1. To investigate the effectiveness of adding TESS for reducing the BESS capacity, two capacities are considered for BESS as given in Table 5.1. When TESS is not employed, the considered capacity for BESS is 825 kWh to achieve peak load shaving. This value will be reduced to 475 kWh when TESS is used as the second EES in the building. On the other hand, the utility company penalizes the educational building when the electricity usage exceeds a predetermined threshold T. A penalty is imposed based on the amount of electric power consumption in pick periods of each day. Therefore, the optimal charging/discharging schedule of ESSs is needed to be defined by PMU to obtain maximum peak load shaving considering the constraints. Then, PSO approach is applied to define the optimal operating schedule of ESSs in PMU. The proposed PMU is detailed by a flowchart in Figure 4.1. Peak load shaving mechanism, the mathematical formulation, the required financial analysis are also given in the following sections.

4.2.1 Mathematical Formulation

The proposed PMU employs an optimization method to determine the optimal charging/discharging schedule of ESSs to shave the peaks with respect to the constraints. In this context, we aim to minimize the electric power consumption during peak periods while maintaining the ESSs charged in off-peak hours. Moreover, the power consumption should not pass the threshold since the utility company imposes a high penalty. Therefore, PMU should try to maintain the electricity consumption near the threshold concerning the ESSs capacity conditions and the price

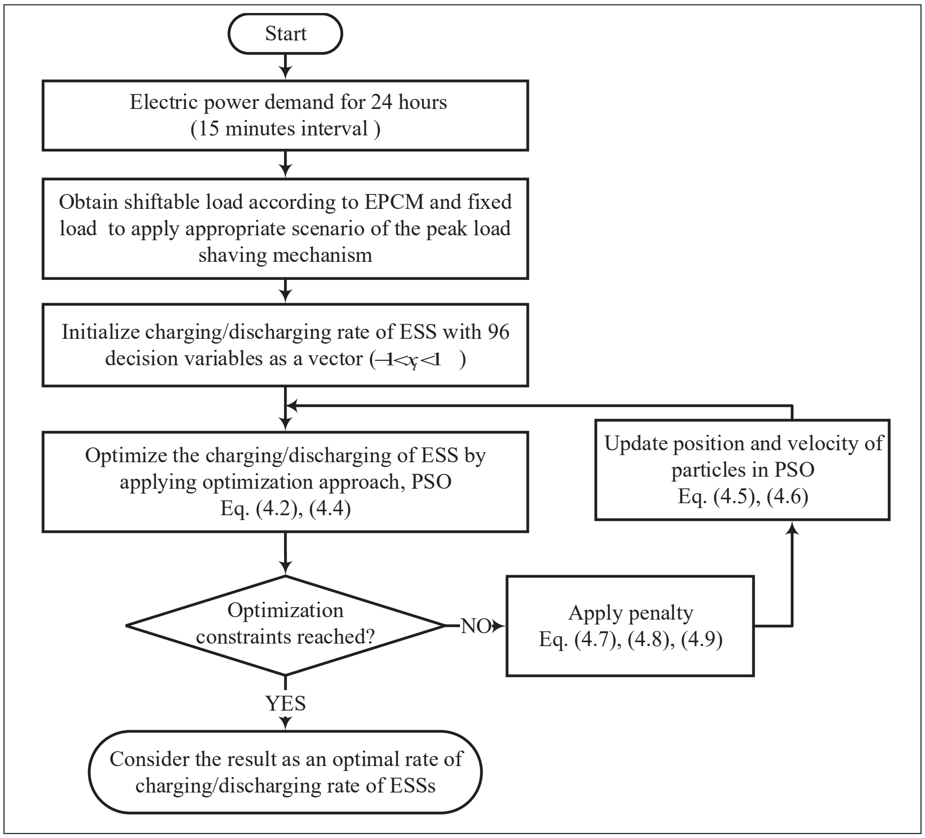

Figure 4.1 Flowchart of the proposed PMU

policy. Taking all the above-mentioned points into account, the cost function of the operating schedule as a function of charging/discharging rate, x, is derived as:

$$
\begin{aligned}
G(\mathbf{x}) &= \sum_{i=1}^{N} ((p_i - T + \kappa x_i)P_r(x_i))^2, \\
\mathbf{p} &= [p_1, ..., p_N], \mathbf{x} = [x_1, ..., x_N],
\end{aligned}
\tag{4.1}
$$

where N is the number of time intervals for a day, x is the decision variable representing the charging/discharging schedule, $\mathbf{p}$ denotes the electric power consumption of the building (kW), P_r and T represent the electricity price function and peak shaving threshold, respectively, and κ is the maximum amount of charging/discharging rate with respect to the efficiency of ESSs. As (4.1) indicates the cost function of the operating schedule, the optimization problem is formulated as:

$$
\begin{aligned}
&\min_{\mathbf{x}}(G(\mathbf{x})) = \sum_{i=1}^{N}((p_i - T + \kappa x_i)P_r(\mathbf{x}))^2, \\
&\text{s.t.} \\
&-1 \leq x_i \leq 1, \\
&0 \leq \upsilon + \mathbf{Z}\,\mathbf{x}^{\mathsf{T}}\tau \leq \mathbf{c},
\end{aligned}
\tag{4.2}
$$

where

$$
\mathbf{Z} = \begin{bmatrix} \kappa & & & 0 \\ \kappa & \kappa & & \\ \vdots & \vdots & \ddots & \\ \kappa & \kappa & \dots & \kappa \end{bmatrix}, \mathbf{c} = \begin{bmatrix} c_{\max} \\ c_{\max} \\ \vdots \\ c_{\max} \end{bmatrix},
$$

where υ is the initial energy stored in ESS (kWh), $c_{\max}$ indicates the maximum capacity of ESS (kWh), and τ as the time interval is fifteen minutes. The decision variable has a positive and negative range that corresponds to the charging and discharging modes, respectively. The second constraint expresses the allowable amount of energy that ESSs can store and deliver.

4.2.1.1 Convexity Of the Optimization Problem

To prove the convexity of the objective function, the second derivative of $G(x)$ should be ≥ 0 for all x in its interval. Our problem is a quadratic function with linear constraints. The first and second derivative of the function is driven.

First derivation:

$$
2\left(\kappa P_r(\mathbf{x}) + (p_i - T + \kappa x_i)\frac{\partial P_r(\mathbf{x})}{\partial \mathbf{x}}\right)((p_i - T + \kappa x_i)P_r(\mathbf{x}))
$$

Second derivation:

$$
4\kappa(p_i - T + \kappa x_i)\frac{\partial P_r(\mathbf{x})}{\partial \mathbf{x}}P_r(\mathbf{x})
$$

It can be verified that the objective function of (4.2) and its feasible set are convex (Chi, Li & Lin, 2017) as long as $\frac{\partial P_r}{\partial x_i} P_r(\mathbf{x})(p_i - T + \kappa x_i) \geq 0, \forall i \in \mathbb{B}$ where $\mathbb{B} = \{i \in \mathbb{N} | 0 \leq i \leq N\}$ [1].

It worth mentioning that based on (4.4), in case of $(p_i + \kappa x_i) < T$ then we have $\frac{\partial P_r}{\partial x_i} P_r(\mathbf{x})(p_i - T + \kappa x_i) = 0$ and if $(p_i + \kappa x_i) > T$ then it will be $\frac{\partial P_r}{\partial x_i} P_r(\mathbf{x})(p_i - T + \kappa x_i) = \kappa \beta^2 (p_i - T + \kappa x_i)^2 \geq 0$.

Hence, the problem is convex and the solution can be obtained by applying the Karush-Kuhn-Tucker (KKT) conditions on the dual of (4.2). The dual function of (4.2) is derived as:

$$\begin{aligned} g(\lambda) = \inf_{\mathbf{x} \in D} L(\mathbf{x}, \lambda) = \inf_{\mathbf{x} \in D} \Bigg[& \sum_{i=1}^{N} ((p_i - T + \kappa x_i) P_r(\mathbf{x}))^2 + \\ & \sum_{k_1=1}^{N} \lambda_{k_1} (\upsilon + \mathbf{z}_i \mathbf{x}^\intercal . \tau - c_{max}) - \lambda_{N+k_1} (\upsilon + \mathbf{z}_i \mathbf{x}^\intercal . \tau) \\ & - \lambda_{2N+i} (x_i + 1) + \lambda_{3N+i} (x_i - 1) \Bigg]. \end{aligned} \tag{4.3}$$

where

$$\begin{aligned} \mathbf{z}_1 &= \begin{bmatrix} \kappa & 0 & . & . & 0 \end{bmatrix}, \\ \mathbf{z}_2 &= \begin{bmatrix} \kappa & \kappa & . & . & 0 \end{bmatrix}, \\ & . \\ \mathbf{z}_N &= \begin{bmatrix} \kappa & \kappa & \kappa & . & \kappa \end{bmatrix}. \end{aligned}$$

In order to have finite $g(\lambda)$, only one of the $\lambda_i, \lambda_{bN+i}, \lambda_{2N+i}, \lambda_{3N+i}$ can be equal zero. Applying KKT conditions on (4.3) leads to:

1) $\lambda_i (\upsilon + \mathbf{z}_i \mathbf{x}^\intercal . \tau - c_{max}) = 0$, which means that $\lambda_i = 0$ or $\upsilon + \mathbf{z}_i \mathbf{x}^\intercal . \tau = c_{max}$.

2) $\lambda_{N+i} (\upsilon + \mathbf{z}_i \mathbf{x}^\intercal . \tau) = 0$, which means that $\lambda_{N+i} = 0$ or $(\upsilon = -\mathbf{z}_i \mathbf{x}^\intercal . \tau)$.

---

[1] In the cases where $\frac{\partial P_r(\mathbf{x})}{\partial \mathbf{x}} P_r(\mathbf{x})(p_i - T + \kappa x_i) \geq 0$ does not hold, the convexity of the objective function should be studied specifically.

3) $-\lambda_{2N+i}(x_i + 1) = 0$, which means that $\lambda_{4N+i} = 0$ or $x_i = -1$.

