SMART HOME ENERGY MANAGEMENT ALGORITHM FOR TOU-BASED DEMAND RESPONSE

WILAWAN PIAWISES

A Thesis Submitted in Partial Fulfillment of the Requirements for

the Degree of Master of Engineering in Electrical Engineering

Suranaree University of Technology

Academic Year 2024

กระบวนการจัดการพลังงานอัจฉริยะภายในบ้านเพื่อการตอบสนองต่อความต้องการพลังงานตามอัตราค่าไฟฟ้าตามช่วงเวลาการใช้งาน

นางสาววิลาวัณย์ เพียวิเศษ

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรมหาบัณฑิต

สาขาวิชาวิศวกรรมไฟฟ้า

มหาวิทยาลัยเทคโนโลยีสุรนารี

ปีการศึกษา 2567

SMART HOME ENERGY MANAGEMENT ALGORITHM

FOR TOU-BASED DEMAND RESPONSE

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

Thesis Examining Committee

....

(Asst. Prof. Dr. Piampoom Sarikprueck)

Chairperson

....

(Assoc. Prof. Dr. Keerati Chayakulkheeree)

Member (Thesis Advisor)

....

(Prof. Dr. Thanatchai Kulworawanichpong)

Member

Tosaphol Ratniyomchai

....

(Asst. Prof. Dr. Tosaphol Ratniyomchai)

Member

Yupaporn

....

(Assoc. Prof. Dr. Yupaporn Ruksakulpiwat)

Vice Rector for Academic Affairs and

Quality Assurance

....

(Assoc. Prof. Dr. Pornsiri Jongkol)

Dean of Institute of Engineering

วิลาวัณย์ เพียวิเศษ : กระบวนการจัดการพลังงานอัจฉริยะภายในบ้านเพื่อการตอบสนองต่อความต้องการพลังงานตามอัตราค่าไฟฟ้าตามช่วงเวลา (SMART HOME ENERGY MANAGEMENT ALGORITHM FOR TOU-BASED DEMAND RESPONSE) อาจารย์ที่ปรึกษา : รองศาสตราจารย์ ดร. กีรติ ชยะกุลคีรี, 154 หน้า.

คำสำคัญ : กระบวนการจัดการพลังงานอัจฉริยะภายในบ้าน / อัตราค่าไฟฟ้าตามช่วงเวลา / การตอบสนองต่อความต้องการ / การจัดตารางการใช้งานของเครื่องใช้ไฟฟ้าภายในบ้าน

วิทยานิพนธ์ฉบับนี้นำเสนอแนวทางการจัดตารางการทำงานของเครื่องใช้ไฟฟ้าในบ้านที่เหมาะสมที่สุด (Optimal Home Appliance Scheduling, OHAS) ภายใต้กรอบการตอบสนอง (Demand Response, DR) ต่ออัตราค่าไฟฟ้าตามช่วงเวลา (Time-of-Use, TOU) โดยใช้วิธีการหาค่าที่เหมาะสมที่สุดแบบผสมผสานระหว่างอัลกอริธึมแบบฝูงอนุภาค (Particle Swarm Optimization, PSO) และการเขียนโปรแกรมเชิงเส้น (Linear Programming, LP) ในระบบบริหารจัดการพลังงานในบ้านอัจฉริยะ (Smart Home Energy Management System, SHEMS)

ในระบบบริหารจัดการพลังงานในบ้านอัจฉริยะที่เสนอนี้ เปิดโอกาสให้เครื่องใช้ไฟฟ้าในบ้านสามารถเลือกแหล่งจ่ายพลังงานได้หลากหลาย ทั้งจากโครงข่ายไฟฟ้าจากการไฟฟ้า (The grid power) ระบบโซลาร์เซลล์บนหลังคา (Rooftop Solar PV) ระบบผลิตไฟฟ้าจากกังหันลม (Wind turbine generation) ระบบกักเก็บพลังงานด้วยแบตเตอรี่ (Battery Energy Storage Systems, BESS) และยานยนต์ไฟฟ้า (Electric Vehicles, EVs) ซึ่งจะทำงานในรูปแบบรถยนต์ไฟฟ้าจ่ายพลังงานกลับสู่บ้าน เพื่อจ่ายพลังงานไฟฟ้าช่วยเหลือในยามที่บ้านต้องการพลังงานฉุกเฉิน (Vehicle to Home, V2H)

ในกรอบวิธีการที่นำเสนอ ขั้นตอนอัลกอริธึมแบบฝูงอนุภาคจะทำหน้าที่สุ่มกำหนดค่าที่เหมาะสมที่สุดของสถานะการชาร์จพลังงาน (State of Charge, SoC) ของแบตเตอรี่ (Battery) และรถยนต์ไฟฟ้า (EV) เพื่อวางแผนการชาร์จและการจ่ายพลังงาน จากนั้นค่าสถานะการชาร์จพลังงานที่ได้จะถูกส่งต่อให้กับขั้นตอนการเขียนโปรแกรมเชิงเส้น ซึ่งจะดำเนินการจัดสรรพลังงานจากแหล่งต่าง ๆ ที่มี เพื่อจัดตารางการใช้งานเครื่องใช้ไฟฟ้าให้เหมาะสม ภายใต้ข้อจำกัดของวิธีปฏิบัติการต่าง ๆ และคำนึงถึงการลดค่าไฟฟ้าอย่างสูงสุด นอกจากนี้ ระบบที่เสนอยังเปิดโอกาสให้สามารถขายพลังงานไฟฟ้าส่วนเกินที่ผลิตได้จากโซลาร์เซลล์บนหลังคาเข้าสู่โครงการรับซื้อไฟฟ้าของการไฟฟ้าในพื้นที่ ซึ่ง

ช่วยเพิ่มรายได้และผลประโยชน์ทางเศรษฐกิจให้กับเจ้าของบ้านที่ผลิตไฟฟ้าได้เอง (Prosumers) อีกด้วย

ในระบบการบริหารจัดการพลังงานในบ้านอัจฉริยะที่ขับเคลื่อนด้วยวิธีการหาค่าที่เหมาะสมที่สุดแบบผสมผสานระหว่างอัลกอริธึมแบบฝูงอนุภาคและการเขียนโปรแกรมเชิงเส้น ช่วยให้ครัวเรือนสามารถจัดสรรภาระโหลดอุปกรณ์เครื่องใช้ไฟฟ้าในบ้านได้อย่างชาญฉลาด หลีกเลี่ยงการใช้ไฟฟ้าในช่วงเวลาที่มีอัตราค่าไฟฟ้าสูง ส่งเสริมการใช้พลังงานหมุนเวียนในบ้านมากยิ่งขึ้น และลดการพึ่งพาพลังงานจากโครงข่ายไฟฟ้า กรอบแนวคิดนี้ได้ผ่านการประเมินผลผ่านสถานการณ์จำลอง 9 กรณีศึกษาที่แตกต่างกันตามพลังงานจากแหล่งพลังงานที่สามารถใช้ได้ เงื่อนไขการทำงานและข้อจำกัดของวิธีปฏิบัติการที่แตกต่างกันไปในแต่ละกรณีศึกษา ผลการจำลองแสดงให้เห็นว่าระบบที่นำเสนอนี้สามารถลดค่าใช้จ่ายไฟฟ้ารายวันได้อย่างมีนัยสำคัญ และเพิ่มความยืดหยุ่นในการบริหารจัดการพลังงานของระบบเมื่อเทียบกับกรณีที่ไม่ได้มีการจัดตารางการทำงานของเครื่องใช้ไฟฟ้าในบ้านที่เหมาะสมที่สุด

ดังนั้น กรอบแนวคิดวิธีการหาค่าที่เหมาะสมที่สุดแบบผสมผสานระหว่างอัลกอริธึมแบบฝูงอนุภาคและการเขียนโปรแกรมเชิงเส้นในระบบการบริหารจัดการพลังงานในบ้านอัจฉริยะที่ได้นำเสนอนี้ จึงไม่เพียงแต่ช่วยให้การจัดการพลังงานในบ้านอัจฉริยะเป็นไปอย่างมีประสิทธิภาพสูงสุดเท่านั้น แต่ยังส่งเสริมแนวทางสู่การอยู่อาศัยที่ชาญฉลาด เป็นมิตรต่อสิ่งแวดล้อม และประหยัดค่าใช้จ่ายในบ้านอัจฉริยะซึ่งเป็นส่วนหนึ่งในบริบทของโครงข่ายไฟฟ้าอัจฉริยะในอนาคตอีกด้วย

สาขาวิชาวิศวกรรมไฟฟ้า ลายมือชื่อนักศึกษา ....

ปีการศึกษา 2567 ลายมือชื่ออาจารย์ที่ปรึกษา ....

WILAWAN PIAWISES : SMART HOME ENERGY MANAGEMENT ALGORITHM FOR TOU-BASED DEMAND RESPONSE

THESIS ADVISOR : ASSOC. PROF. KEERATI CHAYAKULKHEEREE, D.Eng., 154 PP.

Keyword : Smart Home Energy Management / Time-of-Use Tariff / Demand Response / Appliance Scheduling

This thesis proposes a hybrid Particle Swarm Optimization and Linear Programming (Hybrid PSO-LP) approach for optimal home appliance scheduling (OHAS) under a time-of-use (TOU)-based demand response (DR) framework in smart home energy management systems (SHEMS). The primary objective is to minimize total daily electricity costs (TDC). The proposed SHEMS allows household appliances to select their power consumption from various energy resources, including grid power, rooftop solar PV, wind turbines, Battery Energy Storage Systems (BESS), and Electric Vehicles (EV) considered as Vehicle to Home (V2H).

In the proposed framework, the PSO layer first determines the optimal state of charge (SoC) values for the battery and EV, which provides the charging and discharging behavior. These values are then passed to the LP layer, which is concurrently processed to complete the OHAS. The LP layer allocates power from various energy resources, including BESS, V2H, rooftop solar PV, wind turbines, and the grid, for scheduling household appliances while satisfying operational constraints and minimizing electricity costs. In addition to utilizing electricity from the grid, the excess energy from the rooftop solar PV can also be sold to the local utility's household PV purchasing scheme, providing additional economic benefits for prosumers. The hybrid PSO-LP algorithm-based SHEMS enables households to intelligently schedule

appliances, avoid peak hours, rely more on renewable energy availability, and reduce grid dependency.

This framework is evaluated through nine simulation scenarios that consider different energy configurations. The results consistently demonstrate significant reductions in electricity costs and improved system flexibility compared to non-scheduling appliances by the proposed framework. The proposed hybrid PSO-LP framework not only efficiently achieves optimal scheduling in SHEMS but also leads the way toward smarter, greener, and more cost-efficient smart homes in future smart grids.

School of Electrical Engineering

Academic Year 2024

Student's Signature ....

Advisor's Signature ....

ACKNOWLEDGEMENT

First of all, I would like to express my deepest gratitude to Suranaree University of Technology for granting me the Kittibandit Scholarship and providing the financial support that made my master's degree journey possible. This thesis would not have been achievable without many individuals who significantly contributed to it.

I am sincerely appreciative to my advisor, Assoc. Prof. Dr. Keerati Chayakulkheeree, for his valuable guidance, patience, and support throughout this research. His encouragement always gave me the strength to move forward.

My heartfelt gratitude also goes to Asst. Prof. Piampoom Sarikprueck, chair of my thesis defense, and the committee members Prof. Dr. Thanatchai Kulworawanichpong and Asst. Prof. Dr. Tosaphol Ratniyomchai for their insightful comments and valuable suggestions, which helped improve the quality of this work.

I would like to express my sincere thanks to my beloved family for their unwavering support and love, which are my greatest source of strength. I would also like to acknowledge my lecturers for their consistently providing knowledge and guidance throughout my studies and the faculty and staff of the School of Electrical Engineering for their advice and kind assistance. Special thanks go to my lovely friends and the members of the Energy and Power Engineering Research Group (EPERG) for their encouragement, support, and friendship. Lastly, I thank myself for persevering through difficult days and never giving up.

I extend my heartfelt gratitude to everyone who has contributed to this journey. I could not have done this without you.

WILAWAN PIAWISES

TABLE OF CONTENTS

TABLE OF CONTENTS (Continued)

Page

TABLE OF CONTENTS (Continued)

Page

TABLE OF CONTENTS (Continued)

TABLE OF CONTENTS (Continued)

Page

LIST OF TABLES

LIST OF TABLES (Continued)

Table Page

LIST OF FIGURES

Figure Page

LIST OF FIGURES (Continued)

LIST OF FIGURES (Continued)

Figure Page

LIST OF ABBREVIATIONS

BESS	Battery Energy Storage System
DR	Demand Response
ESS	Energy Storage System
EV	Electric Vehicle
LP	Linear Programming
MEA	Metropolitan Electricity Authority
OHAS	The optimal home appliance scheduling
PEA	Provincial Electricity Authority
PSO	Particle Swarm Optimization
PV	Photovoltaic
RE	Renewable Energy
RES	Renewable Energy Sources
RTP	Real-time Pricing
SHEMS	Smart Home Energy Management System
SG	Smart grid
TDC	Total daily cost
TOU	Time-of-Use
V2H	Vehicle-to-home

LIST OF NOMENCLATURES

A_{PV}	Area of the PV panel (m^2).
A_{wind}	Areas swept by wind turbines (m^2).
A_m^t	Binary variable indicating ON/OFF state of operation for each appliance '*m*' at the time '*t*'.
c_1	The cognitive acceleration coefficient.
c_2	The social acceleration coefficient.
C^t	Electricity cost at the time '*t*'.
C_{buy}^t	Electricity cost of buying energy at the time '*t*'.
C_{sell}^t	Electricity cost of selling energy at the time '*t*'.
$capacity_B$	Total capacity of the battery.
$capacity_{EV}$	Total capacity of the battery in an EV.
$gbest^t$	The global best position of particle '*i*' at iteration '*j*'
$pbest_i^t$	The personal best position of particle '*i*' at iteration '*j*'
P_B^t	Power charge/discharge from battery at the time '*t*'.
$P_{B,\,ch}^t$	Power charging from the battery at the time '*t*'.
$P_{B,\,dch}^t$	Power discharging from the battery at the time '*t*'.
$P_{B,\,ch}^{max}$	Maximum power charging limit of the battery.
$P_{B,\,dch}^{max}$	Maximum power discharging limit of the battery.
P_{EV}^t	Power charge/discharge from EV at the time '*t*'.
$P_{EV,\,ch}^t$	Power charging from EV at the time '*t*'.
$P_{EV,\,dch}^t$	Power discharging from EV at the time '*t*'.
$P_{EV,\,ch}^{max}$	Maximum power charging limit of the battery in EV.
$P_{EV,\,dch}^{max}$	Maximum power discharging limit of the battery in EV.

LIST OF NOMENCLATURES (Continued)

P^{t}_{excess}	Power excess for consumption at the time '*t*'.
P^{t}_{grid}	Power supplied by the grid at the time '*t*'.
P^{max}_{grid}	Maximum grid power limit.
P^{t}_{Load}	Power consumption from all appliances at the time '*t*'.
P^{rating}_{m}	Power rating of appliance '*m*'.
P^{t}_{PV}	Solar power availability at the time '*t*'.
P^{t}_{Total}	Total power demand at the time '*t*'.
P^{t}_{wind}	Wind power availability at the time '*t*'.
r_1, r_2	Random values within the range [0,1].
SoC^{t}_{B}	State of charge of the battery at the time '*t*'.
SoC^{max}_{B}	Maximum state of charge limit of battery.
SoC^{min}_{B}	Minimum state of charge limit of battery.
SoC^{t}_{EV}	State of charge of the battery in EV at the time '*t*'.
SoC^{max}_{EV}	Maximum state of charge limit of battery in an EV.
SoC^{min}_{EV}	Minimum state of charge limit of battery in an EV.
$T^{t}_{m,\ ending}$	Ending time of appliance '*m*'.
$T^{t}_{m,\ starting}$	Starting time of appliance '*m*'.
NA	The number of electrical appliances.
NER	The number of energy resources.
NT	The number of time slots.
α	Albert Betz constant.
β	Efficiency of the PV panel.
μ^{t}	Solar irradiance at the time '*t*' (kW/m^2).
ρ^{t}	Air density at the time '*t*' (kg/m^3).

LIST OF NOMENCLATURES (Continued)

η_B	Efficiency of the battery.
η_{EV}	Efficiency of the battery in EV.
η_{inv}	Efficiency of the inverter.
$\eta_{turbine}$	Efficiency of the wind turbine.
υ^t	Wind speeds at the time 't' (m/s).
υ_i	Cut-in speed of wind turbine (m/s).
υ_o	Cut-off speed of wind turbine (m/s).
v_i^j	Velocity of particle 'i' at iteration 'j'.
w	The inertia weight factor.
x_i^j	The position of particle 'i' at iteration 'j'.

CHAPTER I

INTRODUCTION

1.1 General Introduction

In recent years, global electricity demand and consumption have been rising rapidly. This increment causes numerous problems, such as increasing carbon emissions, rising energy prices, reduced reliability of electric services, increased disturbances, power quality issues, and even power system collapse caused by high peak loads resulting in blackouts. Traditionally, most current power systems are centralized power generation with unidirectional power flow that is developing into a decentralized power system, which improves the flexibility, resilience, and reliability of the power grid. Decentralized systems would rely on integrating renewable energy sources (RES), energy storage system (ESS) technologies, and demand response (DR) techniques. One key advantage of decentralized systems is their ability to enable bidirectional power flow, allowing electricity to be both supplied and utilized from the grid, where consumers can act as prosumers to produce their electricity and sell the excess power back to the grid. This concept is an important step toward the development of smart grid (SG) systems. The SG approach relies heavily on demand-side management (DSM) tactics. DR is a part of the DSM technique that encourages smart homes by modifying the pattern of appliance operation by shifting appliances and adjusting their energy consumption behavior from peak to off-peak hours to reduce electricity costs, enhance grid stability, and contribute to sustainable energy practices. As a vital part of smart home energy management systems (SHEMS), DR offers a practical solution that empowers consumers to play an active role in energy efficiency and grid support. In the context of addressing the global energy crisis and improving system reliability, SHEMS is another option that any consumer can readily implement.

1.2 Problem Statement

The increasing global demand for electricity presents numerous challenges, including concerns about reliability, power quality, and peak load issues that increase the burden on power systems. DSM is energy management on the consumer side or operations on the demand side of electricity usage, which is why strategies play a crucial role in resolving the global energy crisis and pushing the traditional power system into the smart grid system. DR is a part of the DSM technique that motivates consumers and prosumers to adapt and manage energy consumption based on price variations and grid conditions, making SHEMS an increasingly critical area of research. Recently, SHEMS have gained attention due to their ability to enhance energy efficiency and reduce reliance on the central grid. SHEMS are continuously developing and becoming more complex because of the increasing function of components such as RES like solar and wind, ESS like batteries, and EVs that can act as vehicle-to-home (V2H). In this study, batteries and EVs are considered both as energy consumers and as backup power resources. Efficiently managing these elements within SHEMS can significantly reduce electricity expenses and dependence on the grid.

In recent years, numerous researchers have developed various optimization techniques to solve complex constrained problems in SHEMS. Traditionally, linear programming (LP) has been successfully applied to appliance scheduling problems within basic SHEMS. In previous research, the author demonstrated through a conference paper that LP can optimize appliance scheduling to minimize daily electricity costs in basic scheduling scenarios. While LP provides an effectively linear and fixed constraint-structured framework for appliance scheduling, in SHEMS with more complex conditions and constraints, using LP alone is insufficient to achieve the best results because LP limitations arise when dealing with non-linear complexities, dynamic system interactions, and real-world uncertainties. To overcome these limitations, researchers have explored hybrid approaches that integrate LP with metaheuristic optimization techniques. Particle Swarm Optimization (PSO) is a well-established stochastic algorithm known for solving non-linear optimization problems, making it well-suited for complex SHEMS.

In this thesis, PSO is applied to manage the state of charge (SoC) of batteries and EVs, determining optimal charge and discharge levels based on demand and available energy resources. Meanwhile, LP optimizes appliance scheduling by efficiently distributing energy from five sources: the power grid, rooftop solar PV, wind power, battery storage, and EVs. The PSO hybrid LP combines the strengths of both methods to improve the flexibility of PSO for nonlinear aspects of complex energy systems with the precision of LP for linear scheduling appliance problems. This hybrid approach effectively balances dynamic storage control with structured appliance scheduling, leading to enhanced smart home energy management.

In Thailand, DR can respond to varying time-of-use (TOU) energy prices, which incentivizes users to adjust their consumption patterns throughout the day. Furthermore, recent developments such as the household PV purchasing scheme project by the Metropolitan Electricity Authority (MEA) and the Provincial Electricity Authority (PEA), in addition to utilizing electricity from the grid, the excess energy from the rooftop solar photovoltaic (PV) can also be sold back to the grid, supporting decentralized energy integration.

Therefore, this thesis proposes a hybrid PSO-LP optimization approach for Optimal Home Appliance Scheduling (OHAS) via TOU-Based DR in SHEMS. The model incorporates multiple energy sources, including rooftop PV generation, wind power, battery energy storage systems (BESS), and V2H integration. Additionally, excess PV energy can be sold to the household solar project. This methodology benefits both consumers and prosumers by improving appliance scheduling efficiency, minimizing electricity costs, reducing peak load demand, and alleviating grid burden. Ultimately, it enhances SHEMS adaptability and contributes to a more sustainable and intelligent energy future.

1.3 Research Objectives

In pursuit of a more sustainable and efficient smart home energy management system, this thesis pursues the following key objectives:

1. To minimize electricity costs for prosumers and consumers in proposed smart homes by implementing a Particle Swarm Optimization Hybrid Linear Programming (Hybrid PSO-LP) approach for Optimal Home Appliance Scheduling (OHAS) using TOU-based demand response.

2. To develop optimal energy management to solve the OHAS problem using the hybrid PSO-LP model, which considers multiple energy sources, including rooftop solar PV power, wind power, battery energy storage, and vehicle-to-home (V2H) integration. This objective focuses on achieving optimal power scheduling, avoiding peak hours, reducing grid dependency, and enhancing peak shaving in the power system.

3. To conduct a comparative analysis of the operational behaviors of battery and EV performance within SHEMS. This involves analyzing power consumption and electricity costs across nine different simulation scenarios to understand their impact on overall SHEMS performance.

1.4 Scope and limitations

1.4.1 Scope

This thesis focuses on the design, implementation, and evaluation of a SHEMS framework that uses a hybrid PSO-LP approach for OHAS through TOU-based DR. The study contains the following details:

1. **SHEMS Configuration:** The proposed smart home model comprises eighteen different electrical appliances, which can decide to consume energy from various distributed energy resources, including rooftop solar PV systems, wind turbines, BESS, and EVs operating in both vehicle-to-home (V2H) and home-to-vehicle (H2V) modes.

2. **Optimization Methodology:** The hybrid PSO-LP technique is utilized to determine the OHAS. In this framework, PSO is applied to manage the SoC of batteries and EVs to handle the non-linear problem, while LP is responsible for appliance scheduling under fixed constraints. The integrated method is designed to minimize electricity costs, reduce grid dependency, and avoid peak load periods under a TOU pricing framework.

3. **Simulation and Case Studies:** To analyze and compare the operational behaviors of batteries and EVs under varied simulation scenarios to better understand their impact on overall energy consumption and electricity cost in a SHEMS. The performance of the proposed model is evaluated through nine case scenarios that represent various combinations of energy sources:

Case I: Appliance scheduling using grid power only.

Case II: Appliance scheduling with power from the grid and BESS.

Case III: Appliance scheduling with power from the grid and V2H.

Case IV: Appliance scheduling with power from the grid, PV, and BESS.

Case V: Appliance scheduling with power from the grid, PV, and V2H.

Case VI: Appliance scheduling with power from the grid, PV, BESS, and V2H.

Case VII: Appliance scheduling with power from the grid, PV, wind, and BESS.

Case VIII: Appliance scheduling with power from the grid, PV, wind, and V2H.

Case IX: Appliance scheduling with power from the grid, PV, wind, BESS, and V2H.

Additionally, for cases 4 through 9, the model is further evaluated by comparing scenarios where excess solar PV energy is sold back to the grid under the household PV purchasing scheme project through the MEA and PEA. The proposed framework has been studied for scalability and includes a preliminary economic impact analysis to ensure both practicality and cost-effectiveness in applications. The performance of the proposed hybrid PSO-LP algorithm is benchmarked against three other optimization techniques: PSO, Genetic Algorithm (GA), and hybrid GA-LP. This comparative study the advantages of the proposed method in terms of electricity cost reduction and solution quality under TOU-based DR and similar system conditions.

1.4.2 Limitations

This study relies on simulations rather than real-world implementation. While simulated scenarios provide valuable insights into system behavior, they do not fully capture practical constraints, environmental uncertainties, or user behavior variations that may influence actual SHEMS performance. The model assumes a consistent energy generation profile from solar and wind power based on average data from April, 2024, in Thailand. However, fluctuations due to weather conditions, seasonal changes, and unexpected demand spikes are not dynamically incorporated, which could affect practical feasibility. The battery and EV behavior are analyzed under specific assumptions; factors such as battery degradation, charging efficiency losses, EV mobility patterns, EV usage frequency, and variations in charging behavior may introduce additional complexities that are beyond the current scope of this thesis.

While these limitations set boundaries for the current research, they also present opportunities for future studies to enhance model adaptability, incorporate real-world uncertainties, and refine battery and EV performance evaluation to advance smarter home energy management.

1.5 Conception

The proposed SHEMS framework consists of six main components: electrical appliances, RES from rooftop solar PV and wind turbines, BESS, EVs that can be V2H operation, and the last part is the connection between a smart home and the power grid. In addition to utilizing electricity from the grid, the excess energy from the rooftop solar PV can also be sold to the household PV purchasing scheme project by the MEA and PEA, providing more economic benefits for prosumers. The main concept of this research is the minimization of electricity costs through OHAS, allowing eighteen different appliances to optimize their power consumption by selecting from any available energy resources. To achieve this objective, a hybrid PSO-LP framework is employed for efficient energy management. This hybrid approach integrates metaheuristic algorithms with mathematical programming to improve OHAS efficiency. The PSO layer determines optimal charging and discharging decisions for BESS and EVs by optimizing the SoC, which ensures that batteries and EVs function both as energy sources and loads within the smart home, thereby improving energy flexibility. Simultaneously, the LP part utilizes available energy resources, including grid power, PV, wind energy, BESS, and V2H, to decide the optimal operation periods for each appliance under TOU-based DR. By implementing PSO-LP, the proposed SHEMS model not only gets the OHAS but also minimizes electricity costs, reduces peak-hour demand, helps alleviate grid dependency, and enhances system stability. The concept of the hybrid PSO-LP based SHEMS model is illustrated in Figure 1.1.

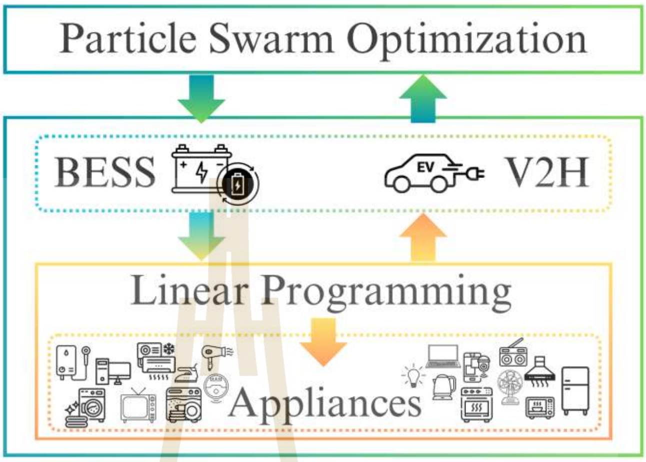


Figure 1.1 The hybrid PSO-LP based SHEMS model

1.6 Research Benefits

This research presents a hybrid PSO-LP-based SHEMS model that provides several benefits for smart home energy management. By intelligently managing household power consumption and optimally scheduling appliances based on the availability of multiple sources, the proposed method not only enhances energy flexibility while minimizing electricity costs for both prosumers and consumers but also reduces grid dependency during peak hours, supports peak shaving, and contributes to a more stable and sustainable power system. Furthermore, this system encourages participation in energy markets by promoting the sale of excess solar energy under Thailand's household solar program administered by MEA and PEA. Overall, the proposed approach supports the development of a decentralized power system and advances the transition toward a more resilient and sustainable smart grid system.

CHAPTER II

THEORETICAL AND RELATED LITERATURE REVIEW

2.1 Introduction

Smart home energy management systems (SHEMS) have been a topic of great interest in recent years due to rising electricity prices, increasing energy demand, and the urgent need to reduce carbon emissions. As global energy consumption continues to increase, optimizing household energy usage has become a crucial aspect of current energy management strategies. Demand response (DR) is a part of the demand-side management (DSM) technique that encourages smart homes to adjust appliance operation patterns by shifting the energy usage from peak hours to off-peak hours to minimize their electricity costs and improve overall system efficiency. Numerous research studies have focused on SHEMS using various technologies, including Battery Energy Storage Systems (BESS), Electric Vehicles (EVs), and Renewable Energy Sources (RES), including rooftop solar photovoltaic (PV) systems and wind turbines. The increasing integration of these components has introduced new levels of complexity to the design and operation of SHEMS, resulting in various problem formulations, constraints, and objectives, such as minimizing household electricity costs, reducing grid dependency, enhancing user participation, or balancing power demand. Despite these variations, the key objective shared across all SHEMS research is to support the development of a more stable, resilient, and sustainable power system.

This chapter provides a comprehensive review of existing research on SHEMS and addresses a variety of developments, challenges, and advancements in the field. The SHEMS literature is categorized based on research objectives, problem formulations, constraints, and optimization methodologies.

2.2 Literature Overview

In recent years, SHEMS have been advanced developments, driven by rising global demand consumption, improved power system reliability, electricity cost reduction, and the integration of RES, ESS, and EVs. At the same time, these developments have improved residential energy efficiency but also introduced more complex challenges for SHEMS. Researchers have proposed various optimization techniques to address these challenges, including conventional methods based on mathematical programming, such as linear and quadratic programming, and developed some metaheuristic techniques to solve nonlinear problems in SHEMS. As a start toward developing smarter, more adaptive, and efficient SHEMS to support a sustainable power system, the researchers have studied a variety of optimization methodologies, each formulated with different objectives to handle SHEMS challenges. This literature review categorizes SHEMS research based on four different energy resource configurations to systematically analyze their methodologies and contributions:

Table 2.1 presents the literature on SHEMS with the grid-connected only.

Table 2.2 reviews the literature on SHEMS with Renewable Energy Sources.

Table 2.3 examines the literature on SHEMS with Energy Storage Systems (ESS).

Table 2.4 focuses on the literature on SHEMS with electric vehicles (EVs).

Following this discussion, a summary table will provide a comparative analysis of the reviewed optimization approaches, highlighting key problem formulations, constraints, and methodologies.

Table 2.1 The SHEMS with the grid-connected only

Reference	Method	Objective	Description
Sou et al., 2011	Mixed Integer Linear Programming algorithm (MILP)	Minimize electricity costs while satisfying operational constraints and consumer preferences.	Developed a scheduling model for smart home appliances, considering uninterruptible and sequential operations. Tested with real spot price data from Sweden and NYC, demonstrating effective cost reduction and insights into tariff design.
Logenthiran et al., 2012	A heuristic-based Evolutionary Algorithm (EA)	Load shifting to minimize peak load demand, reduce costs, and improve sustainability.	Simulated day-ahead scheduling was conducted on a smart grid comprising three smart grid areas (residential, commercial, industrial) with different controllable loads.
Ma et al., 2016	Optimization problem with integer and continuous variables	To develop a power scheduling strategy that minimizes electricity costs and consumer discomfort in smart homes.	An optimal scheduling strategy achieved power scheduling under the day-ahead price. It categorizes appliances into shiftable and non-shiftable types and incorporates user preferences.

Table 2.1 The SHEMS with the grid-connected only (continue)

Reference	Method	Objective	Description
Zhu et al., 2019	A modified simulated annealing RTP (SA-RTP) algorithm	To maximize social welfare by balancing the interests of both electricity suppliers and consumers.	Considers different types of smart home appliances, modeling their behaviors using Markov decision process (MDP).
Pamulapati et al., 2020	Multi-objective evolutionary algorithm (MOEA)	To minimize electricity costs and user dissatisfaction in smart home appliance scheduling.	Proposes a scheduling approach that implicitly models user satisfaction by analyzing past appliance usage patterns obtained from energy disaggregation (ED). Additionally, it allows users to interactively adjust their preferences using priority weights.
Zakaria & Pradhana, 2020	Multi-objective Mixed Integer Linear Programming (MILP)	To minimize electricity costs, reduce peak load demand, and decrease user inconvenience in appliance scheduling.	Incorporates consumer preferences and appliance flexibility under a Time-of-Use (TOU) tariff structure, providing Pareto-optimal solutions that balance cost savings and user comfort.

Table 2.1 The SHEMS with the grid-connected only (continue)

Reference	Method	Objective	Description
Ghole et al., 2023	Swap-Based Butterfly Particle Swarm Optimization (BFPSO)	To minimize electricity costs and peak-to-average power ratio in real-time residential device scheduling.	Proposed a Nowcasting Central Controller (NCC) using continuous real-time pricing (CRTP) and swap-based BFPSO for adaptive and efficient appliance scheduling.
Piawises & Chayakul-kheeree, 2024	Linear programming (LP) algorithm	To optimize energy consumption by avoiding peak hours and reducing daily electricity costs	Applied TOU-based demand response to schedule twelve appliances.

Table 2.2 The SHEMS with Renewable Energy Sources (RES)

Reference	Method	Objective	Description
Ullah et al., 2015	Binary Particle Swarm Optimization (BPSO)	To schedule appliance based on a TOU pricing for reduce the bill of prosumer.	The proposed system integrates Renewable Energy Sources (RES) and treats Electric Vehicles (EVs) as controllable loads.
Qayyum et al., 2015	Mixed-integer programming technique (MILP)	To minimize the total electricity cost and reduce the peak load for operating the appliances based on 24 hours ahead TOU electricity tariff.	The proposed model integrates a photovoltaic (PV) panel as a microgrid and considers seven shiftable appliances alongside EVs treated as controllable loads.
Pawar et al., 2018	The prioritization and scheduling (PAS) algorithm	To minimize total energy consumption and reduce energy usage at each time step under Time-of-Day (TOD) pricing.	The proposed algorithm separately schedules appliance operations assuming only solar power availability and only grid power availability. These schedules are then merged to achieve optimal energy utilization.

Table 2.2 The SHEMS with Renewable Energy Sources (RES) (continue)

Reference	Method	Objective	Description
Yahyaoui et al., 2018	A multi-start random constructive heuristic algorithm	To minimize electricity costs while maintaining user comfort in a smart home environment.	Load scheduling strategy for a smart home supplied with a photovoltaic (PV) plant connected to the grid. The algorithm considers TOU tariffs following the solar radiation availability to optimize appliance operation schedules.
El Makroum et al., 2021	Linear Program-ming algorithm	To minimize energy cost or maximize renewable energy use under dynamic pricing to reduce energy demand based dynamic pricing.	Three household scenarios were studied (lower, middle, and upper class). Optimization either shifts loads to low-price hours or aligns usage with peak solar output. Considered EVs as a load.
El Makroum et al., 2023	Genetic Algorithm (GA)	To optimize energy costs based dynamic pricing and maintaining user comfort.	Developed a HEMS using real-life data from a Moroccan household. The GA schedules load while considering dynamic pricing and user comfort. Considered EVs as a load.

Table 2.3 The SHEMS with Energy Storage System

Reference	Method	Objective	Description
Dang & Ringland, 2012	Linear optimization formulation	To reduce energy cost and reduce peak energy consumption with a dynamic pricing	Three scheduling schemes: immediate, amortize, and lazy scheduling. The model integrates residential PV, battery storage, and EVs as controllable loads to shift demand and reduce grid reliance.
Tsui & Chan, 2012	Convex Programming (CP)	To minimize electricity costs by optimizing appliance scheduling under real-time pricing (RTP).	Battery-assisted appliances are modeled to shift loads between time slots, and the model considers dynamic pricing, RES integration, and battery constraints.
Shirazi & Jadid, 2015	Mixed integer non-linear programming (MINLP)	To minimize energy costs under the RTP schemes by scheduling the controllable appliance and distributed energy resources.	The HEMDAS model coordinates appliance uses and energy resource scheduling while maintaining user comfort and enabling demand aggregation across households.

Table 2.3 The SHEMS with Energy Storage System (continue)

Reference	Method	Objective	Description
Rasheed et al., 2015	A knapsack-based WDO (K-WDO) algorithm	To reduce electricity cost and peak load while preserving user comfort.	The algorithm schedules appliances based on TOU tariffs, balancing energy savings and comfort across multiple scenarios and appliance types.
Kapoor & Sharma, 2019	Genetic Algorithm (GA) and Interior-Point (IP) optimization	To generate an optimal hourly charge/discharge schedule for the BESS to minimize daily energy cost.	Tested on real residential load and solar generation data across varying weather scenarios, accounting for battery constraints and TOU pricing.
Qais et al., 2023	Random Integer Search Optimization algorithm (RISO)	To minimize electricity costs and achieve zero grid energy consumption while maintaining user comfort through price-based DR.	Optimal day-ahead load scheduling based on weather forecasts and user comfort schedules-based habits for residential customers living in Hong Kong with three scenarios (with/without PV, battery).

Table 2.4 The SHEMS with Electric Vehicles

Reference	Method	Objective	Description
Lee & Choi, 2014	Linear programming techniques	To shave peak load at the home by scheduling power consumption.	Utilizes Plug-in Hybrid Electric Vehicle (PHEV) as an energy source via V2G to store energy in home ESS and reduce peak load demand.
Melhem et al., 2017	Mixed Integer Linear Programming algorithm (MILP)	To minimize the electricity cost for households by optimizing the scheduling of energy production and consumption using TOD pricing.	Consider eight different scheduling scenarios combining various residential generation (like PV) and consumption systems. This work integrates DERs (Distributed Energy Resources), including EVs and batteries, under TOD tariffs. The role of EVs is a load.
Duman et al., 2018	Mixed Integer Linear Programming algorithm (MILP)	To both reduce the electricity bills of the consumers and reduce the peak power of the electricity grid.	Load scheduling model under TOU pricing. Appliances, including washing machines, dishwashers, and electric vehicles (EVs) are treated as controllable loads to shift energy usage to off-peak periods.

Table 2.4 The SHEMS with Electric Vehicles (continue)

Reference	Method	Objective	Description
Hou et al., 2019	Mixed integer linear programming (MILP)	To minimize electricity costs while ensuring user satisfaction under RTP.	Proposes a smart home energy management method integrating ESS and V2H systems. The model includes a coordinated charging/ discharging strategy, enabling V2H operation where EVs can supply power to the home.
Singh et al., 2019	Mixed Integer Linear Programming algorithm (MILP)	To reduce residential electricity expenditure using day-ahead TOU pricing.	An appliance scheduling and energy management model that considers grid, PV, battery, and EVs. The framework evaluates three different operational scenarios, including cases with and without V2H integration.
Singh et al., 2021	MILP and Rain flow Cycle Counting algorithm (RCCA)	To minimize energy costs and reduce BESS replacement costs through optimal load and energy management.	This model Incorporating V2H and BESS. A novel aspect is the use of RCCA to estimate battery degradation from charging/discharging cycles.

Table 2.4 The SHEMS with Electric Vehicles (continue)

Reference	Method	Objective	Description
Rehman et al., 2021	Hybrid of GA, WDO, and PSO (HGPDO) algorithm	To minimize electricity cost, peak-to-average ratio (PAR), and carbon emissions under RTP tariff	Each appliance in the smart home is scheduled using GA, BPSO, WDO, BFO and the proposed optimization technique, HGPDO. EVs are handled as controllable loads.
Chreim et al. 2022	Hybrid heuristic algorithm combining PSO and BPSO	To optimize next-day residential load scheduling with a balance between electricity cost reduction and user comfort.	The SHEMS model is validated using real consumption data from a smart home in Loughborough, UK. And enabling V2H operation
Kanakadhurga & Prabaharan, 2024	Binary Particle Swarm Optimization algorithm (BPSO)	To reduce grid dependency and electricity costs by scheduling appliances based on RTP.	This study integrates V2H, RES, and BESS into a SHEMS framework. The proposed approach demonstrates five case scenarios using real RTP tariffs in India.

Table 2.4 The SHEMS with Electric Vehicles (continue)

Reference	Method	Objective	Description
Proposed Framework	Hybrid Particle Swarm Optimization Linear programming algorithm (hybrid PSO-LP)	To minimize electricity costs, manage energy usage to avoid peak hours, and optimize power consumption under TOU-based DR.	Considers energy from grid, RES, ESS, and EVs with V2H functionality, and optimizes the operation of eighteen household appliances.

2.3 The SHEMS with the grid-connected only

In the simplest case, the SHEMS relies solely on the power from the grid, which can be modified and applied in wide problem formulations. Home energy management (HEM) and load scheduling problems with the power grid usually focus on optimizing the scheduling of power consumption in households based on Demand-Side Management (DSM) tactics through various optimization methods to reach different objectives. Many researchers used power scheduling in one process in their framework to implement the main objective. Kin Chong Soo et al. (2011) suggested a smart home appliance scheduling using mixed integer linear programming (MILP) to optimal power and minimize total electricity cost while satisfying operational constraints and consumer preferences. Their study utilized real spot price data from spot pricing in Sweden and New York City. This work introduced the concept of power profile signals to adjust the expected operation duration and power ratings of appliances. Logenthiran et al. (2012) introduced a heuristic-based Evolutionary Algorithm (EA) for day-ahead load shifting, capable of managing a large number of controllable devices of several types and achieving substantial savings while reducing the peak load demand of the smart grid, demonstrating the potential of heuristic approaches in DSM problems. In 2016, Kai Ma et al. studied the power scheduling problem for residential consumers in smart grids. An optimal scheduling strategy for power scheduling under the day-ahead price can achieve a desired trade-off between the electricity payments and the discomfort. When the electricity prices are announced ahead of time, the consumers can regulate the operations of appliances to reduce costs and maintain their comfort. Later, Zhu et al. (2019) developed an algorithm for scheduling smart home appliances that uses the Markov decision process (MDP) to transition the finite power consumption states of the elastic appliance. The study introduced a modified Simulated Annealing algorithm (SA-RTP) is an ideal method to adjust the power balance between supply and demand, which maximizes social welfare based on the MDP. In 2020, Trinadh Pamulapati et al. presented a multi-objective evolutionary algorithm with the optimal Pareto front approach for home appliance scheduling, which considered two conflicting objectives: minimizing user dissatisfaction and minimizing the electricity cost. Their model implicitly modeled user preferences using historical appliance usage patterns obtained through energy disaggregation and enabled interactive adjustment of scheduling priorities. Also in 2020, Zakaria Yahia and Anup Pradhan formulated a Multi-Objective MILP (MOMILP) model for appliance scheduling across multiple households. Their approach aimed to reduce electricity costs, decrease user inconvenience, and flatten the aggregated peak load. The model incorporated consumer preferences and operated under TOU pricing, yielding Pareto-optimal trade-offs between objectives. In 2023, Mukund Subhash Ghole et al. represent an appliance scheduling model having a Nowcasting Central Controller (NCC), which is optimized in real-time. This model is designed for residential devices using continuous RTP and targets optimizing the device schedule in the current time slot using the swap-based Butterfly Particle Swarm Optimization (BFPSO) approach. Recently, W. Piawises and K. Chayakulkheeree (2024) proposed a simple energy management algorithm for smart homes. Each appliance is decided to manage power consumption from the grid using TOU-based demand response (DR) using the linear programming (LP) method, which can reduce electricity costs and the burden on the grid during peak hours. In summary, grid-connected SHEMS models offer a strong foundation for exploring various optimization strategies applied to appliance scheduling. Despite relying solely on grid power, these systems demonstrate a wide range of techniques from exact methods to metaheuristic approaches, which are designed to address different objectives. Their adaptability and simplicity make them flexible bases for extending toward more advanced energy management scenarios, including hybrid systems with renewable integration, which are discussed in the following sections.