4) $\lambda_{3N+i}(x_i - 1) = 0$, which means that $\lambda_{5N+i} = 0$ or $x_i = +1$.

5) $\big(2P_r(\mathbf{x})(p_i - T + \kappa x_i)^2 \frac{\partial P_r(\mathbf{x})}{\partial x_i} + \kappa(p_i - T + \kappa x_i)P_r(\mathbf{x}))$
$+ 2\sum_{k_1=1,k_1\neq i}^{N}(p_i - T + \kappa x_i)^2 P_r(\mathbf{x})\frac{\partial P_r(\mathbf{x})}{\partial x_i} +$
$\sum_{k_2=1}^{N}(\lambda_{k_2} - \lambda_{N+k_2})(\mathbf{z}_i\mathbf{y_i}\tau) - \lambda_{2N+i} + \lambda_{3N+i}\big) = 0.$
where $\mathbf{y_i} = \frac{\partial \mathbf{x}^\intercal}{\partial x_i}$ i.e., $\begin{bmatrix}0 & \dots & 1 & \dots & 0\end{bmatrix}^\intercal$.

Among all the critical points obtained by applying KKT conditions, only one is the optimal solution with the lowest objective function value. Since (4.2) is a convex problem, it has a unique solution. However, obtaining the solution as a function of electric power consumption of the building is complicated since their change affects the KKT conditions. For a given set of parameters, the solution of (4.2) can be obtained mathematically by solving KKT conditions. However, in the case where the number of time intervals and decision variables are numerous, the complexity is increased if using a mathematical approach such as decent gradient-based techniques. Moreover, the mathematical approach cannot converge to the optimum solution when the number of decision variables is enormous. Therefore, the metaheuristic approach, precisely PSO, is adopted to solve our objective function due to simple implementation, computational efficiency, and fast convergence (Parejo, Ruiz-Cortés, Lozano & Fernandez, 2012). The aim of using the metaheuristic algorithm is to find the feasible solution in an acceptable timescale due to high time intervals and decision variables.

4.2.2 Financial Analysis

The electricity price function P_r in (4.1), (4.3), and (4.9) represents a price rate structure that the utility company applies to charge the campus. This structure is based on an annual contract with a minimum monthly billing demand between the building and the utility company. The utility company charges the campus a high price when the electric power consumption excesses the prespecified threshold. Therefore, to prevent being charged, the total electric power demand of the building at any time is not supposed to cross the threshold specified by the main grid. The price rate structure is presented as

$$Price = P_r = \begin{cases} \beta, & (p_i + \kappa x_i) < T \\ \beta(p_i - T + \kappa x_i), & (p_i + \kappa x_i) > T \end{cases} \tag{4.4}$$

where β is the electric power price that is applied to the building . To solve the optimization problem, (4.4) is used in (4.1). One can verify that $\frac{\partial P_r(\mathbf{x})}{\partial \mathbf{x}} P_r(\mathbf{x})(p_i - T + \kappa x_i) \geq 0$ holds for the considered cost function. Thus, our considered problem is a convex problem.

4.2.3 Particle Swarm Optimization

PSO was presented for simulating the social behaviour of birds and fishes (Wang, Tan & Liu, 2017). In this scheme, the first step is to generate the initial population, called a swarm, of candidate solution, named particles, which is obtained randomly. Each particle moves over search space and has three main vectors: the current velocity vector, the best position vector of all particles and its own best position vector. At each iteration of performing PSO, the velocity and position of particle j are updated as:

$$V_j^i = wVj^{i-1} + c_1 r_1 [P_{best} - X_j^{i-1}] + c_2 r_2 [G_{best} - X_j^{i-1}], \tag{4.5}$$

$$X_j^i = X_j^{i-1} + V_j^i \; j = 1, 2, \ldots, M, \tag{4.6}$$

where X_j^i and V_j^i is the position and velocity vectors of the particle j at iteration i of performing PSO, respectively, P_{best} represents the best position of individual particle for objective function, and G_{best} is the best position for all particles. One of the advantages of using PSO is that there are only a few parameters to adjust and control such as cognitive factor, c_1, social factor, c_2, inertia weight, w, random values range, x_i, swarm size, and max iteration. The values of $c_1 = c_2 = 1.49618$ and $w = 0.7298$ as optimization coefficients are based on (Van Den Bergh & Engelbrecht, 2006). Then, the positions are evaluated by the PSO cost function and the best position is determined. This process is repeated until the desired accuracy is obtained. The principle of PSO is detailed in Figure 4.2.

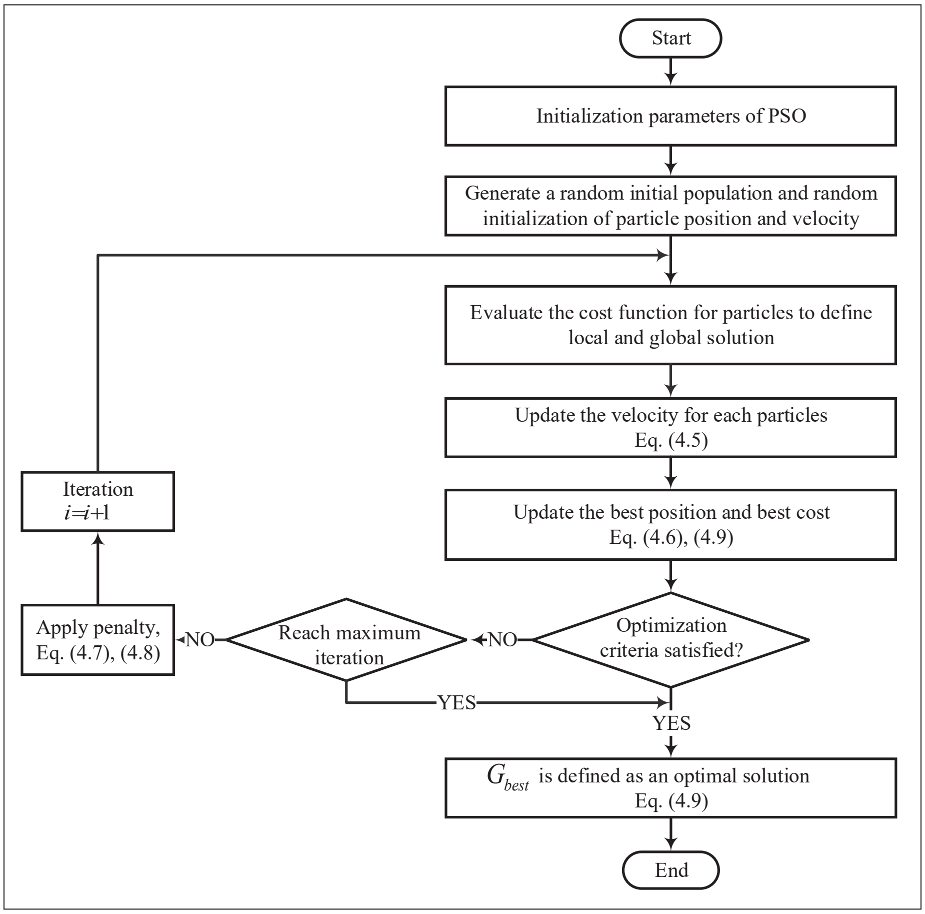

Figure 4.2 Flowchart of PSO

The optimization problem with constraints can be solved by PSO through considering the constraints as the penalties in the cost function. Thus, we define (4.7) for charging mode ($0 \leq x_i \leq 1$),

$$Penalty = \begin{cases} \alpha_1|\mathbf{c} - w|, & w > \mathbf{c} \\ 0, & \text{otherwise.} \end{cases} \tag{4.7}$$

and (4.8) for discharging mode ($-1 \leq x_i < 0$).

$$Penalty = \begin{cases} \alpha_2|\min(0, w)|, & w < 0 \\ 0, & \text{otherwise.} \end{cases} \tag{4.8}$$

where $w = (\upsilon + \mathbf{Z}\,\mathbf{x}^{\intercal}\tau)$ and indicates the amount of the stored energy in the ESSs. As a result, the cost function of PSO is defined as:

$$\min_{\mathbf{x}}(G(\mathbf{x})) = \sum_{i=1}^{N}((p_i - T + \kappa x_i)P_r(\mathbf{x}))^2 + Penalty^2 \tag{4.9}$$

to solve the optimization problem in (4.1).

- benefits of using PSO over other metaheuristic approaches:

  Simplicity: PSO is a simple and easy-to-implement algorithm compared to other metaheuristic approaches, such as Genetic Algorithms.

  Fast convergence: PSO has been shown to converge quickly to a good solution, making it useful for problems where time is a critical factor.

  No requirement for derivative information: PSO does not require knowledge of the derivative of the objective function, which makes it suitable for problems where the derivative is difficult or impossible to compute.

  Robustness: PSO has been shown to perform well on a wide range of optimization problems, including those that are non-linear, non-convex, and multi-modal.

  Ability to handle constraints: PSO can be easily modified to handle constraints, such as inequality and equality constraints, which makes it useful for many real-world optimization problems.

4.3 Optimization Results by PSO

The proposed PMU is employed to perform peak load shaving through the scenario that mainly happens on the university campus. The considered scenario indicates the peak load as the combination of both fixed and shiftable loads. In this context, TESS and BESS are employed to meet the demand for peak load shaving. The metaheuristic optimization approach is used to solve (4.2) and define the optimal operating schedule of TESS and BESS to manage the shiftable and fixed loads, respectively.

The implementation of PSO is done using Matlab. The considered data-set is for 15 minutes intervals for 24 hours, and the optimization is done at the beginning of the day for 24 hours. Therefore, there are ninety-six decision variables (charging/discharging rates) in the optimization problem. The optimal solution using the PSO algorithm is obtained within an acceptable time. The time elapsed to complete an optimization considering 1000 iterations with 1000 swarm size is approximately 106 seconds. In comparison, gradient-based algorithms such as Fmincon function of Matlab failed to converge to the optimal solution.

- **Scenario**

In this plan, TESS and BESS are employed to satisfy the demand and achieve peak load shaving when peak load is a combination of fixed and shiftable loads. Firstly, we considered BESS as the only ESS for peak load shaving. Figure 4.3 demonstrates peak load shaving achieved by using only BESS for one day in January 2019 based on samples of 15 minutes. Peak shaving is achieved in the building by using the high capacity of BESS, 825 kWh. Using high BESS capacity causes more maintenance and replacement expenses due to battery life cycle limitation and degradation. TESS is added in parallel with BESS to compensate for BESS limitations and reduce its capacity.

Figure 4.4 demonstrates the electric power consumption obtained by the peak load shaving mechanism using TESS and BESS in the building. When the electric power consumption is lower than the threshold (off-peak period), the TESS and BESS are charged and electric power consumption is increased up to the threshold level. This figure shows when electric power consumption passes the threshold (peak periods), TESS and BESS deliver the demand load to shave the peak and the electric power consumption is decreased significantly after peak load shaving. Moreover, by integrating the TESS, the capacity for BESS is reduced to 475 kWh that causes less expenses and maintenance. It is worth noting that using simply BESS with the capacity 475 kWh is insufficient to provide complete peak load shaving, as shown in Figure 4.4. Therefore, the need to use TESS in parallel with BESS is getting increased.

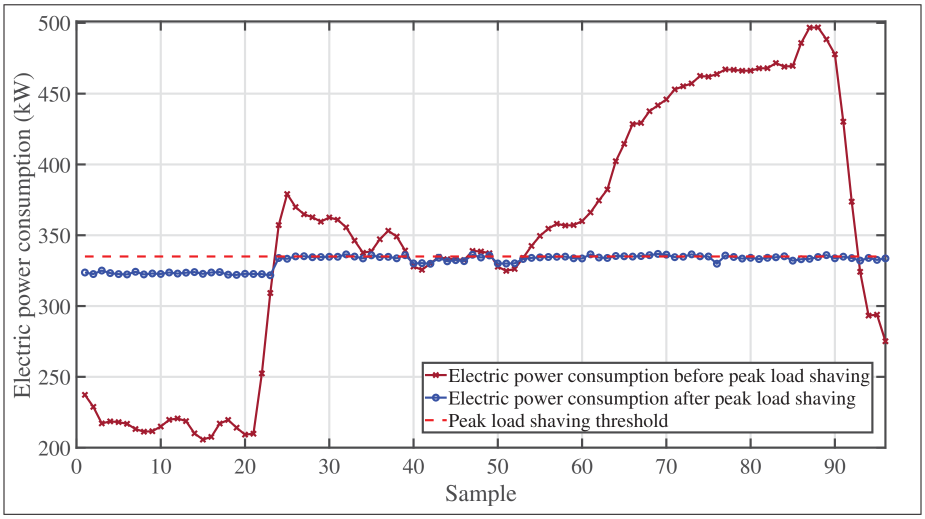

Figure 4.3 Peak load shaving using only BESS with capacity 825 kWh in January 2019

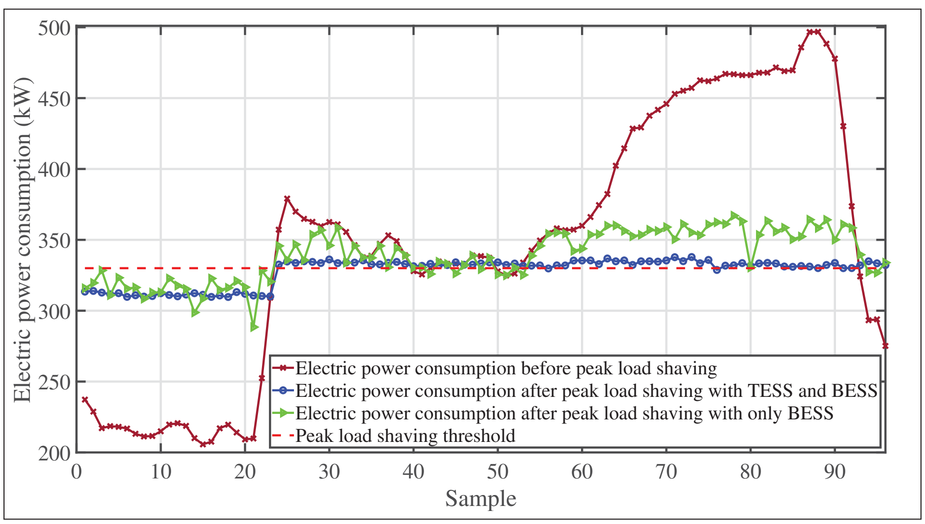

Figure 4.4 Peak load shaving by using BESS and TESS versus using only BESS with capacity 475 kWh for January of 2019

The effect of considering different capacities for BESS on peak load shaving is shown in Figure 4.5. In the case of having different capacities for BESS, the optimization problem defines feasible peak load shaving due to the capacities limitation. It can be concluded that the proposed optimization problem can define the peak load shaving with different capacities of

ESSs. However, to attain complete peak load shaving, the proper capacity for the BESS is 475 kWh that can be used in parallel with the TESS.

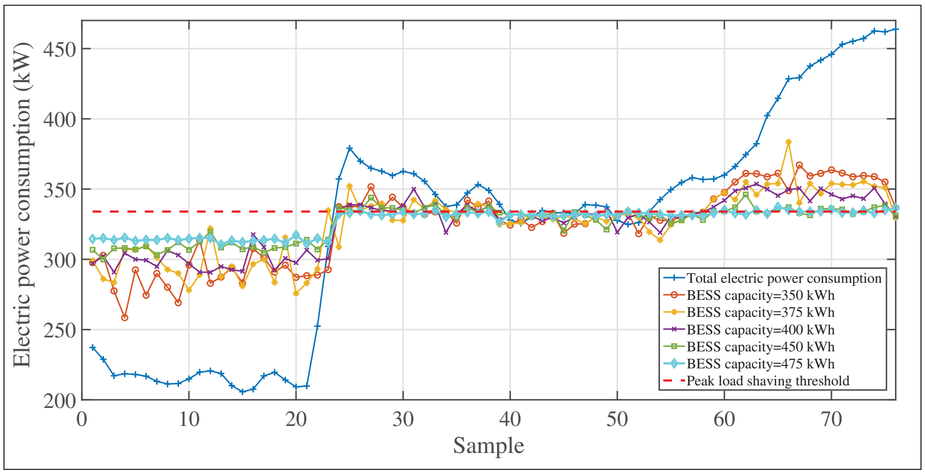

Figure 4.5 Peak load shaving for different capacities of BESS for a day of January of 2019

The optimal charging/discharging schedule of BESS obtained by PSO is presented in Figure 4.6. The decision variable range, which indicates the rate of charging/discharging of BESS, is shown by the left axis of the picture. Positive values are related to charging and the negative numbers express the discharging of BESS. The right axis depicts the pattern of fixed electric power usage before and after peak load shaving. The result demonstrates that PSO can determine the optimal charging/discharging schedule for BESS to reduce peak load.

To show the effectiveness of the proposed approach, we compare the performance of PSO with heuristic rule-based and a gradient-based method to define optimal operation schedule of ESSs. Heuristic rule based (HRB) is considered as a problem-dependent solution strategy (Naghavipour, Soon, Idris, Namvar, Salleh & Gani, 2022). To evaluate HRB approach, we consider the rules: if $\upsilon = \mathbf{c}_{max}$ then, $x_i = 0$, $w_{i+1} = \mathbf{c}_{max}$ and $p_i^{new} = p_i$. When $p_i < T$ and $w_i < \mathbf{c}_{max}$, then $x_i = (\mathbf{c}_{max} - w_i)/\kappa$, $w_{i+1} = (1-\sigma)\, w_i + \kappa x_i \tau$ and $p_i^{new} = p_i + w_{i+1} - w_i$. However, if $p_i^{new} > T$ then $w_{i+1} = \min\{\mathbf{c}_{max}, w_i + T - p_i\}$. On the other hand, when $p_i > T$ and $\upsilon + \kappa\, x_i^{\intercal}\tau \geq p_i - T$ then, $x_i = (p_i - T)/\kappa$, $p_i^{new} = p_i - \kappa\, x_i^{\intercal}\tau$, and $w_{i+1} = (1-\sigma)\, w_i + \kappa x_i \tau \eta$.

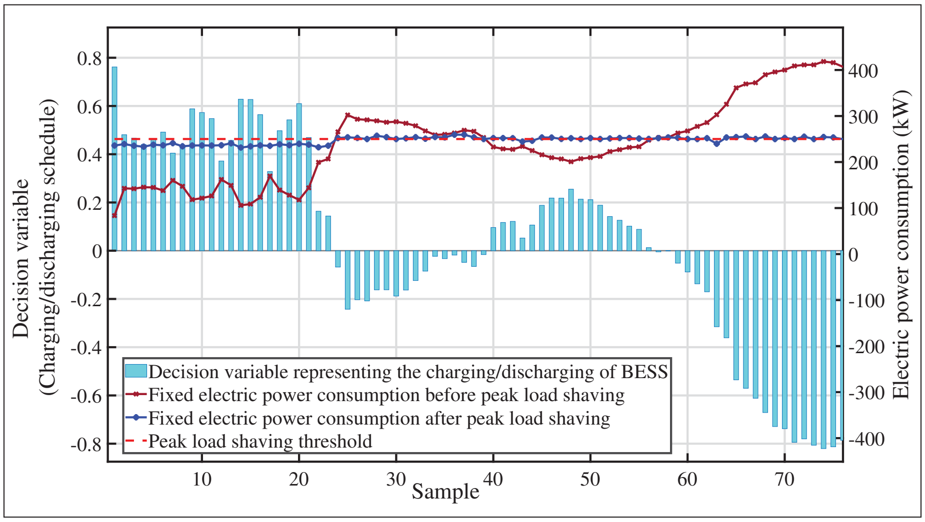

Figure 4.6 Optimal charging/discharging schedule of BESS by PSO

Where $p_i > T$ and $0 \leq \upsilon + \kappa\, x_i^{\mathsf{T}} \tau \geq p_i - T$, $x_i = w_i/\kappa$ then, $p_i^{new} = p_i - \kappa\, x_i^{\mathsf{T}} \tau$, and $w_{i+1}^{new} = 47.5$ kWh. The performance of HRB and PSO to shave the peak is demonstrated in Figure 4.7. Results are compared assuming both TESS and BESS are employed to compensate for shiftable and fixed loads of a day. It can be observed that PSO derives the optimal solution to achieve peak load shaving and smooths the electric power consumption pattern with respect to the constraints within 106 seconds. In contrast, electric power consumption is not maintained in allowable range and the constraints are not fully met by HRB. Although HRB offers fast solutions to solve the problem, the results, in general, are not reliable as optimal solutions for the complex problem with high number of decision variables. Furthermore, we aim to compare our results with a gradient-based method, Fmincon function of Matlab. However, due to high number of the decision values and time intervals, Fmincon could not converge to the optimal solution. Therefore, the comparison of results shows that PSO is suitable and effective to determine the optimal charging/discharging schedule of ESS.