2.4 The SHEMS with Renewable Energy Sources (RES)

The SHEMS integration of RES, such as solar or wind energy, adds a layer of complexity to energy management due to the uncertainty of renewable energy. The power balance of renewable energy generation with grid usage is an important keyword for minimizing electricity costs and alleviating grid burden during peak periods. Over the past decade, numerous studies have explored SHEMS incorporating RES to manage power consumption from the grid and RES, which improves cost efficiency and system sustainability. An appliance scheduling model using Binary Particle Swarm Optimization (BPSO) is presented by Ullah et al. (2015). The home has solar rooftop renewable energy source (RES) generation, six different household appliances, and EV charging as a controllable load. This proposed model efficiently schedules the electricity consumption based on a TOU pricing scheme in a dynamic pricing environment to benefit the consumer by minimizing electricity costs. At the same moment, Qayyum et al. (2015) proposes a solution to the problem of scheduling a smart home based on the mixed-integer programming (MILP) technique. This model adopts a PV panel as a power-producing appliance that acts as a microgrid. Seven different appliances are scheduled with two objectives, the first objective deals with the lowering of electricity cost, and the second objective deals with minimizing peak load for operating the appliances based on a 24-hour ahead TOU electricity tariff. Prakash Pawar et al. (2018) suggested a methodology to carry out demand response management on both the grid power and solar power in unison by dividing scheduling assuming only solar power is available and scheduling assuming only grid power is available and then merging to have the most efficient utilization of the resources available. The prioritization and scheduling (PAS) algorithm was implemented based on time-of-day (TOD) pricing to minimize the total energy consumed by all the loads and minimize the energy consumed in every time step in real-time. For the same moment, Yahyaoui et al. (2018) present a multi-start random constructive heuristic algorithm that balances electricity payments and user comfort. Their model determined the optimal combination of appliance priority and usage time based on the availability of solar energy and TOU pricing. El Makroum et al. (2021) represent a load-scheduling model using linear programming based on dynamic pricing and renewable energy. The proposed model considers multiple constraints along with an optimization function that either minimizes the energy bill or maximizes the use of renewable energy generation within a household to reduce the energy demand in Morocco. After that, El Makroum et al. (2023) developed a home energy management system able to achieve optimized load scheduling for the operation of appliances based on the genetic algorithm (GA), not only taking into account the dynamic pricing of electricity to optimize energy costs but also the optimization for solar energy usage as well as maintaining user comfort, demonstrating the increasing relevance of adaptive and data-driven approaches in RES-integrated SHEMS.

These studies reflect the growing complexity of SHEMS designs that incorporate RES. Despite variations in objectives and optimization techniques, they share a common goal: to build a more flexible, efficient, and sustainable smart home energy ecosystem. These foundational works also provide crucial insights for future research, especially in hybridized systems where RES integration must be carefully managed in conjunction with other distributed energy resources.

2.5 The SHEMS with Energy Storage System (ESS)

The integration of Energy Storage Systems (ESS) into SHEMS enhances system flexibility, reliability, and cost-effectiveness. The smart home integrated battery not only stores surplus energy generated from RES or purchased grid power during off-peak hours for later use but also provides backup energy for smart homes when there is high peak demand and electricity prices. This functionality positions batteries as both consumers and providers of energy, playing a key role in demand response (DR) programs. SHEMS with battery problems offers both advantages and challenges in solving issues. Accordingly, nonlinear and hybrid optimization techniques are frequently employed to manage and optimize battery usage in SHEMS models. Dang and Ringland (2012) present an optimal load-scheduling algorithm for smart grids with local renewable energy sources and energy storage. Their model considers three energy dispatch strategies: immediate, amortized, and lazy scheduling. The grids are assumed to allow consumers to both buy and sell energy, and the retailers have dynamic pricing with inclining block rates. The algorithm achieves its optimality by formulating a linear optimization problem that can be solved efficiently. At the same moment, Tsui and Chan (2012) study a convex programming (CP) DR optimization framework for the automatic load management of various household appliances in a smart home and propose a regularization technique to transform the mixed integer nonlinear program (MINLP) to a standard CP, which can be solved more readily. Electricity allocation of various appliances based on battery-assisted and model-based appliances in the smart home under RTP. Rasheed et al. (2015) introduced a knapsack-based wind-driven optimization (K-WDO) algorithm for residential load scheduling. The model incorporates the different appliances based on hourly electricity prices (TOU) during on-peak and off-peak hours in conjunction with user preferences. Moreover, it proposes that SHEMS incorporate a renewable energy resource during critical hours for grid stability, electricity cost reduction, and user comfort. At the same time, Shirazi and Jadid (2015) represent a mixed integer non-linear programming (MINLP) to achieve home energy management with distributed energy resources (DERs) along with both electrical and thermal appliance scheduling (HEMDAS) to optimize residential energy consumption under dynamic pricing, which tries to achieve a favorable trade-off between minimizing the energy costs as well as the inconvenience for the operation. Household tasks along with DER operation are scheduled according to electricity real-time price (RTP) and natural gas fixed price. HEMDAS offers a feasible solution to optimal energy management for diverse load scenarios. Later, Kapoor and Sharma (2019) developed an optimal charging and discharging schedule for a PV battery storage system formulated to maximize the net saving in the electricity bill of a residential customer considering intermittent PV output due to varying weather conditions. The impact of changing weather conditions on PV power output is considered by taking different cases of cloud cover. The optimal battery scheduling algorithm based on TOU tariffs is implemented by utilizing a conventional interior point (IP) and the genetic algorithm (GA) method. Most recently, Qais et al. (2023) developed a home energy management (HEM) schedule using solar PV and battery systems implemented by a random integer search optimization (RISO) for an optimal day-ahead load schedule based on the day-ahead weather forecast and consumers' comfort time range schedule to help consumers achieve cost-effective, zero-grid energy consumption. This approach not only supports user comfort and carbon footprint reduction without sacrificing comfort load scheduling but also aligns with the Hong Kong government policy of encouraging homeowners to contribute to lowering their carbon footprints by feeding extra PV power into the grid. In summary, SHEMS with ESS enables more adaptive and resilient home energy optimization. The integration of batteries presents both opportunities and technical challenges, encouraging the development of refined optimization algorithms that balance economic and environmental goals while preserving user comfort.

2.6 The SHEMS with Electric Vehicles (EVs).

Nowadays, people are turning to EV users in large numbers because using EVs reduces the need for gasoline and diesel, helping to save the environment instead of using conventional combustion vehicles. The SHEMS addition of EVs is the basic case in recent smart homes. EVs are similar to transportable batteries, as EVs can act as both energy consumers and possible energy sources through vehicle-to-home (V2H) or vehicle-to-grid (V2G) systems, further complicating the energy management process. Many studies apply advanced mathematical and metaheuristic optimization techniques to address these complexities. Lee and Choi (2014), proposed power consumption scheduling for shaving peak load at the home level using linear programming techniques. Their system integrates the grid, residential ESS, and plug-in hybrid electric vehicles (PHEVs), where the optimized energy management system (OEMS) coordinates the charging and discharging processes. PHEVs are utilized as backup storage to alleviate grid load via V2G. Duman et al. (2018) applied a mixed integer linear programming (MILP)-based home energy management system (HEMS) under a TOU rate. In this HEMS, a smart home comprises washing machines, dishwashers, and electric vehicle loads. EVs in this work are considered as a load for a residential household to overcome problems that could possibly arise from high penetration of the EVs to the grid in the near future.

The SHEMS were rapidly developed years ago; many works proposed modeling of the smart home comprised of a conventional power grid, RES such as PV systems and wind turbines, battery storage systems, EVs, and integration of controllable electrical home appliances. This basic modeling pushes the SHEMS problem more challenging. Numerous SHEMS problems can be extended and proposed optimization solutions. For example, Melhem et al. (2017) proposed a Mixed Integer Linear Programming (MILP) method to solve the appliance scheduling model in various smart grid configurations, focusing on minimizing the electricity cost for households by optimizing the scheduling of energy production and consumption by time-of-day (TOD) pricing. Hou et al. (2019) focused on a comprehensive smart home optimization model incorporating RES, ESS, and plug-in EVs (PEVs). Using MILP under real-time pricing (RTP) for a minimized cost of electricity with guaranteed user satisfaction. A dedicatedly designed charging and discharging strategy for both the ESS and EV, considering their capital costs, is proposed to integrate them into the HEMS to provide better flexibility and economic advantages, as well as to extend the life of the batteries. At the same time, Singh et al. (2019) investigated how a Residential Energy Management System (REMS) was used to optimally manage energy from DERs as well as the operation of shiftable appliances using the day-ahead TOU pricing strategy and the MILP technique to achieve the lowest cost. In a subsequent study, Singh et al. (2021) extended a MILP-based Energy Management and Load Scheduling System (EMLSS) model that optimally controls household appliances and manages energy received from DERs other than the utility grid using day-ahead TOU pricing. The simulation of the MILP data was fed into the Rain Flow Cycle Counting algorithm (RCCA) to determine the capacity degradation of the home BESS until it reached the End of Life (EoL). Meanwhile, Rehman et al. (2021) proposed an efficient load scheduling and energy management controller (LSEMC) for smart home buildings achieved by shifting the demand in response to RTP to reduce the electricity bill, peak-to-average ratio (PAR), and carbon emission. LSEMC is implemented by heuristic algorithms, i.e., genetic algorithm (GA), wind-driven optimization (WDO), binary particle swarm optimization (BPSO), and bacterial foraging optimization (BFO), and compared with their suggested hybrid of GA, WDO, and PSO (HGPDO) algorithm. Chreim et al. (2022) developed LOSISH, a price-based demand response (DR) system for load scheduling in smart homes that considers RESs, BESS, and plug-in electric vehicles (PEV). A hybrid PSO-BPSO algorithm for day-ahead load scheduling, balancing electricity cost and user comfort. This research uses consumers' preferences from the real data of their smart home in Loughborough, UK. Most recently, Kanakadhurga and Prabaharan (2024) proposed a Binary Particle Swarm Optimization (BPSO) algorithm for appliance scheduling considering RTP and dynamic availability of DERs, BESS, and EVs were integrated as V2H support. With excess energy exported to the grid under an Indian feed-in tariff scheme. Appliance scheduling using BPSO to reduce grid dependency and electricity costs by optimizing SHEMS.

These studies illustrate a wide range of optimization strategies that address the dual role of EVs in energy consumption and supply. In conclusion, integrating EVs into SHEMS models represents an essential step toward decentralized and resilient energy systems.

2.7 Research Gap based on the Literature Overview

Smart home energy management systems (SHEMS) are an increasingly important problem with multiple methods to optimize and develop SHEMS. Most existing literature has used appliance scheduling to manage energy consumption for a variety of objectives, including minimizing electricity prices, reducing peak load demand, and others. Table 2.5 shows the research gap between the proposed effort and the existing literature. According to the above-mentioned literature survey, a number of previous researchers have applied hybrid stochastic deterministic approaches to address complex optimization problems. Nevertheless, this class of methods remains a subject of ongoing research interest, primarily due to the inherent complexity of the problems and the involvement of multiple interdependent variables.

In this thesis, SHEMS is formulated as a two-layer hybrid optimization framework: a heuristic layer using PSO to determine possibilities of power consumption of battery and EV, and a mathematical programming layer using LP to handle appliance scheduling under TOU tariffs. Recently, in addition to utilizing electricity from the grid, the excess energy from the rooftop PV can also be sold to the household PV purchasing scheme project by the Metropolitan Electricity Authority (MEA) and Provincial Electricity Authority (PEA). The principal concept of this article is TOU-based optimal home appliance scheduling (OHAS) to reduce daily electricity costs and decrease grid dependency, which is implemented by the hybrid PSO-LP algorithm.

Table 2.5 The Research Gap based on the Literature Overview

Ref.	Year	Type of DR	PV	Wind	BESS	EV	Grid	Energy Export	Case Study	Optimization Methods
Soo et al.	2011	Spot pricing	✗	✗	✗	✗	✓	✗	SE & NYC	MILP
Logenthiran et al.	2012	DSM	✗	✗	✗	✗	✓	✗	H	EA
Ma et at.	2016	Day ahead price	✗	✗	✗	✗	✓	✗	H	Scheduling strategy
Zhu et al.	2019	RTP	✗	✗	✗	✗	✓	✗	H	SA-RTP algorithm
Pamulapati et al.	2020	Fixed cost	✗	✗	✗	✗	✓	✗	H	MOEA
Zakaria & Pradhana	2020	TOU	✗	✗	✗	✗	✓	✗	H	MOMILP
Ghole, et al.	2023	CRTP	✗	✗	✗	✗	✓	✗	H	BFPSO
Piawises & Chayakul-kheeree,	2024	TOU	✗	✗	✗	✗	✓	✗	H	LP
Ullah et al.	2015	TOU	✓	✗	✗	✓	✓	✗	H	BPSO
Qayyum et al.	2015	Day ahead TOU	✓	✗	✗	✓	✓	✗	H	MILP
Pawar et al.	2018	TOD	✓	✗	✗	✗	✓	✗	H	PAS algorithm
Yahyaoui et al.	2018	TOU	✓	✗	✗	✗	✓	✗	H	heuristic algorithm
El Makroum et al.	2021	dynamic pricing	✓	✗	✗	✓	✓	✗	MA	LP
El Makroum et al.	2023	dynamic pricing	✓	✗	✗	✓	✓	✗	MA	GA

Table 2.5 The Research Gap based on the Literature Overview (continue)

Ref.	Year	Type of DR	PV	Wind	BESS	EV	Grid	Energy Export	Case Study	Optimization Methods
Dang & Ringland	2012	dynamic pricing	✓	✓	✓	✓	✓	✓	H	LP
Tsui & Chan	2012	RTP	✓	✓	✓	✗	✓	✗	H	CP
Shirazi & Jadid	2015	TOU	✓	✗	✓	✗	✓	✗	H	K-WDO
Rasheed et al.	2015	RTP	✓	✗	✓	✗	✓	✗	H	MINLP
Kapoor & Sharma	2019	TOU	✓	✗	✓	✗	✓	✗	IN	IP and GA
Qais et al.	2023	Price based	✓	✗	✓	✓	✓	✓	HK	RISO
Lee & Choi	2014	hourly peak load	✗	✗	✓	✓	✓	✗	KP	LP
Melhem et al.	2017	TOD	✓	✓	✓	✓	✓	✓	H	MILP
Duman et al.	2018	TOU	✗	✗	✗	✓	✓	✗	TR	MILP
Hou et al.	2019	RTP	✓	✗	✓	V2H	✓	✗	H	MILP
Singh et al.	2019	Day ahead TOU	✓	✓	✓	V2H	✓	✓	H	MILP
Singh et al.	2021	RTP	✓	✓	✓	✓	✓	✗	H	HGPDO
Rehman et al.	2021	Day ahead TOU	✓	✓	✓	V2H	✓	✓	H	MILP and RCCA
Chreim et al.	2022	Price based	✓	✓	✓	V2H	✓	✓	UK	PSO-BPSO
Kanakad-hurga & Prabaharan	2024	RTP	✓	✓	✓	V2H	✓	✓	IN	BPSO
The proposed method		**TOU/RTP**	✓	✓	✓	**V2H**	✓	✓	**TH**	**PSO-LP**

H: Hypothetical (Research formulated based on hypotheses), HK: Hong Kong, IN: India, KR: Korea, MA: Morocco, NYC: New York City, SE: Sweden, TH: Thailand, TR: Turkey, and UK: United Kingdom.

2.8 Optimization Model Formulation

Optimization plays a vital role in the development of Smart Home Energy Management Systems (SHEMS), especially when managing multiple energy sources and scheduling appliances under specific operational constraints. This section introduces the theoretical foundations of two optimization techniques used in this research, which are linear programming (LP) and particle swarm optimization (PSO).

2.8.1. Linear Programming (LP)

Linear programming (LP) is one of the most basic and widely used mathematical techniques in optimization. LP was first formally introduced by George B. Dantzig in 1947, who developed the Simplex Method for solving optimization problems under linear constraints (Dantzig, 1963), which laid the foundation for both theoretical development and practical applications of LP in diverse fields such as operations research, economics, and engineering. LP has become a core component in optimization-based decision-making systems due to its ability to model various problems with clear objectives and constraints when all relationships in the system are linear. Winston (2004) explains that LP problems are especially useful not only for their mathematical tractability but also because they can be solved efficiently, even when involving a large number of decision variables and constraints, provided that both the objective function and constraints are linear. Before formally defining a linear programming problem, it is essential to introduce the concept of a linear function. A function $f(x_1, x_2, \ldots, x_n)$ of $x_1, x_2, \ldots, x_n$ is a linear function if and only if for some set of constants $c_1, c_2, \ldots, c_n$, $f(x_1, x_2, \ldots, x_n) = c_1x_1 + c_2x_2 + \ldots + c_nx_n$. A linear equations system such as:

$$
\begin{gathered}
a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \ldots + a_{1n}x_n = b_1 \\
a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \ldots + a_{2n}x_n = b_2 \\
a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \ldots + a_{3n}x_n = b_3 \\
\vdots \\
a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \ldots + a_{mn}x_n = b_m
\end{gathered}
\tag{2.1}
$$

This system can be written as $A\mathbf{x} = \mathbf{b}$, where

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & 0 \\ a_{m1} & a_{m2} & a_{m3} & \cdots & a_{mn} \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_n \end{bmatrix}. \tag{2.2}$$

When A is the matrix of coefficients, $\mathbf{x}$ is the vector of variables, and $\mathbf{b}$ is the vector of constants. In many practical optimization problems, some relationships are expressed as linear inequalities instead of equalities. For any linear function $f(x_1, x_2, \ldots, x_n)$ and any number b, the inequalities $f(x_1, x_2, \ldots, x_n) \leq b$ and $f(x_1, x_2, \ldots, x_n) \geq b$ are linear inequalities.

In any linear programming problem, maximization or minimization of some function of the decision variables is called the objective function. LP is a mathematical approach for optimizing a linear objective function, subject to the values of the decision variables satisfying a set of constraints. Each constraint must be a linear equation or linear inequality. A sign restriction is associated with each variable. For any variable x_i, the sign restriction specifies that x_i must be either non-negative ($x_i \geq 0$) or unrestricted in sign. The general form of a linear programming problem is as follows:

$$\textit{Minimize} \quad C^T x \tag{2.3}$$

$$\textit{Subject to} \quad Ax \leq b \tag{2.4}$$

$$x \geq 0 \tag{2.5}$$

This standard form is widely used throughout LP applications and is particularly useful in energy optimization, including smart home energy management systems (SHEMS), where decision makers aim to minimize electricity costs while satisfying power demand using multiple energy sources.

2.8.2. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a nature-inspired, population-based optimization technique introduced by Kennedy and Eberhart (1995). PSO is a stochastic search optimization method inspired by the collective behavior of birds flocking, which searches for a population of particles to obtain the best solution. Where particles adjust their positions by learning from their own experience and the experience of their neighbors to discover optimal solutions in a search space. With this concept, the population is defined as a swarm, and the possible solutions are the particles. Unlike classical optimization techniques, PSO does not require the gradient of the objective function, making it suitable for nonlinear, non-differentiable, and complex optimization problems. It has been widely applied in fields such as power systems, control engineering, neural network training, and smart grid energy management due to its simplicity, flexibility, and fast convergence properties (Eberhart & Shi, 2001).

In PSO, each particle represents a potential solution to the optimization problem. The particles move through the search space and iteratively update their positions and velocities based on both personal best position ($pbest_i^t$.) and global best position ($gbest^t$). $pbest_i^t$ is the best solution the particle has found so far, while $gbest^t$ is the best solution found by the entire swarm. The position and velocity update rules for each particle 'i' at iteration 'j' are defined as follows:

$$v_i^{j+1}=wv_i^j+c_1r_1\left(pbest_i^j-\boldsymbol{x}_i^j\right)+c_2r_2\left(gbest^j-\boldsymbol{x}_i^j\right), \tag{2.6}$$

$$\boldsymbol{x}_i^{j+1}=\boldsymbol{x}_i^j+v_i^{j+1}. \tag{2.7}$$

Where,

$\boldsymbol{x}_i^j$ is the position of particle i at iteration j,

v_i^j is the velocity of particle i at iteration j,

w is the inertia weight, which controls the trade-off between exploration and exploitation,

c_1, c_2 are the cognitive and social acceleration coefficients

r_1, r_2 are random numbers within the range [0, 1]

The iterative process continues until a stopping criterion is met, such as a maximum number of iterations or convergence tolerance.

In the context of SHEMS, PSO can be applied to determine optimal values for continuous variables such as the State of Charge (SoC) of batteries or Electric Vehicles (EVs) or to select control parameters that lead to minimal electricity cost while satisfying constraints. In this thesis, PSO is used to determine proper values of SoC for battery and EV systems over a day, then passed to the LP section, which optimally allocates energy from multiple sources to meet appliance demands. This hybrid PSO-LP framework employs the stochastic search capability of PSO and the precision of LP, ensuring both efficient exploration of the solution space and optimal scheduling of energy resources.

2.9 Economic Impact Modeling

The economic evaluation of energy management systems plays a crucial role in determining the feasibility and financial viability of implementing technologies such as battery energy storage, electric vehicles (EVs), and renewable energy integration. In the context of SHEMS, economic impact is often assessed based on cost savings from reduced electricity bills, capital investments, and long-term financial returns. To quantify these economic benefits, various financial indicators are widely used in energy studies. These include the initial investment cost, estimated annual electricity cost savings, and key financial indicators such as Present Value (PV), Net Present Value (NPV), Return on Investment (ROI), and Payback Period (PBP) (Short, Packey, & Holt, 1995).

2.9.1. Initial investment cost (IIC)

The first step in evaluating the economic viability of the system is to determine the total cost of deploying all relevant components. These include energy generation systems, both rooftop PV and wind turbines, and energy storage systems.

$$IIC = C_{PV} + C_{Wind} + C_{Battery} \tag{2.8}$$

Where,

$C_{Battery}$ is the installation cost of the battery energy storage system,

$C_{PV},\ C_{Wind}$ are the installation costs of PV panels and wind turbines.

2.9.2. Estimated annual electricity cost savings (AES)

When the SHEMS is operational, economic benefit is realized through reduced electricity costs. The annual energy saving estimates the amount of money saved per year due to optimized scheduling and renewable energy usage.

$$AES = C_{Base} - C_{Optimized} \tag{2.9}$$

Where,

C_{Base} is the annual electricity cost without optimization,

$C_{Optimized}$ is the annual electricity cost with the proposed SHEMS in place.

2.9.3. Present Value (PV)

Present Value (PV) is a fundamental concept in financial analysis that refers to the current worth of a stream of future cash flows, discounted back to the present using a specific discount rate. It reflects the principle that the monetary value received in the future is worth less than the same amount received today due to inflation, opportunity cost, and risk. According to Short et al. (1995), PV is computed using the following formula:

$$Total\ PV = \sum_{y=1}^{n} \frac{AES}{(1+r)^{y}} \tag{2.10}$$

Where,

r is discount rate per year,

n is the number of years in the evaluation period.

y is specific year of the project.

This concept enables the comparison of future cost savings with present investment and is essential for long-term planning in SHEMS projects.

2.9.4. Net Present Value (NPV)

Net Present Value (NPV) represents the difference between the present value of benefits and the initial investment cost. It is a widely accepted indicator for determining the economic feasibility of a project. A positive NPV indicates that the investment generates more value than it costs, while a negative NPV suggests financial loss.

$$NPV = PV - IIC \tag{2.11}$$

As described by Boardman et al. (2018), NPV is considered the most theoretically sound financial criterion because it measures the absolute value created by a project.

2.9.5. Return on Investment (ROI)

Return on Investment (ROI) is a ratio that expresses the net benefit of a project as a percentage of the total investment cost. It is a simple but effective tool for comparing the relative profitability of different investment options.

$$ROI = \frac{NPV}{IIC} \times 100\% \tag{2.12}$$

2.9.6. Cumulative Discounted Cash Flow

In economic analysis, Cumulative Discounted Cash Flow (CDCF) is a method used to evaluate the financial feasibility of a project by summing the net cash flows over time, while incorporating the time value of money. According to this principle, a unit of currency received today is worth more than the same unit received in the future due to its earning potential. As a result, all future savings or earnings must be discounted to their present value when performing economic evaluations. CDCF is particularly important in renewable energy and smart home investments, where the initial investment costs are significant and the return is accumulated gradually over time through operational cost savings. By tracking the accumulation of discounted cash inflows, CDCF enables investors to determine how long it will take for the project to break even. The CDCF at year y can be mathematically defined as:

$$CDCF_y = -I_0 + \sum_{y=1}^{n} \frac{AES_y}{(1+r)^y} \tag{2.13}$$

Where:

I_0 is initial investment cost,

AES_y is net annual electricity cost savings (or cash inflow) at year y.

The point in time at which the CDCF becomes zero or positive ($CDCF_y \geq 0$) is considered the break-even point, which marks the discounted payback period.

2.9.7. Discounted Payback Period (PBP)

To estimate the Discounted Payback Period (DPBP) more accurately, linear interpolation is applied between the last year when the cumulative discounted cash flow (CDCF) is still negative and the first year it becomes non-negative. This approach enables a more precise identification of the breakeven point in present value terms.

The DPBP is calculated using the following equation:

$$DPBP = (y-1) + \frac{CDCF_{(y-1)}}{CDCF_y - CDCF_{(y-1)}} \tag{2.14}$$

Where,

y is the year in which $CDCF_y \geq 0$

$CDCF_{(y-1)}$ and $CDCF_y$ are the cumulative discounted cash flows in the year before and at the breakeven point, respectively. This method improves upon the traditional payback period by incorporating the time value of money, making it a more realistic tool for evaluating long-term energy investments.

In summary, evaluating the economic impact through financial indicators such as NPV, ROI, PBP, and cumulative cash flows provides a comprehensive understanding of the investment feasibility and long-term benefits of smart home energy systems. These indicators not only support cost-saving decisions but also reinforce the practical value of integrating renewable energy and storage technologies in SHEMS.

CHAPTER III

METHODOLOGY

3.1 Introduction

This chapter outlines the formulation and computational process of the proposed optimal home appliance scheduling (OHAS) model, which aims to minimize daily electricity costs implemented by a hybrid Particle Swarm Optimization–Linear Programming (PSO–LP) approach. The chapter presents the overall system architecture and mathematical representation of the smart home system. The proposed smart home energy management system (SHEMS) comprises four components: electrical appliance data, renewable energy sources (RESs) model, including solar panels, wind turbines, battery energy storage systems (BESS), electric vehicle-to-home (V2H) models, and the connection between the smart home and the grid. An overview of the proposed SHEMS configuration is illustrated in Fig. 3.1. As smart homes incorporate a growing number of RESs, BESS, and EVs, the SHEMS problem becomes increasingly complex due to the variability and interaction among components. Traditional single-method approaches may not be sufficient to handle these challenges. Therefore, a hybrid PSO–LP approach is adopted in this study, combining the global search capability of PSO with the precise and constraint optimization strength of LP. This chapter presents the foundational elements of the proposed model

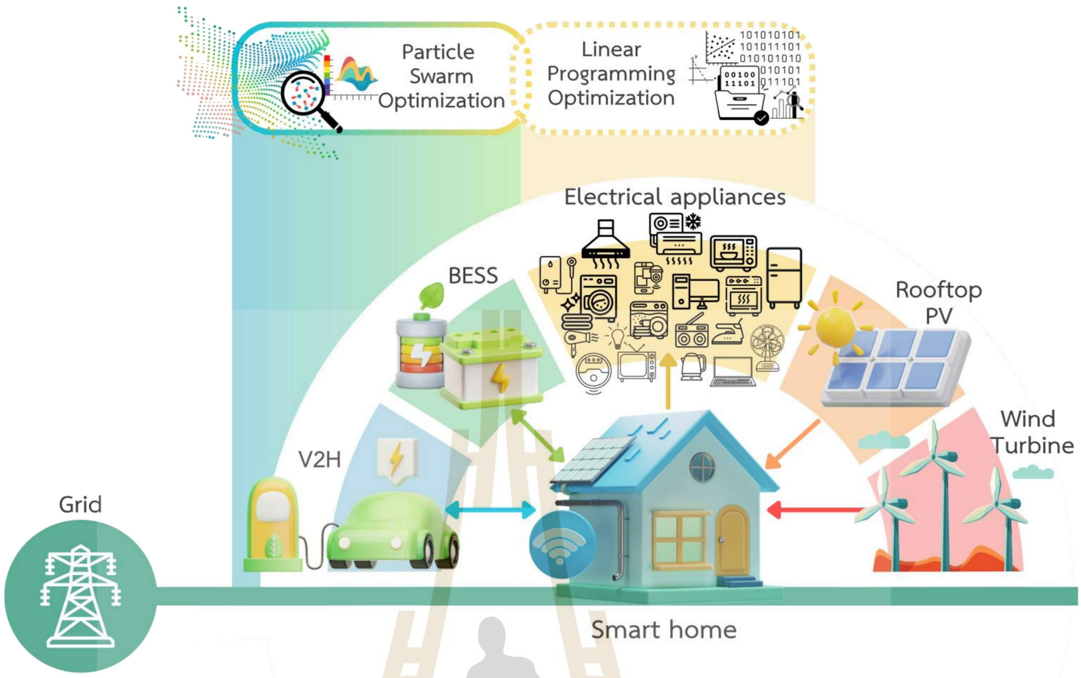


Figure 3.1 Proposed smart home model

3.2 Proposed Smart Home Energy Management System Framework

3.2.1 Electrical appliances

The future smart home is expected to incorporate a large number of electrical appliances with varying energy demands. In this thesis, we present a selection of electrical home appliances that are ubiquitous in every home. These appliances are categorized into two types based on their operational flexibility: shiftable and unshiftable (Melhem et al., 2017). Unshiftable appliances must always be on or have a non-changed period for operation. In contrast, the shiftable appliances can flexibly designate a time to operate to obtain the optimal solution of the proposed system. Each electrical appliance has specific data framed based on the usage pattern of each appliance by the consumer. The power rating (kW), the required duration of operation (hours), and the allowable range of starting and finishing times (hours) of eighteen different appliances (Kanakadhurga & Prabaharan, 2024). are presented in Table 3.1

Table 3.1 The typical appliances data

No.	Appliances	Power rating (kW)	Duration of operation (hours)	Starting time (hours)	Ending time (hours)	Category of appliance	
						Unshiftable	Shiftable
1.	Refrigerator	0.175	24	0	24	✓	
2.	sensor	0.01	24	0	24	✓	
3.	Air conditioner	1.15	12	12	24	✓	
4.	Illumination	0.50	5	19	24	✓	
5.	Dishwasher	1.70	1	9	17		✓
6.	Washing machine	1.80	2	9	12		✓
7.	Dryer	2.50	1	13	18		✓
8.	Oven	2.50	2	15	19		✓
9.	Microwave	1.70	1	7	9		✓
10.	Cooker hood	0.20	1	17	19		✓
11.	Water heater	1.70	2	0	24		✓
12.	Television	0.30	5	19	24		✓
13.	Desktop	0.30	5	14	24		✓
14.	Iron	2.70	2	5	20		✓
15.	Laptop	0.10	3	14	24		✓
16.	Vacuum cleaner	2.00	1	7	20		✓
17.	Radio player	0.20	1	7	9		✓
18.	Others load	3.00	5	0	24		✓

Units of electricity are measured in kWh and the price for a unit of electricity in Thailand is shown in THB per kilowatt hour (THB/kWh).

While Table 3.1 outlines typical usage patterns, it is important to note that the proposed algorithm is designed to accommodate customizable appliance profiles. Households can freely modify the duration, starting or ending time windows, or even the classification of appliances to be shiftable or unshiftable, without compromising the optimization framework. This flexibility ensures the adaptability of the model to a wide range of household settings and user preferences.

3.2.2 Renewable Energy Sources (RES) models

Renewable energy (RE) is an alternative energy to replace energy from fossil fuels or conventional energy that is used to generate electrical power. RE is not only clean and causes no pollution or environmental impact, but it also helps to reduce greenhouse gas emissions, which are the cause of global warming and also promotes community participation in electricity generation. RES are employed in the proposed model to reduce reliance on the conventional grid and enhance the sustainability of energy consumption in smart homes. Among the various RE technologies, solar photovoltaic (PV) and wind energy systems are the most commonly integrated into SHEMS. This thesis includes both solar and wind energy sources based on the geographic and climatic conditions in Thailand, where solar energy harvesting is more consistent and widespread, while wind energy is more unstable and location dependent.

Rooftop solar PV model

The rooftop solar PV systems convert the solar irradiance into electrical energy. The hourly solar power available to the proposed smart home for each hour is calculated using the equation (3.1).

$$P_{PV}^{t} = A_{PV}\,\beta\,\mu^{t}\eta_{inv}\,. \tag{3.1}$$

Where A_{PV} is the area of the PV panel, β is the efficiency of the PV panel, μ^{t} is the solar irradiance at the time *'t'*, and their solar power output is DC power that must be converted into usable AC power for the household and grid by an inverter with inverter efficiency η_{inv}.

Wind model

Wind power output from a wind turbine depends on the wind speed at each hour, subject to operational wind speed limits. The usable range is defined as:

$$v_i \leq v^t \leq v_o. \tag{3.2}$$

Where v_i, v_o, and v^t represent cut-in speed, cut-off speed, and wind speed at the time 't', respectively. A wind turbine reaches its maximum power output when the wind speed is between the wind turbine rate and cut-off speed. Precise values can be obtained from the manufacturer's data sheet for the respective units (Saber and Venayagamoorthy, 2010). The power output of a wind turbine is proportional to kinetic energy; in the proposed system, the wind power is as follows:

$$P_{wind}^t = \frac{1}{2} \alpha \rho^t A_{wind} (v^t)^3 \eta_{turbine} \eta_{inv} . \tag{3.3}$$

Where α is the Albert Betz's constant, ρ^t is the air density at the time 't', A_{wind} is the swept area of the turbine rotor, $\eta_{turbine}$ is the efficiency of the wind turbine rotor. Same as solar power, wind power is DC power that must be converted into AC power via an inverter before being supplied to the smart home.

In this study, it is assumed that appropriately sized inverters are integrated into both the PV and wind systems, ensuring efficient energy conversion and compatibility with household electricity demands. A typical inverter efficiency of 96% is assumed in the proposed SHEMS.

This model enables the system to calculate the availability of renewable power from solar irradiance and wind speed profiles. These available RESs are then integrated into the energy management and optimization framework of the proposed smart home. In Fig. 3.2 The solar and wind power availability for 24 hours was calculated using equations (3.1) and (3.3) based on solar irradiance data (Energy Sector Management Assistance Program [ESMAP], 2019) and wind speed data (Weather Spark, 2018) throughout 24 hours in Thailand, as displayed in Table 3.2

Table 3.2 Solar and wind data for 24 hours [1]

Time (hours)	Solar irradiance (W/m^2)	Wind speed (m/sec)
1	0	4.1172
2	0	3.6031
3	0	3.0846
4	0	3.6031
5	0	3.0846
6	28	4.1172
7	187	3.8602
8	283	4.6492
9	357	4.1172
10	411	4.6492
11	448	4.6492
12	470	4.8951
13	468	4.6492
14	429	5.1410
15	349	4.1172
16	241	5.1410
17	95	5.4092
18	1	6.7056
19	0	5.4092
20	0	4.8951
21	0	4.8951
22	0	5.6774
23	0	5.1633
24	0	5.1633

(1) Average data of Thailand in April 2024

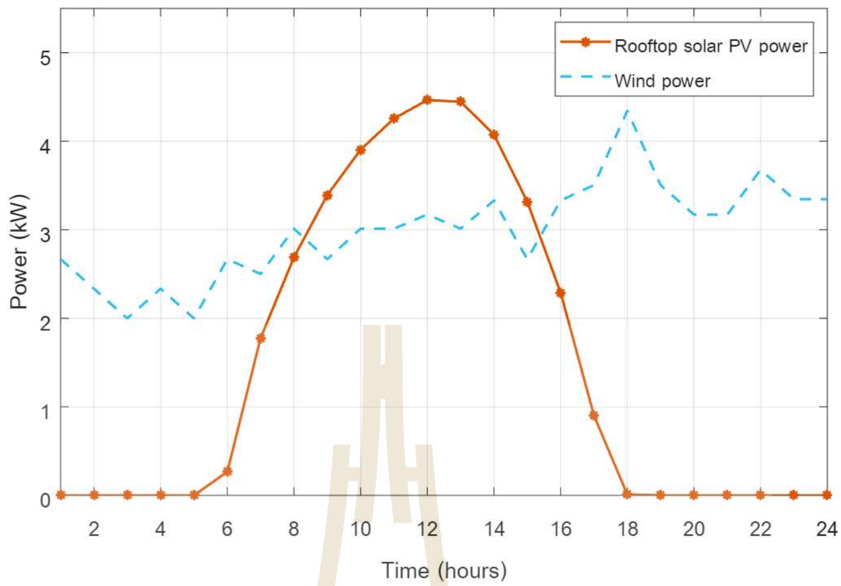


Figure 3.2 The typical solar and wind power in Thailand

In addition, this model allows for flexible input of renewable energy profiles, enabling the replacement or adjustment of solar irradiance and wind speed data for different days, months, or seasons as needed. This capability supports broader scenario analysis and enhances the applicability of the proposed system under varying weather and environmental conditions.

3.2.3 Battery and V2H models

In this work, the battery energy storage system (BESS) and electric vehicles (EVs) can operate as both energy storage devices and auxiliary power sources for the smart home. When electricity prices are low, batteries and EVs can be charged from the grid. Alternatively, when RE produced by households is sufficient and exceeds the energy required for household appliances, surplus REs can charge batteries and EVs. In contrast, when electricity prices are high or REs are insufficient to satisfy electrical appliance demand, batteries and EVs can be discharged to meet energy demands. This BESS and vehicle-to-home (V2H) operation enhances system flexibility and reduces grid dependency by managing energy usage based on dynamic pricing and energy availability. The battery and EV specifications are provided in Table 3.3. In this study, a C-rate of 1 is assumed for both the battery and EV, indicating that the devices can be fully charged or discharged within one hour under rated conditions.

Table 3.3 Battery and EV specifications

	Total capacity	Charging and discharging efficiency	Minimum SoC	Maximum SoC	Arrival time (hour)	Departure time (hour)
Battery	10 kWh	95%	0.2	0.9	-	-
EV	50 kWh	90%	0.2	0.9	17.00	09.00

Battery model

The battery energy storage system (BESS) plays a critical role in enhancing the reliability and flexibility of many smart homes. Battery not only improves reliability in a home's electrical system, but it can also help reduce costs and grid dependency when power from the grid has a high electricity price, the battery can be discharged to supply the demand. The constraints of the state of charge (SoC) limits in the battery are given below,

$$SoC_B^{min} \leq SoC_B^t \leq SoC_B^{max}, \tag{3.4}$$

$$SoC_B^t = SoC_B^{t-1} + \left(\frac{P_{B,\,ch}^t}{\eta_B \times capacity_B} - \frac{P_{B,\,dch}^t \times \eta_B}{capacity_B} \right). \tag{3.5}$$

where SoC_B^t represent the SoC of the battery at the time $'t'$. SoC_B^{min} and SoC_B^{max} are the minimum and maximum limit of the state of charge. Battery should not be charged or discharged more than this limit. In Eq. (3.5), updating the SoC of the battery can provide power to charge or discharge from the battery in each time slot. The power charging and discharging limit of the battery is as follows:

$$0 \leq P_{B,\,ch}^t \leq P_{B,\,ch}^{max}, \qquad \textit{for charging state,} \tag{3.6}$$

$$-P_{B,\,dch}^{max} \leq P_{B,\,dch}^t \leq 0, \qquad \textit{for discharging state.} \tag{3.7}$$

Where, $P^{t}_{B,\,ch}$ and $P^{t}_{B,\,dch}$ are the power charge and discharge from the battery at the time *'t'* respectively, $P^{max}_{B,\,ch}$, and $P^{max}_{B,\,dch}$ are the maximum power charging and discharging limits. These constraints guarantee that the battery only operates within its safe charging and discharging limits. The battery cannot simultaneously charge and discharge in the same time slot.

V2H model

Nowadays, more and more people are turning to electric vehicles (EVs) instead of conventional internal combustion engine vehicles. Recent advancements in EV chargers now support vehicle-to-home (V2H) functionality, allowing EVs to serve not only as transportation but also as portable energy storage units acting as a backup to supply emergency power directly to the home. For this work, the EV is modeled similarly to a battery system, the SoC of the EV battery at the time *'t'* is provided in Eqs. (3.8) - (3.9).

$$SoC^{min}_{EV} \leq SoC^{t}_{EV} \leq SoC^{max}_{EV} \tag{3.8}$$

$$SoC^{t}_{EV} = SoC^{t-1}_{EV} + \left(\frac{P^{t}_{EV,\,ch}}{\eta_{EV} \times capacity_{EV}} - \frac{P^{t}_{EV,\,dch} \times \eta_{EV}}{capacity_{EV}}\right). \tag{3.9}$$

Where SoC^{min}_{EV} and SoC^{max}_{EV} are the minimum and maximum limit of the SoC. Similar to battery modeling, EV battery should not be charged or discharged more than the SoC limit. From The hourly update of the SoC for the EV battery is defined in Eq. (3.9) which can provide power from the EV battery to charge or discharge in each time slot. The EV battery power charging and discharging limits are as follows:

$$0 \leq P^{t}_{EV,\,ch} \leq P^{max}_{EV,\,ch}\,, \qquad \textit{for charging state,} \tag{3.10}$$

$$-P^{max}_{EV,\,dch} \leq P^{t}_{EV,\,dch} \leq 0, \qquad \textit{for discharging state.} \tag{3.11}$$

Where, $P^{t}_{EV,\,ch}$ and $P^{t}_{EV,\,dch}$ are the power charge and discharge from the battery in EV at the time *'t'* respectively, $P^{max}_{EV,\,ch}$ and $P^{max}_{EV,\,dch}$ are the maximum power charging and discharging limits. These constraints ensure that the EV battery operates within safe SoC and power limits during its interaction with the home energy management system.

3.2.4 Connection between the smart home and the grid

Demand Response (DR)

Demand Side Management (DSM) is energy management on the consumer side or operations on the demand side of electricity usage that can be divided into two dimensions: Energy Efficiency (EE) is the improvement of the energy usage process of equipment and systems to use less energy while still getting the same results. And Demand Response (DR) will focus on encouraging electricity consumers to change their behavior or reduce their energy usage in a short period for the main purpose of gaining some benefit from that behavior change. DR is often aimed at reducing energy consumption during peak demand periods.

According to Siano (2014), Demand Response involves "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized". There are two fundamental categories of DR options:

The price-based DR is the price of electricity that fluctuates following variations in the underlying costs of electricity production, such as TOU, RTP, and CPP rates.

Incentive-based DR represents contractual arrangements designed by policymakers, grid operators, and load-serving entities to elicit customer demand reductions at critical times such as peak hours (Qdr, 2006).

In the proposed system, price-based demand response (DR) plays a vital role in guiding the scheduling of appliances, battery storage, and electric vehicles.

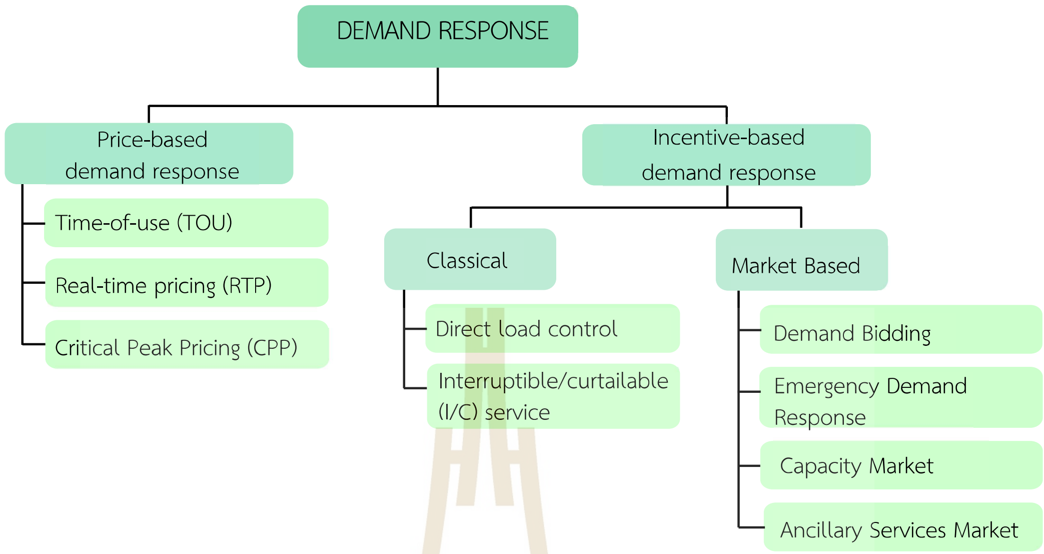


Figure 3.3 Demand Response Options

Time of Use (TOU)

Time-of-use rates have a common goal to incentivize customers to consume energy when the electricity prices are low because the country has low electricity demand, allowing power plants to operate using fuels with lower prices to produce electricity (off-peak hours) and to disincentive energy consumption when the electricity prices are high because the country has a high electricity demand. The Electricity Generating Authority of Thailand (EGAT) must provide all types of fuel, both high and low prices, to produce electricity in order to meet the demand during this period (peak hours). The Time of Use Tariff in Thailand is an electricity tariff that reflects the cost of electricity production (Metropolitan Electricity Authority [MEA], 2023), divided into two time periods:

Peak : 09.00 a.m.–10.00 p.m., Monday–Friday

Off-Peak : 10:00 p.m.–9:00 a.m. Monday–Friday

: Time 00.00–24.00 Saturday-Sunday, National Labor Day, Royal Ploughing Ceremony Day that falls on Saturday-Sunday, and normal public holidays (excluding compensatory holidays).

Table 3.4 Time of Use (TOU)

Time of Use Rate (TOU)	Energy Charge (Bath/kWh)		Service Charge (Bath/Month)
	Peak	Off-Peak	
At voltage level 12-24 kV	5.1135	2.6037	312.24
At voltage level lower than 12 kV	5.7982	2.6369	24.62

For residential in the proposed system, time of use rates (TOU) at voltage levels lower than 22 kV. Energy charge when peak is 5.7982 THB/kWh and off-peak is 2.6369 THB/kWh. Shown in Fig.3.4

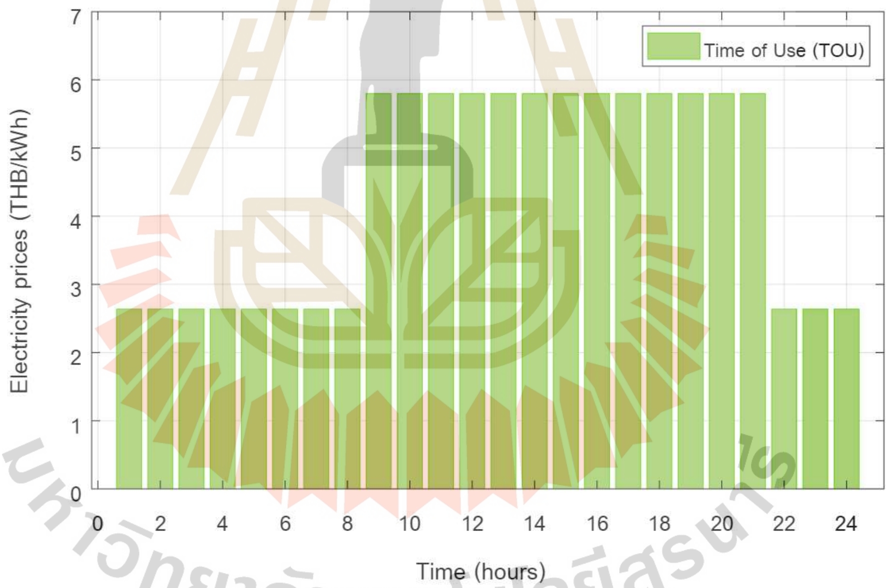


Figure 3.4 Hourly electricity time-of-use tariff in Thailand

The household PV purchasing scheme

The household PV purchasing scheme is a government-supported initiative implemented by the Metropolitan Electricity Authority (MEA) and the Provincial Electricity Authority (PEA) to promote residential solar photovoltaic (PV) adoption. Under this program, electricity generated from rooftop PV systems is primarily intended for self-consumption within the household. Any surplus energy not consumed on-site can be sold back to the grid. This project contains four conditions. First, the household rooftop PV energy is generated for self-consumption in smart homes; if there are excessive amounts, the excess solar energy can be sold to MEA or PEA. Second. Being a natural or juristic person who consumes Type I residential electricity. Third. Own an electrical meter to accurately measure the amount of electrical energy delivered or received from the grid. And fourth, the installed PV system must be connected to a low-voltage network and comply with local technical regulations regarding capacity and safety standards.

In this work, the conventional household PV purchasing model is extended. The proposed model not only allows the household to sell excess PV generation to the grid but also incorporates the proposed SHEMS to optimize when and how PV energy is used, stored, or sold, depending on electricity prices, demand levels, and system constraints.

Table 3.5 Electricity purchase information

Electricity purchase rate (THB/unit)	Electricity purchase period (years)
2.20	10

Grid power limit

The power supplied by the utility grid in the proposed smart home is constrained by a maximum allowable limit. This assumption ensures that the residence always retains the option to consume electricity from the grid when renewable or stored energy sources are insufficient. The constraint is defined as follows:

$$0 \leq P_{grid}^{t} \leq P_{grid}^{max}. \tag{3.12}$$

Where, P_{grid}^{t} denotes the power drawn from the grid at time $'t'$, P_{grid}^{max} represents the maximum grid power limit.

3.3 Objective Function

The proposed method applies a hybrid Particle Swarm Optimization–Linear Programming (PSO–LP) approach to solve the Optimal Home Appliance Scheduling (OHAS) under TOU-based Demand Response (DR). The model aims to determine the proper hours and optimal energy management to operate each electrical appliance and optimally allocate energy from can select energy to consume from 5 available energy resources comprising power from the grid, rooftop solar PV, wind turbine, battery, and EV to pursue minimum daily electricity costs. In this framework, PSO is responsible for searching the optimal State of Charge (SoC) values for the battery and EV, while the optimal power value is processed to LP to complete the OHAS concurrently. In addition, appliances can select power from each energy source to consume. This synergy combines the global search capability of PSO and the constraint-handling precision of LP to minimize electricity costs. The objective of the proposed system is to minimize the total daily electricity cost (TDC), expressed as:

$$\text{Minimize } TDC = \sum_{t=1}^{NT} C^{t} \times P_{Total}^{t}\,, \tag{3.13}$$

Where, P_{Total}^{t} is the total power demand and C^{t} is the electricity cost at the time *‘t’*.

$$P_{Total}^{t} = \sum_{m=1}^{NA} (P_{Load}^{t} - P_{PV}^{t} - P_{Wind}^{t} + P_{B}^{t} + P_{EV}^{t})\,, \tag{3.14}$$

$$P_{B}^{t} = \begin{cases} P_{B}^{t},\ P_{B,\,ch}^{t} \\ -P_{B}^{t},\ P_{B,\,dch}^{t} \end{cases}, \tag{3.15}$$

$$P_{EV}^{t} = \begin{cases} P_{EV}^{t},\ P_{EV,\,ch}^{t} \\ -P_{EV}^{t},\ P_{EV,\,dch}^{t} \end{cases}. \tag{3.16}$$

for $m = 1, 2, 3, \ldots, NA$, and time $t = 1, 2, 3, \ldots, 24$ hours, when,

P_{load}^{t} is the optimization variable in the LP section, which is the sum of power consumption from all appliances in each time slot,

P_B^t and P_{EV}^t are the optimization variables in the PSO section, that is, a power charge or discharge from the battery and battery in EV, which can be obtained from the SoC_B and SoC_{EV} at the time *'t'*,

P_{PV}^t and P_{wind}^t are the available RE power generated from the rooftop solar PV and wind turbine at any time slot *'t'*, respectively.

For P_{Total}^t and C^t the conditions are defined as follows:

$$P_{Total}^t = \begin{cases} P_{grid}^t, & P_{Total}^t > 0 \\ P_{excess}^t, & P_{Total}^t \leq 0 \end{cases}, \tag{3.17}$$

$$C^t = \begin{cases} C_{buy}^t, & P_{total}^t = P_{grid}^t \\ C_{sell}^t, & P_{total}^t = P_{excess}^t \end{cases}. \tag{3.18}$$

Where, P_{total}^t refers to either the power drawn from the grid (P_{grid}^t) or to the excess power (P_{excess}^t). When P_{total}^t is more than zero, it indicates that there is insufficient power for P_{load}^t to consume during that time slot or that P_B^t and P_{EV}^t require more power to charge the battery than REs power are available. The grid will always provide power in this situation. On the other hand, P_{total}^t is less than zero, which indicates that P_{load}^t has adequate power to consume during that time slot, and the smart home gets the excess discharge power from P_B^t, and P_{EV}^t. However, the proposed method permits the sale of additional power generated by the rooftop solar PV to the household PV purchasing scheme project from MEA. Then, the excess energy from other resources will be neglected and not considered when calculating the minimum TDC.

From Eq. (3.18), define C^t as the cost of electricity at the time 't', which can switch between the cost of buying energy (C_{buy}^t) and the income from selling excess energy (C_{sell}^t). When P_{total}^t is greater than zero, C_{buy}^t gets used to compute grid power usage with TOU rates. Conversely, P_{total}^t is less than zero, and C_{sell}^t is used to calculate the power excess with the purchasing rate power from MEA.

Although the household may receive energy from RESs, or discharge from BESS and V2H, the electricity cost is only incurred when energy is drawn from the grid. Therefore, the optimization aims to shift energy usage to cheaper time periods and prioritize renewable and stored energy whenever possible.

3.4 Constraints

In addition to the battery and EV charge/discharge constraints previously defined in Eq. (3.6) and Eq. (3.9), the objective of electricity cost minimization must be achieved by satisfying several operational constraints. These include appliance operation constraints, power balance constraints, and OHAS constraints and boundaries.

3.4.1 Appliance operation constraints

In the proposed model, household appliances are classified into shiftable and unshiftable loads. Unshiftable loads are fixed and must operate during a specific time, whereas shiftable appliances are scheduled flexibly within a defined duration of operation and starting to ending time range.

$$A_m^t = \begin{cases} 0, \text{ if } t < T_{m,\,starting}^t \text{ and } t > T_{m,\,ending}^t \\ 1, \text{if } t \geq T_{m,\,starting}^t \text{ and } t \leq T_{m,\,ending}^t \end{cases}. \tag{3.19}$$

Where A_m^t is the binary variable ON/OFF state of operation for each appliance *‘m’* at the time *‘t’* using the binary variables ‘1’ denotes ON and ‘0’ denotes OFF status. When appliance *‘m’* is within their starting to ending time range, the status of operation A_m^t can be either ‘1’ or ‘0’ which is decided by their duration of operation, all available energy resources, and the hybrid PSO-LP based on the TOU or RTP tariff.

3.4.2 Power balance constraints

To ensure the reliable operation of the SHEMS, the total power supplied must always be balanced with the total power demanded. This requirement is represented by the power balance constraint as given by:

$$P^t_{grid}+P^t_{PV}+P^t_{wind}+P^t_{B,\,dch}+P^t_{EV,\,dch}=P^t_{Load}+P^t_{B,\,ch}+P^t_{EV,\,ch}+P^t_{excess}, \tag{3.20}$$

Power consumption from all appliances is calculated by the product of the proper ON/OFF state of operation A^t_m and the power rating of each *'m'* appliance for $m = 1, 2, 3, \ldots, NA$, The total load power consumption from all appliances at time *'t'* is calculated as below,

$$P^t_{Load}=\sum_{m=1}^{NA}\left(A^t_m\cdot P_m^{rating}\right). \tag{3.21}$$

3.4.3 OHAS Constraints and boundary

In the proposed SHEMS framework, LP is utilized to determine the optimal home appliance scheduling (OHAS) and P^t_{Load} to achieve the objective function in Eq. (3.13). P^t_{Load} is derived from the optimal power scheduling matrix $\boldsymbol{P_{Load}}$, which represents the scheduled power consumption for all household appliances across all time slots.

Boundary

To ensure feasibility, the total scheduled load power must remain within the range defined by available energy resources. The lower boundary of $\boldsymbol{P_{Load}}$ is zero, denotes the minimum allowable power usage, while the upper boundary is $\boldsymbol{P_{ERS}}$, represents the maximum power available from all energy resources throughout the day. Therefore,

$$0\le \boldsymbol{P_{Load}}\le \boldsymbol{P_{ERS}}. \tag{3.22}$$

Where,

$$\mathbf{P}_{load} = [\ \mathbf{P}_{load,1},\ \mathbf{P}_{load,2},\ \mathbf{P}_{load,3},\ldots,\ \mathbf{P}_{load,NA}\ ]_{(24\times NA\times NER)\times 1}, \tag{3.23}$$

$$\mathbf{P}_{ERS} = [\ \mathbf{P}_{ERS,1},\ \mathbf{P}_{ERS,2},\ \mathbf{P}_{ERS,3},\ldots,\ \mathbf{P}_{ERS,NA}\ ]_{1\times(24\times NA\times NER)}. \tag{3.24}$$

For each appliance *m*, the power consumption and available power energy resource *n* are represented as:

$$\mathbf{P}_{load,\,m} = [\mathbf{PL}_{m,1}, \mathbf{PL}_{m,2}, \mathbf{PL}_{m,3}, \ldots, \mathbf{PL}_{m,NER}]_{(24\times NER)\times 1}, \tag{3.25}$$

$$\mathbf{P}_{ERS,\,m} = [\mathbf{PE}_{m,1}, \mathbf{PE}_{m,2}, \mathbf{PE}_{m,3}, \ldots, \mathbf{PE}_{m,NER}]_{1\times(24\times NER)}. \tag{3.26}$$

Each energy resource $\mathbf{P_{m,\,n}}$ is detailed as follows:

$$\mathbf{PL}_{m,\,n} = [PL^{1}_{m,\,n}, PL^{2}_{m,\,n}, PL^{3}_{m,\,n}, \ldots, PL^{24}_{m,\,n}]_{24\times 1}, \tag{3.27}$$

$$\mathbf{PE}_{m,\,n} = [PE^{1}_{m,\,n}, PE^{2}_{m,\,n}, PE^{3}_{m,\,n}, \ldots, PE^{24}_{m,\,n}]_{1\times 24}. \tag{3.28}$$

Where $m = 1, 2, 3, \ldots, NA$, $n = 1, 2, 3, \ldots, NER$, and time $t = 1, 2, 3, \ldots, 24$ hours. $PL^{t}_{m,\,n}$ is the power consumption from appliance *‘m’* from *‘n’* energy resources at the time *‘t’* and $PE^{t}_{m,\,n}$ is the power available from *‘n’* energy resources at the time *‘t’* for each appliance *‘m’*. This constraint ensures that the total power allocated to appliance operation does not exceed the system’s energy capacity at any given time slot, enabling reliable and cost-effective energy management.

Equality constraints

These constraints are used to ensure that each shiftable appliance operates for the appropriate duration for turning appliances on or off, considering all possibilities within 24 hours of operating. The total scheduled power consumption must match the predetermined demand pattern for each appliance, considering its power rating and operational duration. The constraint is expressed as:

$$\mathbf{AS} \cdot \mathbf{P_{Load}} = \mathbf{DP}\,. \tag{3.29}$$

Where,

$$\mathbf{AS} = \begin{bmatrix} \mathbf{AS_1} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{AS_2} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{AS_3} & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{AS_{NA}} \end{bmatrix}. \tag{3.30}$$

For each appliance *m*, the submatrix $\mathbf{AS_m}$ is defined as:

$$\mathbf{AS_m} = [\mathbf{ASH}_{\mathrm{m,\,1}}, \mathbf{ASH}_{\mathrm{m,\,2}}, \mathbf{ASH}_{\mathrm{m,\,3}}, \ldots, \mathbf{ASH}_{\mathrm{m,\,NER}}]_{1\times(24\times\mathrm{NER})}. \tag{3.31}$$

Each $\mathbf{ASH_{m,\,n}}$ is represented as:

$$\mathbf{ASH_{m,\,n}} = [ASH^{1}_{m,\,n}, ASH^{2}_{m,\,n}, ASH^{3}_{m,\,n}, \ldots, AS^{24}_{m,\,n}]_{1\times 24}. \tag{3.32}$$

Additionally, the duration matrix $\mathbf{DP}$ is expressed as:

$$\mathbf{DP} = [DP_m, DP_m, DP_m, \ldots, DP_m]^{\mathrm{T}}_{1\times\mathrm{NA}}. \tag{3.33}$$

For $m = 1, 2, 3, \ldots, NA$, $n = 1, 2, 3, \ldots, NER$, and time $t = 1, 2, 3, \ldots, 24$ hours.

The matrix $\mathbf{AS}$ is a block diagonal matrix whose diagonal contains blocks of smaller matrices of $\mathbf{AS_m}$ corresponds to the status of appliance *m.* Each $ASH^{t}_{m,\,n}$ represents the ON status with a range of starting and finishing times (hours) for each *'m'* appliance at time *'t'* for $t = 1, 2, 3, , \ldots, 24$ hours with energy resource $n = 1, 2, \ldots, NER$, and DP_m is the total energy (in kWh) required by each appliance over the entire scheduling period, calculated as the duration of operation (hours) multiplied by power rating each *'m'* appliance. This equality ensures that the optimization process strictly enforces appliance power demands over the day.

Inequality constraints

The inequality constraints ensure that the total power consumption from all scheduled appliances does not exceed the available power from all energy sources at each time slot. This is important for maintaining system feasibility and preventing the load from demanding more power than the system can provide. The constraint is defined as:

$$\mathbf{AR} \cdot \mathbf{P_{Load}} \leq \mathbf{PR}. \tag{3.34}$$

Where,

$$\mathbf{AR}= \begin{bmatrix} \mathbf{E_1} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{E_2} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{E_3} & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{E_{NA}} \end{bmatrix}. \tag{3.35}$$

Each block $\mathbf{E_m}$ is defined as:

$$\mathbf{E_m}= [I_{m,\,1}, I_{m,\,2}, I_{m,\,3}, \ldots, I_{m,\,NER}]_{24\times(24\times\mathrm{NER})}. \tag{3.36}$$

And the power limit $\mathbf{PR}$ is expressed as:

$$\mathbf{PR} = [PR_m, PR_m, PR_m, \ldots, PR_m]^{\mathrm{T}}_{1\times(24\times\mathrm{NA})}. \tag{3.37}$$

For $m = 1, 2, 3, \ldots, NA$, $n = 1, 2, 3, \ldots, NER$, and time $t = 1, 2, 3, \ldots, 24$ hours. The matrix $\mathbf{AR}$ is a block diagonal matrix containing blocks of smaller matrices $\mathbf{E_m}$ for each *'m'* appliance, Each $I_{m,\,n}$ is the identity matrix used for the load appliances to select energy resources to consume with energy resource $n = 1, 2, \ldots, NER$, ensuring that each energy resource is uniquely selected for each time slot *'t'*, and Furthermore, PR_m represents the power consumed by appliance *m*, which can be calculated by $ASH^{t}_{m,\,n}$ multiplied by the power rating for each *'m'* appliance ($P_{m,\,rating}$). This constraint guarantees that the optimization process selects only feasible combinations of appliance operation that respect the limitations of the available energy resources at any given hour.

Based on the typical appliance characteristics summarized in Table 3.1, the possible ON status along with a range of starting and finishing times (hours) for each *'m'* appliance in any *'n'* energy resources ($ASH^{t}_{m,\,n}$) is shown in Table 3.6. This variable is computed using the proposed SHEMS framework implemented by the hybrid PSO-LP method. Together with the system constraints, the ASH determines the OHAS for all appliances in 24 hours. Unshiftable appliances such as refrigerators, sensors, air conditioners, and illumination have an unchanging operational time. Leftover shiftable appliances, such as irons and dishwashers, can be scheduled to obtain the optimal solution of OHAS in the SHEMS problem.

In summary, the constraints outlined in this section ensure that the proposed SHEMS operates feasibly and efficiently within system boundaries. These constraints provide a strong framework for load scheduling optimization using the hybrid PSO–LP approach, ensuring operational practicality while minimizing electricity costs under the TOU tariff

.

Table 3.6 The possible ON status for each appliance

Appli-ances / Time (Hours)	The status of each '*m*' appliance																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1	1[a]	0[b]	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
2	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
3	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
4	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
5	1	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1
6	1	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1
7	1	1	0	0	0	0	0	0	1	0	1	0	0	1	0	1	1	1
8	1	1	0	0	0	0	0	0	1	0	1	0	0	1	0	1	1	1
9	1	1	0	0	1	1	0	0	1	0	1	0	0	1	0	1	1	1
10	1	1	0	0	1	1	0	0	0	0	1	0	0	1	0	1	0	1
11	1	1	0	0	1	1	0	0	0	0	1	0	0	1	0	1	0	1
12	1	1	1	0	1	1	0	0	0	0	1	0	0	1	0	1	0	1
13	1	1	1	0	1	0	1	0	0	0	1	0	0	1	0	1	0	1
14	1	1	1	0	1	0	1	0	0	0	1	0	1	1	1	1	0	1
15	1	1	1	0	1	0	1	1	0	0	1	0	1	1	1	1	0	1
16	1	1	1	0	1	0	1	1	0	0	1	0	1	1	1	1	0	1
17	1	1	1	0	1	0	1	1	0	1	1	0	1	1	1	1	0	1
18	1	1	1	0	0	0	1	1	0	1	1	0	1	1	1	1	0	1
19	1	1	1	1	0	0	0	1	0	1	1	1	1	1	1	1	0	1
20	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	0	1
21	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	0	0	1
22	1	1	1	1	0	0	0	0	0	0	1	1	1	0	1	0	0	1
23	1	1	1	1	0	0	0	0	0	0	1	1	1	0	1	0	0	1
24	1	1	1	1	0	0	0	0	0	0	1	1	1	0	1	0	0	1

[a] '1' assign as the appliance is 'ON', and [b] '0' assign as the appliance is 'OFF'

3.5 Hybrid PSO-LP algorithm

The system is initialized by random population positions in a searching space. Each particle in the swarm is influenced by the current position of the other particles, as well as its own personal best position. Then, the particles are updated in the next iterations. The adaptive velocities will update the particles and record the best position they have ever been in.

The particles are influenced by the global ($gbest^t$) and personal best positions ($pbest_i^t$) and use their velocity to move within the search space to find the optimal solution to the problem. In every iteration, particles update their velocity and position according to the following equations:

$$v_i^{j+1}=wv_i^j+c_1r_1\left(pbest_i^j-\boldsymbol{x}_i^j\right)+c_2r_2\left(gbest^j-\boldsymbol{x}_i^j\right), \tag{3.38}$$

$$\boldsymbol{x}_i^{j+1}=\boldsymbol{x}_i^j+v_i^{j+1}. \tag{3.39}$$

When, $\boldsymbol{x}_i^j$ is the position of particle *i* at iteration *j* where superscript j and j+1 denote the iteration number of the variables.

In this work, PSO is used to find the optimal state of charge (SoC) for both the battery and EV across 24 hours. These SoC values are essential to determine when and how much energy should be charged or discharged, depending on the TOU-based DR, power consumption demand, and energy resource availability.

In order to obtain OHAS, the SoC values for the battery (SoC_B^t) and EV (SoC_{EV}^t) originally defined in Equations (3.5) and (3.9), respectively. These SoC are represented as the particle in the PSO framework. The best SoC schedule for each particle across the day is considered as personal best (*pbest*), while the overall schedule that provides the minimum TCD in achieving the objective function in Eq. (3.13) is considered the global best (*gbest*). The set of populations is formulated as:

$$\boldsymbol{x}=\begin{bmatrix}X_{SoC_B}\\X_{SoC_{EV}}\end{bmatrix}, \tag{3.40}$$

$$\boldsymbol{X_{SoC_B}} = [\boldsymbol{x_{SoC_B,\,1}}, \boldsymbol{x_{SoC_B,\,2}}, \boldsymbol{x_{SoC_B,\,3}}, \ldots, \boldsymbol{x_{SoC_B,\,NP}}], \tag{3.41}$$

$$\boldsymbol{x_{SoC_B,i}} = [x_{SoC_B,\,1}, x_{SoC_B,\,2}, x_{SoC_B,\,3}, \ldots, x_{SoC_B,\,24}], \tag{3.42}$$

$$\boldsymbol{X_{SoC_{EV}}} = [\boldsymbol{x_{SoC_{EV},\,1}}, \boldsymbol{x_{SoC_{EV},\,2}}, \boldsymbol{x_{SoC_{EV},\,3}}, \ldots, \boldsymbol{x_{SoC_{EV},\,NP}}], \tag{3.43}$$

$$\boldsymbol{x_{SoC_{EV},i}} = [x_{SoC_{EV},\,1}, x_{SoC_{EV},\,2}, x_{SoC_{EV},\,3}, \ldots, x_{SoC_{EV},\,24}]\,. \tag{3.44}$$

Where $\boldsymbol{x_{SoC_B,i}}$ and $\boldsymbol{x_{SoC_{EV},i}}$ are the set of the state of charge of the battery (SoC_B^t) and EV (SoC_{EV}^t) for $t = 1, 2, 3, \ldots, 24$ hours.

$\boldsymbol{X_{SoC_B}}$ and $\boldsymbol{X_{SoC_{EV}}}$ represent the populations for particles $i = 1, 2, 3, \ldots, NP$.

The hybrid PSO–LP method approach for optimal home appliance scheduling (OHAS) under a TOU tariff aims to minimize the total daily electricity cost (TDC). In this framework, the PSO layer first identifies the optimal state of charge (SoC) values for the battery and electric vehicle (EV), which determines the charging and discharging power for the battery and EV. The PSO provides these values to the LP layer, which is concurrently processed to complete the OHAS. Then, the LP layer allocates power from various energy resources, including batteries, EVs, rooftop solar, wind turbines, and the grid, for scheduling household appliances in a way that satisfies operational constraints while minimizing electricity costs. The power consumption from all appliances in 24 hours obtained from OHAS will be updated and used to calculate the objective function again to obtain the proper duration to operate each appliance, the optimal power consumption, and the minimum TDC. Figure 3.5 shows the flowchart of hybrid PSO-LP for OHAS in the proposed smart home.

The hybrid PSO–LP structure presents the strengths of both methods: PSO provides a global search across the complex, nonlinear space of SoC values, while LP ensures that the final appliance scheduling is computed with high precision under a specified set of constraints. However, it is necessary to set the constraints as mentioned previously so that the proposed hybrid PSO-LP can efficiently solve the OHAS problem.

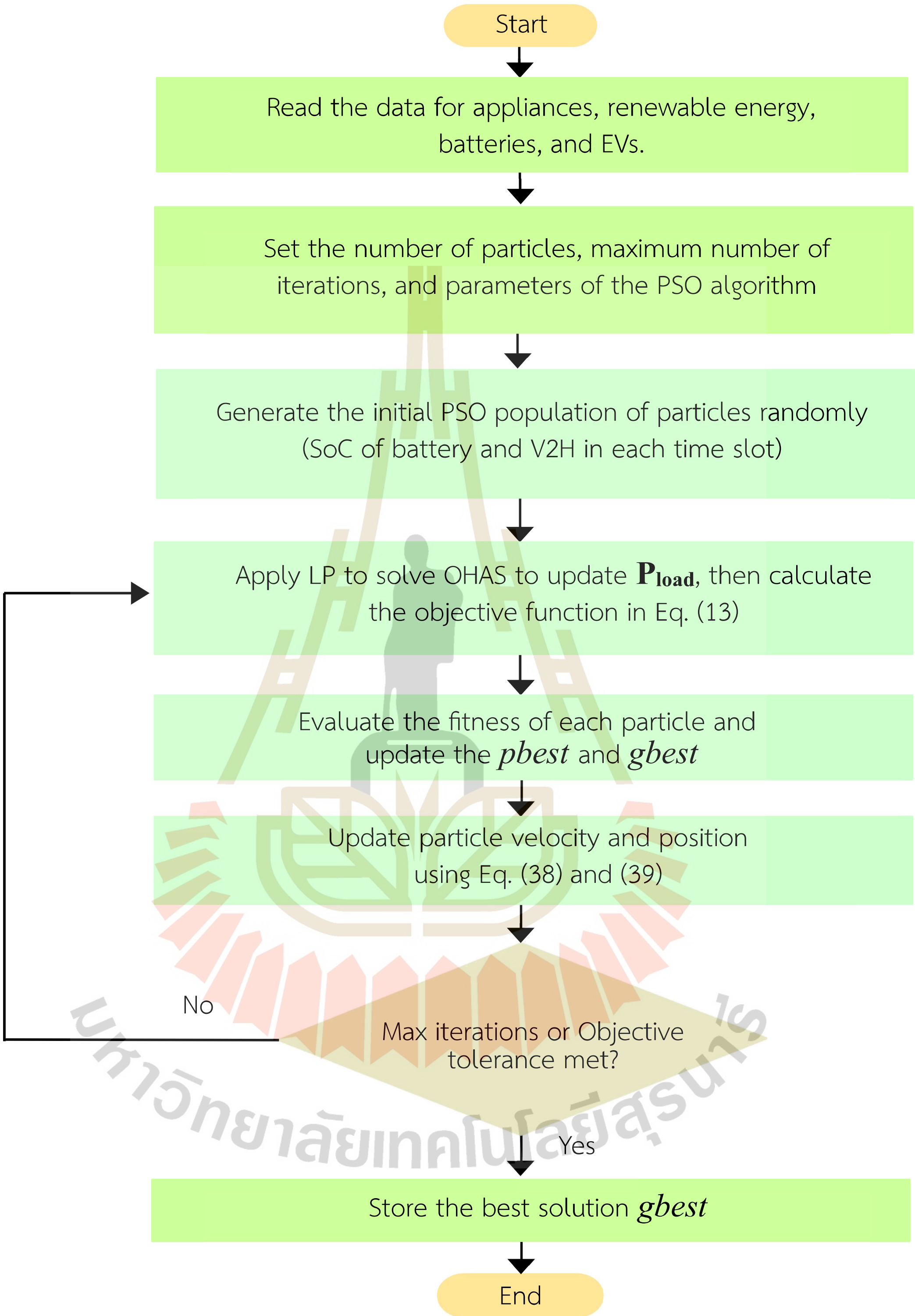


Figure 3.5 Flowchart of hybrid PSO-LP for OHAS in the proposed smart home

3.5.1 Computational Procedure of the proposed Hybrid PSO–LP

The computational procedure for solving OHAS under TOU-based DR using the hybrid PSO-LP can be given as follows:

Step 1: Initialize all the proposed SHEMS constraints, including PSO parameters, and the initial power load schedule P^t_{Load}.

Step 2: Randomly generate the initial positions and velocities of all particles, where each particle represents as the state of charge (SoC) values for the battery ($x^j_{SoC_B,\ i}$) and EV ($x^j_{SoC_{EV},\ i}$).

Step 3: For each particle, using as input to the LP model to solve the OHAS problem and determine the updated $\mathbf{P_{load}}$. Then, calculate the objective function based on the LP result.

Step 4: Evaluate the fitness of each particle and update the personal best (*pbest*) and global best (*gbest*) positions.

Step 5: After each iteration, the velocity of each particle is to be updated using Eq. (3.38)

Step 6: Update the position of each particle based on new velocity using Eq. (3.39) to explore the solution space for better SoC schedules.

Step 7: The procedure is to be repeated from step 3 to 6 until the stopping condition either the maximum number of iterations is reached or the change in objective value is below a tolerance value.

3.5.2 Pseudocode of the Hybrid PSO–LP Algorithm

Pseudocode of the proposed hybrid PSO–LP algorithm for minimizing total daily electricity cost under TOU-based demand response. The PSO layer searches for optimal SoC values for the battery and EV, while the LP layer allocates energy for scheduling appliances consequently.

Algorithm Hybrid PSO-LP Algorithm

Input: Appliance data, RES profiles, BESS and V2H parameters

Output: Optimal SoC schedule (X) and minimum total daily cost (TDC)

Set a number of particles, maximum iterations, PSO parameters, and the initial power load schedule P_{Load}^{t}.

PSO generates the initial population of particles randomly

(SoC of battery and V2H in each time slot; X)

Set iteration = 0

While iteration *'j'* < maximum iterations

    For each particle *'i'* in the PSO population

        Check all of the constraints

        Use LP to solve OHAS and update $\mathbf{P_{load}}$ based on X_i

        Calculate the objective function f(X_i) based on updated P_{Load}^{t}

        Evaluate the fitness value for each particle

        Update ***pbest*** and ***gbest***

    END For

Update particle velocity and position using Eq. (3.38) and (3.39)

Iteration *'j'* = iteration *'j'* + 1

END While

Return Output best solution (X) and corresponding minimum TCD (f(X))

CHAPTER IV

SIMULATION RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the simulation results and discussion of the performance of a smart home energy management system (SHEMS) using a hybrid particle swarm optimization (PSO) and linear programming (LP) approach to address the optimal home appliances scheduling (OHAS) problem under the time-of-use (TOU)-based DR framework. The objective of this thesis is not only to validate the ability of this model to minimize total daily electricity costs (TDC) but also to assess the flexibility and effectiveness when adapted to a variety of energy sources, such as rooftop solar PV, wind turbines, battery energy storage systems (BESS), and electric vehicles (EVs) operating under vehicle-to-home (V2H) conditions. This study introduces nine different case studies formulated with various configurations of energy sources, focusing on demonstrating the behavior of batteries and EVs, overall power consumption, and efficiency reduction in electricity costs. The influence of PSO parameter settings is analyzed for optimal algorithm performance. Furthermore, the scalability of the system is examined to determine its adaptability to larger household configurations, while a preliminary economic assessment is conducted at the household level. In addition, the proposed hybrid PSO-LP-based SHEMS has been benchmarked against other commonly used optimization techniques, including Genetic Algorithm (GA), hybrid GA-LP, and PSO, to evaluate its comparative performance and advantages.

The results and analyses provided in this chapter offer strong evidence that the proposed SHEMS framework offers effective energy flexibility management and can be adapted to various system conditions and case scenarios.

4.2 Parameter setting

This section presents the parameter selection process for the proposed hybrid PSO-LP algorithm applied to the optimal home appliance scheduling (OHAS) problem. To achieve effective optimization performance, it is necessary to set the PSO parameters accurately. This section focuses on adjusting the inertia weight (w) and acceleration coefficients (C_1 and C_2). These parameters play a crucial role in balancing the exploration of the search space, directly influencing both convergence speed and solution quality. In this work, Case IX is used to test the parameter setting. Table 4.1 presents the result of electricity cost and run-time comparison under various PSO parameter combinations.

Table 4.1 Comparison of electricity cost and computational time under different PSO parameter settings in Case IX

Parameter			Electricity cost (THB)	Runtime (sec)
C_1	C_2	w		
1.5	1.5	0.1	85.708	10843.82
		0.6	88.959	10824.94
		1.1	112.30	10132.26
1	1	0.1 – 1.1	80.230	10413.42
1	2		85.527	10946.82
1.5	1.5		77.813	10695.03
2	1		86.406	10030.55
2	2		89.597	10808.34

Table 4.1 summarizes the effect of varying PSO parameters on electricity cost and computational time in case IX. When varying the inertia weight (w) with fixed cognitive acceleration coefficient (C_1) and social acceleration coefficient (C_2) = 1.5, the results show that smaller inertia weights tend to lead to lower electricity costs but longer computation time. Conversely, higher inertia values reduce runtime and

promote faster convergence but increase electricity costs, as the search process may terminate prematurely without fully exploring the solution space. This observation aligns with PSO theory, which suggests that w controls the balance between exploration and solution: a larger w promotes global search, while a smaller w encourages local search. Figure 4.1 portrays the convergence behavior when fixing the acceleration coefficient constraint and varying w. Meanwhile, Fig. 4.2 illustrates the convergence curves under fixing w and varying C_1 and C_2. Adjusting C_1 and C_2 have relatively small effects on the result. However, the convergence trends reveal behavioral differences in each particle learning. When varying the C_1 with a low value, convergence is more stable and smoother than with the high value, as particles rely less on their individual best positions (*pbest*). On the other hand, when C_2 is high value, the particles are more socially influenced by the global best (*gbest*), which may cause the swarm to converge rapidly. While this may reduce runtime, it can also increase the risk of early convergence to local optima.

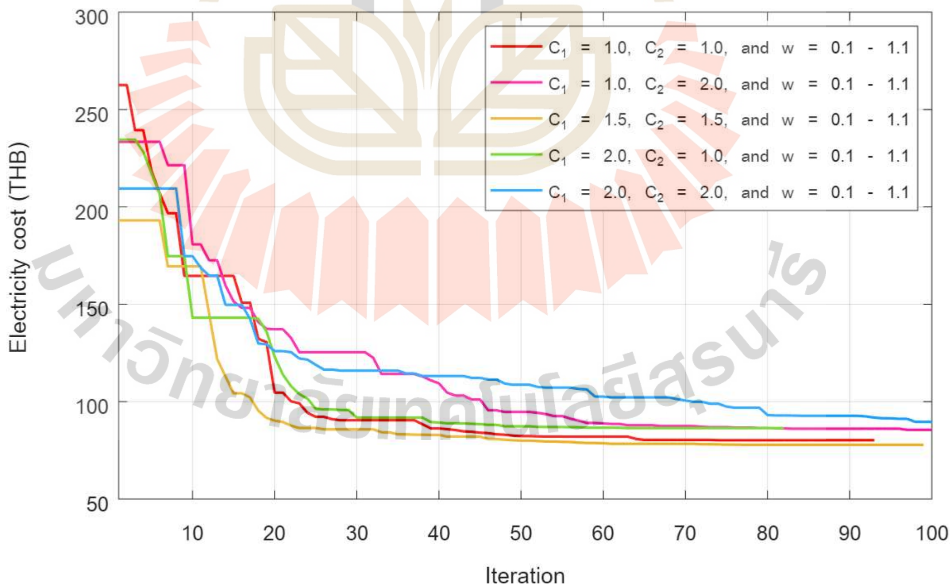


Figure 4.1 Comparison of PSO parameter when adjusted C_1 and C_2

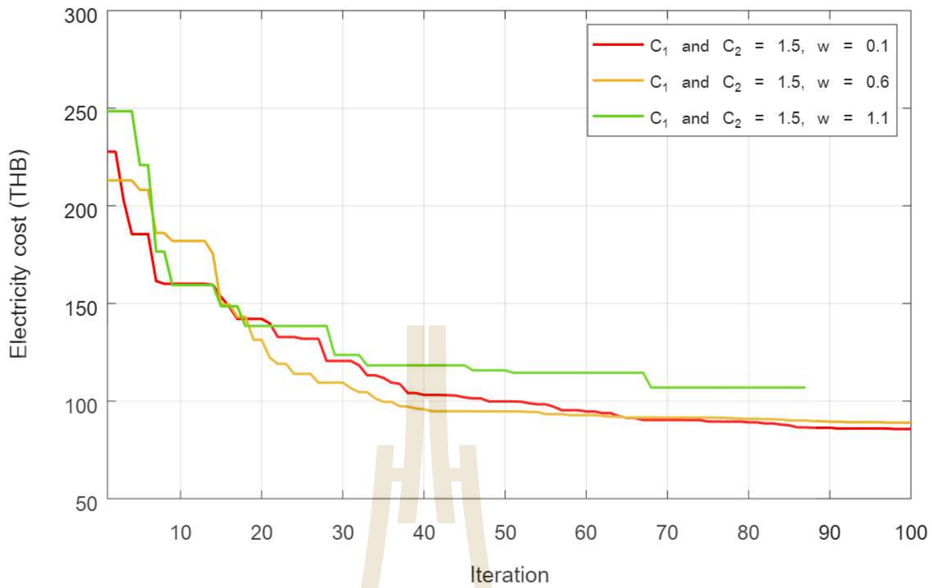


Figure 4.2 Comparison of PSO parameter values at when adjusted w

Based on this tuning, the parameter configuration of C_1 = 1.5, C_2 = 1.5, and w linearly decreasing from 1.1 to 0.1 is selected for the proposed hybrid PSO-LP algorithm. This configuration is widely supported in the PSO literature, where equal cognitive and social coefficients promote a balanced learning behavior between personal experience and collective swarm intelligence. Furthermore, the linearly decreasing inertia weight encourages global exploration in early iterations and gradually shifts toward fine-tuning the solution space, enhancing convergence stability. This setting effectively balances exploration and enhances convergence stability, solution quality, and computational efficiency.

4.3 Appliance Scheduling and Power Consumption

This section analyzes the optimal scheduling of eighteen household appliances with the objective of minimizing total daily electricity costs. Each appliance can choose power consumption from any available energy resources, including grid electricity, RES, BESS, and V2H systems. Batteries and EVs are modeled as bidirectional components, capable of acting both as energy resources and loads. In the proposed approach, RESs are prioritized as the primary energy sources for appliance consumption, and the surplus power after appliance consumption is considered to charge the battery and EV, depending on their available capacity and state of charge (SoC) constraints. The RES from rooftop solar PV is either self-consumed or, if surplus, can be sold back to the grid through the extended household PV purchasing scheme by MEA. The battery and EV charging or discharging are determined based on their SoC constraints, power demand, and electricity costs for each hour, with optimization performed under the operational constraints defined in Chapter 3. To evaluate the system comprehensively, nine case studies are formulated, as summarized in Table 4.2. These cases highlight how different energy source combinations affect appliance scheduling, overall power consumption, and electricity cost reduction.