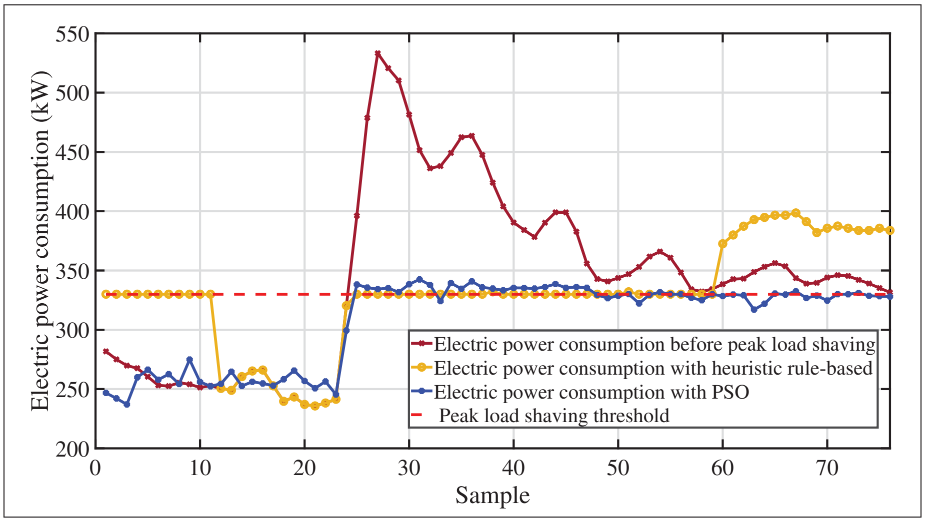

Figure 4.7 Optimal charging/discharging schedule obtained by PSO and heuristic rule-based approach

4.3.1 Robustness of the proposed PSO optimization approach

To investigate the robustness of the proposed metaheuristic approach, three different days are considered. Since PSO is a random search algorithm based on population evolution, the algorithm is repeated one hundred times for each day to show the similarity in the solutions under different runs. Furthermore, the statistical information, including the best value, mean value, median, and standard deviations (SD), are calculated for obtained best costs of each day. The mean value, median, and SD demonstrate the distribution of the best values over hundred runs to express the robustness and reliability of the proposed approach. Moreover, the effectiveness and robustness of the proposed method are also studied by observing the algorithm's performance in achieving maximum peak load shaving while different electric power consumption patterns are applied. In addition, the performance of the proposed algorithm under various initial SOC for BESS is investigated to evaluate the robustness and sensitivity. To compare and test the performance of the algorithm, the considered initial capacity values for TESS and BESS are 50% of total capacity, and the same maximum iterative number and population size are applied using MATLAB on an Intel(R) Xeon(R) CPU E3-1225 v6 @ 3.30GHz computer with 16.0 GB RAM.

In Table 4.1, the best solution, statistical information, and percentage of peak shaving computed by PSO algorithm are presented. It can be seen that the optimization algorithm attains acceptable and approximately similar results in different runs for three days. When the metaheuristic algorithm results are almost similar in different runs, the low value of SD represents the robustness of the algorithm (Meng, Li, Wang, Sait & Yıldız, 2021). It can be seen that SD is obtained less than 1 for all cases, which consequently justifies the robustness of the approach. Furthermore, the values of peak load shaving with TESS in Table 4.1 present the effectiveness of the proposed approach and TESS's role in achieving the maximum peak load shaving.

Moreover, Figure 4.8 shows the box plot of distributions of best solutions achieved by PSO for three different days. Box plot contains five parts: median as the middle value of the data, first quartile, third quartile, minimum, and maximum (Babura, Adam, Abdul Samad, Fitrianto & Yusif, 2018). It is shown that the box plot is short and in the same range, which states that the results are distributed near the median value, and proves the reliability and robustness of the proposed algorithm over different runs.

Furthermore, the convergence plot is presented in Figure 4.9 that expresses the convergence rate of the objective function over 1000 iterations to reach the best solution for three considered days. Results show that PSO determines the best acceptable solution in an acceptable time within 106 seconds.

In addition, Figure 4.10 represents the electric power consumption of building when varying initial SOC including 0%, 25%, 50%, 75%, and 100% of full capacity are considered for BESS. It can be observed that the proposed approach achieves the best acceptable performance under different initial SOC. The optimal charging/discharging schedule is successfully defined considering the initial capacities and constraints. Therefore, it can be justified that the proposed algorithm is robust to different electric power consumption patterns and varying initial SOC for ESS.

Table 4.1 statistical information and peak load shaving achieved by PSO for three different days in January

Information	Case I 8th day	Case II 15th day	Case III 23th day
Best value	289.7191	287.4177	292.3048
Mean	290.3078	288.07	292.61
Median	290.2830	287.98	292.58
SD	0.4012	0.4307	0.1908
Time (s)	106	106	106
Peak load shaving without TESS (%)	65.82	28.34	33.28
Peak load shaving with TESS (%)	94.86	92.08	92.25

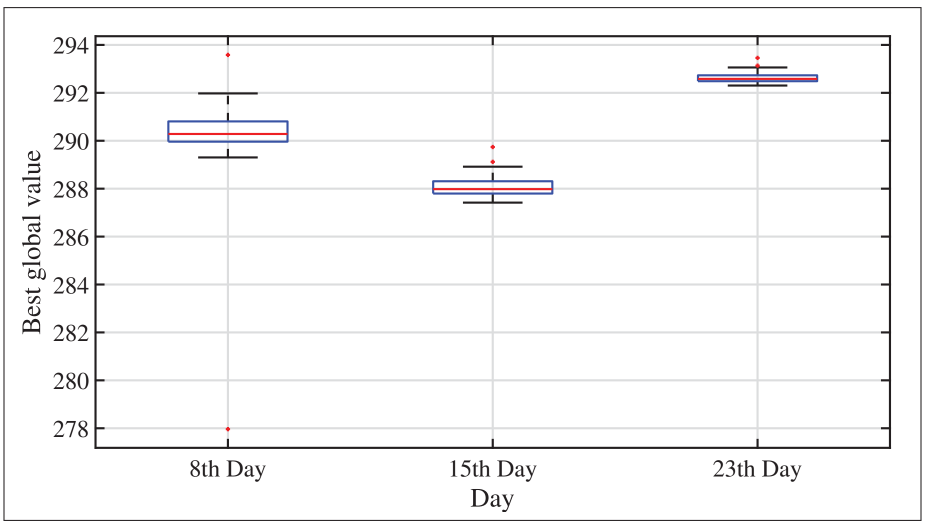

Figure 4.8 Box plots of distributions of best global value obtained by PSO for three days in January

4.3.2 Potential of implementing the proposed approach for real-time platforms

The main focus of this thesis is to employ TESS alongside BESS to reduce the required BESS's capacity and achieve complete peak load shaving. The proposed method is based on an off-line optimization problem. For off-line applications, the historical data are used in PMU and the optimization problem is solved by PSO by considering ninety-six decision variables for twenty-four hours-ahead with fifteen minutes time intervals.

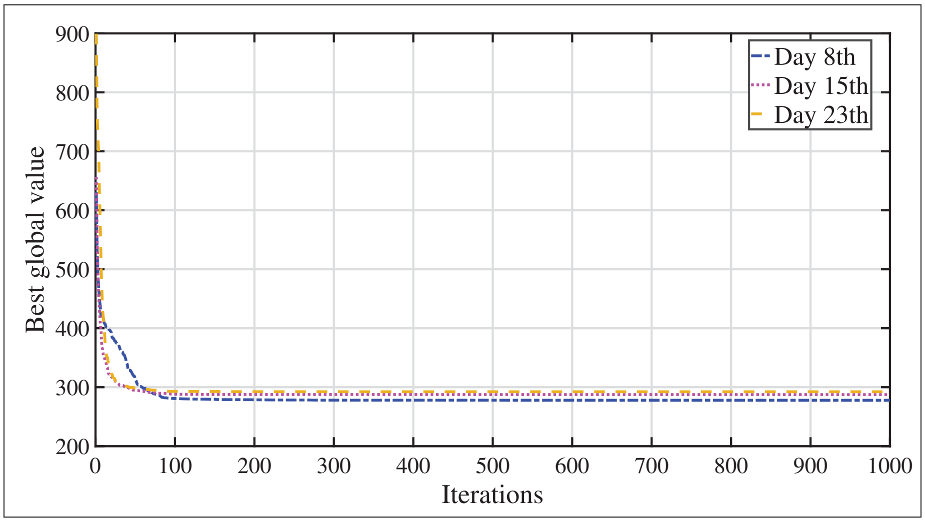

Figure 4.9 Convergence plot of proposed metaheuristic approach for three different days in January