Table 4.2 The different cases of appliance scheduling

Cases	Type of energy resource					
	Grid	PV	Wind	BESS	V2H	Energy export
I	✓	✗	✗	✗	✗	✗
II	✓	✗	✗	✓	✗	✗
III	✓	✗	✗	✗	✓	✗
IV	✓	✓	✗	✓	✗	✓
V	✓	✓	✗	✗	✓	✓
VI	✓	✓	✗	✓	✓	✓
VII	✓	✓	✓	✓	✗	✓
VIII	✓	✓	✓	✗	✓	✓
IX	✓	✓	✓	✓	✓	✓

4.3.1 The appliances scheduling with power from the grid (Base case)

The power consumption for each appliance can be explained in two parts: Appliance Scheduling and Non-Scheduling. Non-scheduling describes an unoptimized schedule with the proposed algorithm. In this part, appliances can operate during peak hours and be overlooked when electricity prices are lowest. The non-scheduling part is similar to what is occurring in real life, with consumption reaching peaks during times when people are generally off their work shift and perform all their electricity-consuming activities during those hours. This base case is a benchmark for comparison with other optimized scenarios in which power consumption can be flexibly allocated across different time slots and energy sources.

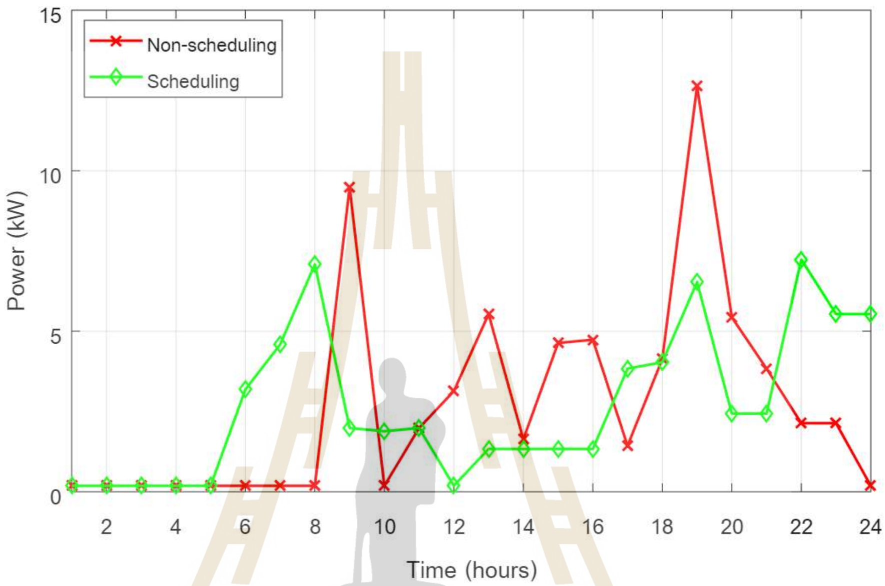


Figure 4.3 Comparison of power consumption between appliance scheduling and non-scheduling

Figure 4.3 illustrates a comparison of daily power consumption between appliance scheduling and non-scheduling appliance operation when using only grid power (Base Case). Across all case studies, the comparison is between appliance scheduling and non-scheduling. The proposed algorithm notices that peak load is occurring and knows when the lowest electricity prices are based on the TOU tariff. As a result of appliance scheduling, the algorithm successfully minimizes electricity costs by shifting appliance usage to off-peak hours and avoiding peak hours. In contrast, the non-scheduling scenario reflects typical user behavior, where appliances are used without consideration of electricity pricing, often during peak demand periods. Figure 4.4 presents the power consumption profile of each appliance in the non-scheduled case, where devices are allowed to operate during high-demand periods without regard for cost optimization.

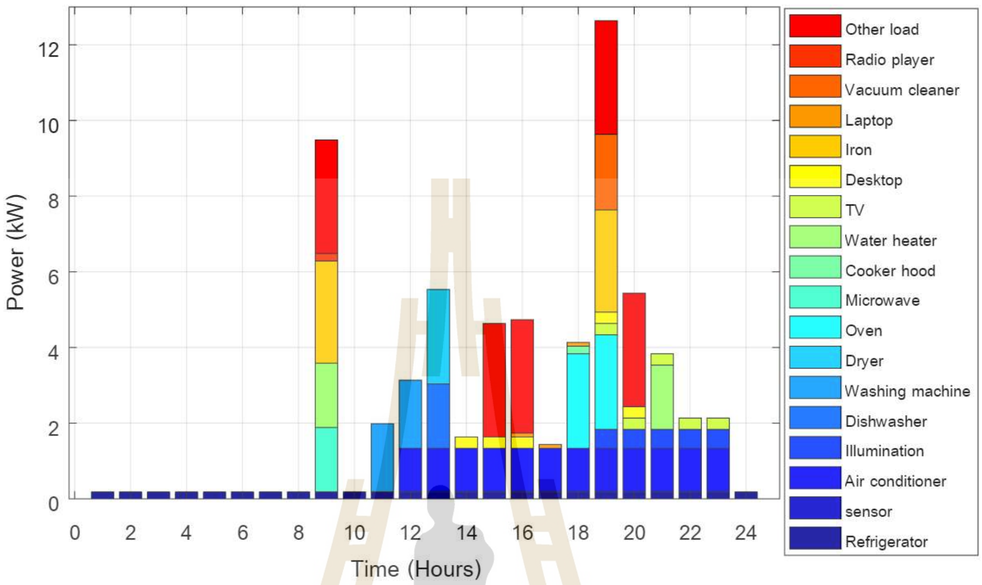


Figure 4.4 Appliance non-scheduling in a day

4.3.2 Appliances Scheduling with power from the grid and BESS

For case II, appliance scheduling is performed using both grid power and BESS. Figure 4.5 demonstrates that the consumer depends on the grid power over 24 hours. However, the battery alone is not capable of fully supporting the household demand at any time interval. In some periods, the battery even draws power from the grid to recharge. Hence, the daily energy provided by the grid is 72.325 kWh, after accounting for the battery's contribution. Consequently, the daily electricity cost in this case is 256.121 THB. Figure 4.6 illustrates the scheduled power consumption of each appliance under this configuration.

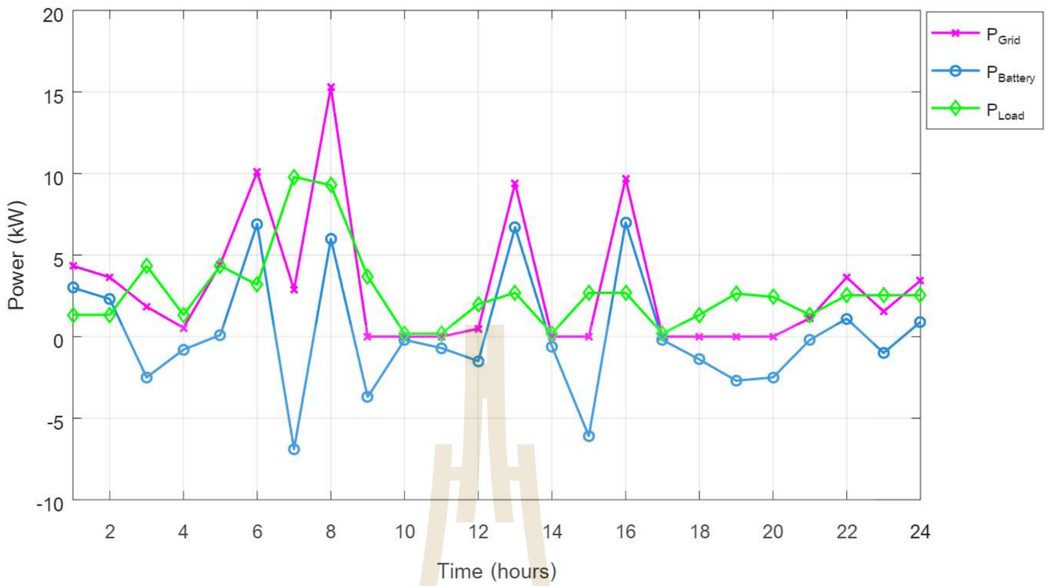


Figure 4.5 The daily power consumption in Case II

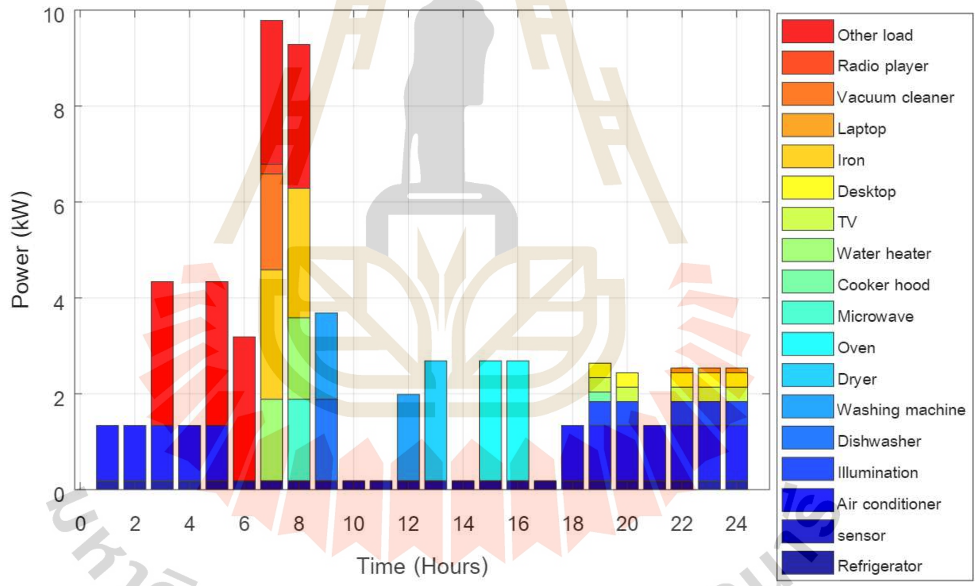


Figure 4.6 Appliance scheduling in Case II

Figure 4.7 illustrates the charging and discharging behaviors of the BESS along with its state of charge (SoC) over 24 hours in Case II. The result reveals that the BESS undergoes multiple charge and discharge cycles. The battery discharges to supply power to appliances and tends to reduce grid dependency. Overall, the BESS demonstrates flexible participation in energy balancing, though its limited capacity means that it cannot fully replace grid power. Instead, it functions as a supplementary resource that enhances scheduling flexibility and contributes to electricity cost reduction.

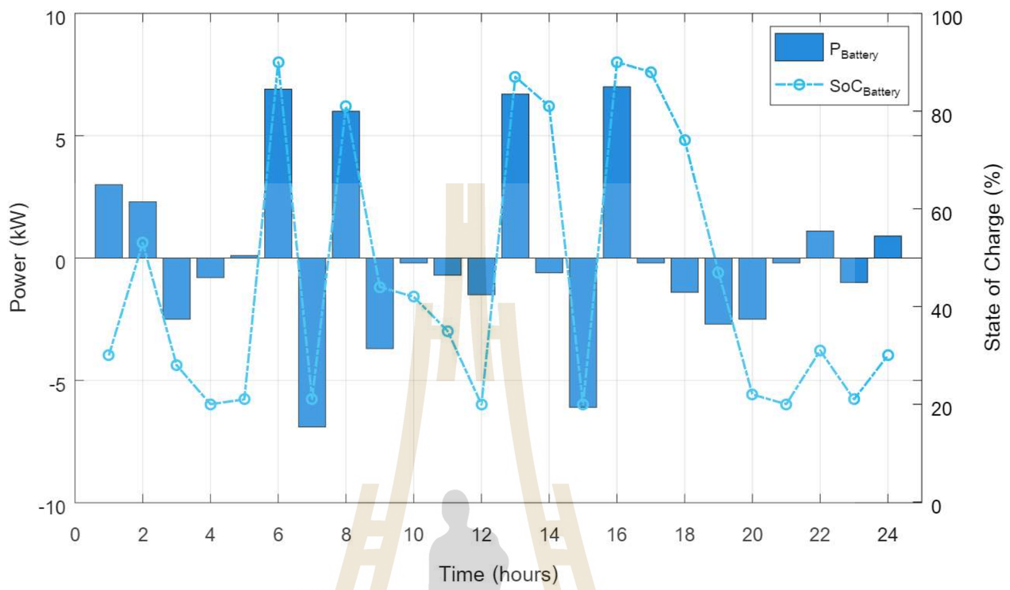


Figure 4.7 BESS behaviours in Case II

4.3.3 Appliances Scheduling with power from the grid and V2H

In case III, the appliance scheduling is considered power from the grid and V2H system. This configuration is designed to reflect typical energy usage patterns in Thai households. Figure 4.8 displays the daily power consumption in the smart home, where the consumer relies heavily on grid power for all 24 hours, similar to Case II. When the EV departs from home, all appliances consume power from the grid. However, once the EV returns, the EV is capable of supplying power to partially meet household demand, thus reducing the grid dependency. When the EV requires recharging power from the grid, a significant amount of power is drawn from the grid to recharge the EV. Hence, the net electricity drawn from the grid amounts to 100.50 kWh, and the daily electricity cost is 310.737 THB. The detailed power usage of each appliance under the scheduled condition is displayed on Fig. 4.9.

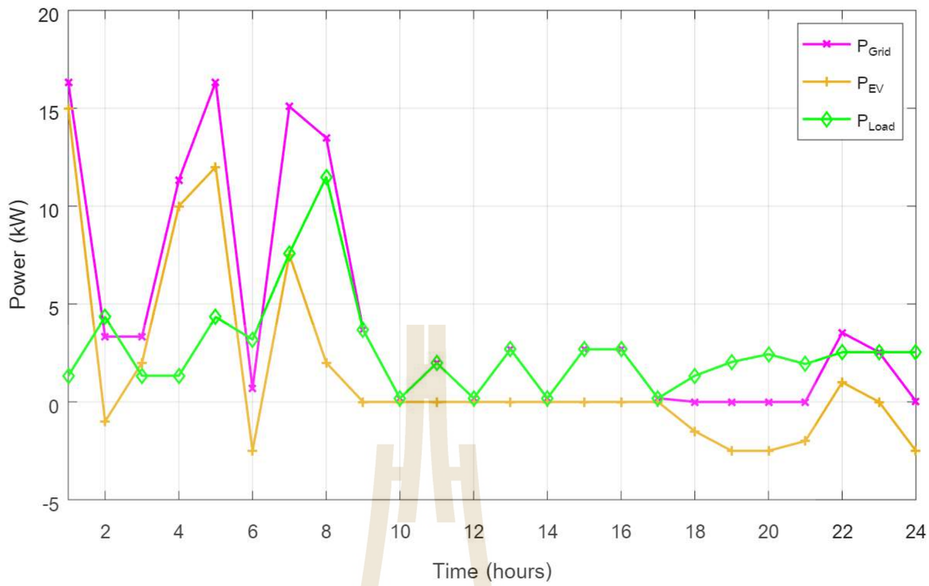


Figure 4.8 The daily power consumption in Case III

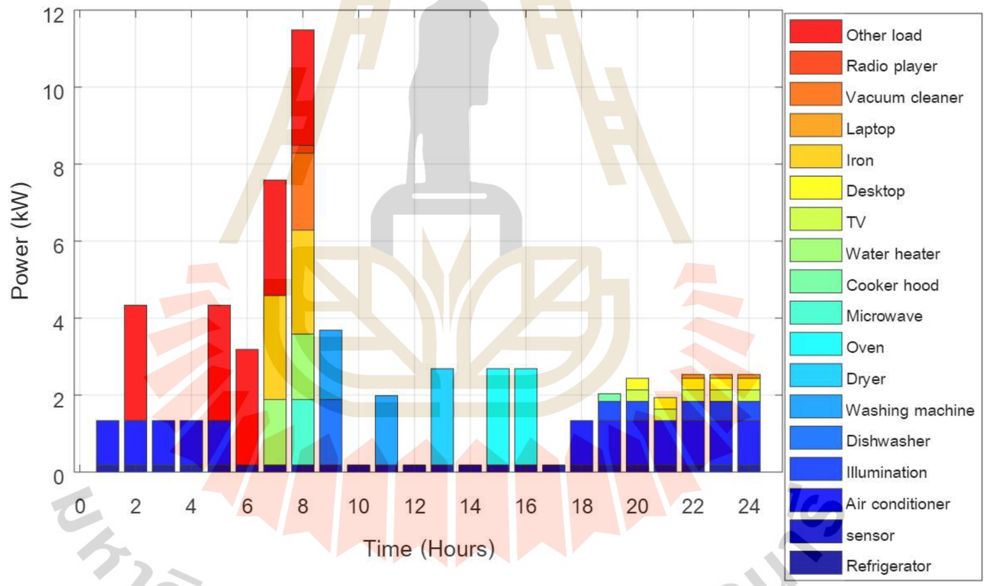


Figure 4.9 Appliance scheduling in Case III

Overall, the EV plays a supplementary role similar to the BESS, supporting peak load periods and reducing the burden on the grid. However, due to the EV's charging demand and limited availability time slot, its contribution is less flexible and more dependent on usage patterns. The charging and discharging behaviours of the EV under the V2H configuration in Case III, along with its state of charge throughout the 24-hour period, are illustrated in Fig. 4.10.

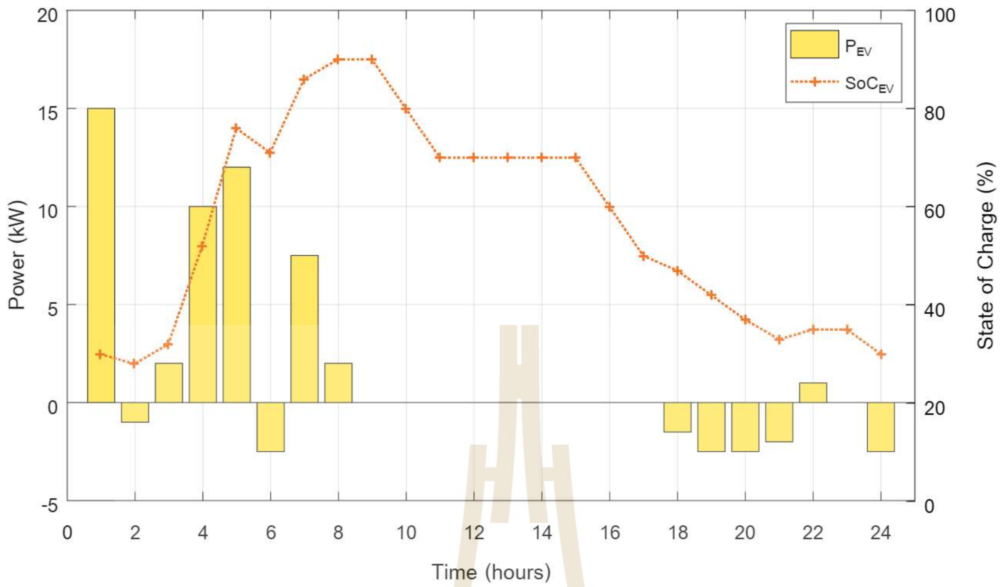


Figure 4.10 V2H behaviours in Case III

4.3.4 Appliances Scheduling with power from the grid, PV, and BESS

This case represents the emerging situation in many countries, including Thailand, where installing rooftop PV with BESS is becoming increasingly common in residential households. Figure 4.11 illustrates the power consumption in a smart home with batteries and PV. This result shows that most of the power load demand in the smart home is consumed by PV and BESS due to their availability, which reduces dependency on the grid power. The BESS supplies power to meet the load demand, enabling the PV to have more excess energy to sell into the grid as much as possible. As a result, the overall daily electricity cost and the power consumption from the grid decrease. The energy supplied by the grid is 42.017 kWh, while 9.1525 kWh of excess PV energy is exported to the grid, resulting in a daily electricity cost of 93.2293 THB.

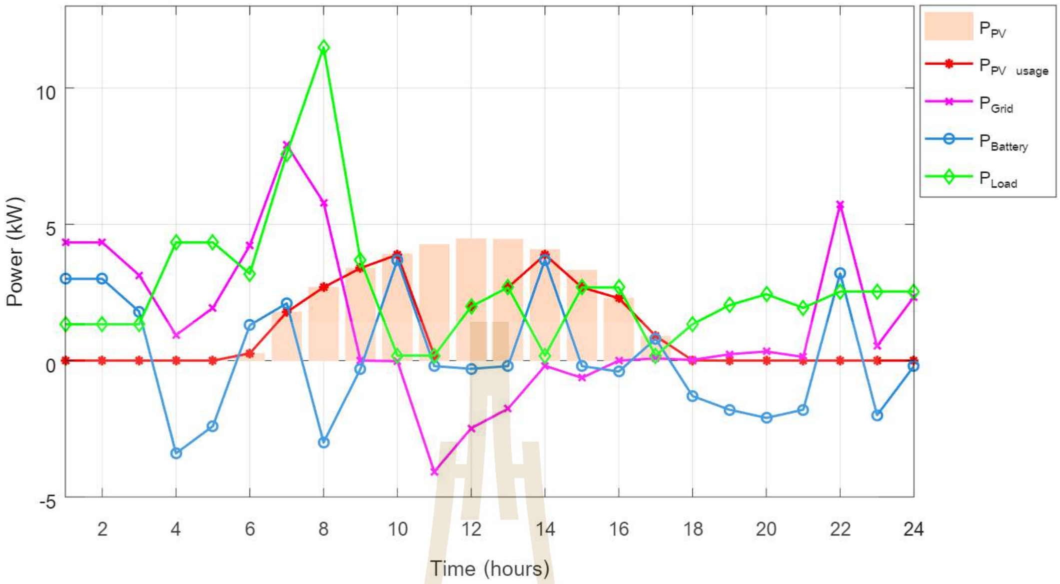


Figure 4.11 The daily power consumption in Case IV

Figure 4.12 shows self-consumption and export of PV power in Case IV. During peak hours with high electricity costs, the BESS is charged using available PV power to reduce grid dependency and minimize cost. Figure 4.13 presents the scheduled power consumption of each appliance under the same scenario.

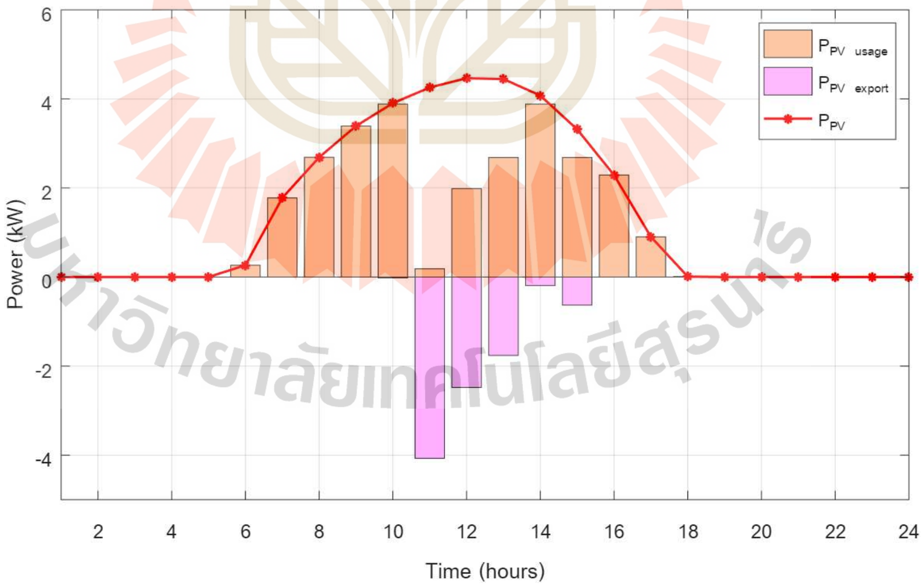


Figure 4.12 PV power usage and export in Case IV

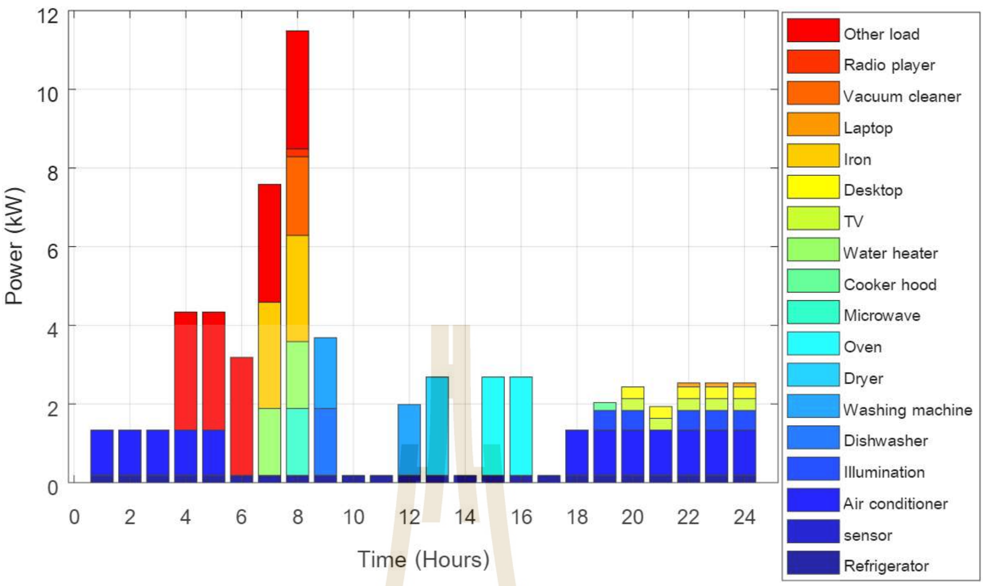


Figure 4.13 Appliance scheduling in Case IV

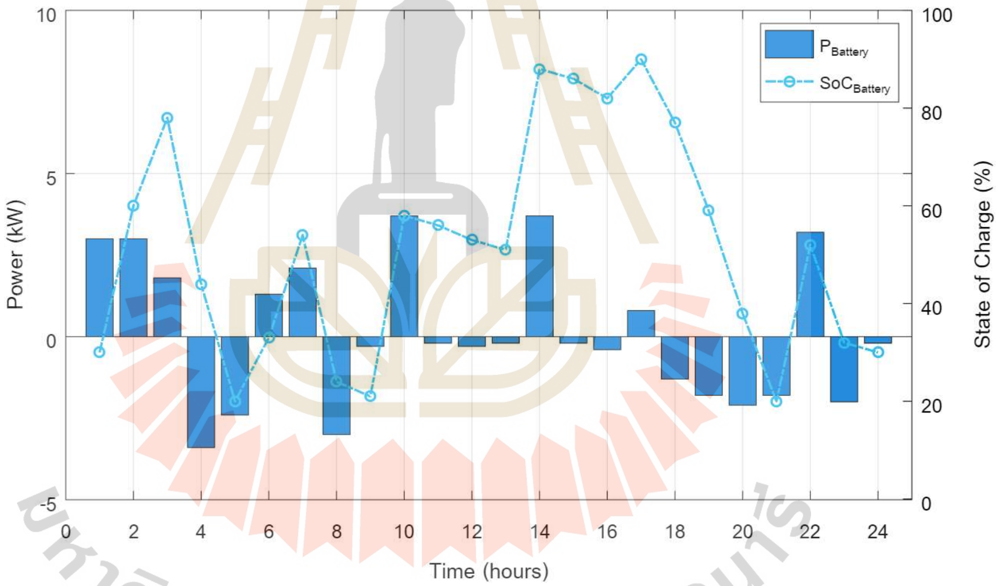


Figure 4.14 BESS behaviours in Case IV

Figure 4.14 displays the charging and discharging behavior of the Battery Energy Storage System (BESS) along with its state of charge (SoC) in Case IV, where the household utilizes power from the grid, rooftop PV, and BESS. In this case, the battery is charged during daylight hours using energy from the solar PV system and discharges during peak hours to support household demand. BESS has a crucial role in managing solar power and power consumption, enabling greater self-consumption sufficiency and enhanced electricity cost reduction.

4.3.5 Appliances Scheduling with power from the grid, PV, and V2H

In case V, Fig. 4.15 reveals the daily power consumption in a smart home configuration that integrates rooftop PV and V2H capability. Figure 4.16 shows PV power usage and export in this case. This scenario examines how the availability of PV energy and the mobility behavior of the EV influence household power consumption patterns and overall energy cost.

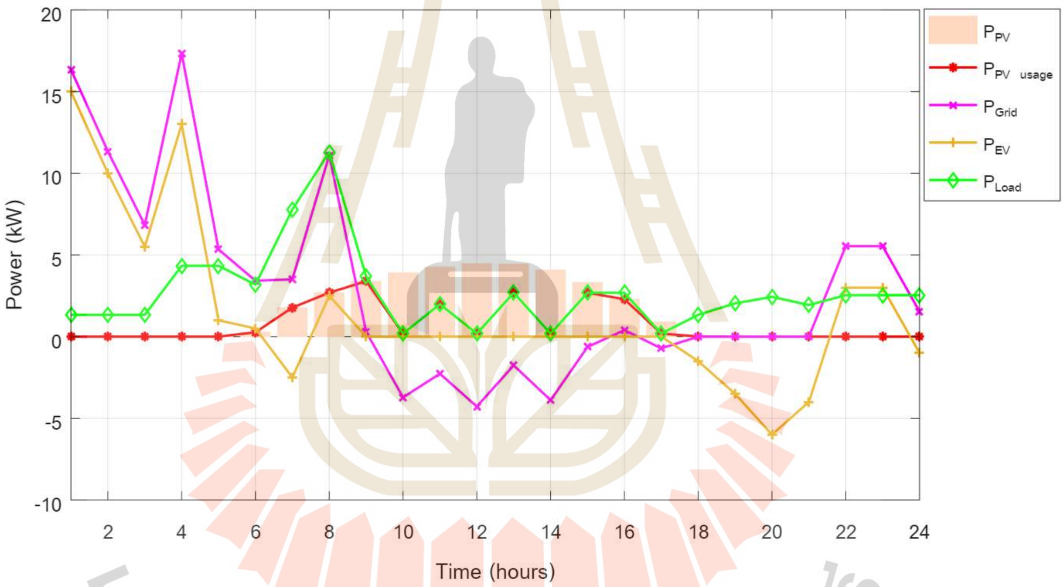


Figure 4.15 The daily power consumption in Case V

As a result, when PV power is available simultaneously, the EV departs from home. Load demand is primarily met by PV power, which reduces dependency on the grid power in peak hours. During such periods, surplus PV energy is exported to the grid. On the other hand, when the EV arrives and begins charging, the EV behaves like a heavy load and consumes a significant amount of energy. This significantly increases the household’s energy requirement. Therefore, both the overall electricity cost and grid energy usage increase compared to Case IV, which involved PV and BESS. The energy supplied by the grid is 88.493 kWh, while the energy surplus from PV is 17.270 kWh, resulting in a daily electricity cost of 197.531 THB. Figure 4.17 shows the scheduled power consumption of each appliance under this case

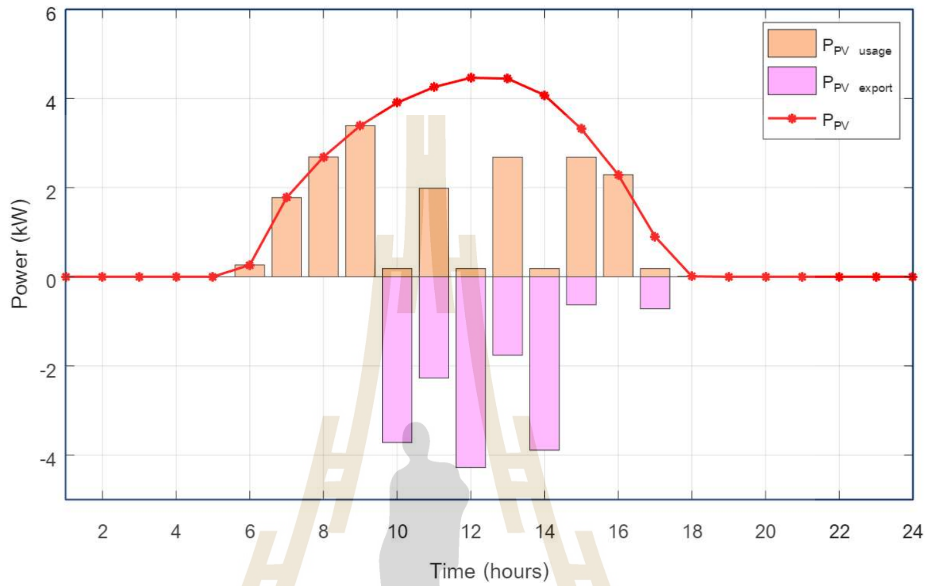


Figure 4.16 PV power usage and export in Case V

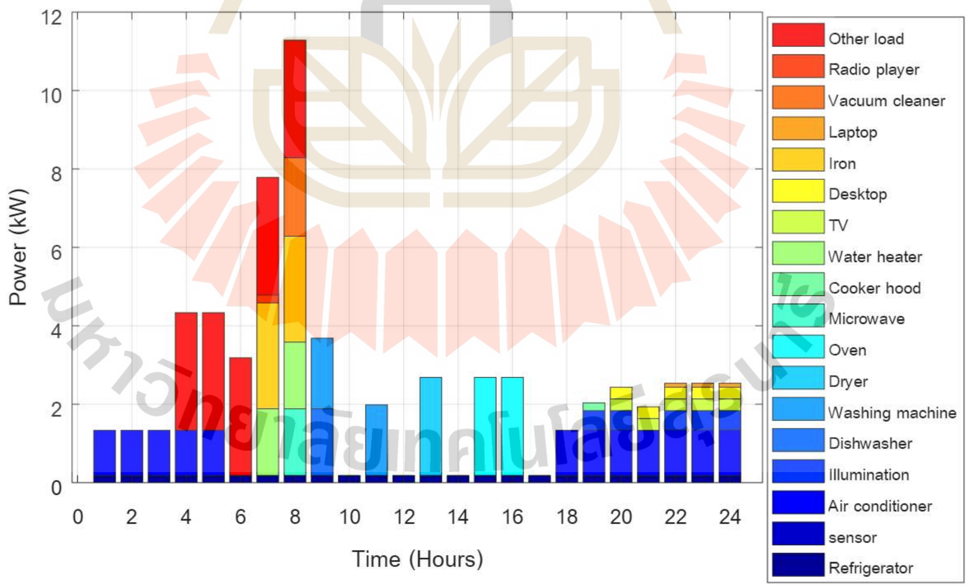


Figure 4.17 Appliance scheduling in Case V

Figure 4.18 presents the charging and discharging behaviours of V2H configuration in Case V, along with SoC in a day. Although this configuration enables high PV energy surplus export to the grid when EVs depart from home, it also results in greater reliance on grid electricity due to the EV's significant charging requirements when EVs arrive. This demonstrates that while V2H provides potential flexibility, its impact on electricity cost can be less advantageous than using a BESS, especially when EV charging behavior aligns conversely with PV availability.

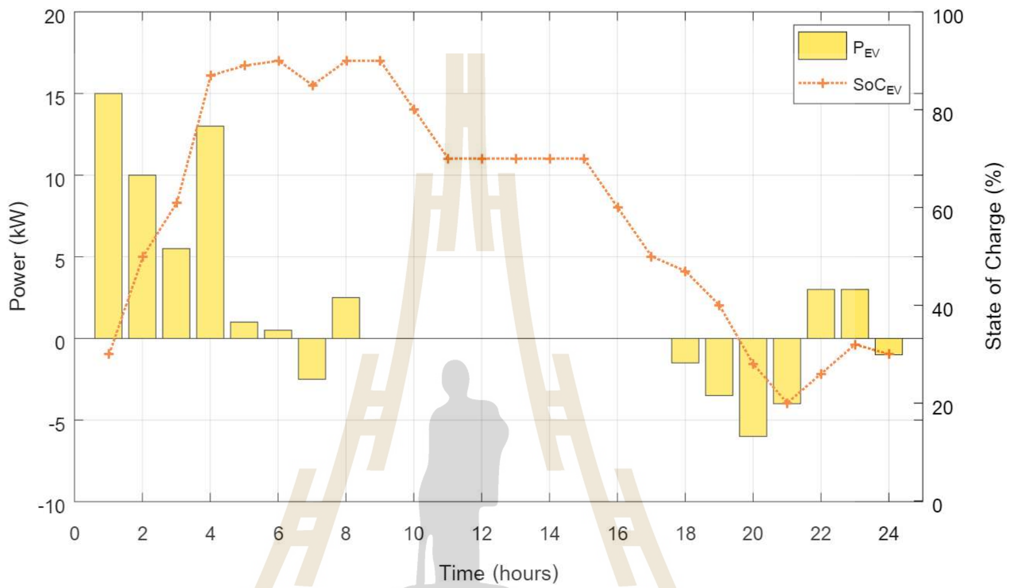


Figure 4.18 V2H behaviours in Case V

4.3.6 Appliances Scheduling with power from the grid, PV, BESS, and V2H

Figure 4.19 illustrates the power consumption in a smart home integrated with rooftop PV, BESS, and V2H operating in case VI. As a result, when PV is available simultaneously, the EV departs from home. The PV energy produced is utilized to satisfy both the household load and to charge the BESS, reducing reliance on grid power during peak hours. The absence of the EV during daytime hours also allows the PV to have some excess energy to sell to the grid under the household PV scheme. The utilization and export of solar PV power in Case VI is shown in Fig.4.20. On the other hand, when the EV arrives and charges, which is consumes a significant amount of energy from the grid. However, unlike Case V, due to this case, the BESS can provide some power for charging EVs to minimize costs. Then, the total daily electricity cost and the power consumption from the grid increase more than in Case IV but less than in Case V. The total grid-supplied energy is 81.939 kWh, and 12.6745 kWh of excess PV energy is exported to the grid. The daily electricity cost in this scenario is 188.292 THB. Figure 4.21 shows the detailed appliance scheduling for this scenario.

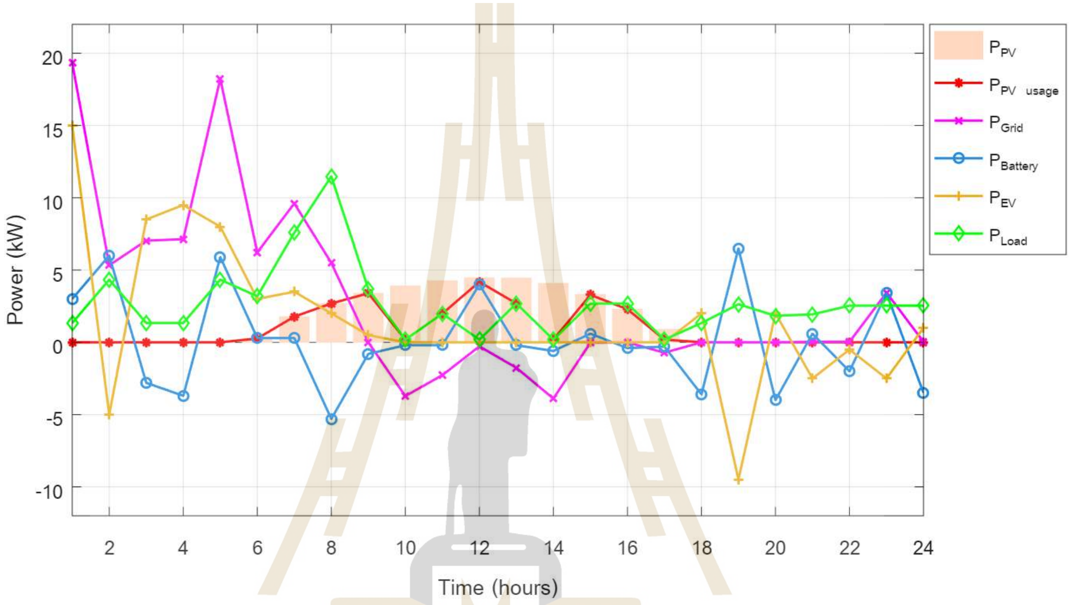


Figure 4.19 The daily power consumption in Case VI

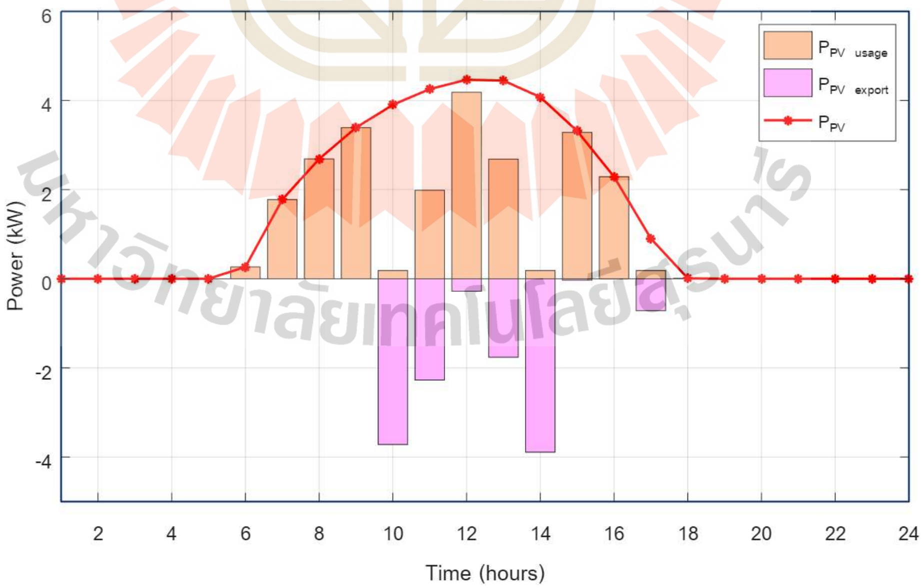


Figure 4.20 PV power usage and export in Case VI

Figure 4.21 displays the PV power consumption behavior when integrating both BESS and EV in the proposed system. When comparing cases IV, V, and VI, where only a BESS is integrated, the PV power export is the lowest because the battery is charged using PV power during the day. In case V, EVs depart from home during PV generation hours, reducing a large amount of power consumption from EVs and resulting in the highest PV power export among all cases.

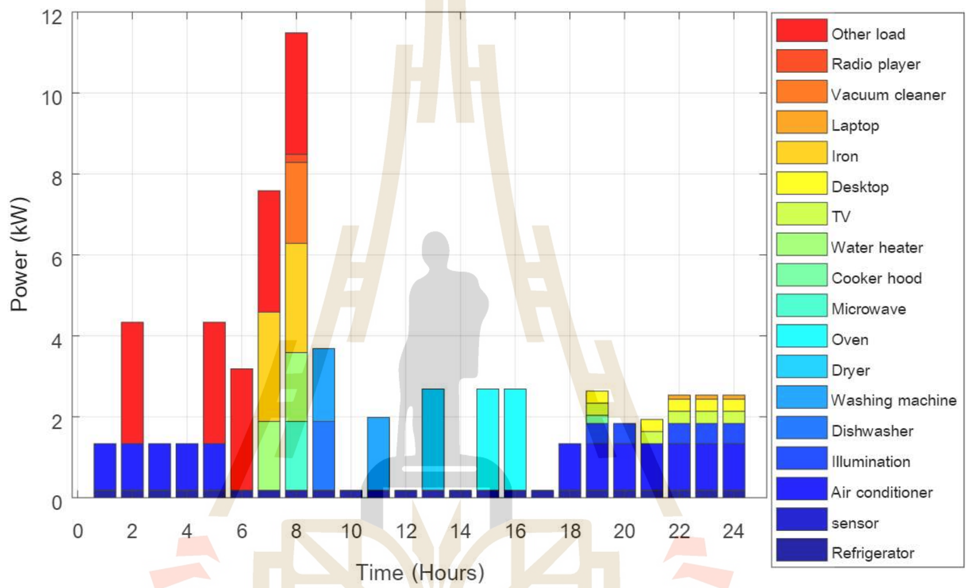


Figure 4.21 Appliance scheduling in Case VI

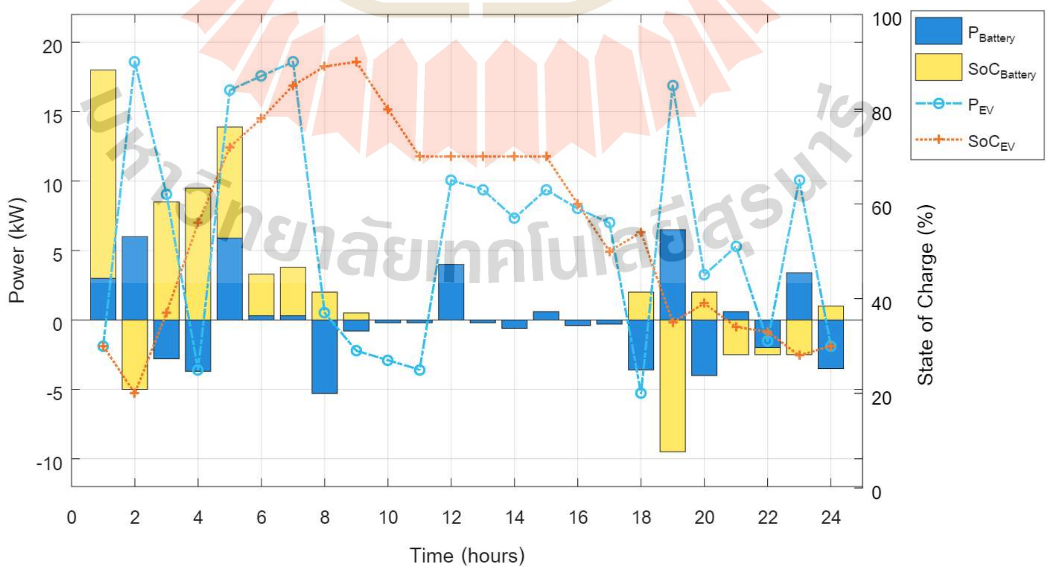


Figure 4.22 BESS and V2H in Case VI

Figure 4.22 illustrates the integrated charging and discharging behaviors of both BESS and V2H configurations in Case VI, along with their respective SoC. During daytime hours, solar PV energy is used to meet household demand and to charge the BESS, while EVs depart from home. In the evening, both the BESS and EV participate in supplying household loads, while the BESS is able to partially assist with the EV's charging demand. This cooperative discharge pattern helps reduce grid usage during peak hours. Overall, the combination of BESS and V2H improves energy flexibility, enables PV energy export to the grid, and reduces grid dependency more effectively than configurations using either component alone.

4.3.7 Appliances Scheduling with power from the grid, PV, wind, and BESS

In case VII, Figure 4.23 portrays the power consumption in the smart home when the PV, wind, and BESS are considered. Due to the availability of two RES, the system gains greater flexibility in energy allocation. The BESS charging and discharging are more adaptable. Wind power assists batteries in providing power when PV power is unavailable, allowing batteries to charge and discharge more strategically. This synergy between wind and solar resources allows the battery to make better decisions to minimize the strain on PV power. As a result, PV has more excess power to feed into the grid to reduce electricity costs. This coordinated utilization of both RES and storage ensures not only demand satisfaction but also maximizes economic benefit in the household. Then, the daily grid consumption is only 13.512 kWh, while 19.4146 kWh of excess PV energy is exported. Consequently, the total electricity cost becomes negative at -6.9987 THB, reflecting net earnings for the household due to reverse power flow and energy export revenues. Figure 4.24 PV power usage and export, and wind power usage in Case VII, and the appliance scheduling for this scenario is displayed in Fig. 4.25.

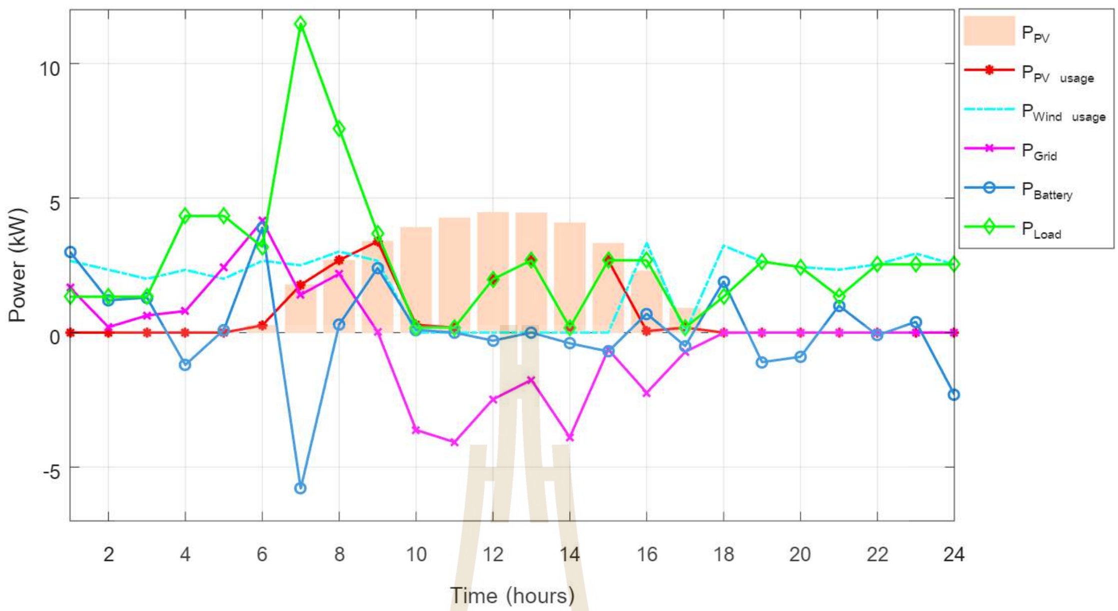


Figure 4.23 The daily power consumption in Case VII

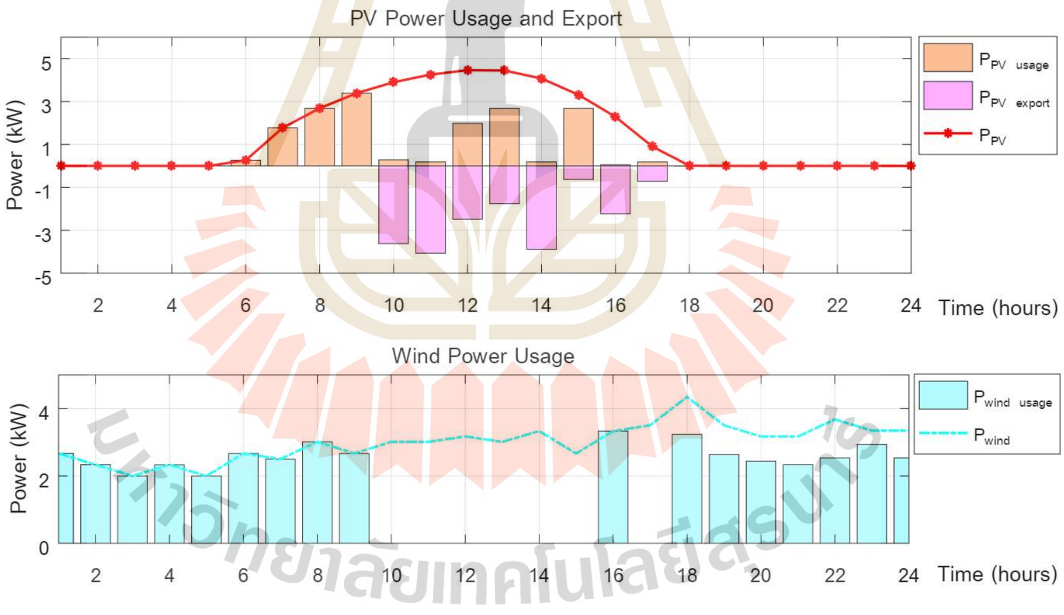


Figure 4.24 PV power usage and export and wind power usage in Case VII

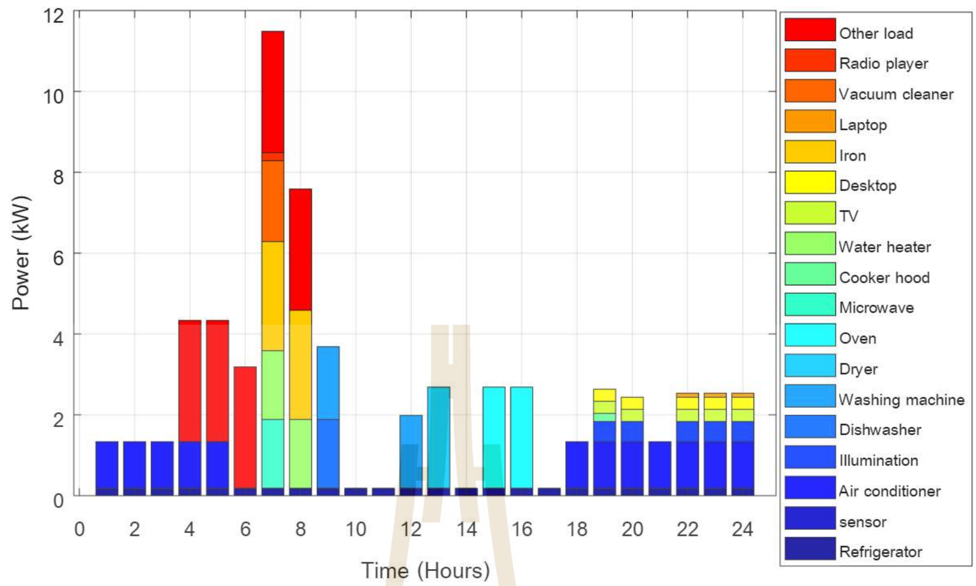


Figure 4.25 Appliance scheduling in Case VII

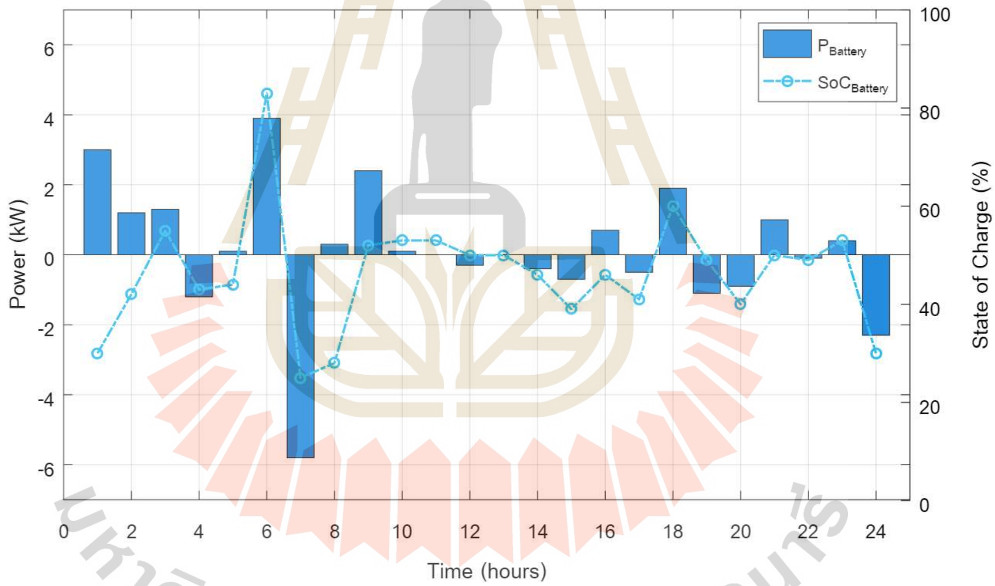


Figure 4.26 BESS behaviours in Case VII

Figure 4.26 presents the overall behaviours of the BESS in Case VII, where the system integrates solar PV, wind power, and battery energy storage. Wind energy complements solar PV by contributing power during early morning and evening hours, allowing the battery to recharge even when solar energy is not available. This synergy enables the battery to operate more flexibly, responding to short-term load fluctuations and reducing the need to draw power from the grid. The system achieves a minimal daily electricity cost as the battery efficiently supports energy allocation, thereby improving self-sufficiency, enhancing power balancing, and maintaining increased PV export to the grid.

4.3.8 Appliances Scheduling with power from the grid, PV, wind, and V2H

For case VIII, Figure 4.27 illustrates the smart home power consumption scenario where power is supplied by the grid, PV, wind, and V2H systems. PV and wind power consumption behavior is shown in Fig. 4.28. Although the EV represents a large load when charging, the availability of two RES made EV charging and discharging more relaxed. When the EV departs from home, wind power assists in providing power to load demand, allowing PV to have more surplus power to feed into the grid to reduce household costs. Moreover, when the EV returns and begins charging, wind power helps the grid charge EVs during hours when PV is unavailable. Figure 4.29 provides appliance scheduling in this case. In this case, the energy drawn from the grid is 55.686 kWh, and the excess energy exported from PV is 17.2795 kWh. The total daily electricity cost is 108.824 THB.

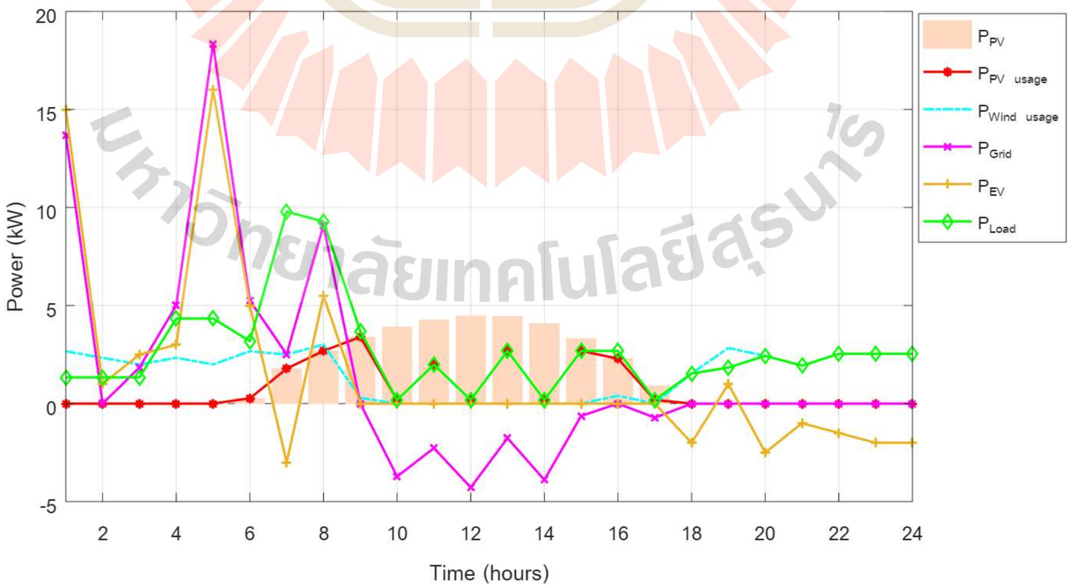


Figure 4.27 The daily power consumption in Case VIII

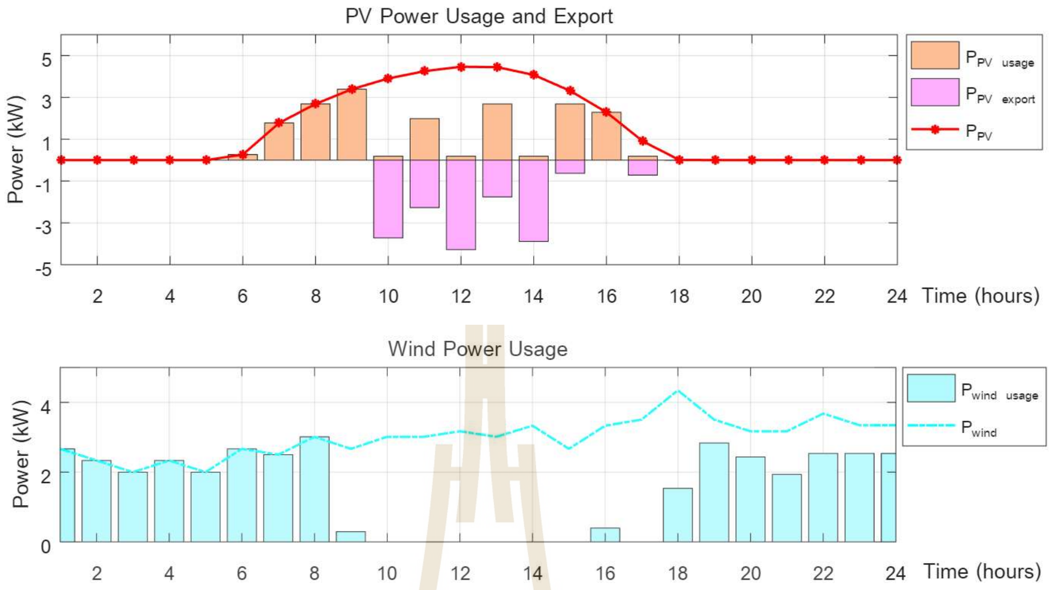


Figure 4.28 PV power usage and export and wind power usage in Case VIII

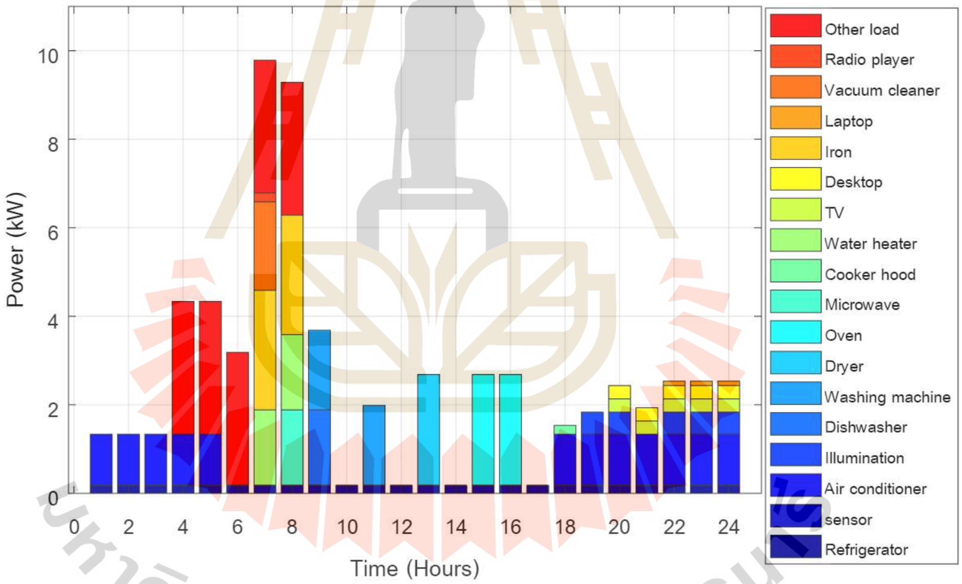


Figure 4.29 Appliance scheduling in Case VIII

Figure 4.30 presents the state of charge and power flow of the EV in Case VIII, where the system is supported by both solar PV and wind energy. The inclusion of wind energy in this case reduces the burden on the grid during EV charging. When the EV returns and begins discharging, wind energy again supports the household load, allowing the EV to maintain a relatively stable SoC while still participating in V2H. This enhanced energy flexibility, achieved by combining multiple RES with V2H, reduces grid dependency, improves cost-effectiveness, and ensures more strategic use of the EV as a distributed energy resource.

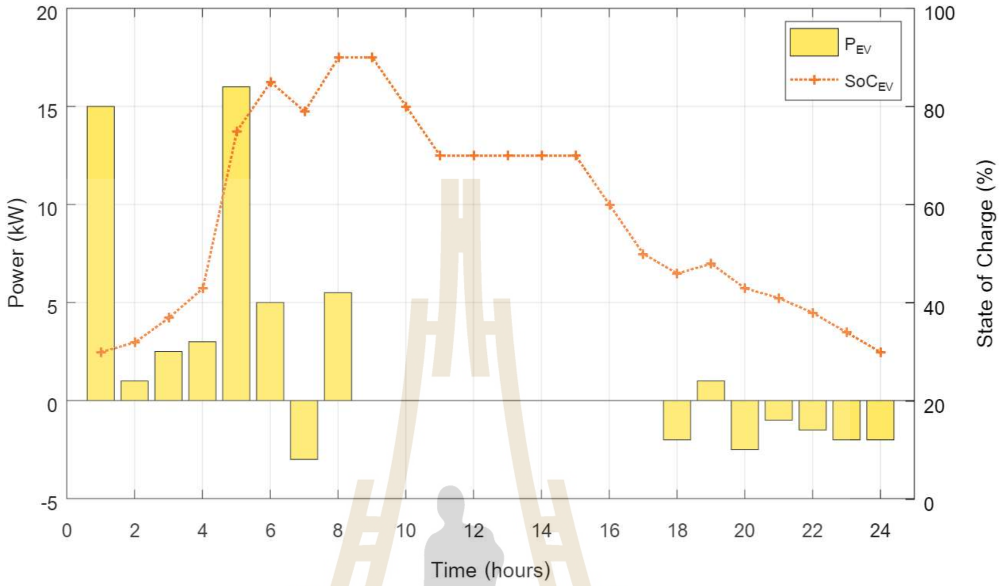


Figure 4.30 V2H behaviours in Case VIII

4.3.9 Appliances Scheduling with power from the grid, PV, wind, BESS, and V2H

In case IX, Fig. 4.31 represents power consumption in the smart home when the PV, wind, BESS, and V2H are considered. The integration of two RES provides greater flexibility for battery operations. BESS is strategically charged using RES during off-peak hours to alleviate grid dependence. Batteries help discharge power when there is insufficient RES to satisfy demand or high electricity price intervals. When an EV arrives at a smart home, the EV contributes a minor amount of power to satisfy the load demands. EVs can draw energy from the wind and batteries. This coordination of energy sources helps reduce peak demand and overall reliance on grid power. The total energy supplied by the grid is 48.0491 kWh, and the excess energy exported from PV is 22.2595 kWh. As a result, the total daily electricity cost is 77.8126 THB, reflecting the economic and operational benefits of full energy integration.

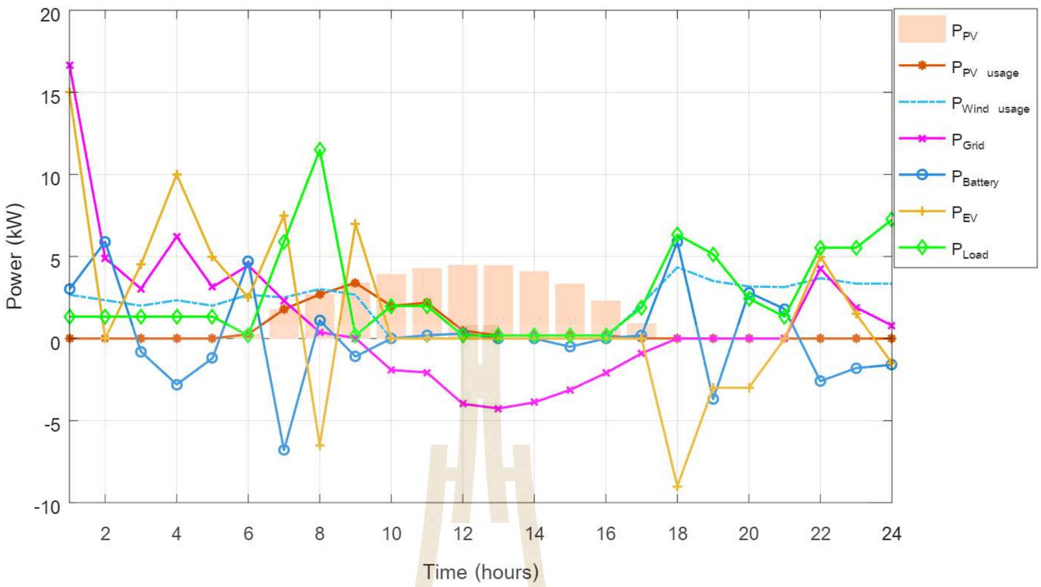


Figure 4.31 The daily power consumption in Case IX

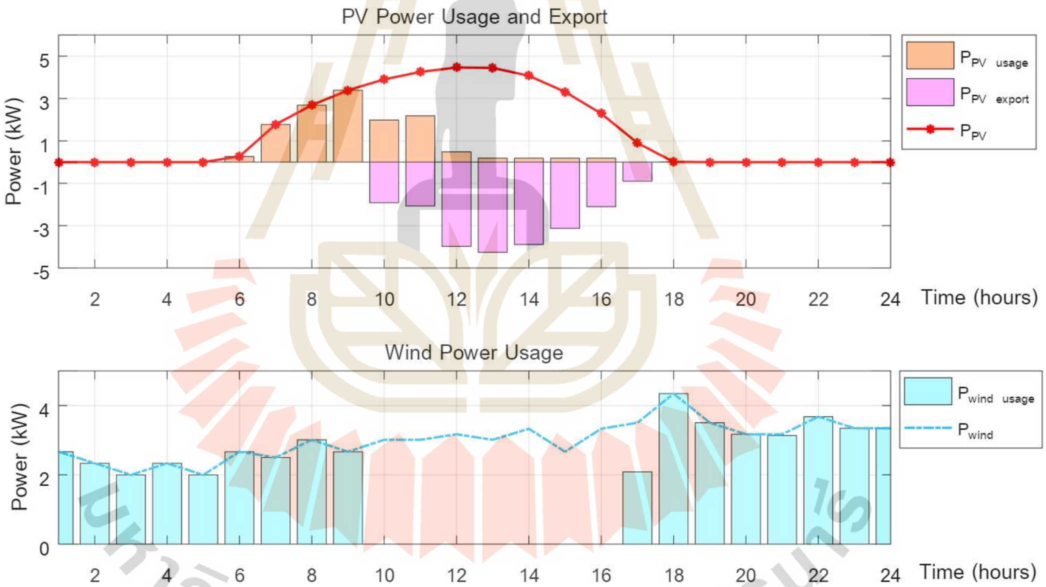


Figure 4.32 PV power usage and export and wind power usage in Case IX

When comparing the result of PV export in cases VII, VIII, and IX. Figure 4.32 illustrates the PV and wind power consumption behavior when integrating BESS and EV. As a result, this case has the highest PV power export to the grid due to the combined advantage of the battery and EV systems. In addition, wind energy integration helps alleviate appliance load demand, allowing the battery to be primarily charged utilizing other energy resources instead of PV while the EV departs from home during PV availability. This allows more excess PV power to be exported to the grid. Figure 4.33 gives the corresponding appliance scheduling details for this case.

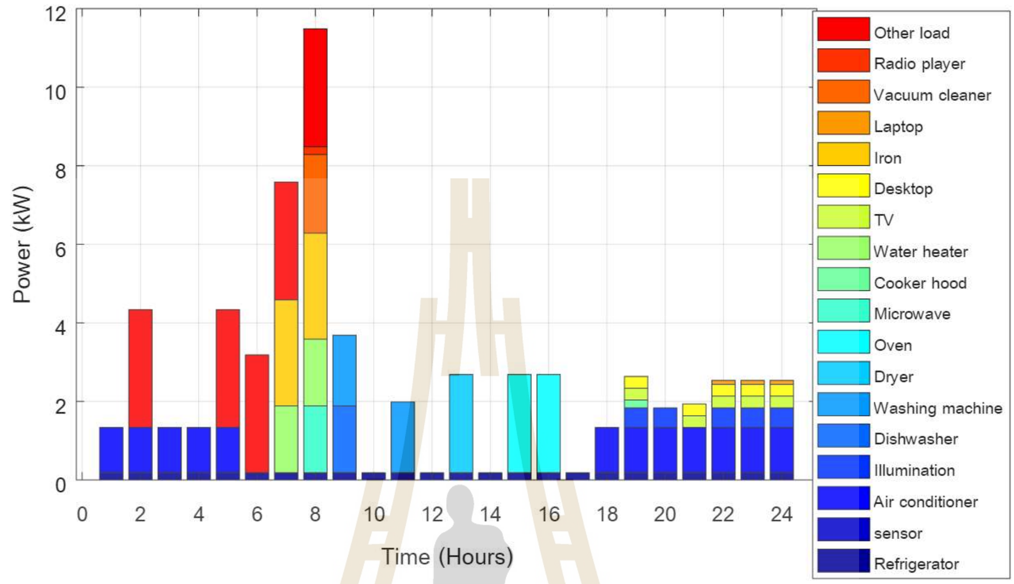


Figure 4.33 Appliance scheduling in Case IX

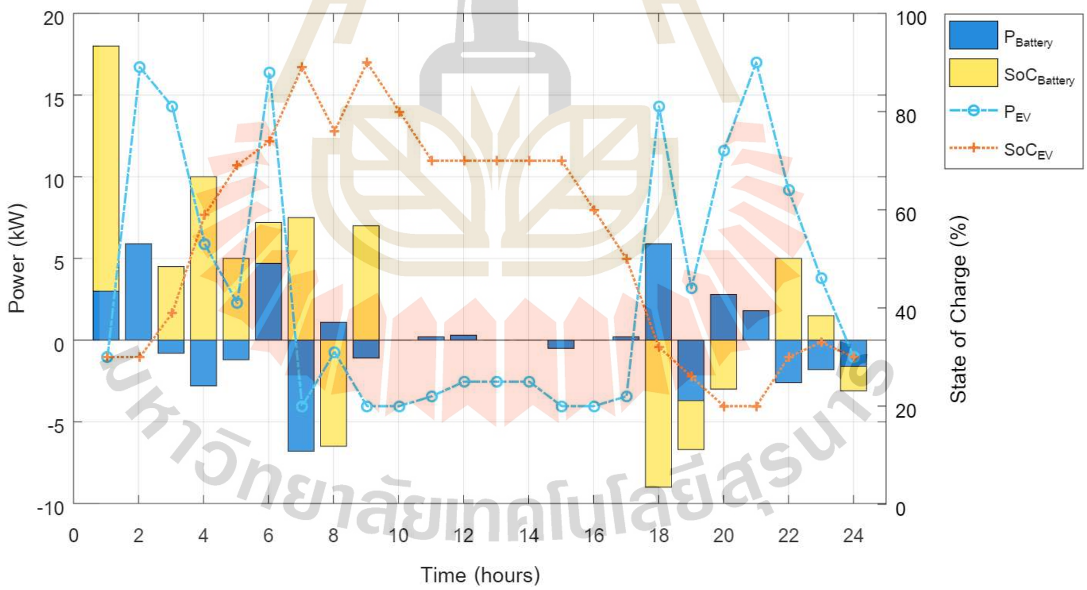


Figure 4.34 Battery and EV behaviour in Case IX

Figure 4.34 visualizes the coordinated charging and discharging behaviors of both the BESS and EV under the fully integrated smart home configuration in Case IX. The plot showcases how both battery systems respond dynamically to household demand, RES availability, and TOU pricing. Wind can provide power to support when the EV is intensively charged, and BESS begins discharging to supply immediate demand when RESs are unavailable. When the EV arrived, the EV and BESS partially supported household loads and each other's charging demand. The synchronized behavior of the SoC of the battery and the EV reflects a strategic sharing of energy responsibilities. As a result, this case achieves the highest PV energy export to the grid due to the coordination among RESs, BESS, and V2H, significantly enhancing system flexibility, reducing grid reliance, and optimizing electricity cost savings. This case represents the most economically efficient and operationally resilient configuration in the SHEMS study. Figure 4.35 shows the convergence curve of the minimum TDC in case IX.

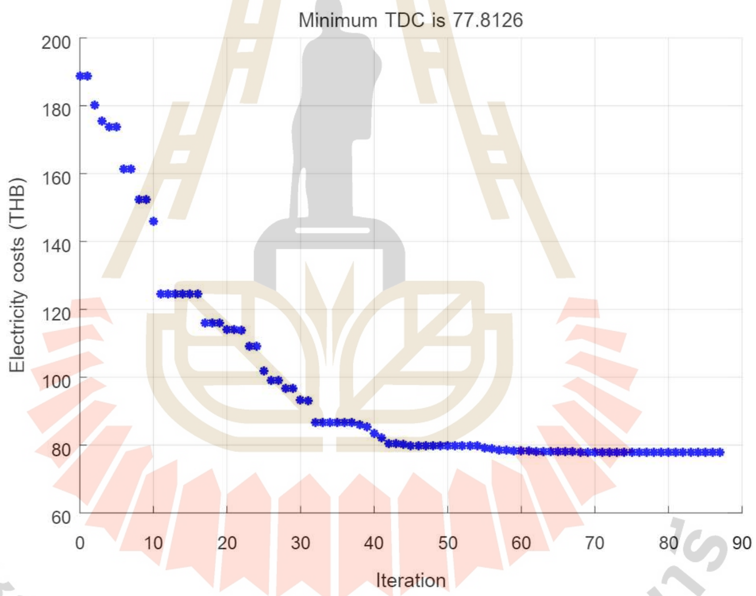


Figure 4.35 The minimum TDC in Case IX

Table 4.3 presents the hourly power balance for Case IX. In this table, a positive value indicates the needed power consumption from any energy source, while a negative value denotes energy being discharged to supply the demand.

Table 4.3 The power balance of each time slot in case IX

Power / Time (hours)	P_{grid} (kW)	$P_{PVusage}$ (kW)	$P_{wind,usage}$ (kW)	P_B (kW)	SoC_B (%)	P_{EV} (kW)	SoC_{EV} (%)	P_{Load} (kW)
1	16.67	0	2.667	3	30	15	30	1.335
2	4.901	0	2.334	5.9	89	0	30	1.335
3	3.036	0	1.998	-0.8	81	4.5	39	1.335
4	6.201	0	2.334	-2.8	53	10	59	1.335
5	3.136	0	1.998	-1.2	41	5	69	1.335
6	4.452	0.266	2.667	4.7	88	2.5	74	0.185
7	2.308	1.7765	2.501	-6.8	20	7.5	89	5.885
8	0.384	2.6885	3.012	1.1	31	-6.5	76	11.485
9	0.026	3.3915	2.667	-1.1	20	7	90	0.185
10	-1.919	1.985	0	0	20	-5	80	1.985
11	-2.071	2.185	0	0.2	22	-5	70	1.985
12	-3.98	0.485	0	0.3	25	0	70	0.185
13	-4.261	0.185	0	0	25	0	70	0.185
14	-3.890	0.185	0	0	25	0	70	0.185
15	-3.130	0.185	0	-0.5	20	0	70	0.185
16	-2.104	0.185	0	0	20	-5	60	0.185
17	-0.9025	0	2.085	0.2	22	-5	50	1.885
18	0	0.0095	4.344	5.9	81	-9	32	6.335
19	0	0	3.504	-3.7	44	-3	26	5.135
20	0	0	3.171	2.8	72	-3	20	2.435
21	0	0	3.135	1.8	90	0	20	1.335
22	4.2568	0	3.678	-2.6	64	5	30	5.535
23	1.8899	0	3.345	-1.8	46	1.5	33	5.535
24	0.7899	0	3.345	-1.6	30	-1.5	30	7.235

Across all case studies, the appliance scheduling patterns demonstrate similar trends, primarily driven by the TOU pricing scheme on energy management decisions.

The scheduling algorithm always shifts appliance operations to avoid peak hours and toward lower electricity cost time slots instead. Energy sources contribute to improving power consumption, enhancing system flexibility, and providing more opportunities to reduce electricity costs.

Therefore, variations in electricity cost across cases are largely attributed to the variety of energy resources utilized to supply the scheduled appliances, rather than significant differences in the scheduling of each appliance.

4.4 Electricity Cost Analysis

4.4.1 Electricity cost analysis under TOU Scheme

This section analyzes the electricity cost benefits of optimized energy management using the proposed framework. Table 4.4 presents a comparative analysis of daily grid power consumption, excess PV energy, and resulting electricity costs between two scenarios: non-scheduled appliance operation and optimized scheduling using the proposed hybrid PSO-LP algorithm. This comparison is conducted across all nine simulation cases to demonstrate the minimization of electricity cost potential and resource utilization efficiency of the proposed SHEMS.

Table 4.4 The electricity cost and total power consumption comparison

Case	Non-Scheduling			Scheduling with PSO hybrid LP		
	Energy grid usage (kWh)	Energy excess from PV (kWh)	Electricity cost (THB)	Energy Grid usage (kWh)	Energy excess from PV (kWh)	Electricity cost (THB)
I	64.740	-	356.61	64.740	-	255.13
II	85.710	-	331.38	72.325	-	256.12
III	155.30	-	499.15	100.50	-	310.74
IV	61.343	10.769	215.43	42.017	9.1525	93.230
V	141.99	15.874	478.66	88.493	17.270	197.53
VI	125.54	9.494	442.90	81.939	12.674	188.29
VII	34.986	15.271	82.079	13.512	19.415	-6.999
VIII	102.82	18.955	325.45	55.686	17.280	108.82
IX	101.99	14.855	280.69	48.049	22.260	77.813

As a result, nine different cases were analyzed to evaluate the impact of various energy sources on daily electricity costs and grid dependency.

Case I represents the base case, where appliance scheduling relies solely on power from the grid. This scenario refers to the average Thai household, which depends on the grid for 24 hours.

Case II, when adding a battery in the home, compares to Case III, EV integration. The results show that the consumer relies heavily on grid power for all 24 hours. Although batteries and EVs can discharge power to assist the load demand, both also need to charge power from the grid. The result shows that EV integration in Case III leads to higher power consumption and electricity cost than BESS in Case II, due to the EV's significant charging demand.

Rooftop PV systems are added in Cases IV to VI. In these cases, PV power significantly reduces grid dependency. However, the presence of EVs in Cases V and VI still increases total consumption due to EV charging demand. However, when EV departure enables the PV to have some surplus power to export to the grid, it is more than in cases that include batteries. In Case VI, which combines PV, EV, and BESS. As a result, power consumption in a day is more flexible than in the previous cases, and adding a battery benefits EVs, which have more energy resources for charging.

Cases VII to IX include wind energy in the system. The availability of two RES makes the battery and EV more flexible in deciding power for charging, allowing more excess power from PV to be injected into the grid to reduce electricity costs. Case VII, which includes PV, wind, and BESS, results in the lowest electricity cost and grid consumption. Wind power assists batteries in providing power when PV power is unavailable, allowing batteries to efficiently provide power to meet load demands. This case has less power consumption from the grid and electricity cost than any other case. However, when adding EV, like in case IX, the net electricity cost is 77.8126 THB. The energy from the grid in a day is 48.0913 kWh, and the energy excess from PV is 22.2595 kWh, which increases all results compared to case VII because EVs need a large amount of power. The results show that the SHEMS using the hybrid PSO-LP efficiently minimizes electricity costs and handles load schedules to avoid peak hours.

The results above clearly show that the SHEMS using the hybrid PSO-LP efficiently optimizes energy consumption and schedules load to avoid peak hours. The computation reliability of the proposed method had been verified by 30 trial runs of case IX as shown in Fig. 4.36. The minimum and maximum daily cost from optimization of the SHEMS obtained by hybrid PSO-LP is 77.8126 THB/day and 101.653 THB/day, respectively. The average daily electricity cost in the optimization system is 89.3548 THB. The results show that the proposed computational procedure can successfully provide stable and reliable results for SHEMS.

Figure. 4.36 The solution with 30 trials of Case IX

4.4.2 Adaptability to Real-Time Pricing (RTP) Scheme

In addition to TOU electricity cost analysis, the adaptability of the proposed hybrid PSO-LP framework was further evaluated by replacing the traditional TOU pricing scheme with a real-time pricing (RTP) scheme in the simulation scenarios. In this work, the RTP tariff reflects highly dynamic power demand in Thailand conditions, in which, in low demand, the RTP prices also decrease. RTP presents greater challenges for optimal scheduling due to frequent and unpredictable changes in electricity prices. The performance of the proposed SHEMS under RTP was assessed in terms of computational efficiency, solution quality, and the ability to maintain cost savings in case IX.

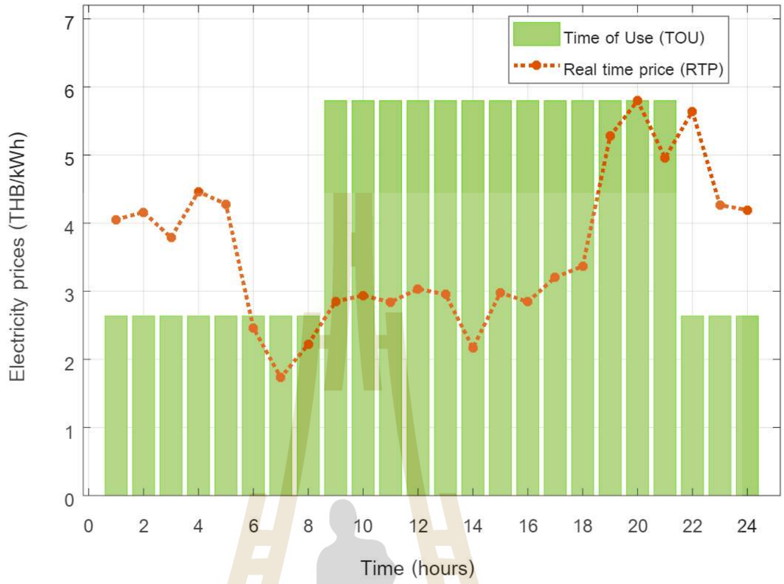


Figure. 4.37 The electricity TOU and RTP tariff

Table 4.5 The electricity cost and total power consumption comparison between TOU and RTP tariff in case IX

Tariff	Non-Scheduling			Scheduling with PSO hybrid LP		
	Energy grid usage (kWh)	Energy excess from PV (kWh)	Electricity cost (THB)	Energy Grid usage (kWh)	Energy excess from PV (kWh)	Electricity cost (THB)
TOU	101.998	14.855	280.687	48.0913	22.2595	77.8126
RTP	96.4613	4.3105	357.649	50.2270	17.4206	87.3628

The results in Table 4.5 demonstrate that the proposed hybrid PSO-LP algorithm effectively reduces electricity costs under both TOU and RTP schemes. In the RTP scenario, the minimum electricity cost is 87.36 THB, which is higher than the TOU case. The system still maintains performance despite the increased volatility of electricity prices. The RTP scenario also shows a reduced amount of excess PV energy exported to the grid due to RTP short-term price fluctuations in daylight hours. This is primarily because real-time electricity prices tend to be lower during daylight hours, thus incentivizing the algorithm to schedule appliances to operate at lower prices. This highlights the flexibility of the proposed framework in responding to complex pricing signals while ensuring economic benefits. The hybrid PSO-LP demonstrates high adaptability and remains cost-effective even under RTP environments.