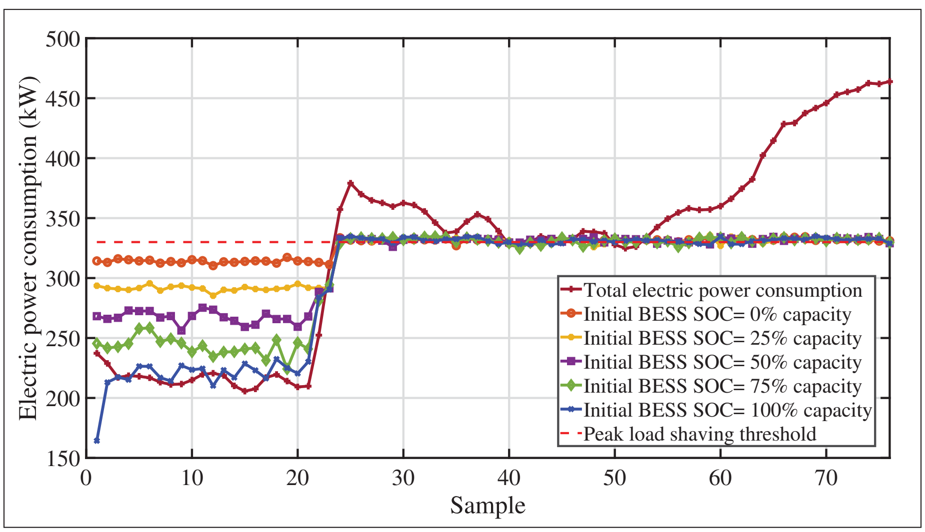

Figure 4.10 Peak load shaving obtained by PSO with considering different initial SOC for BESS

To implement the proposed approach in real-time platforms, the load forecasting approach is required to estimate the future load demand in a building (Dagdougui, Bagheri, Le & Dessaint, 2019; Ji, Buechler & Rajagopal, 2020; Kong, Dong, Jia, Hill, Xu & Zhang, 2019). In this thesis, the perfect forecasting is considered due to assuming the same consumption pattern for the future and the same days of previous years. In this regard, to implement the proposed approach in a real-time application, the estimated demand loads derived by prediction approaches can be used instead of historical data to obtain the optimal charging/discharging schedule of TESS and BESS in the building. In the case of considering a short-term load forecasting for 12 samples ahead which is equal to three hours-ahead, the computational time of the optimization approach is 62 seconds since the decision variables are twelve. It is worth to be mentioned that the time to complete the optimization algorithm for 24 hours-ahead with 96 variables is 106 seconds which is significantly less than the length of the time interval between two samples which is 15 minutes. Therefore, the proposed approach overcomes the computational burden and can be implemented in a real-time platform with a reliable short-term prediction. Moreover, due to the robustness and simplicity of PSO, and its dealing with a large number of decision variables, the proposed approach can be considered as a prominent approach to be employed in both off-line and real-time applications to define the optimal charging/discharging of ESSs.

In the next chapter, the proposed approach will be extended to develop a PMU framework capable of implementing in on-line platforms. We intend to employ machine learning specifically model-free reinforcement learning to enhance the accuracy of results and reduce the capacity of the BESS as well as achieving peak load shaving. In addition, real-time optimization method to define the optimal charging/discharging schedule of ESS in real-time platform is investigated.

CHAPTER 5

PEAK LOAD SHAVING MECHANISM USING REINFORCEMENT LEARNING

5.1 Optimization Problem Formulation

The building can take advantage of ESS for peak load shaving. As it is shown in Figure 5.1 , a PMU is designed to find an optimal policy to optimize the charging/discharging schedule of ESSs based on the pricing information provided by the utility company with respect to the threshold load (Rostamnezhad & Dessaint, 2023). Therefore, the load that should be supplied by the grid as grid load z_t is represented as follows:

$$z_t = max(l_c, l_t + q_{ESS,t}) \tag{5.1}$$

where l_c is the allowable value of load defined by the utility company, $q_{ESS,t}$ is related to the charging/discharging schedule of ESSs such as TESS and BESS, and l_t is the electric power consumption of the smart building. The changes in the electric power load demand during a day raise the need for ESSs to supply the required load for peak load shifting to smooth the profile. To achieve peak load shaving properly, the load demand of the building is divided into shiftable and fixed loads which are related to the electric power demand load for the HVAC system and plug-in loads, respectively. Fixed load has a significant portion of total electric power demand. This load is measured by the metering devices in the building and related to electric devices such as lights, computers, and laboratories. Shiftable load is calculated by using historical data and the thermodynamics principle. It is obtained by defining the correlation between the operation of HVAC devices and electrical usage.

The fixed and shiftable loads are collected at each time interval. The day is discretized based on the sampling time intervals, represented by Δt. The models for TESS and BESS are explained to derive the constraints and dynamics of the system.

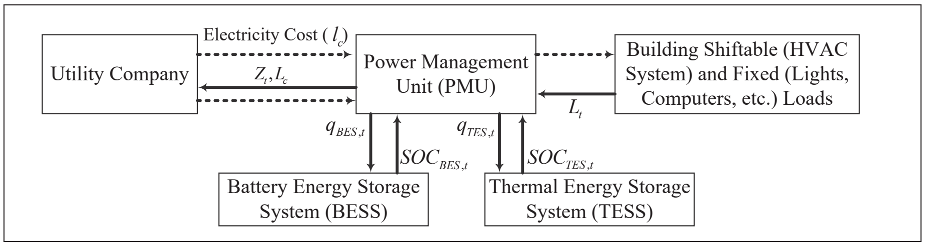

Figure 5.1 Illustration of power management framework using thermal and battery energy storage systems

5.1.1 Mathematical Formulation

The aim of optimization is to define the optimal rate of charging/discharging of ESSs in the smart building. The system cost consists of the electric power consumption of the building at tth time interval, the electricity price and peak load shaving threshold based on the grid policy. Thus, the cost given system state s_t and action taken a_t can be written as

$$g(s_t, a_t) = \mathbb{P}_t \times z_t \tag{5.2}$$

where $q_{i,t}$ represents the charging/discharging schedule of each ESSs, l_t denotes the electric power consumption of the building, $\mathbb{P}_t$ and l_c represent the electricity price function and constant load supplied by the utility company, respectively. Here, $\mathbb{P}_t$ as price function is given as follows:

$$\mathbb{P}_t = \begin{cases} \beta, & (l_t + q_{i,t}) < l_c \\ \frac{\beta(l_t+q_{i,t}-l_c)}{l_c} + \beta, & (l_t + q_{i,t}) > l_c \end{cases} \tag{5.3}$$

where β is power cost determined by utility company. It is worth to mention that the capacity of BESS is limited and is considered as one of the constraints for the optimization problem as formulated in equation (5.4).

$$SOC_{BES}^{min} \le SOC_{BES,t} \le SOC_{BES}^{max}$$
$$q_{BES}^{min} \le q_{BES,t} \le q_{BES}^{max} \tag{5.4}$$

where, C_{BES}, SOC_{BES}^{min}, SOC_{BES}^{max}, q_{BES}^{min},and q_{BES}^{max}, represent the capacity of BESS, the minimum and maximum limit of the state of charge (SOC), and minimum and maximum power rate of charging and discharging, respectively. Furthermore, the charging/discharging rate of the water tank is limited between maximum and minimum rate, denoted by q_{TES}^{max} and q_{TES}^{min}, respectively. Besides, the capacity of the water tank, is constrained by the maximum value, c^{max}, as given by (5.5)

$$q_{TES}^{min} \le q_{TES,t} \le q_{TES}^{max},$$
$$0 \le C_{TES}^{init} + q_{TES,t}\Delta t \le C_{TES}^{max}, \tag{5.5}$$

where, C_{TES}^{max} and C_{TES}^{init} represent the maximum capacity and the initial capacity, respectively.

5.2 Power Management Unit Model Using MDP

Various investigations have been done to deal with defining the optimal charging/discharging schedule of the buildings components and energy management system such as numerical methods and soft computing techniques. However, traditional approaches such as linear programming (Riffonneau, Bacha, Barruel & Ploix, 2011) have a problem adapting to unpredictable load profiles and need an exact mathematical model of the system. Moreover, metaheuristic approaches such as PSO, are mostly employed in solving the power management problems (Badawy & Sozer, 2017). However, these approaches need separate algorithms for forecasting and prediction to deal with sudden changes in the environment. Besides, the learning component is not considered in these methods. Thus, for every new change in loads, they need optimization iterations which are computationally expensive (Arwa & Folly, 2020).

RL algorithms can be trained for general loads without requiring an accurate model of the system and environment. Therefore, they are considered to deal with the aforementioned gaps and employed significantly in recent investigations. Unlike other optimization approaches, using artificial neural networks (ANN) in RL algorithms named deep learning is capable of providing accurate predictions without the need for a separate forecasting model.

Based on literature review, RL consists of five elements: agent, action, state, reward function, environment. The problems in RL, are formulated as a Markov decision process (MDP). A MDP provides the dynamics of the environment to observe the reactions of the environment to the action taken by the agent at a given state. A MDP contains a transition function that given the current state of the environment and an action, defines a probability of moving to any of the next states and a reward function. Due to difficulties in defining the transition function for the environment, model-free reinforcement learning is considered to estimate the optimal policy without using the dynamics of the environment. The optimal policy is derived by considering a value function which evaluates a state (or an action taken in a state), for all states.

5.2.1 Problem formulation with MDP

Following the previous research studies (Giaconi, Gunduz & Poor, 2018; Shateri, Messina, Piantanida & Labeau, 2020; Sun, Lampe & Wong, 2018), the problem of finding an optimum policy for PMU can be formulated as a MDP. A MDP is obtained by a state space S, an action space $A(s)$ related to $s \in S$, the environment dynamics $p(s_{t+1}|s_t, a_t)$ and $r(s_t, a_t)$ as the reward function when an action is taken in the state $s_i(t)$ (Richardson, Thomson & Infield, 2008).