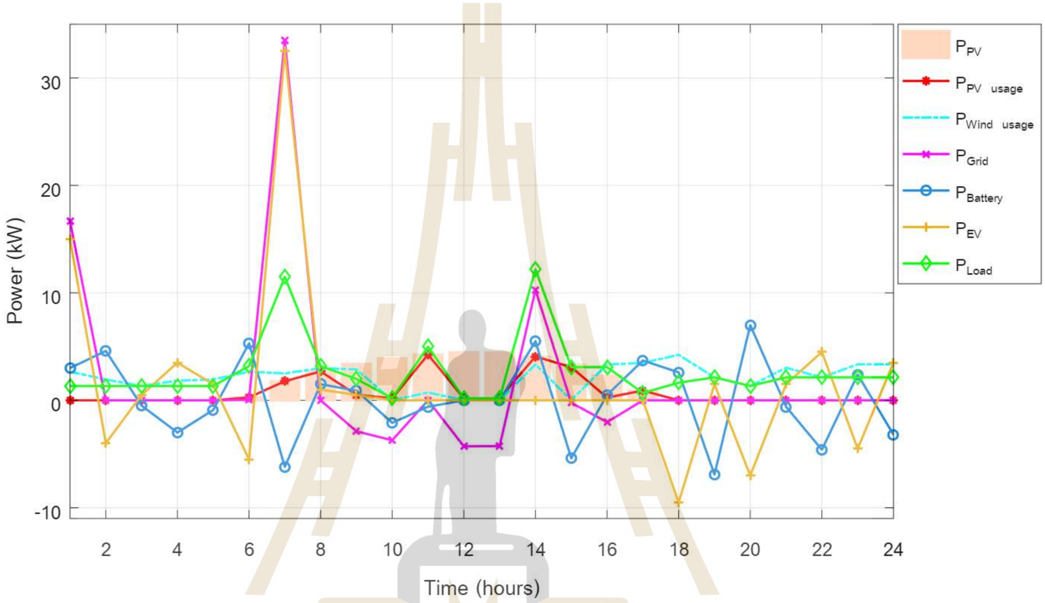


Figure. 4.38 The daily power consumption under RTP tariff

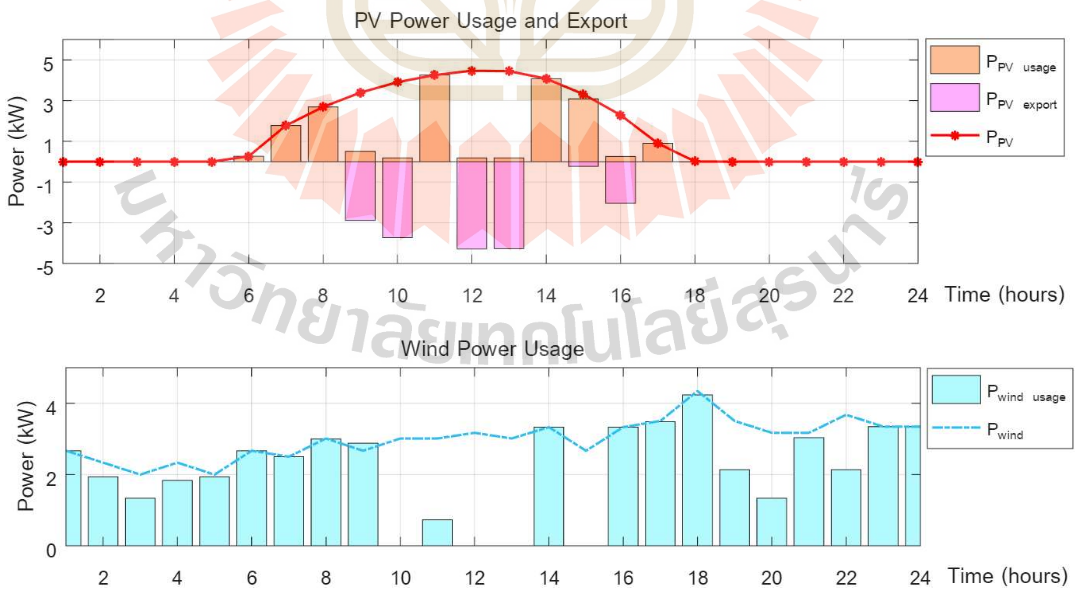


Figure 4.39 PV power usage and export and wind power usage in Case RTP

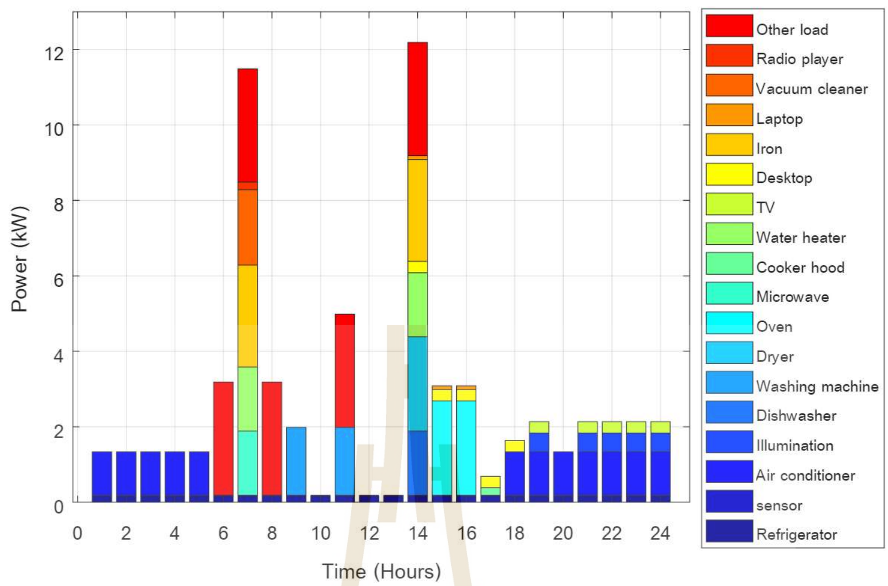


Figure. 4.40 Appliance scheduling under RTP tariff

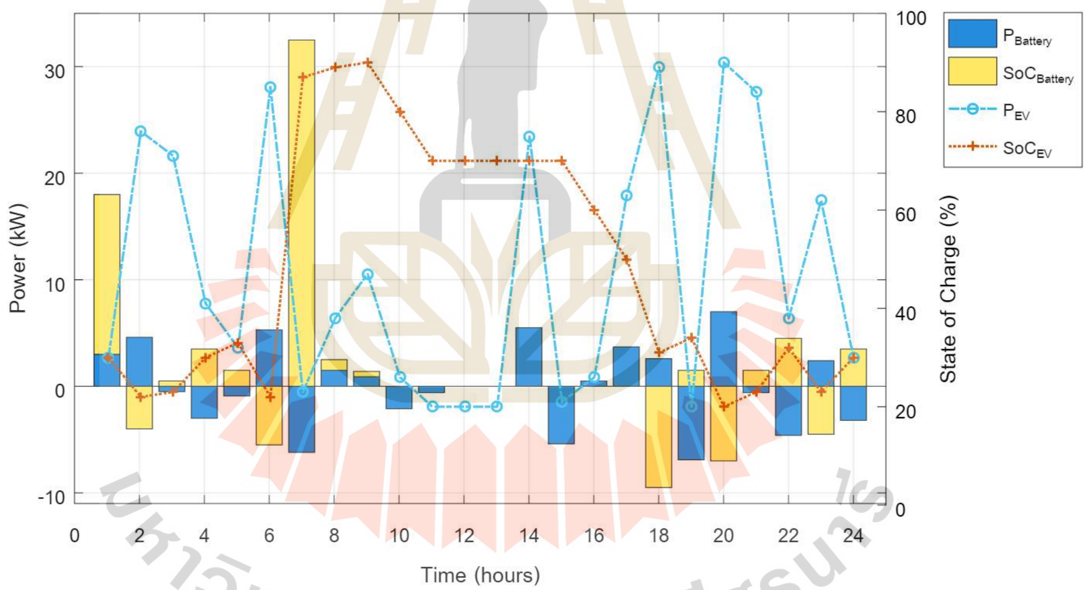


Figure. 4.41 BESS and V2H behaviours under RTP tariff

Figure 4.38 provides the daily power consumption under the RTP tariff. Although the RTP pricing is unpredictable, the proposed SHEMS maintains an appliance schedule that avoids high electricity cost periods as much as possible, reflecting the algorithm scheduling capability. Figure 4.40 highlights the appliance scheduling pattern, which shows a more flexible arrangement compared to the TOU case. This behaviour demonstrates how RTP encourages BESS and V2H to make a decision to manage energy in each time slot. The BESS responds more actively to price signals, charging during very low-price hours and discharging to support the load demand strategically. Meanwhile, the EV arrives to support household demand through V2H, but EV charging behaviour is dependent on the low-price hours of the RTP tariff.

Figure 4.42 illustrates the convergence behavior of the proposed hybrid PSO-LP algorithm under both TOU and RTP pricing schemes. As a result, the algorithm successfully converges under both pricing models, but the TOU scheme allows for faster and smoother convergence due to the TOU structured price pattern. This observation further reinforces the adaptability of the proposed algorithm in responding to varying tariff conditions while maintaining reliable optimization performance.

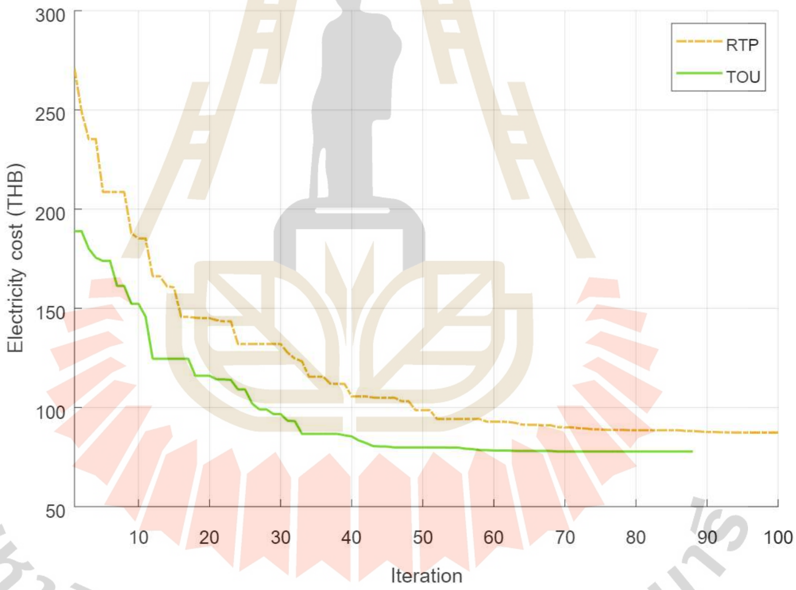


Figure. 4.42 The convergence curve under TOU and RTP tariff

4.5 Comparative Performance with Other Methods

This section presents simulation results used to ensure the efficient performance of the proposed hybrid PSO-LP algorithm for optimal home appliance scheduling (OHAS). This section provides a comparative analysis between the proposed method and other commonly used optimization techniques, including PSO, Genetic

Algorithm (GA), and hybrid GA-LP. Each method is tested under the same system configuration in Case IX and constraints to ensure an appropriate comparison. The algorithm-specific parameters and hyperparameter configurations are summarized in Table 4.6. The performance comparison focuses on key metrics such as electricity cost, computational time, and convergence behavior. Table 4.7 presents the result of the proposed hybrid PSO-LP compared to the other algorithm-based SHEMS.

Table 4.6 The parameters setting for different methods

Parameters	Method	
	PSO/ PSO-LP	GA/ GA-LP
Populations	50	50
Iterations	100	100
C_1	1.5	-
C_2	1.5	-
w	0.1 – 1.1	-
Elite Count	-	2
Crossover Fraction	-	Scattered, 0.8
Mutation Function	-	mutation gaussian
Selection Function	-	Stochastic Uniform
Function Tolerance	10^{-6}	10^{-6}

In this study, in PSO and PSO-LP after parameter tuning, the proposed framework uses the default parameter setting, therefore the parameter values for the Genetic Algorithm (GA) were set according to the default recommendations of MATLAB. This approach ensures fairness and accuracy in the baseline comparison between the proposed method and other algorithms, which minimizes potential bias that could arise from individual parameter tuning.

Table 4.7 The comparison results of the proposed hybrid PSO-LP and the other algorithm-based SHEMS

Method	Energy from grid (kWh)	Energy injected to grid (kWh)	Total cost (THB/day)	Runtime (sec)
GA	58.5800	10.2550	131.890	240.7304
GA-LP	43.2899	16.3815	80.3955	12004.90
PSO	47.2780	12.4635	113.152	300.4936
Hybrid PSO-LP	48.0913	22.2595	77.8126	10695.03

Under the same simulation conditions in case IX and using the hyperparameters provided in Table 4.6. The comparative results demonstrate that the proposed hybrid PSO-LP significantly outperforms the other methods in minimizing electricity costs. When using the PSO, the daily electricity cost is 113.152 THB, while the proposed hybrid PSO-LP reduces it to 77.8126 THB. For GA hyperparameters with the same condition, the GA and GA-LP, the electricity costs are 131.890 and 80.3955 THB per day, respectively.

Although the proposed hybrid PSO-LP algorithm has the longest runtime, the performance of the results in reducing electricity costs can improve significantly. As shown in Figure 4.43, the convergence behavior of the hybrid PSO-LP is more stable and directed toward the global optimum, indicating its effectiveness in exploring complex search spaces with higher solution quality.

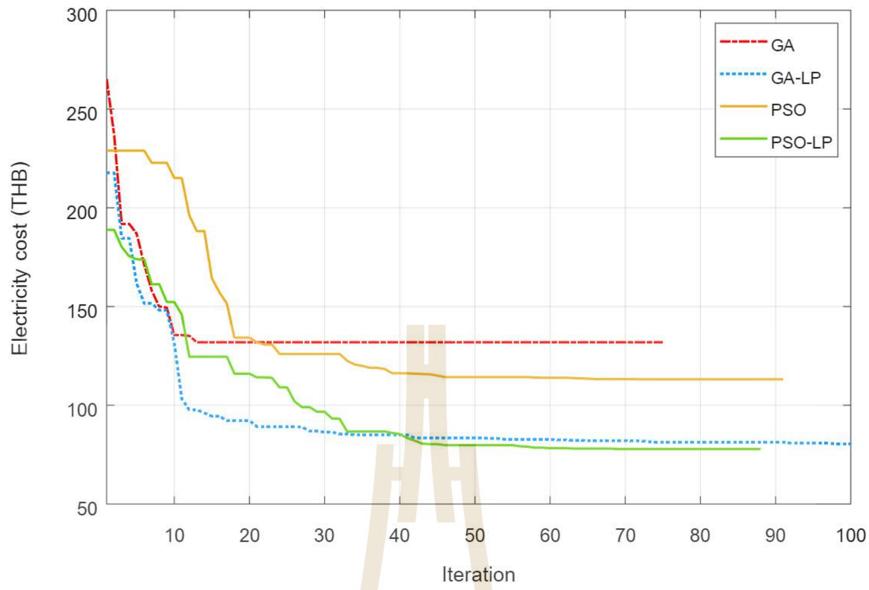


Figure. 4.43 The convergence behaviors of different methods

Although the hybrid PSO-LP algorithm requires longer computational time compared to the other methods, this limitation is acceptable in the context of this study. The optimization is designed for day-ahead appliance scheduling under a TOU or RTP pricing framework, therefore a runtime of several hours does not impact the practical implementation, since the optimized schedule will be applied the following day. The focus remains on minimizing electricity costs and optimal energy allocation.

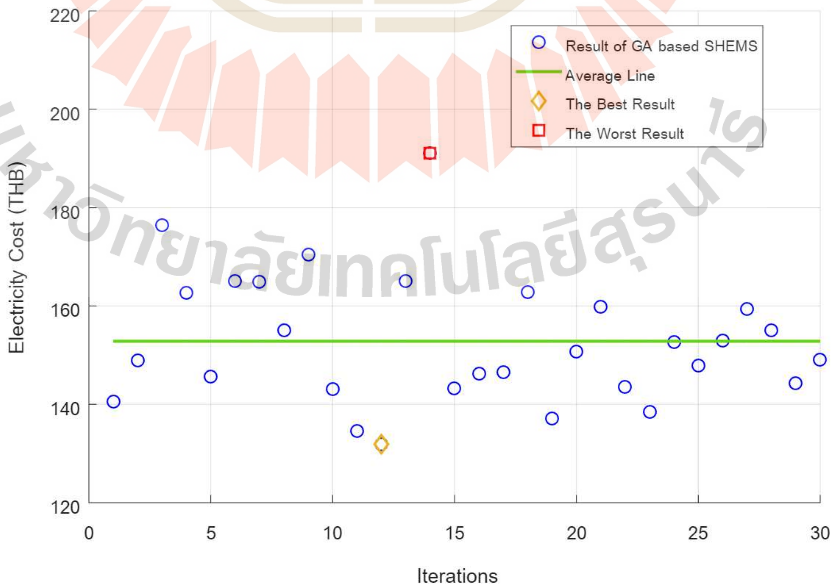


Figure. 4.44 The solution with 30 trials of Case IX using GA

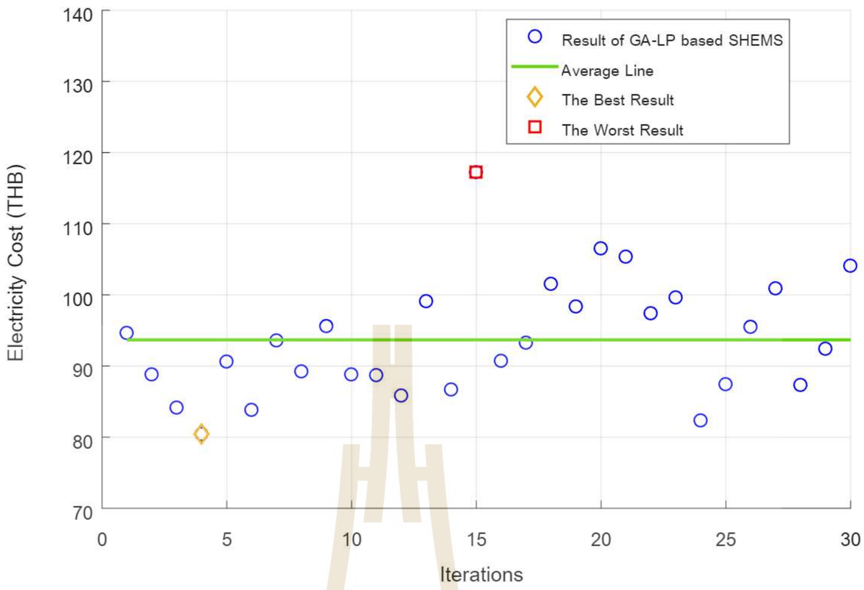


Figure. 4.45 The solution with 30 trials of Case IX using GA-LP

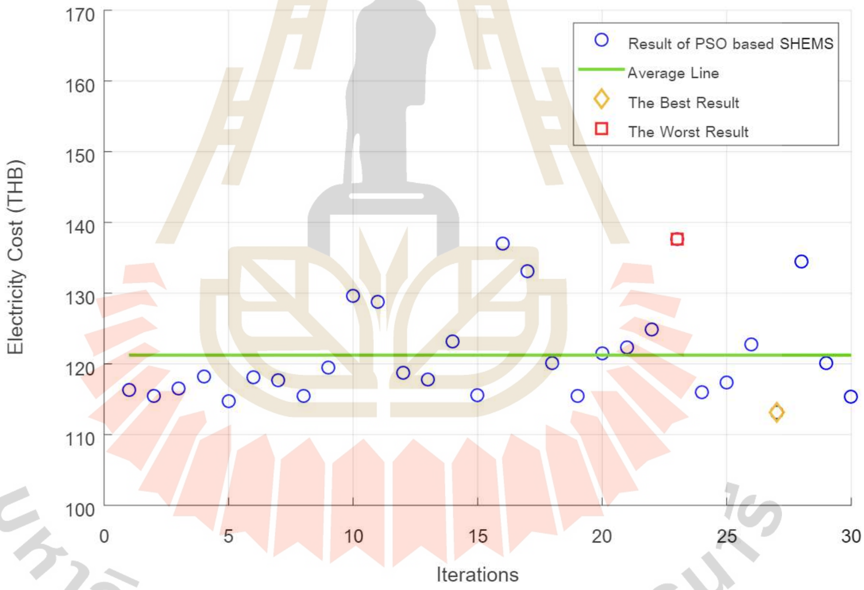


Figure. 4.46 The solution with 30 trials of Case IX using PSO

Figures 4.44 to 4.46 present the results of 30 independent trials for Case IX using GA, GA-LP, and PSO, respectively. The variation in electricity cost results across multiple trials highlights the stability and quality of each algorithm. The GA and PSO methods demonstrate more fluctuations in their solutions, which may be attributed to early convergence or improper setting in the search process. In contrast, the hybrid GA-LP and particularly the hybrid PSO-LP demonstrate more consistent performance and lower variability, indicating higher convergence reliability toward optimal solutions. These results support the advantage of hybrid metaheuristic algorithms with mathematical programming techniques like LP for improved scheduling quality and stability.

4.6 The Scalability of the Hybrid PSO-LP

The scalability of the proposed hybrid PSO-LP based SHEMS is evaluated to ensure this framework has adaptability in more realistic and demanding conditions. Table 4.8 provides the scalability of hybrid PSO-LP in Case IX. This includes scaling the number of household appliances.

Table 4.8 The scalability of hybrid PSO-LP in Case IX

Number of appliances	Time slots (hours)	Total cost (THB/day)	Energy from grid (kWh)	Energy injected to grid (kWh)	Runtime (sec)
18	24	77.8126	48.0491	22.2595	10695.03
36	24	232.602	97.6817	11.3525	46826.16
18	48	133.712	75.4705	29.9670	35761.25

As shown in Table 4.8, the system remains computationally feasible and effective even under larger-scale scenarios. Additionally, Figure 4.47 illustrates the daily power consumption profile when the number of household appliances is doubled from 18 to 36. Despite the increased scheduling complexity, the proposed hybrid PSO-LP framework successfully manages energy allocation, ensuring efficient operation while minimizing grid dependency. The results confirm that the proposed method is achieving effective appliance scheduling and continued electricity cost reductions even as the number of appliances increases.

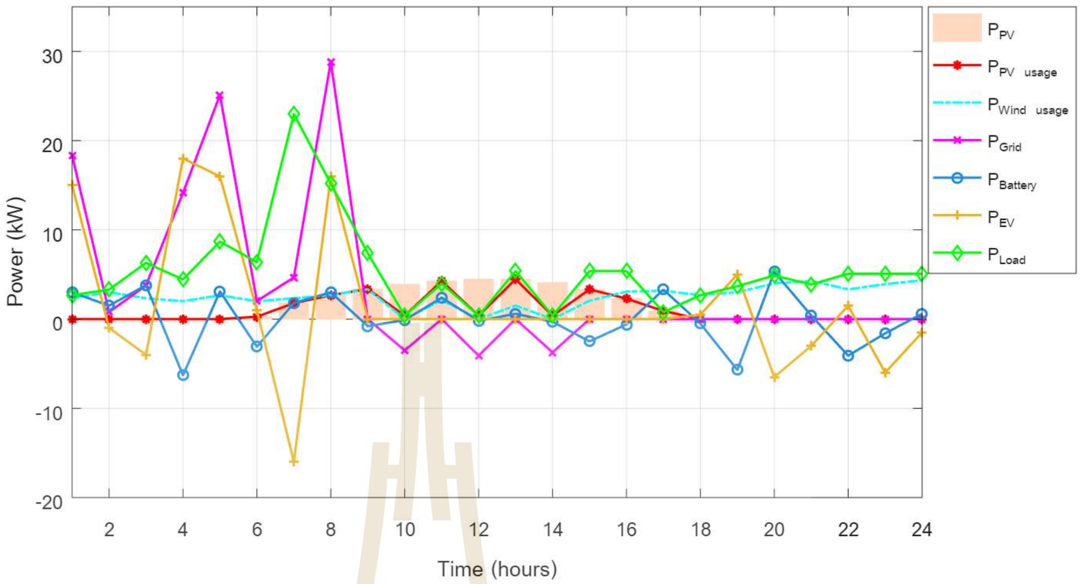


Figure. 4.47 The daily power consumption in 36 appliances case

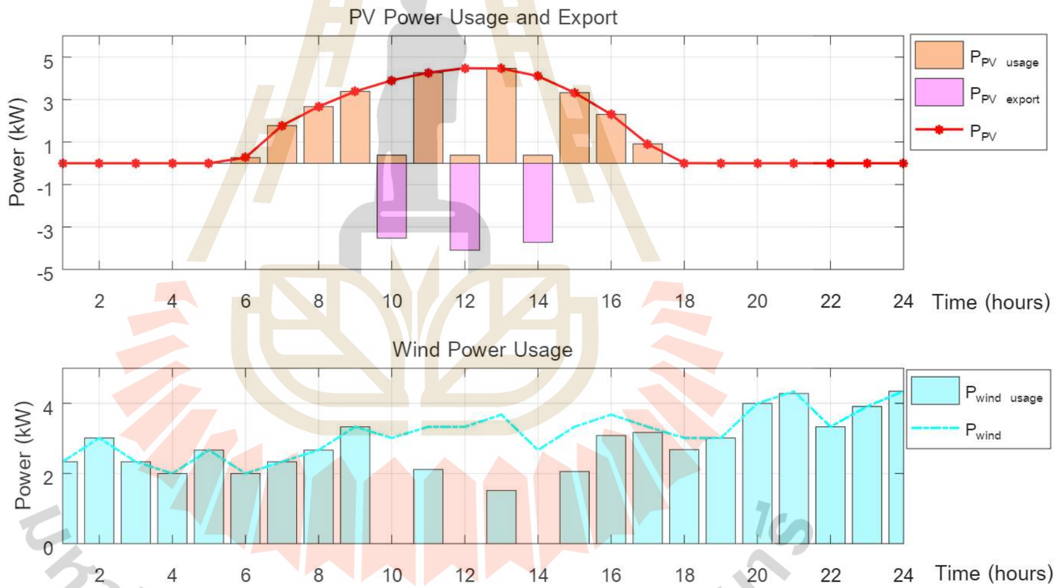


Figure. 4.48 PV power usage and export and wind power usage in 36 appliances case

Figure 4.48. shows the RESs consumption behavior in the 36 appliances case. The total electricity consumption increased significantly, resulting in 97.68 kWh of grid power usage to meet all power demand and 11.35 kWh of PV power export to the grid. The increase in appliance usage not only intensifies energy demand but also expands the complexity of scheduling appliances. Specifically, the appliance scheduling matrix extends proportionally with the number of appliances, leading to a longer runtime for the optimization algorithm. This reflects the increased

computational burden in managing a larger number of variables and constraints while still maintaining cost-effective operation under TOU-based DR.

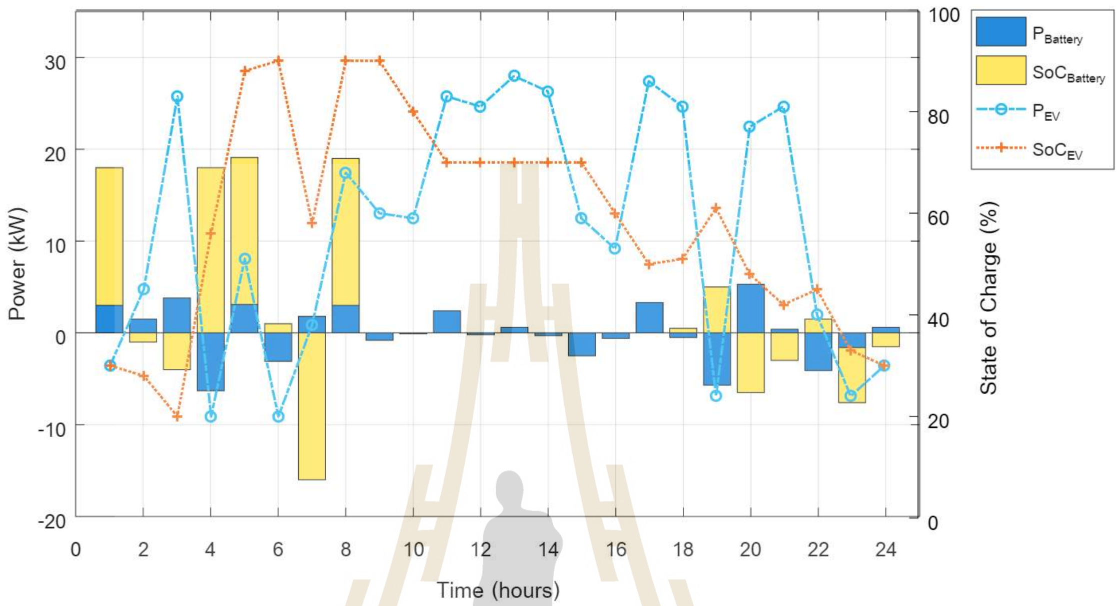


Figure. 4.49 BESS and V2H behaviours in 36 appliances case

In order to investigate the scalability of the proposed SHEMS, the scheduling horizon was extended from 24 hours to 48 hours. In this extended scenario, the availability profiles of solar and wind power were varied between the two days to reflect more realistic renewable energy generation patterns. The simulation results show that the total electricity consumption from the grid was approximately 75.47 kWh, while the PV export was 29.97 kWh. Figure 4.50 presents the daily power consumption in the 48-hour case, and the RESs consumption behavior is shown in Fig. 4.51.

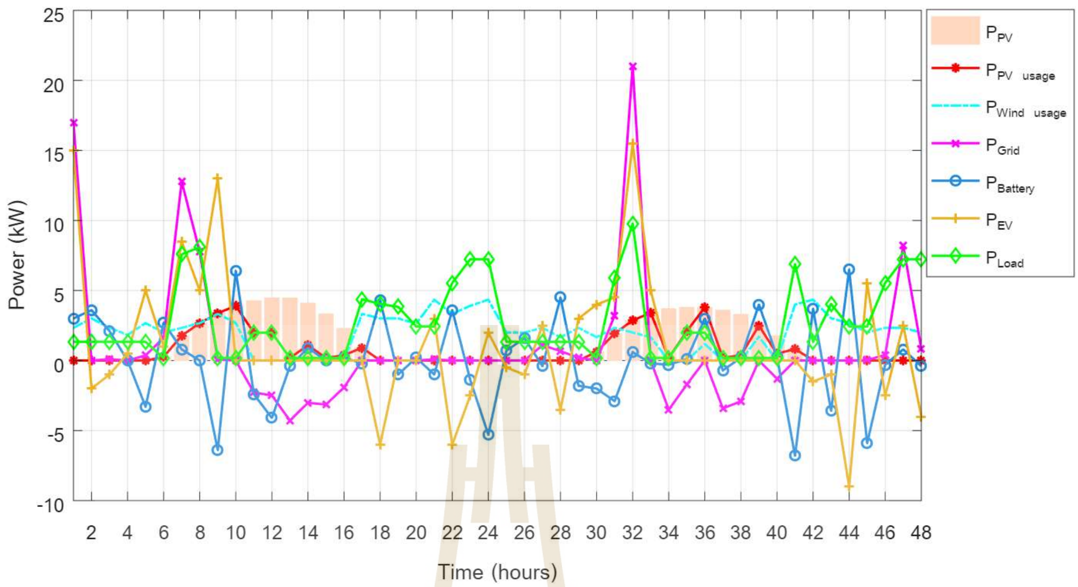


Figure. 4.50 The daily power consumption in 48 hours case

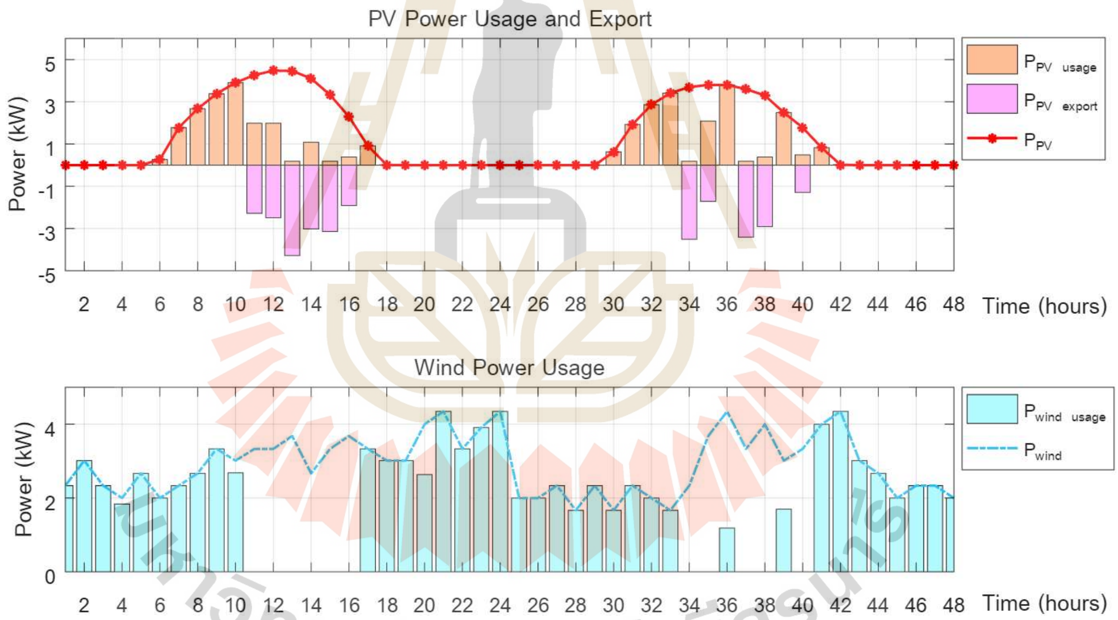


Figure. 4.51 PV power usage and export and wind power usage in 48 hours case

With the doubled time scheduling horizon, the runtime of the optimization algorithm remained approximately the same as that of the scalability test with doubled appliance load. This may be attributed to the structure and number of decision variables used in the Particle Swarm Optimization (PSO) phase. In the 48-hour scenario, the randomly generated SoC variable vector consisted of twice as many elements, potentially contributing to a slightly longer processing time. Nevertheless, the proposed algorithm remained computationally efficient and manageable. These findings suggest that the runtime is influenced not only by the number of appliances but also by the dimensionality of the decision variables.

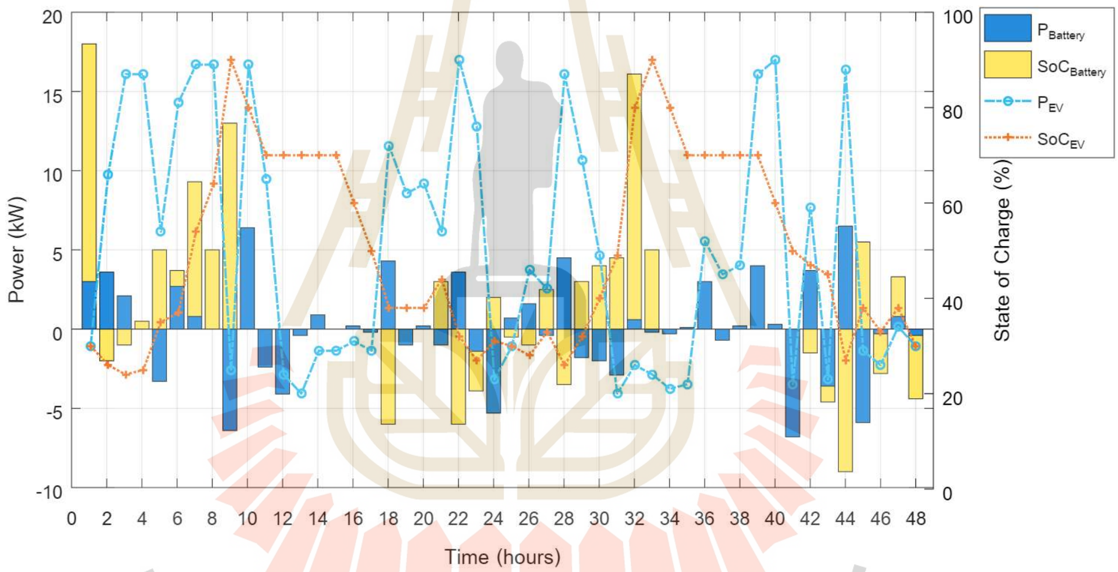


Figure. 4.52 BESS and V2H behaviours in 48 hours case

Although the proposed algorithm may require a longer runtime in larger problem sizes, it effectively reduces electricity costs and alleviates grid dependency, demonstrating its practical value for smart home energy management.

4.7 Economic Impact of the Proposed SHEMS

This section presents a preliminary economic analysis that includes the initial investment cost (IIC), estimated annual electricity cost savings (AES), and key financial indicators such as present value (PV), net present value (NPV), return on investment (ROI), and discounted payback period (DPBP). The objective is to examine whether using the hybrid PSO-LP-based SHEMS has long-term financial advantages. Table 4.9 provides a summary of the investment cost for the proposed SHEMS.

Table 4.9 Summary of the Investment Cost for the Proposed SHEMS

	Specification	Total Cost (THB)
Battery Energy Storage System	10kWh	220000
Rooftop Solar PV System	5kW	215000
Vertical-Axis Wind Turbine	5kW	150000

In this study, the total initial investment cost for this project is estimated to be approximately 585000.00 THB, which includes a 5 kW rooftop solar PV system, a vertical-axis wind turbine (VAWT), and 10 kWh BESS. It is important to note that the cost of the EV is excluded from the investment calculation, as it is assumed that the EV is already owned by the user and is utilized solely as an auxiliary energy storage unit through Vehicle-to-Home (V2H) integration. Based on the projected electricity cost savings between scheduling appliances using the proposed system and non-scheduling, annual electricity cost savings of approximately 101762.15 THB. Table 4.10 summarizes the key financial indicators, evaluated using a discount rate (DCR) ranging from 1% to 5% to reflect varying economic conditions.

Table 4.10 Economic impact on this proposed SHEMS in case IX

	discount rate (DCR)				
	1%	2%	3%	4%	5%
initial investment	585000.00 THB				
AES	101762.15 THB.				
PV	963820.27	914087.12	868051.75	825382.16	785780.32
NPV	378820.27	329087.13	283051.75	240382.16	200780.32
ROI	64.76%	56.25%	48.38%	41.09%	34.32%
DPBP	5 Years 11 Months	6 Years 2 Months	6 Years 5 Months	6 Years 8 Months	6 Years 11 Months

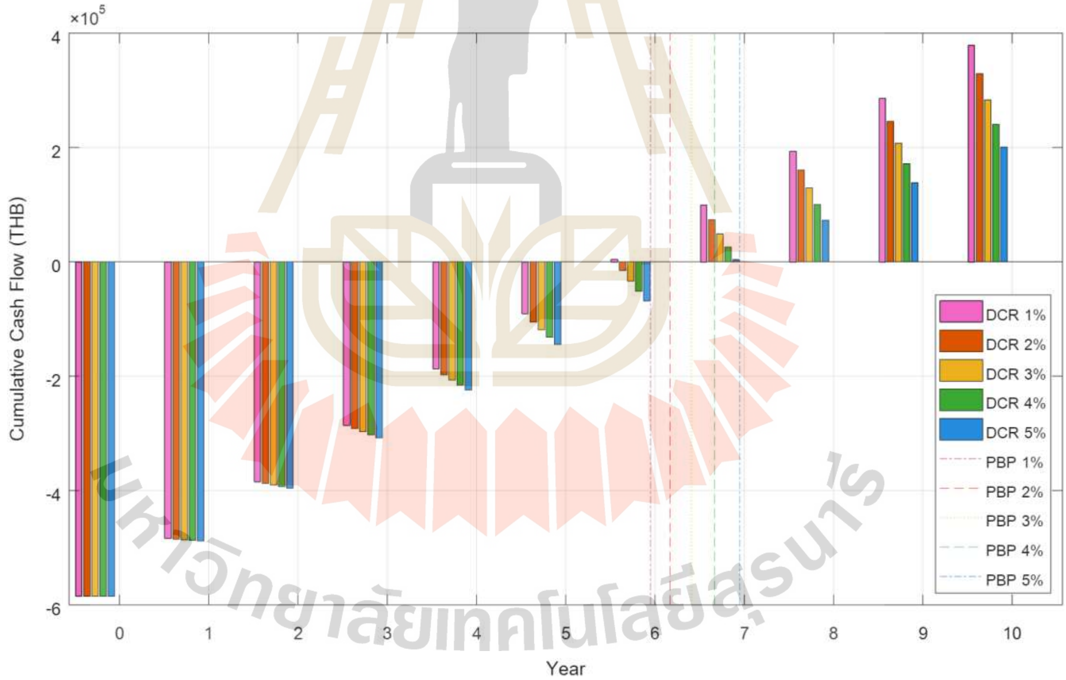


Figure 4.53 Cumulative discounted cash flow over 10 years

Using a DCR of 5%, the present value of these savings over 10 years is estimated at 785780.32 THB. Consequently, the NPV of the project is about 200780.32 THB, and a return on investment of approximately 34.32% over 10 years. Since both the NPV and ROI are positive, this indicates that the investment is economically viable under the system conditions. Figure 4.34 presents the cumulative discounted cash flow over 10 years and the DPBP with a DCR of 1% to 5%. In addition, a sensitivity analysis was conducted by varying the DCR from 1% to 5%.

The results indicate that a lower discount rate results in a higher present value of future energy savings, thus making the overall project more financially attractive and enhancing the long-term financial benefits of implementing the proposed PSO-LP-based hybrid SHEMS.

CHAPTER V
CONCLUSION

5.1 Conclusion

This thesis proposed a hybrid Particle Swarm Optimization–Linear Programming (PSO-LP) framework to address the Optimal Home Appliance Scheduling (OHAS) problem under a Time-of-Use (TOU)-based Demand Response (DR) scheme and improve smart home energy management systems (SHEMS). The proposed SHEMS allows household appliances to select their power consumption from various energy resources, including grid power, rooftop solar PV, wind turbines, Battery Energy Storage Systems (BESS), and Vehicle-to-Home (V2H) integration. The battery and V2H can charge when renewable energy sufficiently meets load consumption and discharge when renewable energy is insufficient to satisfy load demands or during peak hours. Integrating BESS and V2H made SHEMS more flexible in energy management, allowing rooftop PV to have more surplus power to feed into the grid under the household PV purchasing scheme by MEA and PEA, which can reduce household costs. The simulation results comparing appliance scheduling with non-scheduling in all scenarios demonstrated that not only was a significant reduction in daily electricity costs achieved, but the burden on the grid during the peak hour decreased by implementing the proposed hybrid PSO-LP to solve the SHEMS problem. Moreover, nine simulation scenarios were developed to investigate how different combinations of energy sources affect appliance scheduling, system flexibility, and electricity cost reduction. The results show that integrating RESs with BESS and V2H can significantly reduce grid reliance and enable surplus PV energy export in both TOU and RTP pricing schemes.

The proposed PSO-LP was benchmarked against conventional PSO, GA, and GA-LP approaches. The results confirmed that the hybrid PSO-LP consistently achieved better convergence behavior, more stable solutions, and lower electricity costs across all trials. Despite having a longer computation time, it remains acceptable for day-ahead scheduling, as the optimization can be performed in advance without affecting real-time operations. In summary, the proposed hybrid PSO-LP-based SHEMS efficiently reduces electricity costs and achieves optimal scheduling in SHEMS but also leads the way toward smarter, greener, and more cost-efficient smart homes in future smart grids.

5.2 Future Work

Although the proposed hybrid PSO-LP framework has shown strong performance in optimizing appliance scheduling and reducing electricity costs, there are still areas for future enhancement, such as RES uncertainty and battery factor. However, in reality, solar and wind power are naturally uncertain due to weather and environmental variations. The current model assumes deterministic renewable energy profiles. Therefore, incorporating uncertainty analysis for RES would enhance the adaptability of this model to real-world conditions. For the battery factor, the behaviors of batteries and electric vehicles (EVs) in this thesis are modeled under simplified assumptions. Important battery factors such as battery degradation, charging and discharging efficiency losses, and stochastic EV mobility patterns are not included. Future research could focus on developing more detailed models that capture these requirements, thereby improving both the precision and long-term practicality of the proposed smart home energy management systems.

REFERENCES

Sou, K. C., Weimer, J., Sandberg, H., and Johansson, K. H. (2011). Scheduling smart home appliances using mixed integer linear programming. *In 2011 50th IEEE conference on decision and control and European control conference* (pp. 5144-5149). IEEE. doi: 10.1109/CDC.2011.6161081

Logenthiran, T., Srinivasan, D., and Shun, T. Z. (2012). Demand side management in smart grid using heuristic optimization. *IEEE transactions on smart grid*, 3(3), 1244-1252. doi: 10.1109/TSG.2012.2195686

Ma, K., Yao, T., Yang, J., and Guan, X. (2016). Residential power scheduling for demand response in smart grid. *International Journal of Electrical Power & Energy Systems*, 78, 320-325. doi: 10.1016/j.ijepes.2015.11.099

Zhu, H., Gao, Y., Hou, Y., Wang, Z., and Feng, X. (2019). Real-time pricing considering different type of smart home appliances based on Markov decision process. *International Journal of Electrical Power & Energy Systems*, 107, 486-495. doi: 10.1016/j.ijepes.2018.12.002

Pamulapati, T., Mallipeddi, R., and Lee, M. (2020). Multi-objective home appliance scheduling with implicit and interactive user satisfaction modelling. *Applied Energy*, 267, 114690. doi: 10.1016/j.apenergy.2020.114690

Yahia, Z., & Pradhan, A. (2020). Multi-objective optimization of household appliance scheduling problem considering consumer preference and peak load reduction. *Sustainable Cities and Society*, 55, 102058. doi: 10.1016/j.scs.2020.102058

Ghole, M. S., Paliwal, P., and Thakur, T. (2023). A nowcasting central controller with continuous RTP for residential device scheduling using swap-based BFPSO. *Arabian Journal for Science and Engineering*, 48(11), 14463-14477.

Piawises, W., and Chayakulkheeree, K. (2024, March). Smart Home Energy Management Algorithm for TOU-Based Demand Response. *In 2024 12th International Electrical Engineering Congress (iEECON)* (pp. 1-5). doi: 10.1109/iEECON60677.2024.10537929.

Ullah, I., Javaid, N., Khan, Z. A., Qasim, U., Khan, Z. A., and Mehmood, S. A. (2015). An incentive-based optimal energy consumption scheduling algorithm for residential users. *Procedia computer science*, 52, 851-857. doi: 10.1016/j.procs.2015.05.142

Qayyum, F. A., Naeem, M., Khwaja, A. S., Anpalagan, A., Guan, L., and Venkatesh, B. (2015). Appliance scheduling optimization in smart home networks. *IEEE access*, 3, 2176-2190. doi: 10.1109/ACCESS.2015.2496117

Pawar, P., Sampath, S., Ghosh, T., and Vittal, K. P. (2018, December). Load scheduling algorithm design for smart home energy management system. *In 2018 IEEE 7th international conference on power and energy (PECon)* (pp. 304-309). IEEE. doi: 10.1109/PECON.2018.8684141.

Yahyaoui, I., Tadeo, F., Rocha, H., and Fiorotti, R. (2018). Optimal load scheduling of a smart home supplied by a photovoltaic grid-connected plant. IFAC-Papers On Line, 51(28), 292-296. doi: 10.1016/j.ifacol.2018.11.717

El Makroum, R., Khallaayoun, A., Lghoul, R., and Chraibi, M. (2021, April). A Linear Programming Based Load Scheduling System Considering Dynamic Pricing and Renewable Energy. *In 2021 12th International Renewable Engineering Conference (IREC)* (pp. 1-5). IEEE. doi: 10.1109/IREC51415.2021.9427821

El Makroum, R., Khallaayoun, A., Lghoul, R., Mehta, K., and Zörner, W. (2023). Home Energy Management System Based on Genetic Algorithm for Load Scheduling: A Case Study Based on Real Life Consumption Data. *Energies*, 16(6), 2698. doi: 10.3390/en16062698

Dang, T., and Ringland, K. (2012, November). Optimal load scheduling for residential renewable energy integration. *In 2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm)* (pp. 516-521). IEEE. doi: 10.1109/SmartGridComm.2012.6486037

Tsui, K. M., and Chan, S. C. (2012). Demand response optimization for smart home scheduling under real-time pricing. *IEEE Transactions on Smart Grid*, 3(4), 1812-1821. doi: 10.1109/TSG.2012.2218835

Rasheed, M. B., Javaid, N., Ahmad, A., Khan, Z. A., Qasim, U., and Alrajeh, N. (2015). An efficient power scheduling scheme for residential load management in smart homes. *Applied Sciences*, 5(4), 1134-1163. doi: 10.3390/app5041134

Shirazi, E., and Jadid, S. (2015). Optimal residential appliance scheduling under dynamic pricing scheme via HEMDAS. *Energy and Buildings*, 93, 40-49. doi: 10.1016/j.enbuild.2015.01.061

Kapoor, A., and Sharma, A. (2019). Optimal charge/discharge scheduling of battery storage interconnected with residential PV system. *IEEE Systems Journal*, 14(3), 3825-3835. doi: 10.1109/JSYST.2019.2959205

Qais, M., Loo, K. H., Hasanien, H. M., and Alghuwainem, S. (2023). Optimal Comfortable Load Schedule for Home Energy Management Including Photovoltaic and Battery Systems. *Sustainability*, 15(12), 9193. doi: 10.3390/su15129193

Lee, J. Y., and Choi, S. G. (2014, February). Linear programming based hourly peak load shaving method at home area. *In 16th international conference on advanced communication technology* (pp. 310-313). IEEE. doi: 10.1109/ICACT. 2014.6778971.

Melhem, F. Y., Grunder, O., Hammoudan, Z., & Moubayed, N. (2017, June). Optimal residential load scheduling model in smart grid environment. In *2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE*

Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe) (pp. 1-6). IEEE. doi: 10.1109/EEEIC.2017.7977436

Duman, A. C., Güler, Ö., Deveci, K., and Gönül, Ö. (2018, April). Residential load scheduling optimization for demand-side management under time-of-use rate. *In 2018 6th International Istanbul Smart Grids and Cities Congress and Fair (ICSG)* (pp. 193-196). IEEE. doi: 10.1109/SGCF.2018.8408971

Hou, X., Wang, J., Huang, T., Wang, T., and Wang, P. (2019). Smart home energy management optimization method considering energy storage and electric vehicle. *IEEE access*, 7, 144010-144020. doi: 10.1109/ACCESS.2019.2944878

Singh, P., Tayal, N., Verma, Y. P., and Singh, B. (2019, March). Optimum scheduling of residential appliances along with the management of distributed energy resources using mixed integer linear programming. *In 2019 IEEE 5th International Conference for Convergence in Technology (I2CT)* (pp. 1-6). IEEE. doi: 10.1109/I2CT45611.2019.9033899

Singh, P., Dhundhara, S., Verma, Y. P., and Tayal, N. (2021). Optimal battery utilization for energy management and load scheduling in smart residence under demand response scheme. *Sustainable Energy, Grids and Networks*, 26, 100432. doi: 10.1016/j.segan.2021.100432

Rehman, A. U., Wadud, Z., Elavarasan, R. M., Hafeez, G., Khan, I., Shafiq, Z., and Alhelou, H. H. (2021). An optimal power usage scheduling in smart grid integrated with renewable energy sources for energy management. *IEEE Access*, 9, 84619-84638. doi: 10.1109/ACCESS.2021.3087321.

Chreim, B., Esseghir, M., and Merghem-Boulahia, L. (2022). LOSISH—LOad Scheduling In Smart Homes based on demand response: Application to smart grids. *Applied Energy*, 323, 119606. doi: 10.1016/j.apenergy.2022.119606

Kanakadhurga, D., and Prabaharan, N. (2024). Smart home energy management using demand response with uncertainty analysis of electric vehicle in the presence of renewable energy sources. *Applied Energy*, 364, 123062. doi: 10.1016/j.apenergy. 2024.123062

Dantzig, G. B. (1963). Linear programming and extensions. Princeton University Press.

Winston, W. L. (2004). *Operations research: applications and algorithm*. Thomson Learning, Inc.

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of ICNN'95-international conference on neural networks* (Vol. 4, pp. 1942-1948). ieee.

Shi, Y. (2001). Particle swarm optimization: developments, applications and resources. In *Proceedings of the 2001 congress on evolutionary computation (IEEE Cat. No. 01TH8546)* (Vol. 1, pp. 81-86). IEEE.

Short, W., Packey, D. J., & Holt, T. (1995). *A manual for the economic evaluation of energy efficiency and renewable energy technologies* (No. NREL/TP-462-5173). National Renewable Energy Lab.(NREL), Golden, CO (United States).

Boardman, A. E., Greenberg, D. H., Vining, A. R., & Weimer, D. L. (2020). Efficiency without apology: consideration of the marginal excess tax burden and distributional impacts in benefit–cost analysis. *Journal of Benefit-Cost Analysis*, *11*(3), 457-478.

Saber, A. Y., & Venayagamoorthy, G. K. (2010). Plug-in vehicles and renewable energy sources for cost and emission reductions. *IEEE Transactions on Industrial electronics*, *58*(4), 1229-1238. doi: 10.1109/TIE.2010.2047828

Energy Sector Management Assistance Program (ESMAP). (2019). global solar atlas. Retrieved from https://globalsolaratlas.info/map?c=13.721173,100.63366 7,10&r=THA:THA.3_1

Weather Spark (2018). April 2024 Weather History in Bangkok. Retrieved from https://weatherspark.com/h/m/113416/2024/4/Historical-Weather-in-April-2024-in-Bangkok-Thailand

Siano, P. (2014). Demand response and smart grids—A survey. *Renewable and sustainable energy reviews*, *30*, 461-478. doi: 10.1016/j.rser.2013.10.022

Qdr, Q. J. U. D. E. (2006). *Benefits of demand response in electricity markets and recommendations for achieving them*. US Dept. Energy, Washington, DC, USA, Tech. Rep, 2006, 95.

Metropolitan Electricity Authority (MEA). (2023, August 8). *Tariff Calculation*: Type 1 Residential Service. Retrieved from https://www.mea.or.th/our-services/tariff-calculation/other/D5xEaEwgU

Metropolitan Electricity Authority (MEA). (2023, March 21). *Household's Solar Project*. Retrieved from https://www.mea.or.th/other-services/electricity-producers/Wkbfgxgy/Sc02OdhGF

APPENDIX

APPENDIX A

The power balance in every case scenario

Appendix A represents the daily power balance of all energy resources, including grid power, rooftop solar PV, wind turbines, Battery Energy Storage Systems (BESS), and Vehicle-to-Home (V2H) integration. The table below reveals power consumption from each energy source to satisfy load demand in each time *'t'*. The power balance in each case study is as follows:

Case I: Appliance scheduling using grid power only.

Table A.1 The power balance of each time slot case I

Power / Time (hours)	P_{grid} (kW)	$P_{PV,usage}$ (kW)	$P_{wind,usage}$ (kW)	P_B (kW)	SoC_B (%)	P_{EV} (kW)	SoC_{EV} (%)	P_{Load} (kW)
1	0.185	0	0	0	0	0	0	0.185
2	0.185	0	0	0	0	0	0	0.185
3	0.185	0	0	0	0	0	0	0.185
4	0.185	0	0	0	0	0	0	0.185
5	0.185	0	0	0	0	0	0	0.185
6	3.185	0	0	0	0	0	0	3.185
7	4.585	0	0	0	0	0	0	4.585
8	7.085	0	0	0	0	0	0	7.085
9	1.985	0	0	0	0	0	0	1.985
10	1.885	0	0	0	0	0	0	1.885
11	1.985	0	0	0	0	0	0	1.985
12	0.185	0	0	0	0	0	0	0.185
13	1.335	0	0	0	0	0	0	1.335
14	1.335	0	0	0	0	0	0	1.335
15	1.335	0	0	0	0	0	0	1.335
16	1.335	0	0	0	0	0	0	1.335
17	3.835	0	0	0	0	0	0	3.835
18	4.035	0	0	0	0	0	0	4.035
19	6.535	0	0	0	0	0	0	6.535
20	2.435	0	0	0	0	0	0	2.435
21	2.435	0	0	0	0	0	0	2.435
22	7.235	0	0	0	0	0	0	7.235
23	5.535	0	0	0	0	0	0	5.535
24	5.535	0	0	0	0	0	0	5.535

Case II: Appliance scheduling with power from the grid and BESS.

Table A.2 The power balance of each time slot in case II

Power / Time (hours)	P_{grid} (kW)	$P_{PV,usage}$ (kW)	$P_{wind,usage}$ (kW)	P_B (kW)	SoC_B (%)	P_{EV} (kW)	SoC_{EV} (%)	P_{Load} (kW)
1	4.335	0	0	3	30	0	0	1.335
2	3.635	0	0	2.3	53	0	0	1.335
3	1.835	0	0	-2.5	28	0	0	4.335
4	0.535	0	0	-0.8	20	0	0	1.335
5	4.435	0	0	0.1	21	0	0	4.335
6	10.085	0	0	6.9	90	0	0	3.185
7	2.885	0	0	-6.9	21	0	0	9.785
8	15.285	0	0	6	81	0	0	9.285
9	0	0	0	-3.7	44	0	0	3.685
10	0	0	0	-0.2	42	0	0	0.185
11	0	0	0	-0.7	35	0	0	0.185
12	0.485	0	0	-1.5	20	0	0	1.985
13	9.385	0	0	6.7	87	0	0	2.685
14	0	0	0	-0.6	81	0	0	0.185
15	0	0	0	-6.1	20	0	0	2.685
16	9.685	0	0	7	90	0	0	2.685
17	0	0	0	-0.2	88	0	0	0.185
18	0	0	0	-1.4	74	0	0	1.335
19	0	0	0	-2.7	47	0	0	2.635
20	0	0	0	-2.5	22	0	0	2.435
21	1.135	0	0	-0.2	20	0	0	1.335
22	3.635	0	0	1.1	31	0	0	2.535
23	1.535	0	0	-1	21	0	0	2.535
24	3.435	0	0	0.9	30	0	0	2.535

Case III: Appliance scheduling with power from the grid and V2H.

Table A.3 The power balance of each time slot in case III

Power / Time (hours)	P_{grid} (kW)	$P_{PV,usage}$ (kW)	$P_{wind,usage}$ (kW)	P_B (kW)	SoC_B (%)	P_{EV} (kW)	SoC_{EV} (%)	P_{Load} (kW)
1	16.335	0	0	0	0	15	30	1.335
2	3.335	0	0	0	0	-1	28	4.335
3	3.335	0	0	0	0	2	32	1.335
4	11.335	0	0	0	0	10	52	1.335
5	16.335	0	0	0	0	12	76	4.335
6	0.685	0	0	0	0	-2.5	71	3.185
7	15.085	0	0	0	0	7.5	86	7.585
8	13.485	0	0	0	0	2	90	11.485
9	3.685	0	0	0	0	0	90	3.685
10	0.185	0	0	0	0	-5	80	0.185
11	1.985	0	0	0	0	-5	70	1.985
12	0.185	0	0	0	0	0	70	0.185
13	2.685	0	0	0	0	0	70	2.685
14	0.185	0	0	0	0	0	70	0.185
15	2.685	0	0	0	0	0	70	2.685
16	2.685	0	0	0	0	-5	60	2.685
17	0.185	0	0	0	0	-5	50	0.185
18	0	0	0	0	0	-1.5	47	1.335
19	0	0	0	0	0	-2.5	42	2.035
20	0	0	0	0	0	-2.5	37	2.435
21	0	0	0	0	0	-2	33	1.935
22	3.535	0	0	0	0	1	35	2.535
23	2.535	0	0	0	0	0	35	2.535
24	0.035	0	0	0	0	-2.5	30	2.535

Case IV: Appliance scheduling with power from the grid, PV, and BESS.

Table A.4 The power balance of each time slot in case IV

Power / Time (hours)	P_{grid} (kW)	$P_{PV,usage}$ (kW)	$P_{wind,usage}$ (kW)	P_B (kW)	SoC_B (%)	P_{EV} (kW)	SoC_{EV} (%)	P_{Load} (kW)
1	4.335	0	0	3	30	0	0	1.335
2	4.335	0	0	3	60	0	0	1.335
3	3.135	0	0	1.8	78	0	0	1.335
4	0.935	0	0	-3.4	44	0	0	4.335
5	1.935	0	0	-2.4	20	0	0	4.335
6	4.219	0.266	0	1.3	33	0	0	3.185
7	7.9085	1.7765	0	2.1	54	0	0	7.585
8	5.7965	2.6885	0	-3	24	0	0	11.485
9	0	3.3915	0	-0.3	21	0	0	3.685
10	-0.0195	3.885	0	3.7	58	0	0	0.185
11	-4.071	0.185	0	-0.2	56	0	0	0.185
12	-2.48	1.985	0	-0.3	53	0	0	1.985
13	-1.761	2.685	0	-0.2	51	0	0	2.685
14	-0.1905	3.885	0	3.7	88	0	0	0.185
15	-0.6305	2.685	0	-0.2	86	0	0	2.685
16	0	2.2895	0	-0.4	82	0	0	2.685
17	0.0825	0.9025	0	0.8	90	0	0	0.185
18	0.0255	0.0095	0	-1.3	77	0	0	1.335
19	0.235	0	0	-1.8	59	0	0	2.035
20	0.335	0	0	-2.1	38	0	0	2.435
21	0.135	0	0	-1.8	20	0	0	1.935
22	5.735	0	0	3.2	52	0	0	2.535
23	0.535	0	0	-2	32	0	0	2.535
24	2.335	0	0	-0.2	30	0	0	2.535

Case V: Appliance scheduling with power from the grid, PV, and V2H.

Table A.5 The power balance of each time slot in case I

Power / Time (hours)	P_{grid} (kW)	$P_{PV,usage}$ (kW)	$P_{wind, usage}$ (kW)	P_B (kW)	SoC_B (%)	P_{EV} (kW)	SoC_{EV} (%)	P_{Load} (kW)
1	16.335	0	0	0	0	15	30	1.335
2	11.335	0	0	0	0	10	50	1.335
3	6.835	0	0	0	0	5.5	61	1.335
4	17.335	0	0	0	0	13	87	4.335
5	5.335	0	0	0	0	1	89	4.335
6	3.419	0.266	0	0	0	0.5	90	3.185
7	3.5085	1.7765	0	0	0	-2.5	85	7.785
8	11.0965	2.6885	0	0	0	2.5	90	11.285
9	0.2935	3.3915	0	0	0	0	90	3.685
10	-3.7195	0.185	0	0	0	-5	80	0.185
11	-2.271	1.985	0	0	0	-5	70	1.985
12	-4.28	0.185	0	0	0	0	70	0.185
13	-1.761	2.685	0	0	0	0	70	2.685
14	-3.8905	0.185	0	0	0	0	70	0.185
15	-0.6305	2.685	0	0	0	0	70	2.685
16	0.3955	2.2895	0	0	0	-5	60	2.685
17	-0.7175	0.185	0	0	0	-5	50	0.185
18	0	0.0095	0	0	0	-1.5	47	1.335
19	0	0	0	0	0	-3.5	40	2.035
20	0	0	0	0	0	-6	28	2.435
21	0	0	0	0	0	-4	20	1.935
22	5.535	0	0	0	0	3	26	2.535
23	5.535	0	0	0	0	3	32	2.535
24	1.535	0	0	0	0	-1	30	2.535

Case VI: Appliance scheduling with power from the grid, PV, BESS, and V2H.

Table A.6 The power balance of each time slot in case VI

Power / Time (hours)	P_{grid} (kW)	$P_{PV,usage}$ (kW)	$P_{wind,usage}$ (kW)	P_B (kW)	SoC_B (%)	P_{EV} (kW)	SoC_{EV} (%)	P_{Load} (kW)
1	19.335	0	0	3	30	15	30	1.335
2	5.335	0	0	6	90	-5	20	4.335
3	7.035	0	0	-2.8	62	8.5	37	1.335
4	7.135	0	0	-3.7	25	9.5	56	1.335
5	18.235	0	0	5.9	84	8	72	4.335
6	6.219	0.266	0	0.3	87	3	78	3.185
7	9.6085	1.7765	0	0.3	90	3.5	85	7.585
8	5.4965	2.6885	0	-5.3	37	2	89	11.485
9	0	3.3915	0	-0.8	29	0.5	90	3.685
10	-3.7195	0.185	0	-0.2	27	-5	80	0.185
11	-2.271	1.985	0	-0.2	25	-5	70	1.985
12	-0.28	4.185	0	4	65	0	70	0.185
13	-1.761	2.685	0	-0.2	63	0	70	2.685
14	-3.8905	0.185	0	-0.6	57	0	70	0.185
15	-0.0305	3.285	0	0.6	63	0	70	2.685
16	-0.0045	2.2895	0	-0.4	59	-5	60	2.685
17	-0.7175	0.185	0	-0.3	56	-5	50	0.185
18	0	0.0095	0	-3.6	20	2	54	1.335
19	0	0	0	6.5	85	-9.5	35	2.635
20	0	0	0	-4	45	2	39	1.835
21	0.035	0	0	0.6	51	-2.5	34	1.935
22	0.035	0	0	-2	31	-0.5	33	2.535
23	3.435	0	0	3.4	65	-2.5	28	2.535
24	0.035	0	0	-3.5	30	1	30	2.535

Case VII: Appliance scheduling with power from the grid, PV, wind, and BESS.

Table A.7 The power balance of each time slot in case VII

Power / Time (hours)	P_{grid} (kW)	$P_{PV,usage}$ (kW)	$P_{wind,usage}$ (kW)	P_B (kW)	SoC_B (%)	P_{EV} (kW)	SoC_{EV} (%)	P_{Load} (kW)
1	1.667662	0	2.667338	3	30	0	0	1.335
2	0.200723	0	2.334277	1.2	42	0	0	1.335
3	0.636634	0	1.998366	1.3	55	0	0	1.335
4	0.800723	0	2.334277	-1.2	43	0	0	4.335
5	2.436634	0	1.998366	0.1	44	0	0	4.335
6	4.151662	0.266	2.667338	3.9	83	0	0	3.185
7	1.40766	1.7765	2.50084	-5.8	25	0	0	11.485
8	2.184504	2.6885	3.011996	0.3	28	0	0	7.585
9	0.026162	3.3915	2.667338	2.4	52	0	0	3.685
10	-3.6195	0.285	0	0.1	53	0	0	0.185
11	-4.071	0.185	0	0	53	0	0	0.185
12	-2.48	1.985	0	-0.3	50	0	0	1.985
13	-1.761	2.685	0	0	50	0	0	2.685
14	-3.8905	0.185	0	-0.4	46	0	0	0.185
15	-0.6305	2.685	0	-0.7	39	0	0	2.685
16	-2.23511	0.05439	3.33061	0.7	46	0	0	2.685
17	-0.7175	0.185	0	-0.5	41	0	0	0.185
18	-0.0095	0	3.235	1.9	60	0	0	1.335
19	0	0	2.635	-1.1	49	0	0	2.635
20	0	0	2.435	-0.9	40	0	0	2.435
21	0	0	2.335	1	50	0	0	1.335
22	0	0	2.535	-0.1	49	0	0	2.535
23	0	0	2.935	0.4	53	0	0	2.535
24	0	0	2.535	-2.3	30	0	0	2.535

Case VIII: Appliance scheduling with power from the grid, PV, wind, and V2H.

Table A.8 The power balance of each time slot in case VIII

Power / Time (hours)	P_{grid} (kW)	$P_{PV,usage}$ (kW)	$P_{wind,usage}$ (kW)	P_B (kW)	SoC_B (%)	P_{EV} (kW)	SoC_{EV} (%)	P_{Load} (kW)
1	13.66766	0	2.667338	0	0	15	30	1.335
2	0.000723	0	2.334277	0	0	1	32	1.335
3	1.836634	0	1.998366	0	0	2.5	37	1.335
4	5.000723	0	2.334277	0	0	3	43	4.335
5	18.33663	0	1.998366	0	0	16	75	4.335
6	5.251662	0.266	2.667338	0	0	5	85	3.185
7	2.50766	1.7765	2.50084	0	0	-3	79	9.785
8	9.084504	2.6885	3.011996	0	0	5.5	90	9.285
9	0	3.3915	0.2935	0	0	0	90	3.685
10	-3.7195	0.185	0	0	0	-5	80	0.185
11	-2.271	1.985	0	0	0	-5	70	1.985
12	-4.28	0.185	0	0	0	0	70	0.185
13	-1.761	2.685	0	0	0	0	70	2.685
14	-3.8905	0.185	0	0	0	0	70	0.185
15	-0.6305	2.685	0	0	0	0	70	2.685
16	0	2.2895	0.3955	0	0	-5	60	2.685
17	-0.7175	0.185	0	0	0	-5	50	0.185
18	-0.0095	0	1.535	0	0	-2	46	1.535
19	0	0	2.835	0	0	1	48	1.835
20	0	0	2.435	0	0	-2.5	43	2.435
21	0	0	1.935	0	0	-1	41	1.935
22	0	0	2.535	0	0	-1.5	38	2.535
23	0	0	2.535	0	0	-2	34	2.535
24	0	0	2.535	0	0	-2	30	2.535

Case IX: Appliance scheduling with power from the grid, PV, wind, BESS, and V2H.

Table A.9 The power balance of each time slot in case IX

Power / Time (hours)	P_{grid} (kW)	$P_{PV,usage}$ (kW)	$P_{wind,usage}$ (kW)	P_B (kW)	SoC_B (%)	P_{EV} (kW)	SoC_{EV} (%)	P_{Load} (kW)
1	16.66766	0	2.667338	3	30	15	30	1.335
2	4.900723	0	2.334277	5.9	89	0	30	1.335
3	3.036634	0	1.998366	-0.8	81	4.5	39	1.335
4	6.200723	0	2.334277	-2.8	53	10	59	1.335
5	3.136634	0	1.998366	-1.2	41	5	69	1.335
6	4.451662	0.266	2.667338	4.7	88	2.5	74	0.185
7	2.30766	1.7765	2.50084	-6.8	20	7.5	89	5.885
8	0.384504	2.6885	3.011996	1.1	31	-6.5	76	11.485
9	0.026162	3.3915	2.667338	-1.1	20	7	90	0.185
10	-1.9195	1.985	0	0	20	-5	80	1.985
11	-2.071	2.185	0	0.2	22	-5	70	1.985
12	-3.98	0.485	0	0.3	25	0	70	0.185
13	-4.261	0.185	0	0	25	0	70	0.185
14	-3.8905	0.185	0	0	25	0	70	0.185
15	-3.1305	0.185	0	-0.5	20	0	70	0.185
16	-2.1045	0.185	0	0	20	-5	60	0.185
17	-0.9025	0	2.085	0.2	22	-5	50	1.885
18	0	0.0095	4.34424	5.9	81	-9	32	6.335
19	0	0	3.504364	-3.7	44	-3	26	5.135
20	0	0	3.171303	2.8	72	-3	20	2.435
21	0	0	3.135	1.8	90	0	20	1.335
22	4.256882	0	3.678118	-2.6	64	5	30	5.535
23	1.889943	0	3.345057	-1.8	46	1.5	33	5.535
24	0.789943	0	3.345057	-1.6	30	-1.5	30	7.235

APPENDIX B

List of publications

W. Piawises and K. Chayakulkheeree (2024), Smart Home Energy Management Algorithm for TOU-Based Demand Response, 2024 International Electrical Engineering Congress (iEECON2024), Pattaya, Thailand.

W. Piawises and K. Chayakulkheeree (2025), Intelligent Energy Management for Prosumer Smart Home System with Multi Energy Resources. International Journal of Intelligent Engineering and Systems.

2024 International Electrical Engineering Congress (iEECON 2024)
March 6-8, 2024, Pattaya Chonburi, THAILAND

Smart Home Energy Management Algorithm for TOU-based Demand Response

Wilawan Piawises, Keerati Chayakulkheeree
School of Electrical Engineering
Institute of Engineering,
Suranaree University of Technology
Nakhonratchasima, Thailand
pws.wilawan@gmail.com, keerati.ch@sut.ac.th

***Abstract*— This paper proposes a linear programming (LP) method approach for optimal scheduling of the load of electrical appliances in the residential to respond to time-of-use (TOU) electricity prices at various periods. Appliance scheduling by TOU-based Demand Response (ASTDR) can give electricity consumers a benefit. Appliance loads should be shifted from the high electricity price periods not only to minimize the total electricity cost per day but also to reduce peak load demand by controlling the shiftable loads. The simulation result shows that the proposed method can efficiently reduce electricity costs and also help reduce peak demand from the grid during the peak hour by implementing ASTDR.**

Keywords*— *Demand Response, Home Energy Management, Load scheduling, Time of Use (TOU)

I. Introduction

Nowadays, the electricity power demand and consumption are increasing rapidly worldwide. This increment causes many problems, such as increasing carbon emissions, deficiencies in electric service reliability, increased disturbances, power quality issues, and power system collapse caused by high peak loads that lead to blackouts [1–2]. Presently, most of the current power system is centralized power generation with unidirectional power flow that is moving into smart grid (SG) systems [3]. Demand-side management (DSM) strategies play a crucial role in the SG concept [4]. Demand Response (DR) is a part of the demand-side management (DSM) technique that encourages smart homes to modify the pattern of appliance operation by shifting the appliances from peak hours to off-peak hours to minimize their electricity costs [5]. That can be called part of a home energy management system (HEMS). HEMS are the main tools for DSM, which provide significant opportunities for both consumers and energy traders [6].

Both HEMS and DR are important parts of pushing the SG to come true in the power system. in the future, so electricity consumers can get the most benefit from the demand response process. Load scheduling is one of the HEMS tools that manages the load of electrical appliances in the home to respond to the electricity price at various times. When the electricity price is high, the low-priority loads should be shifted to the period when the electricity price is lower [7]. Therefore, not only does it reduce electricity costs, but it also helps reduce power consumption during peak demand periods, which is very beneficial to managing electrical energy crises and easily improves the stability of electric power both in the short and long term [8].

There is a lot of research on load scheduling. Numerous researchers have developed optimization models to solve the energy management problem in smart grids, especially for residential consumers [3]. In Ref. [3], an optimal residential load scheduling model in a smart grid environment is proposed by using mixed integer linear programming (MILP). In Ref. [5], each appliance can be scheduled by using binary particle swarm optimization with demand response (DR) implementation based on real-time pricing (RTP). In the paper [9], the authors presented the appliance load scheduling using linear programming (LP) based dynamic pricing and renewable energy. While in [10], a MILP-based smart appliance scheduling framework is proposed based on actual spot prices, the MILP technique is used in papers [11–12] to schedule residential appliances based on the TOU rate. Nonetheless, LP is both explicit to understand and to operate to solve energy management problems.

In this paper, Appliance Scheduling by TOU-based Demand Response (ASTDR) is presented. First, that represents the load scheduling of each appliance in a smart home by TOU-based demand response using the linear programming (LP) method. Then, compare the shifted power consumption of appliances with that of not shifting. The proposed method resulted in minimizing the electricity cost per day for consumers.

The organization of this paper is as follows: In Section II, we describe the proposed method for scheduling power consumption appliances in homes and minimizing electricity costs using the LP technique. Section III explains the LP method for ASTDR. The simulation results compare power consumption costs between appliances that are scheduled and not scheduled in Section IV. Lastly, we conclude in Section V.

II. Applilance Scheduling Model

A. Appliances Data

The future smart home will include a large number of electrical appliances. In this paper, we propose some electrical home appliances that can be found in every home. Appliances can be divided into two types: shiftable and unshiftable. Unshiftable appliances have to always be on or must be non-changed time for operation. For Shiftable, the appliance can designate a time to operate. Each electrical appliance has a specific power rating (kW), a duration of operation (hours), and a possible range of starting and finishing times (hours) [3, 5]. Table I presents the appliance data.

2024 12th International Electrical Engineering Congress (iEECON) | 979-8-3503-8359-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/IEECON60677.2024.10537929

2024 International Electrical Engineering Congress (iEECON 2024)
March 6-8, 2024, Pattaya Chonburi, THAILAND

TABLE I. THE APPLIANCE DATA

No.	Appliances	Power rating (kW)	Duration of operation (hours)	Starting time (hours)	Ending time (hours)
		Unshiftable			
1	Refrigerator	0.18	24	0	24
2	sensor	0.01	24	0	24
3	Air conditioner	1.15	12	12	24
4	Illumination	0.50	5	18	24
		Shiftable			
5	Dish washer	1.70	1	8	22
6	Washing machine	1.80	2	8	12
7	Microwave	1.70	1	7	10
8	Cooker hood	0.20	1	16	19
9	Iron	2.70	2	5	21
10	Laptop	0.10	3	13	24
11	Vacuum cleaner	2.00	1	7	22
12	Other load	3.00	5	0	24

Units of electricity are measured in kWh and the price for a unit of electricity in Thailand is shown in Baht per kilowatt hour (B/kWh).

B. Time of Use (TOU)

Time-of-use rates have a common goal to incentivize customers to consume energy when the cost of generating electricity is cheap (off-peak hours) and to disincentive energy consumption when the cost of generating electricity is high (peak hours). The Time of Use Tariff in Thailand is an electricity tariff that reflects the cost of producing electricity divided into two time periods:

Peak: 09.00 a.m.–10.00 p.m., Monday–Friday

Off-Peak: 10:00 p.m.–9:00 a.m. Monday–Friday

for residential, time of use rates (TOU) at voltage levels lower than 22 kV. Energy charge when Peak is 5.7982 B/kWh and Off-Peak is 2.6369 B/kWh.

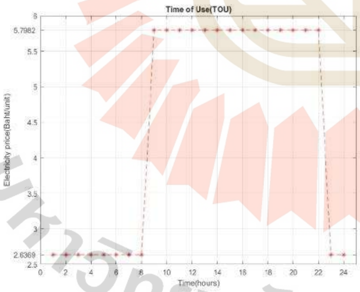


Fig. 1 Hourly electricity time-of-use tariff in Thailand

C. Appliance scheduling

This paper presents linear programming (LP)-based appliance scheduling by TOU-based Demand Response (ASTDR) that focuses on shiftable appliances.

Using LP to solve ASTRD gives proper hours to operate appliances that minimize electricity costs. then ASTDR should not only avoid manipulating to operate appliances during peak hours but also shift appliances to off-peak hours that have lower electricity prices. ASTDR proposes calculating the operating costs in a day for each appliance as follows:

$$\mathbf{AOC_i} = PR_i \times \mathbf{TR_t}. \tag{1}$$

Where,

$\mathbf{AOC_i} \quad = [AOC_i^1, AOC_i^2, AOC_i^3, \dots, AOC_i^{24}]_{1\times 24}$,

$\mathbf{TR_t} \quad = [TR_1, TR_2, TR_3, \dots, TR_{24}]_{1\times 24}$,

for *i = 1, 2, 3, …, NA*, and time *'t'* for *t = 1, 2, 3, …, 24* hours.

AOC_i^t is the electricity cost for an *'i'* appliance when it is operated at time *'t'*,

TR_t is a time-of-use rate (B/kWh) at time *'t'*, and

PR_i is the power rating (kW) of the *'i'* appliance.

From equation (1), we comprehend all possibilities of operating each appliance with TOU rate prices and use this information to locate the proper time to ON any appliance in Section III.

III. LP-Based ASTDR Problem Formulation

A. ASTDR Objective function

This work represents the scheduling of each appliance in a consumer home based on the TOU using LP-based optimization. The objective of ASTDR is to minimize the electricity cost for consumers. The objective function is given below,

$$\textbf{Electricity cost} = \mathbf{f} \cdot \mathbf{x}^\mathbf{T}. \tag{2}$$

Where,

$\mathbf{f} \quad = [\mathbf{AOC_1}, \mathbf{AOC_2}, \mathbf{AOC_3}, \dots, \mathbf{AOC_{NA}}]_{1\times(24\times \mathrm{NA})}$,

$\mathbf{x} \quad = [\mathbf{PH_1}, \mathbf{PH_2}, \mathbf{PH_3}, \dots, \mathbf{PH_{NA}}]_{1\times(24\times \mathrm{NA})}$,

$\mathbf{PH_i} \quad = [Ph_i^1, Ph_i^2, Ph_i^3, \dots, Ph_i^{24}]_{1\times 24}$,

for *i = 1, 2, 3, …, NA*, when,

Ph_i^t is the optimization variable, which is the proper duration to operate an *'i'* appliance at a time *'t'* for *t = 1, 2, 3, …, 24* hours.

B. Constraints and boundary

ASTDR uses LP to solve a simple linear program with linear inequalities, linear equalities, and bounds.

- Boundary

In this problem, the bound is the ON/OFF status of the appliance per day. That '1' is denoted as ON and '0' is denoted as OFF. Therefore,

$$Ph_i^t \in \{0, 1\}. \tag{3}$$

For *i = 1, 2, 3, …, NA*, and time *t = 1, 2, 3, …, 24* hours.

- Equality constraints

These constraints are used to locate a proper duration to turn on or off the appliance in all possibilities within 24 hours of operating, as below:

$$\mathbf{AO_i} \cdot \mathbf{PH_i} = DO_i. \tag{4}$$

2024 International Electrical Engineering Congress (iEECON 2024)
March 6-8, 2024, Pattaya Chonburi, THAILAND

Where,

$\mathbf{AO_i} \;= [AO_i^1, AO_i^2, AO_i^3, \ldots, AO_i^{24}]_{1\times 24}$, for $i = 1, 2, \ldots, NA$.

AO_i^t is an ON condition with a range of starting and finishing times (hours) for each *'i'* appliance at a time *'t'* for $t = 1, 2, 3, \ldots, 24$ hours, and

DO_i is the duration of operation (hours) for *'i'* appliance.

- Inequality constraints

The inequality constraints are used to find the minimum electricity cost of operating any *'i'* appliance as follows:

$$\mathbf{AC_i} \cdot \mathbf{PH_i} \le DC_i. \tag{5}$$

Where,

$\mathbf{AC_i} \;= [AC_i^1, AC_i^2, AC_i^3, \ldots, AC_i^{24}]_{1\times 24}$, for $i = 1, 2, \ldots, NA$.

AC_i^t is AOC_i^t multiplied by AC_i^t Therefore, AC_i^t is the *'i'* appliance operating cost at time *'t'* for $t = 1, 2, 3, \ldots, 24$ hours, and

DC_i is the minimum AOC_i multiplied by the duration of operation, Then DC_i is the minimum an *'i'* appliance's daily operating cost.

In order to obtain the most suitable hours for scheduling the load of each electrical appliance, it is necessary to set the above-mentioned constraints so that LP can efficiently solve the ASTDR problem and locate the proper duration to operate each appliance in 24 hours. The ASTDR problem computational procedure can be illustrated as shown in Fig. 2.

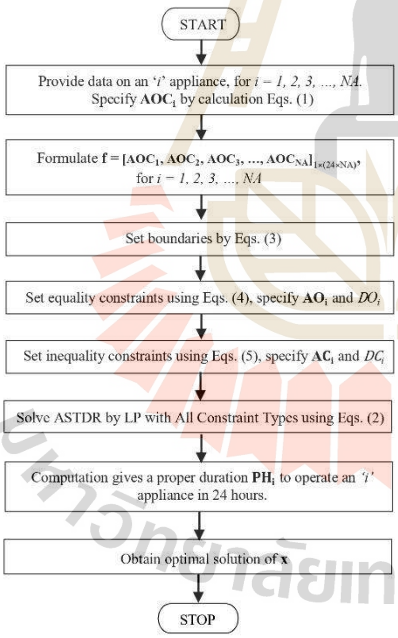


Fig. 2 Flowchart of the LP based ASTDR

IV. Simulation Results

From the appliance data in Section II, we obtain the appliance operating cost for all appliances in 24 hours (AOC_i) in Table II.

TABLE II. THE APPLIANCE'S DAILY OPERATING COST

Appli-ances / Time (Hours)	The electricity cost (Baht)											
	1	2	3	4	5	6	7	8	9	10	11	12
1	0.4746	0.0264	3.0324	1.3185	4.4827	4.7464	4.4827	0.5274	7.1196	0.2637	5.2738	7.9107
2	0.4746	0.0264	3.0324	1.3185	4.4827	4.7464	4.4827	0.5274	7.1196	0.2637	5.2738	7.9107
3	0.4746	0.0264	3.0324	1.3185	4.4827	4.7464	4.4827	0.5274	7.1196	0.2637	5.2738	7.9107
4	0.4746	0.0264	3.0324	1.3185	4.4827	4.7464	4.4827	0.5274	7.1196	0.2637	5.2738	7.9107
5	0.4746	0.0264	3.0324	1.3185	4.4827	4.7464	4.4827	0.5274	7.1196	0.2637	5.2738	7.9107
6	0.4746	0.0264	3.0324	1.3185	4.4827	4.7464	4.4827	0.5274	7.1196	0.2637	5.2738	7.9107
7	0.4746	0.0264	3.0324	1.3185	4.4827	4.7464	4.4827	0.5274	7.1196	0.2637	5.2738	7.9107
8	0.4746	0.0264	3.0324	1.3185	4.4827	4.7464	4.4827	0.5274	7.1196	0.2637	5.2738	7.9107
9	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
10	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
11	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
12	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
13	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
14	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
15	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
16	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
17	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
18	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
19	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
20	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
21	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
22	1.0437	0.0580	6.6679	2.8991	9.8569	10.437	9.8569	1.1596	15.655	0.5798	11.596	17.395
23	0.4746	0.0264	3.0324	1.3185	4.4827	4.7464	4.4827	0.5274	7.1196	0.2637	5.2738	7.9107
24	0.4746	0.0264	3.0324	1.3185	4.4827	4.7464	4.4827	0.5274	7.1196	0.2637	5.2738	7.9107

Table II shows the possible electricity cost of power consumption for each appliance in 24 hours based on the TOU tariff. With all the conditions for using LP mentioned in Section III, LP can be implemented in the ASTDR objective function to minimize the daily electricity cost.