5.2.1.1 State Space and Action Space

In this study, a finite horizon time model is considered that is expressed by $t \in T$. The total energy storage systems, W, including TESS and BESS are employed for peak load shaving. The state vector of TESS and BESS at time t is represented by $\phi_{TES,t}$ and $\phi_{BES,t}$, respectively. Thus, the state vector related to total ESSs is given by $\phi_t = \{\phi_{TES}, \phi_{BES}\}$. The state vector of building demand load expressed by l_t is $s_t = [l_t, \phi_t] \in S$ at time t. It should be noted that S denotes the state space. Moreover, the state vector related to BESS is shown by $\phi_{BES,t} = SOC_{BES,t}$ at time t. For TESS, $\phi_{TES,t} = S_{TES,t}$ is indicated the state vector at time t.

The actions that PMU should take to define the optimal policy are expressed by the rate of charging/discharging of electric power for ESSs as $a_t = [q_{TES,t}, q_{BES,t}]$ at time t with respect to the ESSs constraints. The $q_{i,t}$ for both TESS and BESS has a positive range and negative range that correspond to the charging and discharging states, respectively.

5.2.1.2 System Dynamics

After defining the state vectors and actions, the next step is to obtain the system state transition probability. We assume the building demand load transition probabilities between states s_t and s_{t+1} is independent from actions a_t based on a Markov chain. Thus, the environment transition probability $p(s_{t+1}|s_t, a_t)$ when action a_t is taken can be rewrite as follows:

$$\begin{aligned} p(s_{t+1}|s_t, a_t) = p(l_{t+1}, \phi_{t+1}|l_t, \phi_t, a_t) = \\ p(l_{t+1}|l_t, \phi_t, a_t)p(\phi_{t+1}|l_t, \phi_t, a_t) = \\ p(\phi_{t+1}|\phi_t, a_t)p(l_{t+1}|l_t) \end{aligned} \tag{5.6}$$

For TESS, the environment transition probabilities are assumed to not be affected by action $q_{TES,t}$ as well as the amount of energy stored in TESS as S_{TES} based on Markov chain. Therefore, its transition probabilities with respect to constraints of TESS can be expressed as:

$$p_{\phi_{TES,t+1}|\phi_{TES,t}, q_{TES,t}} = \begin{cases} p_{S_{TES,t+1}|S_{TES,t}}, & \text{if (5.4), (5.5) hold} \\ 0, & \text{otherwise.} \end{cases} \tag{5.7}$$

For BESS the environment transition probabilities for BESS is given by following:

$$\begin{aligned} & p_{\phi_{BES,t+1}|\phi_{BES,t}, q_{BES,t}} = \\ & \begin{cases} p_{SOC_{BES,t+1}|SOC_{BES,t}}, & \text{if (5.4) hold} \\ 0, & \text{otherwise.} \end{cases} \end{aligned} \tag{5.8}$$

Here, we consider an assumption that environment transition probabilities is independent of action $q_{BES,t}$ and SOC_{BES} of BESS.

5.2.1.3 Reward Function

The aim of optimization is to define the optimal rate of charging/discharging of ESSs in the smart building. The system cost consists of the electric power consumption of the building at tth time interval, the electricity price and peak load shaving threshold based on the grid policy. Thus, the cost given system state s_t and action taken a_t can be written as

$$g(s_t, a_t) = \mathbb{P}_t \times z_t \tag{5.9}$$

where $q_{i,t}$ represents the charging/discharging schedule of each ESSs, l_t denotes the electric power consumption of the building, $\mathbb{P}_t$ and l_c represent the electricity price function and constant load supplied by the utility company, respectively. Here, $\mathbb{P}_t$ as price function is given as follows:

$$\mathbb{P}_t = \begin{cases} \beta, & (l_t + q_{i,t}) < l_c \\ \frac{\beta(l_t + q_{i,t} - l_c)}{l_c} + \beta, & (l_t + q_{i,t}) > l_c \end{cases} \tag{5.10}$$

The cost function at time t given system state s_t and action taken a_t is defined as follows:

$$c(s_t, a_t) = g(s_t, a_t).\ t \in T \tag{5.11}$$

One of the most important components of MDP is the reward function. Reward function based on the MDP framework should be maximized. Therefore, we rewrite the (5.9) to define the objective function based on reward as follow:

$$c(s_t, a_t) = -r(s_t, a_t) = g(s_t, a_t).\ t \in T \tag{5.12}$$

where $r(s_t, a_t)$ represents the reward and the minus is considered based on the reward framework which is maximization.

5.3 Power Management Algorithm Using Q-Learning

In this section, the solution for solving the MDP and finding the optimal policy for PMU is demonstrated. Due to the dynamic environment and difficulties to define and approximate the transition probability model for the environment of MDP, a model-free learning algorithm to obtain the solution for the objective problem is presented. In this context, Q-learning is considered as the main candidate to solve the MDP with unknown transition probabilities due to its simplicity (Andrew, 1998).

5.3.1 Q-Learning Algorithm

The Q-Learning (QL) as a tabular RL method is used to learn the optimal state-action value function Q^*. The best action a_t at state s_t is obtained through maximizing Q^*. The QL updates the Q function by taking an action a_t at the sate s_t through some policy $\pi(s_t, a_t)$ as follow (Andrew, 1998):

$$\Delta Q(s_t, a_t) = \alpha \left[r(s_t, a_t) + \gamma \max Q(s_{t+1}, a_t) - Q(s_t, a_t) \right], \tag{5.13}$$

where $\alpha \in [0, 1]$ represents the learning rate. This parameter should be chosen properly due to its important role in transferring the information from current Q value of a_t at s_t and $c(s_t, a_t)$ to the observed state s_{t+1} and $c(s_{t+1}, a_t)$. During the learning phase, the QL algorithm is updated through the ϵ-greedy policy. The PMU updates the Q-function by taking an action randomly with probability ϵ and, then the action with probability 1-ϵ is taken to maximize the Q-value. To gain more benefits of taking other actions, the QL explores the action space, while QL exploits the learned Q-function which is known as the exploration-exploitation dilemma. Therefore, to start learning, the PMU initializes the Q-function by following ϵ-greedy policy to move forward to next state and update Q-function. This step is repeated until the end of the episode, when the

Q-function converges to Q^* with probability one. The optimal action based on optimal policy is determined for all time intervals. The QL process is presented precisely in Algorithm 5.1.

Algorithm 5.1 Q-learning algorithm

Initialize Q-function value and set the learning and weighting parameters.
for number of episodes **do**
  Define the electricity cost information $\mathbb{P}_t$, $t \in T$.
  Set the initial state $s_1 = [S_{TES,1}, SOC_{BES,1}, l_1]$.
  for $t = 1, \ldots, T$ **do**
    Observe the state $s_t = [S_{TES,t}, SOC_{BES,t}]$.
    Select feasible action a_t using $\epsilon-$greedy algorithm.
    Calculate reward $r(s_t, a_t)$ from equation (5.12).
    Update the next state s_{t+1} based on (5.5) and (5.4).
    Update the Q-function by minimizing (5.13).
    $t = t + 1$
  end for
end for

5.4 Optimization Results by RL

This thesis considers the electricity consumption of campus in a university located in Canada. The electric power consumption of a campus is divided into two categories: fixed load and shiftable load (Ruzbahani *et al.*, 2019). Shiftable load is related to HVAC systems that can be shifted from peak to off-peak hours in the building. In contrast, fixed load is electric power consumption by lights, laboratory, computers, etc. which cannot be shifted. Figure 5.2 represents the average percentages of shiftable and fixed distribution in total electric power consumption and in peak hours. It can be seen that although the amount of fixed load is significant, the share of shiftable load in peak hours and total electric consumption cannot be neglected. Hence, this thesis considers both loads for achieving peak load shaving. In this context, fixed load is measured by smart metering devices and shiftable load is calculated based on the thermodynamic principles and the historical data of consuming electricity by HVAC systems for winter time in the smart building.

The HVAC system includes an electric boiler with 98% efficiency, and a chiller with a cooling capacity of 703.3 kW, efficiency 0.447 kW/ton and COP 5. To store the energy, a water tank storage and a Lithium-Ion battery bank are considered for TESS and BESS, respectively. The characteristics of the considered TESS and BESS are presented in Table 5.1.

Table 5.1 Characteristics of each ESSs

ESS description		Value	Unit
BESS	Battery capacity with TESS	475	kWh
	Minimum State of Charge (SoC)	10	%
	Maximum State of Charge (SoC)	95	%
	Maximum charge/discharge of power	200	kW
	Efficiency	90	%
TESS	TESS capacity	2000	kWh
	TESS temperature	37	°C
	Heat loss per hour	0.002	°C
	Efficiency	87.6	%

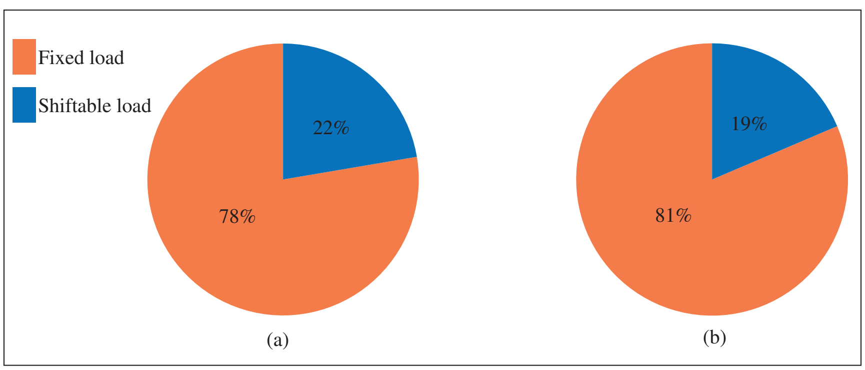

Figure 5.2 Power Consumption distribution of Fixed and shiftable loads in: (a) total electric power consumption, (b) peak hours

In this thesis, the data set is recorded with sample time Δt =15 minutes and an episode is obtained over a day. The data set consists of 31 vectors related to the days of a month with the length of 96 which is related to samples in a day. The power load threshold determined by the utility company is l_c = 330 kW. The electricity price function $\mathbb{P}_t$ in (5.9) represents a price rate structure that the utility company applies to charge the campus which is expressed by (5.10). This structure is based on an annual contract with a minimum monthly billing demand between the building and the utility company. The off-peak price, β is about \$13 per kW and the campus is charged by the utility company with a high price when the electric power consumption excesses the determined threshold.

Moreover, the total number of 20K episodes are used with a learning factor $\alpha = 0.4$ and a discount factor $\gamma = 0.88$ based on (5.13). The resolution to converge to the solution is considered to be 5. Therefore, according to the definition of state s_t and tabular RL, the Q-function is a table with size 380×96×800 which indicates the state space related to $\phi_{TES,t}$ and $\phi_{BES,t}$, number of the samples, and action space related to a_t, respectively. The optimal solution using the model-free RL is obtained within an acceptable time. The time elapsed to complete a Q-table considering 20K iterations, is approximately 104 seconds.

Due to considering all loads in the building, TESS and BESS are responsible to compensate for peaks caused by shiftable and fixed loads, respectively. The power electric consumption related to fixed load and the performance of RL to achieve peak load shaving using BESS is presented in Figure 5.3. The initial capacity of BESS is considered to be half of the maximum capacity. It can be seen that BESS is charged to its maximum capacity, then starts discharging to achieve peak load shaving and follows the pattern of the peaks.

The optimal charging/discharging schedule of BESS to store and release the energy during one day in winter is shown in Figure 5.4. In each state, based on the threshold and BESS SOC, an action is taken to gain the maximum reward with respect to satisfy the problem constraints. Positive values expresses charging and the negative numbers are related to the discharging of BESS which are obtained by QL.

The main focus of this thesis is to use BESS and TESS in parallel to achieve more benefits in cost saving and reducing the BESS capacity. TESS is considered to meet the shiftable load demand and satisfy the heating demand in peak hours. Therefore, a part of the peak would be compensated by TESS that leads to have reduction in BESS capacity. Figure 5.5 represents the

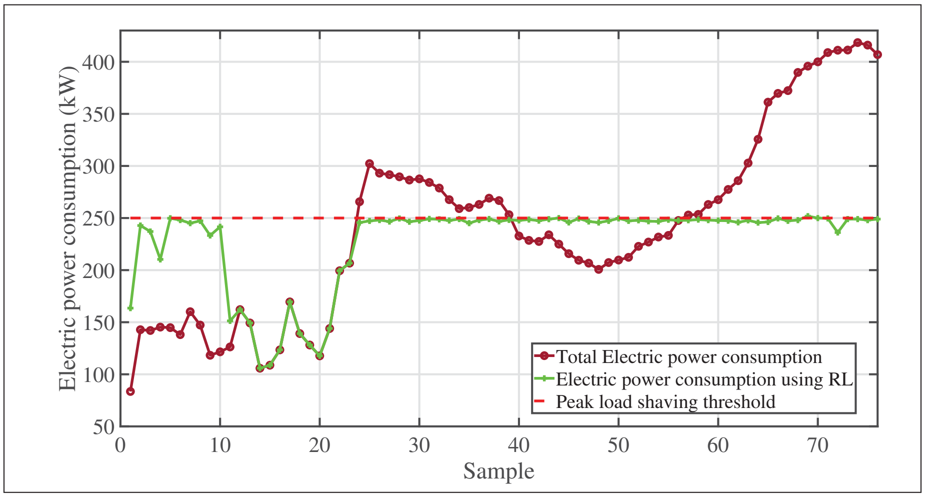

Figure 5.3 Electric power consumption in presence of BESS by using RL

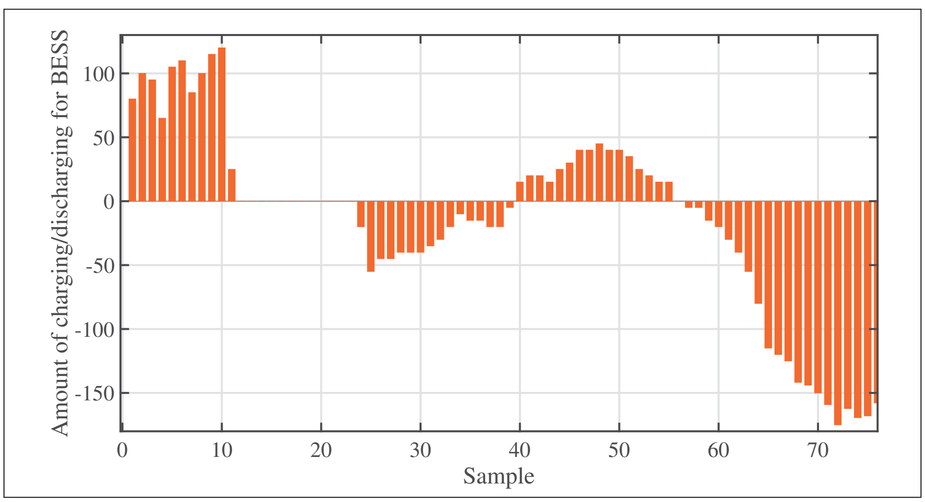

Figure 5.4 The charging/discharging schedule of BESS defined by RL

peak load shaving related to shiftable load using TESS and employing RL when initial capacity is half of its maximum capacity. It can be seen that shiftable load with load threshold, 80 kW, is completely shaved with TESS by using RL while it has up-and-down pattern.

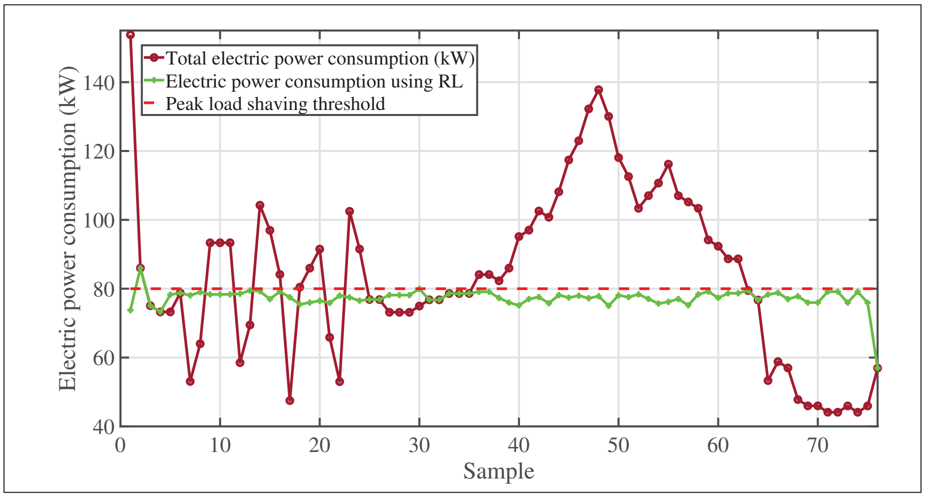

Figure 5.5 Electric power consumption in presence of TESS by using RL

Besides, the charging/discharging schedule for TESS obtained by Q-Learning is demonstrated in Figure 5.6. Positive values and negative numbers express the charging and discharging of TESS, respectively. The result shows that RL is able to define the optimal schedule for TESS to shave peaks of the shiftable load while the pattern has significant disturbances.

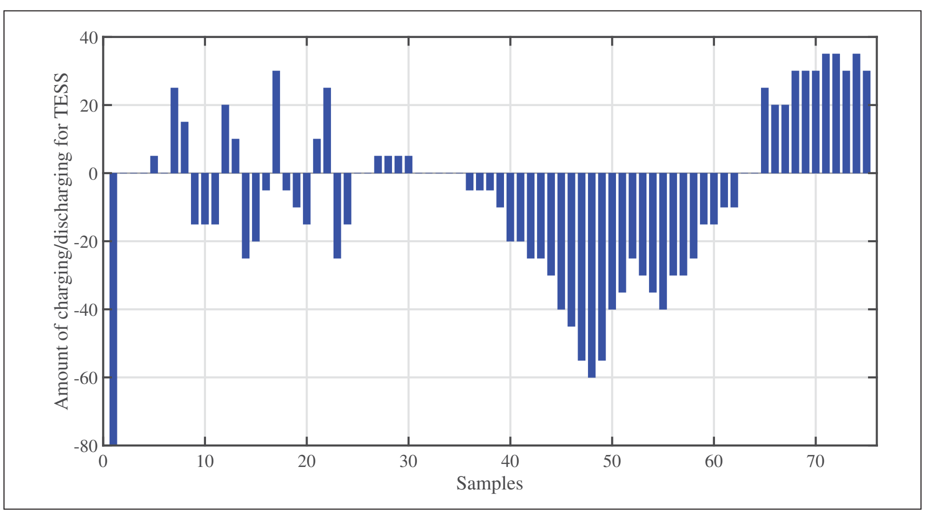

Figure 5.6 The charging/discharging schedule of TESS defined by RL

Finally, Figure 5.7 presents the total power consumption in the building and peak load shaving obtained by employing RL in PMU and simultaneously usage of TESS and BESS. The initial capacity of BESS and TESS are considered to be 50% of their total capacity. Therefore PMU starts charging ESSs until their capacity is getting full. Then, based on peaks, the ESSs are discharging the energy to achieve complete peak load shaving. It can be seen that QL is able to obtain optimal charging/discharging to achieve peak load shaving while two types of EESs with different characteristics are employed at the same time in the building.

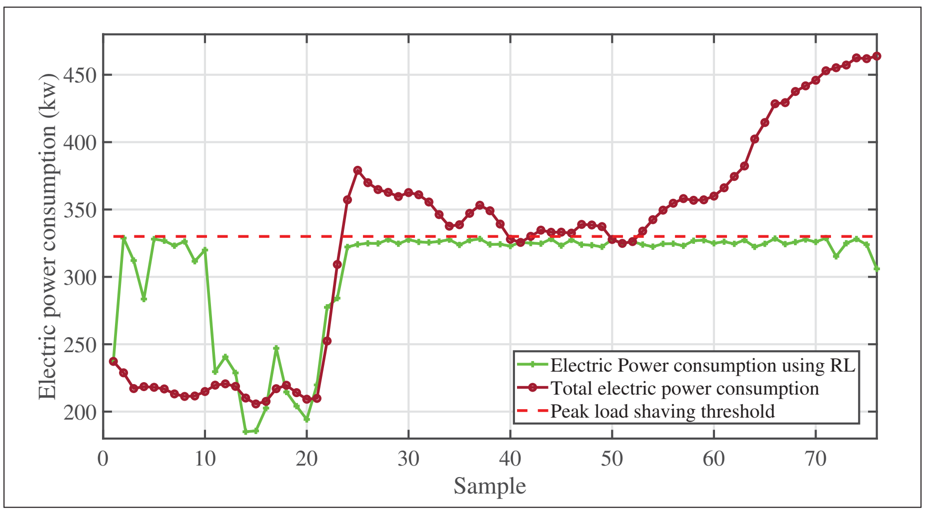

Figure 5.7 Peak load shaving for total power consumption using BESS and TESS and RL

5.5 Comparison RL Results with PSO Results

PSO is recognized as an effective approach to solve optimization problems in energy and power management units (Rostamnezhad, Mary, Dessaint & Monfet, 2023). To validate the result obtained by RL, PSO is employed to achieve peak load shaving as one of the powerful approaches of optimizing. Figure 5.8 demonstrates the peak load shaving achieved by using PSO and simultaneously application of TESS and BESS in the smart building. Moreover, the optimal charging/discharging schedule of BESS and TESS obtained by PSO is presented in Figure 5.9 and Figure 5.10, respectively. The amount of charging/discharging of ESSs is presented by the left axis of the picture. Positive values are related to charging and the negative numbers express the discharging of ESSs. The right axis in Figure 5.9 demonstrates the fixed electric power usage before and after peak load shaving using BESS and PSO. In Figure 5.10, the right axis represents the shiftable load and peak load shaving obtained by TESS and PSO.

The performance of RL to obtained the optimal charging /discharging schedule for BESS and TESS shown in Figure 5.4 and Figure 5.6 are similar to the optimal operation schedule for BESS and TESS obtained by PSO given in Figure 5.9 and Figure 5.10, respectively. The initial capacities for BESS and TESS are considered 50% of their maximum capacity in both optimization approaches. As can be seen, optimization results by RL in Figure 5.7 and PSO in Figure 5.8 are quite similar. In charging, both algorithms charge EESs to their maximum capacities. PMU is discharging EESs during peak period times and achieves peak load shaving by using PSO and RL in the smart building. Therefore, the performance of RL is validated by results provided by PSO.

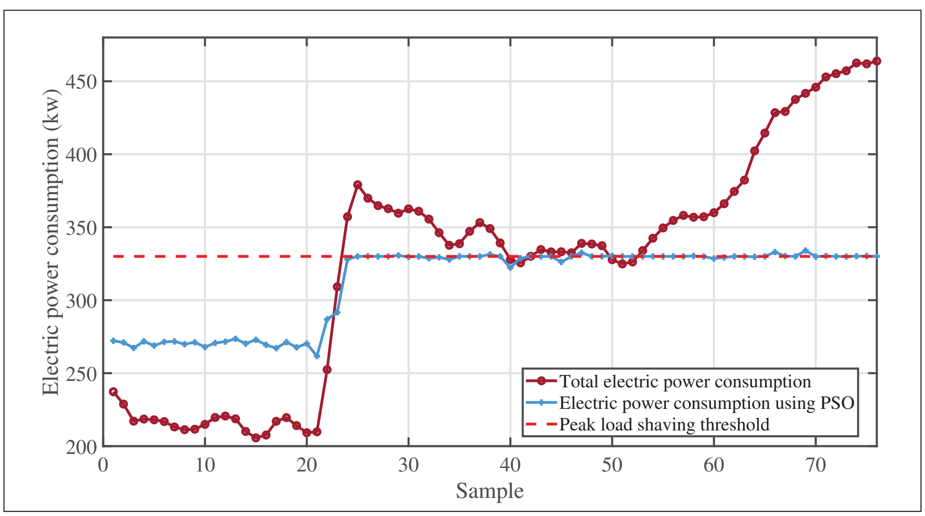

Figure 5.8 Peak load shaving for total power consumption using BESS and TESS and PSO

It is worth mentioning that the PSO is highly dependent on the environment model while the model-free RL operates independently. Furthermore, PSO has a tendency to get stuck in local

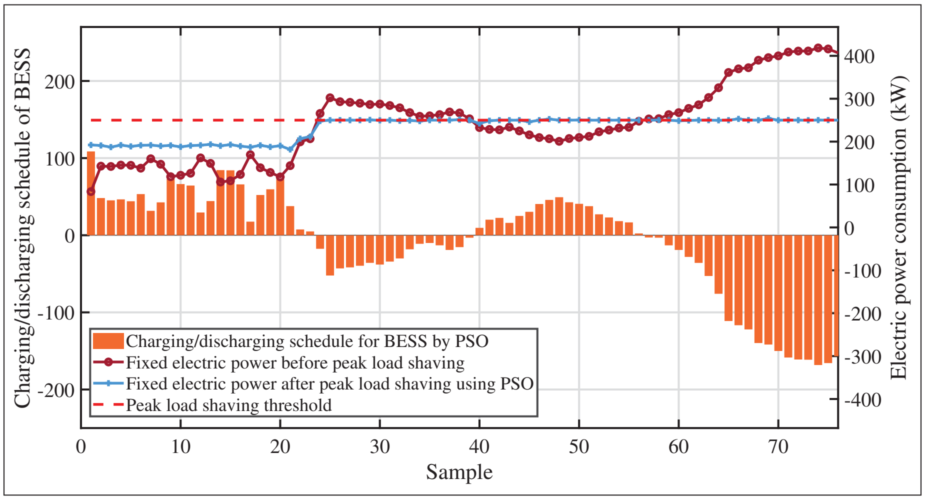

Figure 5.9 Optimal operation of BESS to shave peaks related to the fixed load by PSO

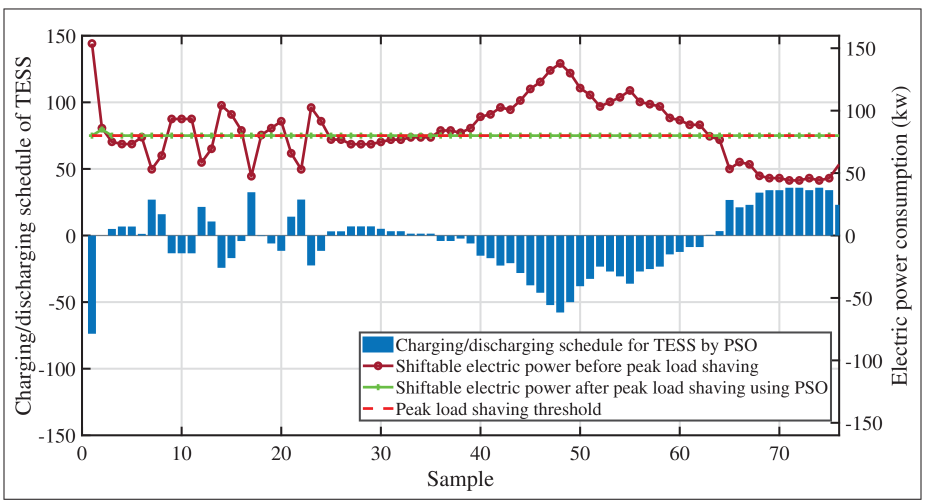

Figure 5.10 Optimal charging/discharging schedule of TESS to shave peaks related to the shiftable load by PSO

optimal solutions especially for large-size problems and it is complicated to obtain an accurate solution (Lin, Lian, Gu & Jiao, 2014). In contrast, the result obtained by QL as a tabular RL is considered as a global optimal solution when the convexity of the optimization problem is proven. Therefore, for large-scale optimization problems such as our problem, RL is more effective and reliable.

CONCLUSION AND RECOMMENDATIONS

Résumé

In this thesis, a comprehensive framework of power management unit has been proposed to have peak load shaving in a campus building. The proposed scheme has employed TESS and BESS as two prominent ESS to attain peak load shaving. The optimal charging/ discharging schedule of TESS and BESS has been formulated as an optimization problem. The convexity of the problem and the uniqueness of the solution have been proved by the mathematical optimization approach. Firstly, the optimization problem has been solved by using PSO and the optimal operation of ESSs have been defined. Then, in order to use RL, the optimization problem has been formulated as a Markov decision process and the reward function, environment state, and action have been defined. To evaluate the performance of the RL, the optimal charging/discharging schedule of EESs with the same initial conditions has been obtained by PSO. To assess the proposed method, HVAC components, BESS, TESS, and loads have been modeled by grey-box modeling. In order to improve the efficiency of the ESSs, the building load is divided into shiftable and fixed loads that are supported by TESS and BESS, respectively. Results have expressed that integrating TESS into the campus reduces the capacity of the battery by 42.2% and compensates for the power consumption in peak hours. Therefore, it can be concluded that it is not profitable only using BESS in institutional buildings. Moreover, RL and PSO can be considered as a potential candidate to be employed in large-size optimization problems to define the global optimal solution. Results have shown the effectiveness of RL and PSo in achieving complete peak load shaving when different types of ESSs are employed in smart buildings. The outcome of this work can also be utilized in different buildings to shift loads and smooth the peak.

As for future work, the proposed approach will be extended to develop a PMU framework capable of forecasting short-term loads to be implemented in on-line platforms. Furthermore, we intend to employ machine learning based methods to enhance the accuracy of results, considering the demand load prediction, and reduce the capacity of the BESS as well as achieving peak load shaving. In addition, real-time optimization methods to define the optimal charging/discharging schedule of ESS in real-time platform is deserved to be investigated.

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