TABLE III. THE OPTIMAL SCHEDULING OF APPLIANCES

Appli-ances / Time (Hours)	Optimal hours											
	1	2	3	4	5	6	7	8	9	10	11	12
1	1	1[a]	0[b]	0	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0	0	0
3	1	1	0	0	0	0	0	0	0	0	0	0
4	1	1	0	0	0	0	0	0	0	0	0	0
5	1	1	0	0	0	0	0	0	0	0	0	0
6	1	1	0	0	0	0	0	0	0	0	0	1
7	1	1	0	0	0	0	1	0	1	0	0	1
8	1	1	0	0	1	1	0	0	1	0	1	1
9	1	1	0	0	0	0	0	0	0	0	0	0
10	1	1	0	0	0	0	0	0	0	0	0	0
11	1	1	0	0	0	0	0	0	0	0	0	0
12	1	1	1	0	0	1	0	0	0	0	0	0
13	1	1	1	0	0	0	0	0	0	0	0	0
14	1	1	1	0	0	0	0	0	0	0	0	0
15	1	1	1	0	0	0	0	0	0	0	0	0
16	1	1	1	0	0	0	0	1	0	0	0	0

2024 International Electrical Engineering Congress (iEECON 2024)
March 6-8, 2024, Pattaya Chonburi, THAILAND

Time (Hours) \ Appliances	Optimal hours											
	1	2	3	4	5	6	7	8	9	10	11	12
17	1	1	1	0	0	0	0	0	0	0	0	0
18	1	1	1	1	0	0	0	0	0	0	0	0
19	1	1	1	1	0	0	0	0	0	0	0	0
20	1	1	1	1	0	0	0	0	0	0	0	0
21	1	1	1	1	0	0	0	0	0	0	0	0
22	1	1	1	1	0	0	0	0	0	1	0	0
23	1	1	1	1	0	0	0	0	0	1	0	1
24	1	1	1	1	0	0	0	0	0	1	0	1

a. '1' assign as the appliance is 'ON', and b '0' assign as the appliance is 'OFF'

Table III presents the proper hours (Ph_i) to schedule and operate any appliance in 24 hours. Unshiftable appliances such as refrigerators, sensors, air conditioners, and illumination have an unchanging operational time. Leftover shiftable appliances, such as irons and dishwashers, can be scheduled to obtain the optimal solution to the ASTDR problem.

TABLE IV. THE APPLIANCES POWER CONSUMPTION COSTS IN 24 HOURS

Time (Hours) \ Appliances	The electricity cost (Baht)											
	1	2	3	4	5	6	7	8	9	10	11	12
1	0.4746	0.0264	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.4746	0.0264	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
3	0.4746	0.0264	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
4	0.4746	0.0264	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5	0.4746	0.0264	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
6	0.4746	0.0264	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	7.9107
7	0.4746	0.0264	0.0000	0.0000	0.0000	0.0000	4.4827	0.0000	7.1196	0.0000	0.0000	7.9107
8	0.4746	0.0264	0.0000	0.0000	4.4827	4.7464	0.0000	0.0000	7.1196	0.0000	5.2738	7.9107
9	1.0437	0.0580	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10	1.0437	0.0580	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
11	1.0437	0.0580	0.0000	0.0000	0.0000	10.437	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
12	1.0437	0.0580	6.6679	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
13	1.0437	0.0580	6.6679	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
14	1.0437	0.0580	6.6679	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
15	1.0437	0.0580	6.6679	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
16	1.0437	0.0580	6.6679	0.0000	0.0000	0.0000	0.0000	1.1596	0.0000	0.0000	0.0000	0.0000
17	1.0437	0.0580	6.6679	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
18	1.0437	0.0580	6.6679	2.8991	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
19	1.0437	0.0580	6.6679	2.8991	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
20	1.0437	0.0580	6.6679	2.8991	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
21	1.0437	0.0580	6.6679	2.8991	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
22	1.0437	0.0580	6.6679	2.8991	0.0000	0.0000	0.0000	0.0000	0.0000	0.5798	0.0000	0.0000
23	0.4746	0.0264	3.0324	1.3185	0.0000	0.0000	0.0000	0.0000	0.0000	0.2637	0.0000	7.9107
24	0.4746	0.0264	3.0324	1.3185	0.0000	0.0000	0.0000	0.0000	0.0000	0.2637	0.0000	7.9107

The power consumption cost for each appliance can be explained in two parts: appliance scheduling and non-scheduling.

Non-scheduling describes an unoptimized schedule with ASTDR. In this part, appliances can operate during peak hours and be overlooked when electricity prices are lowest. The non-scheduling part is similar to what is occurring in real life, with consumption reaching peaks during times when people are generally off their work shift and perform all their electricity-consuming activities during those hours.

In the scheduled appliance case, ASTDR notices that peak load is occurring and knows when the lowest electricity prices are. Then we can shift appliances in a consumer's home to avoid an hourly peak load, like in Table IV.

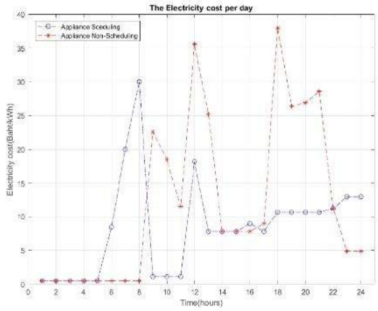


Fig 3. The power consumption cost in 24 hours.

TABLE V. THE ELECTRICITY COST OF ALL APPLIANCES

Time (Hours)	TOU Rate	The electricity cost (Baht)	
		Non-Scheduling	Optimal Scheduling
1	OFF-PEAK	0.5010	0.5010
2	OFF-PEAK	0.5010	0.5010
3	OFF-PEAK	0.5010	0.5010
4	OFF-PEAK	0.5010	0.5010
5	OFF-PEAK	0.5010	0.5010
6	OFF-PEAK	0.5010	8.4117
7	OFF-PEAK	0.5010	20.0141
8	OFF-PEAK	0.5010	30.0343
9	PEAK	22.5550	1.1017
10	PEAK	18.4963	1.1017
11	PEAK	11.5384	11.5384
12	PEAK	35.6009	7.7696
13	PEAK	25.1642	7.7696
14	PEAK	7.7696	7.7696
15	PEAK	7.7696	7.7696
16	PEAK	7.7696	8.9292
17	PEAK	8.9292	7.7696
18	PEAK	37.9202	10.6687
19	PEAK	26.3238	10.6687
20	PEAK	26.9036	10.6687
21	PEAK	28.6431	10.6687
22	PEAK	11.2485	11.2485
23	OFF-PEAK	4.8519	13.0263
24	OFF-PEAK	4.8519	13.0263
Electricity cost per day		290.344	202.460

Finally, the result is revealed in Fig. 3 and Table IV. Figure 3 shows the comparison of results obtained for the proposed system between non-scheduling and scheduled appliances. In Fig. 3, the ASTDR efficiently schedules the load appliances to avoid peak demand hours. Table V provides the electricity cost in two cases: For non-scheduling appliances, the power consumption cost of all appliances within 24 hours is 290.344 baht.

And for scheduled appliances, the power consumption cost is 202.460 baht. The result shows that the electricity cost of the consumer's home is saved by 87.884 Baht per day by using the proposed method.

V. Conclusion

This work introduces the problem formulation and computational procedure for ASTDR using LP. The simulation results not only proved that the reduction in electricity cost is achieved by implementing residential appliance scheduling in the home but also that the burden on the grid during the peak hour is reduced by implementing the proposed LP-based ASTDR for HEMS. Future work could be focused on managing the energy of the smart house by combining renewable energy sources such as micro-wind turbines, solar rooftops, etc., with power from the grid, including energy storage systems, to improve the efficiency of the smart home system.

Acknowledgments

We would like to express our heartfelt appreciation to the Suranaree University of Technology for their invaluable support in the completion of this research.

References

[1] Alhelou HH, Golshan MEH, Siano P. Frequency response models and control in smart power systems with high penetration of renewable energy sources. Comput Electr Eng 2021;129:1–13.

[2] Jae Yong Lee and Seong Gon Choi, "Linear Programming Based Hourly Peak Load Shaving Method at Home Area", 16th International Conference on Advanced Communication Technology, Pyeongchang, Korea (South), 16-19 February, 2014.

[3] Fady Y. Melhem, Olivier Grunder, Zakaria Hammoudan and Nazih Moubayed, "Optimal Residential Load Scheduling Model in Smart Grid Environment" IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), 06-09 June, 2017.

[4] Yasaman Farzambehboudi "Economic Impact Analysis of Load Shifting in a Smart Household", International Conference on Smart Energy Systems and Technologies (SEST), 10-12 September, 2018.

[5] Dharmaraj Kanakadhurga and Natarajan Prabaharan, "Demand response-based peer-to-peer energy trading among the prosumers and consumers", Energy Reports Volume 7, pp. 7825-7834, November 2021.

[6] Özkan, H.A.n., "Appliance based control for home power management systems. Energy", Energy 114, pp. 693–707, 2016.

[7] Muhammad Raisul Alam, Marc St-Hilaire, and Thomas Kunz, "Cost Optimization via Rescheduling in Smart Grids – A Linear Programming Approach" IEEE International Conference on Smart Energy Grid Engineering (SEGE), 28-30 August 2013.

[8] Thai-Smartgird, 2018. Demand Response and Energy Management System: EMS, URL https://thai-smartgrid.com/

[9] Reda El Makroum "A Linear Programming Based Load Scheduling System Considering Dynamic Pricing and Renewable Energy", 12th International Renewable Engineering Conference (IREC), 14-15 April 2021.

[10] Kin Cheong Sou, James Weimer, Henrik Sandberg, and Karl Henrik Johansson, "Scheduling Smart Home Appliances Using Mixed Integer Linear Programming", 50th IEEE Conference on Decision and Control and European Control Conference, Orlando, FL, USA,12-15 December 2011.

[11] A. Can Duman, Önder Güler, Kaan Deveci, and Ömer Gönül, "Residential Load Scheduling Optimization for Demand-Side Management under Time-of-Use Rate", 6th International Istanbul Smart Grids and Cities Congress and Fair (ICSG), Istanbul, Turkey, 12 July 2018.

[12] Paramvir Singh, Nisha Tayal, Yajvender Pal Verma and Baljit Singh, "Optimum Scheduling of Residential Appliances along with the Management of Distributed Energy Resources using Mixed Integer Linear Programming", IEEE 5th International Conference for Convergence in Technology (I2CT), Bombay, India, 12 March 20

Biography

Ms. Wilawan Piawises received her B.Eng. in EE (First Class Honors) from Suranaree University of Technology, Thailand, in 2023. She is currently pursuing M.Eng. in EE at the School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology. Her research interests currently focus on energy management system analysis and optimization.

Assoc. Prof. Dr. Keerati Chayakulkheeree received his B.Eng. in EE from King Mongkut Institute of Technology Ladkrabang, Thailand, in 1995, M.Eng. and D.Eng. degrees in Electric Power System Management from Asian Institute of Technology, in 1999 and 2004, respectively. His primary areas of research interest include protection, optimization, AI applications in power systems, and related fields.

Received: April 2, 2025. Revised: May 16, 2025. 395

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Intelligent Energy Management for Prosumer Smart Home System with Multi-Energy Resources

Wilawan Piawises[1] **Keerati Chayakulkheeree**[1]*

[1]*School of Electrical Engineering, Institute of Engineering,*
Suranaree University of Technology, Nakhonratchasima, Thailand
* Email: keerati.ch@sut.ac.th

Abstract: This article presents a hybrid particle swarm optimization-linear programming (PSO-LP) approach for smart home intelligent energy management systems (SHIEMS). The proposed method formulates the objective function as the minimization of total daily electricity costs, considering various home appliances, electricity from a rooftop photovoltaic (PV) system, and wind power generation, as well as a battery energy storage system (BESS) and vehicle-to-home (V2H) integration. The optimal BESS and V2H scheduling obtained from PSO is then incorporated into LP to complete the optimal home appliance scheduling. Seven case studies under a time-of-use tariff were conducted to evaluate the effectiveness of the proposed method in solving the problem under different conditions and benefiting prosumers by optimizing and managing energy in smart homes. The results demonstrate that the proposed hybrid PSO-LP-based SHIEMS effectively minimizes daily electricity costs for prosumers by 16.48% compared to the non-scheduling. Additionally, the proposed framework maximizes PV electricity sales for prosumers by 17.941 kWh and minimizes energy usage from the grid by 0.608 kWh, which helps alleviate the grid burden during peak hours.

Keywords: Smart home energy management, Time-of-use tariff, Demand response, Appliance scheduling.

Notation	Description
A_m^t	The binary variables on or off status of each appliance *'m'* at the time *'t'*.
c_1	The cognitive acceleration coefficient.
c_2	The social acceleration coefficient.
C^t	The electricity cost at the time *'t'*.
C_{buy}^t	The cost of buying energy.
C_{sell}^t	income from selling excess energy.
$gbest^j$	The global best position of particle *'i'* at iteration *'j'*.
$pbest_i^j$	The personal best position of particle *'i'* at iteration *'j'*.
P_B^t	The power charge or discharge from the battery at time *'t'*.
$P_{B,\,ch}^{max}$	Maximum power battery charging limit.
$P_{B,\,dch}^{max}$	Maximum power battery discharging limit.
P_{EV}^t	The power charge or discharge from the battery in EV at the time *'t'*.
$P_{EV,\,ch}^{max}$	Maximum power EV charging limit.
$P_{EV,\,dch}^{max}$	Maximum power EV discharging limit.
P_{excess}^t	The excess PV power at the time *'t'*.
P_{grid}^t	The power from the grid at the time *'t'*.
P_{grid}^{max}	Maximum grid power limit.
P_{Load}^t	Power consumption from all appliances at the time *'t'*.
P_m^{rating}	The power rating of each appliance *'m'*.
P_{PV}^t	The PV power at the time *'t'*.
P_{Wind}^t	The wind power at the time *'t'*.
P_{Total}^t	The total power demand at the time *'t'*.
r_1, r_2	The random values within the range of 0 and 1.
SoC_B^t	The SoC of the battery at the time *'t'*.
SoC_B^{min}	Minimum limits of the SoC of the battery.
SoC_B^{max}	Maximum limits of the SoC of the battery.
SoC_{EV}^t	The SoC of the EV at the time *'t'*.
SoC_{EV}^{min}	Minimum limits of the SoC of the EV.
SoC_{EV}^{max}	Maximum limits of the SoC of the EV.
$T_{m,\,ending}^t$	Ending time of appliance *'m'* at the time *'t'*.
$T_{m,\,starting}^t$	Starting time of appliance *'m'* at the time *'t'*.
TDC	Total daily cost.
NA	The number of electrical appliances.
NER	The number of energy resource.
NT	The number of time slot.
η_B	Efficiency of the battery.

Received: April 2, 2025. Revised: May 16, 2025.

η_{EV}	Efficiency of the EV.
v_i^j	The velocity of particle 'i' at iteration 'j'.
w	The inertia weight factor.
x_i^j	The position of particle 'i' at iteration 'j'.

1. Introduction

Currently, the global demand and consumption of power are increasing rapidly. This increment causes numerous problems, such as increasing carbon emissions, rising energy prices, deficiencies in electric service reliability, increased disturbances, power quality issues, and power system collapse caused by high peak loads that lead to blackouts [1]. Most of the current power systems are centralized power generation with unidirectional power flow that is developing into a decentralized power system, which improves the flexibility, resilience, and reliability of the power grid [2, 3]. Decentralized systems can enable bidirectional power flow, allowing electricity to be both supplied and used from the grid, where consumers can act as prosumers to produce their electricity and sell the excess power back to the grid. This concept is an essential step toward developing smart grid (SG) systems [4]. The SG approach relies heavily on demand response (DR), which is a part of the demand-side management (DSM) tactics [5] that motivates both consumers and prosumers to adapt and manage energy consumption behavior in their smart homes to reduce electricity costs and support the stability of the power system [6, 7]. That can be considered a vital component of a smart home intelligent energy management system (SHIEMS) [8]. Load scheduling is one of the SHEMS tools that manages the power consumption of electrical appliances in the home to respond to the electricity price at various times [9, 10]. To solve the global energy crisis and improve the reliability of the power system. SHIEMS is an alternative that every consumer can readily implement.

Recent advancements in SHIEMS have increased complexity because of rising global energy demand, improved power system reliability, electricity cost reduction efforts, and the integration of renewable energy sources (RES), energy storage systems (ESS), and electric vehicles (EVs) [11]. Researchers have proposed different objectives for SHIEMS using various optimization strategies. DSM plays a crucial role in SHIEMS [12], using day-ahead load shifting to minimize peak demand and electricity costs and enhance sustainability. Optimized power scheduling uses integer and continuous variables under day-ahead pricing [13]. Appliance scheduling via TOU minimizes daily electricity costs using LP [14], using mixed integer linear programming (MILP) applied spot pricing [15]. A Markov decision process (MDP) algorithm adjusts the power balance under real-time pricing (RTP) to maximize social welfare [16]. A multi-objective evolutionary algorithm (MOEA) and multi-objective mixed integer linear programming (MOMILP) approach balances user satisfaction and electricity cost [17, 18]. Early research of SHIEMS relies only on grid power, which can be applied to various problem formulations.

Integrating RES like solar and wind into SHIEMS complicates energy management. In [19], the prioritization and scheduling (PAS) algorithm minimizes real-time total energy consumption under time-of-day (TOD) pricing. Scheduling appliances based on TOU to reduce the total electricity cost and peak load using MILP [20], Binary Particle Swarm Optimization (BPSO) [21], and a multi-start random constructive heuristic algorithm [22]. The load scheduling model based on dynamic pricing and RES using LP to minimize energy bills or maximize RES usage [23]. After that, [24] developed load scheduling using the genetic algorithm (GA) to optimize energy costs and solar energy usage.

SHIEMS with ESS enhances flexibility and reliability by storing excess RES or grid power during off-peak hours for later use and provides energy for smart homes when in peak demand. LP optimizes load scheduling with RES to reduce energy costs and peak demand under dynamic pricing [25]. Day-ahead load scheduling based on weather forecasts to minimize energy costs and achieve zero energy consumption from the grid [26]. Under RTP, convex programming (CP) [27] and mixed integer non-linear programming (MINLP) [28] optimize load scheduling to minimize electricity costs. Under TOU, optimizing appliance scheduling to reduce electricity costs and high peaks via the knapsack-based WDO (K-WDO) algorithm [29]. While GA and Interior-Point (IP) optimization are proposed to schedule charge/discharge battery storage systems to minimize cost [30]. Most SHIEMS with ESS studies always integrate RES for various objectives, including appliance and battery scheduling.

Integrating EVs into SHIEMS presents an interesting scenario for handling potential issues that may arise from the imminent high penetration of EVs into the grid. EVs are similar to transportable batteries, which can act as energy consumers and possible energy sources through vehicle-to-home (V2H) or vehicle-to-grid (V2G) systems. In [1], EV is considered V2G for peak shaving using LP. MILP for TOU-based load scheduling to reduce electricity bills [31]. MILP for scheduled energy production and consumption under TOD pricing [4]. A hybrid of GA,

 DOI: 10.22266/ijies2025.0731.25

Received: April 2, 2025. Revised: May 16, 2025.

WDO, and PSO (HGPDO) algorithms for optimal power scheduling to reduce costs and carbon emission-based RTP [32]. According to all the research above, EVs are considered a household load. Recently, there has been much research about V2H, which acts as a backup to supply emergency power directly to the home. To schedule energy for a minimum cost based on DR implemented by MILP [33, 34], in addition to optimizing BESS lifespan through optimal energy management using the Rain Flow Cycle Counting algorithm (RCCA) [35]. Load scheduling for the upcoming day achieves a balance between electricity cost and consumer comfort [36]. In Ref. [37], scheduling appliances based on the RTP to reduce grid dependency and electricity costs using BPSO.

The SHIEMS is an increasingly important problem and requires complex solving methods. Most existing studies have used appliance scheduling to manage energy consumption for various objectives, including minimizing electricity prices, reducing peak load demand, and others. Table I shows the research gap between the proposed effort and the existing literature. A number of previous researches have applied hybrid stochastic-deterministic approaches to address complex optimization problems. Nevertheless, this class of methods remains a subject of ongoing research interest, primarily due to the inherent complexity of the problems and the involvement of multiple interdependent variables. In this study, SHIEMS is formulated as a two-layer hybrid optimization framework: a heuristic layer using PSO to determine possibilities of power consumption of battery and EV, and a mathematical programming layer using LP to handle appliance scheduling under TOU tariffs. In Thailand, for example, DR can respond to varying TOU energy prices, which are the main factors in managing daily energy consumption. Recently, in addition to utilizing electricity from the grid, the excess energy from the rooftop PV can also be sold to the household PV purchasing scheme project by the Metropolitan Electricity Authority (MEA) and Provincial Electricity Authority (PEA) [38]. The principal concept of this article is TOU-based optimal home appliance scheduling (OHAS) to reduce electricity costs and decrease grid dependency, which is implemented by the hybrid PSO-LP algorithm.

Therefore, this paper proposes a hybrid PSO-LP framework for SHIEMS. The proposed approach aims to minimize total daily electricity costs while considering multiple energy sources, including rooftop PV generation, wind power, BESS, and V2H integration. The optimization process is divided into two stages: first, PSO is employed to determine the optimal scheduling of BESS and V2H operations; then, LP is used to refine the scheduling of home appliances for enhanced energy efficiency. To evaluate the effectiveness of the proposed method, seven case studies under a time-of-use tariff are conducted, analyzing different scenarios and their impacts on prosumers. The results confirm that the hybrid PSO-LP framework not only reduces electricity costs for consumers but also maximizes electricity sales opportunities for prosumers while alleviating grid demand during peak hours.

The organization of the paper is as follows: Section 2 presents the proposed SHIEMS framework. Section 3 addresses the hybrid PSO-LP-based SHIEMS problem formulation. Section 4 discusses the simulation results and findings. Finally, the conclusion is provided in Section 5.

2. Proposed SHIEMS framework

The proposed smart home system comprises five components: electrical appliances, RES models, BESS model, V2H model, and the connection between the smart home and the grid. In this study, the electricity tariff and household PV purchasing scheme are used. The proposed SHIEMS model is shown in Fig. 1. Figure 2 illustrates the proposed PSO-LP based SHIEMS framework.

2.1 Electrical appliances

This article presents a selection of ubiquitous home appliance usage to test the algorithm given in [4-11], which can be divided into two types: unshiftable appliances have a non-changed period for operation, and shiftable appliances can designate a time to operate to obtain the optimal solution of the proposed system.

Figure. 1 The proposed SHIEMS model

Received: April 2, 2025. Revised: May 16, 2025.

Table 1. Research Gap from Literature Survey

Ref.	Year	Type of DR program	PV	Wind	BESS	EV	Grid	Electricity Export	Case Study	Optimization Methods
[15]	2011	Spot pricing	✗	✗	✗	✗	✓	✗	SE[1] & NYC	MILP
[12]	2012	DSM	✗	✗	✗	✗	✓	✗	H	EA
[13]	2016	day-ahead price	✗	✗	✗	✗	✓	✗	H	Scheduling strategy
[16]	2019	RTP	✗	✗	✗	✗	✓	✗	H	SA-RTP algorithm
[17]	2020	Fixed cost	✗	✗	✗	✗	✓	✗	H	MOEA
[18]	2020	TOU	✗	✗	✗	✗	✓	✗	ZA	MOMILP
[14]	2024	TOU	✗	✗	✗	✗	✓	✗	H	LP
[21]	2015	TOU	✓	✗	✗	✓	✓	✗	H	BPSO
[20]	2015	day-ahead TOU	✓	✗	✗	✓	✓	✗	H	MILP
[19]	2018	TOD	✓	✗	✗	✗	✓	✗	H	PAS algorithm
[22]	2018	TOU	✓	✗	✗	✗	✓	✗	H	heuristic algorithm
[23]	2021	dynamic pricing	✓	✗	✗	✗	✓	✗	MA	LP
[24]	2023	dynamic pricing	✓	✗	✗	✗	✓	✗	MA	GA
[25]	2012	dynamic pricing	✓	✓	✓	✗	✓	✓	H	LP
[27]	2012	RTP	✓	✓	✓	✗	✓	✗	H	CP
[29]	2015	TOU	✓	✗	✓	✗	✓	✗	H	K-WDO
[28]	2015	RTP	✓	✗	✓	✗	✓	✗	H	MINLP
[30]	2019	TOU	✓	✗	✓	✗	✓	✗	H	IP and GA
[26]	2023	Price based	✓	✗	✓	✓	✓	✓	HK	RISO
[1]	2014	hourly peak load	✗	✗	✗	✓	✓	✗	KR	LP
[4]	2017	TOD	✓	✓	✓	✓	✓	✓	H	MILP
[31]	2018	TOU	✗	✗	✗	✓	✓	✗	TR	MILP
[33]	2019	RTP	✓	✗	✓	V2H	✓	✗	H	MILP
[34]	2019	day-ahead TOU	✓	✓	✓	V2H	✓	✓	H	MILP
[32]	2021	RTP	✓	✓	✓	✓	✓	✗	H	HGPDO
[35]	2021	day-ahead TOU	✓	✓	✓	V2H	✓	✓	H	MILP and RCCA
[36]	2022	Price based	✓	✓	✓	V2H	✓	✓	UK	heuristic algorithm
[37]	2024	RTP	✓	✓	✓	V2H	✓	✓	IN	BPSO
Proposed Framework		TOU/RTP	✓	✓	✓	V2H	✓	✓	TH	hybrid PSO-LP

[1]H: Hypothetical (Research formulated based on hypotheses), HK: Hong Kong, IN: India, KR: Korea, MA: Morocco, NYC: New York City, SE: Sweden, TH: Thailand, TR: Turkey, UK: United Kingdom, and ZA: South Africa.

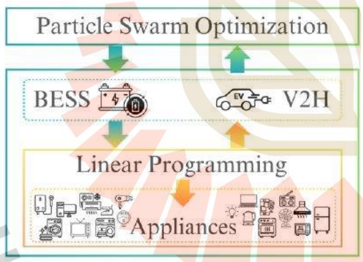


Figure. 2 The hybrid PSO-LP based SHIEMS model

2.2 Renewable Energy Sources (RES) models

The home RESs are the rooftop PV and wind electricity systems, which can be model as P_{PV}^{t} and P_{wind}^{t} in each time slot, respectively [39].

2.3 BESS model

Batteries improve reliability in a home electrical system and can also help reduce costs when power from the grid has a high electricity price. The constraints of the state of charge (SoC) limits in the battery are given below,

$$SoC_{B}^{min} \leq SoC_{B}^{t} \leq SoC_{B}^{max}, \tag{1}$$

$$SoC_{B}^{t} = SoC_{B}^{t-1} + \left(\frac{P_{B,ch}^{t}}{\eta_B \times capacity_B} - \frac{P_{B,dch}^{t} \times \eta_B}{capacity_B}\right). \tag{2}$$

The battery should not be charged or discharged more than this limit. In Eq. (2), updating the SoC of the battery can provide power to charge or discharge from the battery in each time slot. The power charging and discharging limit of the battery is as follows:

$$0 \leq P_{B,ch}^{t} \leq P_{B,ch}^{max}, \quad \textit{for charging state} \tag{3}$$

$$-P_{B,dch}^{max} \leq P_{B,dch}^{t} \leq 0, \quad \textit{for discharging state.} \tag{4}$$

 DOI: 10.22266/ijies2025.0731.25

Received: April 2, 2025. Revised: May 16, 2025. 399

For each hour, the power from the battery can only be charged or discharged within the limits of the battery capacity.

2.4 V2H model

The EV chargers with batteries have been developed for V2H applications, acting as a backup to supply emergency power directly to the home. For this work, the SoC of the EV at the time *'t'* is provided in Eqs. (5) – (6).

$$SoC_{EV}^{min} \leq SoC_{EV}^{t} \leq SoC_{EV}^{max}, \quad (5)$$

$$SoC_{EV}^{t} = SoC_{EV}^{t-1} + \left(\frac{P_{EV,\,ch}^{t}}{\eta_{EV} \times capacity_{EV}} - \frac{P_{EV,\,dch}^{t} \times \eta_{EV}}{capacity_{EV}}\right). \quad (6)$$

The SoC of the EV battery can provide power to charge or discharge in each time slot. The EV battery power charging and discharging limits are as follows:

$$0 \leq P_{EV,\,ch}^{t} \leq P_{EV,\,ch}^{max}, \quad \textit{for charging state} \quad (7)$$

$$-P_{EV,\,dch}^{max} \leq P_{EV,\,dch}^{t} \leq 0. \quad \textit{for discharging state} \quad (8)$$

2.5 Connection between smart home and the grid

The power supplied by the grid should be within a fixed limit to simulate a regular residence that can always have a choice to consume electricity power from the grid if other resources are unavailable, as follows:

$$0 \leq P_{grid}^{t} \leq P_{grid}^{max}. \quad (9)$$

With the proposed problem formulation, both TOU tariff and RTP can be handled in the hybrid PSO-LP based SHIEMS framework.

3. Hybrid PSO-LP based SHIEMS problem formulation

3.1 SHIEMS objective function

The hybrid PSO-LP based SHIEMS proposes proper hours and optimal energy management to operate each appliance, which load appliances can select energy to consume from five energy resources comprising power from the grid, rooftop PV, wind turbine, battery, and EV to pursue minimum daily electricity costs. The PSO system determines the optimal power of the BESS and EV, while the optimal power value is processed to complete the OHAS using LP concurrently. The objective function of this work is given as,

$$\text{Minimize } TDC = \sum_{t=1}^{NT} C^{t} \times P_{Total}^{t}, \quad (10)$$

$$P_{Total}^{t} = \sum_{m=1}^{NA}\left(P_{Load}^{t} - P_{PV}^{t} - P_{Wind}^{t} + P_{B}^{t} + P_{EV}^{t}\right), \quad (11)$$

$$P_{Total}^{t} = \begin{cases} P_{grid}^{t}, \ \text{for } P_{Total}^{t} > 0 \\ P_{excess}^{t}, \ \text{for } P_{Total}^{t} \leq 0 \end{cases}, \quad (12)$$

$$C^{t} = \begin{cases} C_{buy}^{t}, \text{for } P_{Total}^{t} = P_{grid}^{t} \\ C_{sell}^{t}, \text{for } P_{Total}^{t} = P_{excess}^{t} \end{cases}. \quad (13)$$

For appliance $m = 1, 2, 3, \ldots, NA$, and time $t = 1, 2, 3, \ldots, NT$ hours.

3.2 Constraints

3.2.1. Appliance operation constraints

The shiftable appliances are scheduled within the duration of operation and starting to ending time range.

$$A_{m}^{t} = \begin{cases} 0, \text{ if } t < T_{m,\,starting}^{t} \text{ and } t > T_{m,\,ending}^{t} \\ 1, \text{if } t \geq T_{m,\,starting}^{t} \text{ and } t \leq T_{m,\,ending}^{t} \end{cases}. \quad (14)$$

When appliance *'m'* is within their starting to ending time range. The status of operation A_m^t can be either '1' or '0', which is decided by their duration of operation, all available energy resources solved by the hybrid PSO-LP based on the TOU or RTP tariff.

3.2.2. Power balance constraints

The power balance constraint checks the balance between power generated and power consumed. Power generation and demand should be equal for the system to operate reliably.

$$P_{grid}^{t} + P_{PV}^{t} + P_{wind}^{t} + P_{B,\,dch}^{t} + P_{EV,\,dch}^{t} = P_{Load}^{t} + P_{B,\,ch}^{t} + P_{EV,\,ch}^{t} + P_{excess}^{t}. \quad (15)$$

Power consumption from all appliances is calculated by the product of the proper ON/OFF state of operation A_m^t and the power rating of each appliance, (P_m^{rating}) as below,

$$P_{Load}^{t} = \sum_{m=1}^{NA}\left(A_m^t \cdot P_m^{rating}\right). \quad (16)$$

Received: April 2, 2025. Revised: May 16, 2025.

3.2.3. SHIEMS constraints and boundary

In the proposed SHIEMS framework, LP is utilized to determine the optimal home appliance scheduling (OHAS) and P_{Load}^{t} to achieve the objective function in Eq. (10). P_{Load}^{t} is derived from the optimal power scheduling matrix $\boldsymbol{P_{Load}}$. This matrix represents the scheduled power usage of all electric appliances. The power consumption is constrained by the available energy resources, where 0 denotes the minimum allowable power usage, while $\boldsymbol{P_{ERS}}$ represents the maximum power available from all energy resources throughout the day. Therefore,

$$0 \leq \boldsymbol{P_{Load}} \leq \boldsymbol{P_{ERS}}. \tag{17}$$

The equality Constraints are used to determine the appropriate duration for turning appliances on or off, considering all possibilities within 24 hours of operating, the equation is formulated as Eq. (18)

$$\boldsymbol{AS} \cdot \boldsymbol{P_{Load}} = \boldsymbol{DP}, \tag{18}$$

$$\boldsymbol{AS} = \begin{bmatrix} \boldsymbol{AS_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \boldsymbol{AS_{NA}} \end{bmatrix}, \tag{19}$$

$$\boldsymbol{AS_m} = \left[\boldsymbol{ASH_{m,1}}, \ldots, \boldsymbol{ASH_{m,NER}}\right]_{1\times(24\times NER)}, \tag{20}$$

$$\boldsymbol{ASH_{m,n}} = [\boldsymbol{ASH^{1}_{m,n}}, \ \ldots, \boldsymbol{AS^{24}_{m,n}}]_{1\times 24}, \tag{21}$$

$$\boldsymbol{DP} = [\boldsymbol{DP_m}, \boldsymbol{DP_m}, \ldots, \boldsymbol{DP_m}]^{T}_{1\times NA}. \tag{22}$$

The matrix $\boldsymbol{AS}$ is a block diagonal matrix whose diagonal contains blocks of smaller matrices of $\boldsymbol{AS_m}$ corresponds to the status of appliance *'m'*. Each $\boldsymbol{ASH^{t}_{m,n}}$ represents the ON status with a range of starting and finishing times for each appliance at time *'t'*, with energy resource $n = 1, 2, \ldots, NER$, and $\boldsymbol{DP_m}$ is the duration of operation multiplied by power rating for each appliance.

The inequality constraints are formulated to determine the amount of power consumption from the appropriate energy resources as Eq. (23)

$$\boldsymbol{AR} \cdot \boldsymbol{P_{Load}} \leq \boldsymbol{PR}, \tag{23}$$

$$\boldsymbol{AR} = \begin{bmatrix} \boldsymbol{I_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \boldsymbol{I_{NA}} \end{bmatrix}, \tag{24}$$

$$\boldsymbol{I_m} = [\boldsymbol{I_{m,1}}, \boldsymbol{I_{m,2}}, \ldots, \boldsymbol{I_{m,NER}}]_{24\times(24\times NER)}, \tag{25}$$

$$\boldsymbol{PR} = [\boldsymbol{PR_m}, \boldsymbol{PR_m}, \ldots, \boldsymbol{PR_m}]^{T}_{1\times(24\times NA)}. \tag{26}$$

The matrix $\boldsymbol{AR}$ is a block diagonal matrix containing blocks of smaller matrices $\boldsymbol{I_m}$ for each *'m'* appliance, Each $\boldsymbol{I_{m,n}}$ is the identity matrix used for the load appliances to select energy resources to consume with energy resource *'n'* ensuring that each energy resource is uniquely selected for each time *'t'*, $\boldsymbol{PR}$ is the power limit and PR_m represents the power consumed by each appliance, which can be calculated by $\boldsymbol{ASH^{t}_{m,n}}$ multiplied by P_m^{rating}.

3.3 Constraints

The particles are influenced by the global and personal best positions and use their velocity to move within the search space to find the optimal solution to the problem. The updating velocities of the particle equation can be described as:

$$v_i^{j+1} = wv_i^j + c_1 r_1\left(pbest_i^j - x_i^j\right) + c_2 r_2\left(gbest^j - x_i^j\right), \tag{27}$$

$$x_i^{j+1} = x_i^j + v_i^{j+1}, \tag{28}$$

$$\boldsymbol{x} = \begin{bmatrix} X_{SoC_B} \\ X_{SoC_{EV}} \end{bmatrix}. \tag{29}$$

The SoC_B^t in Eq. (2) and the SoC_{EV}^t in Eq. (6) is used as the particle x_i^j in Eq. (27). The set of best SoC populations is formulated as Eq. (29). The PSO system identifies the optimal SoC of the battery and EV throughout the day for achieving the objective function in Eq. (10), which is processed simultaneously to complete the OHAS using LP. The optimal daily power consumption from all appliances obtained from OHAS will be updated and used to calculate the objective function. The computational procedure for the hybrid PSO-LP-based OHAS problem is described below,

Algorithm Hybrid PSO-LP Algorithm

Read data for appliances, RES, BESS, and V2H
Read a number of particles, maximum iterations, and PSO parameters
PSO generates the initial population randomly (SoC of battery and V2H in each time slot; X)
Set iteration = 0
While iteration < maximum iterations
  For each particle in the PSO
    Check all of the constraints
    Solve LP to update $\mathbf{P_{Load}}$
    Evaluate the fitness function for each particle
    Update *pbest* and *gbest*
  END For
Calculate the objective function; f(*X*)

Received: April 2, 2025. Revised: May 16, 2025.

Update particle velocity and position using Eq. (27) and (28)
iteration = iteration + 1
END While
Return Output best (X) and min TCD ($f(X)$)

4. Simulation results and discussion

This section addresses the test data and simulation results of the proposed framework. The proposed hybrid PSO-LP based SHIEMS had been tested with the same case study of [37] and benchmarked against other commonly used optimization techniques, including GA, GA-LP, and PSO. The hyperparameters used for different methods as shown in Table 2. The comparison demonstrates that the advantages of the hybrid approach improve solution quality and system efficiency. The proposed method was also evaluated using Thailand's distribution system condition. The home battery energy storage, EV, and REs specifications are given in Table 3. Meanwhile, the solar and wind power availabilities are obtained from solar irradiance and wind speed data throughout 24 hours in Thailand, as shown in Fig. 3.

Table 2. The parameters different methods

Method	Comparison condition			Thailand's system condition
	BPSO [37]	PSO/ PSO-LP	GA/ GA-LP	PSO-LP
Populations	50	50	50	50
Iterations	100	100	100	100
c_1	2.5	2.5	-	1.49
c_2	2.5	2.5	-	1.49
w	0.4-0.9	0.4-0.9	-	0.1-1.0
Elite Count	-	-	10	-
Crossover Fraction	-	-	0.8	-

Table 3. Battery, EV, and REs specifications

	Battery	EV	PV	wind
Total capacity	10 kWh	50 kWh	5kW	5kW
Charging/ discharging efficiency	95%	95%	-	-
Minimum SoC	0.2	0.2	-	-
Maximum SoC	0.9	0.9	-	-
Departure time (hour)	-	09.00	-	-
Arrival time (hour)	-	17.00	-	-

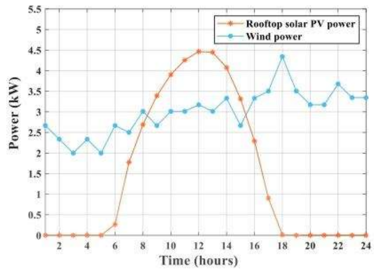


Figure. 3 The typical solar and wind power in Thailand

4.1 Case A: The result of hybrid PSO-LP based SHIEMS

The result of the proposed hybrid PSO-LP compared to the other algorithm-based SHIEMS is represented in Table 4. With the same RE profile, RTP of the Indian energy exchange, the feed-in tariff of 5 rupees for the power injected into the grid, EV changing constraints of [37], and the PSO hyperparameters, using the BPSO, the electricity sold is 3.414 rupees/day. When using the PSO is 356.36 rupees/day. On the other hand, using the hybrid PSO-LP is 418.26 rupees/day. For GA hyperparameters in the same condition, the GA and GA-LP, the electricity sold is 282.66 and 280.62 rupees/day, respectively. Although the proposed algorithm has the longest runtime, the performance of the results in reducing electricity cost can improve significantly. Figure 4 displays the convergence behaviors of different methods. The power consumption and appliance scheduling using the proposed framework are shown in Fig. 5.

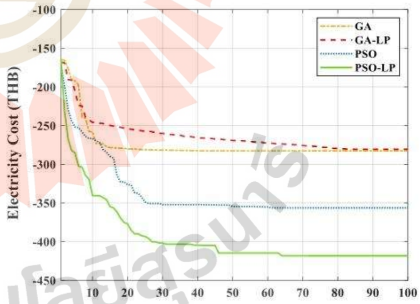


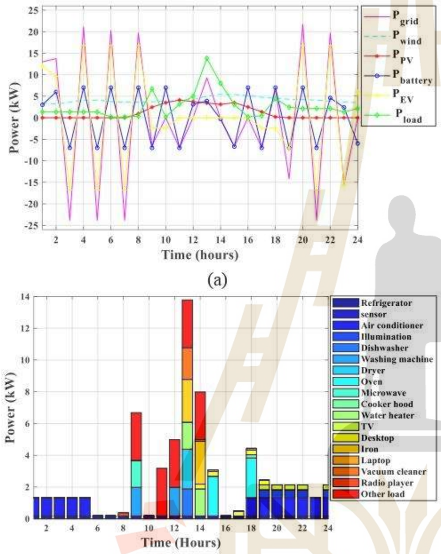
Figure. 4 The convergence behaviours of different methods

 DOI: 10.22266/ijies2025.0731.25

Received: April 2, 2025. Revised: May 16, 2025.

Table 4. The comparison results of the proposed hybrid PSO-LP and the other algorithm-based SHIEMS.

Method	Energy from grid (kWh)	Energy injected to grid (kWh)	Net Electricity buy(+)/ sell(-) (Rupee)	Run Time (sec)
BPSO [37]	20.344	40.808	-3.414	-
GA	79.415	99.360	-282.66	697.63
PSO	124.88	140.36	-356.36	893.08
GA-LP	112.00	124.38	-280.62	1297.77
PSO-LP	113.96	148.08	-418.26	4068.31



(b)

Figure. 5 The hybrid PSO-LP based SHIEMS: (a) The power consumption from appliances scheduling and (b) Appliances scheduling

4.2 Case B: The case study with Thai's distribution system condition

In this case, The TOU tariff in Thailand is an electricity tariff that reflects the cost of electricity production divided into two time periods [40]. For the proposed SHIEMS, households at a voltage level lower than 12 kV have to pay an energy charge of 5.7982 THB/kWh for peak hours and 2.6369 THB/kWh for off-peak hours. For the household PV scheme project, household rooftop PV energy is generated for self-consumption in smart homes. The household can sell the excess solar energy to MEA or PEA at an electricity purchase rate of 2.20 THB/unit with a purchasing period of 10 years [38].

4.2.1 Case B1: SHIEMS with V2H

This case shows average consumers in Thailand. Figure 6 illustrates the daily power consumption in the smart home, where the consumer relies heavily on grid power for all 24 hours. When the EV departs, all appliances consume power from the grid. When the EV arrives, EVs can provide some power to assist grid-supplied load demand, but when the EV is charged with power from the grid, EVs require a large amount of power.

4.2.2 Case B2: SHIEMS with PV and BESS

This case represents the emerging situation in many countries, including Thailand, where the number of prosumer smart homes with PV rooftops and BESSs is increasing. Figure 7 shows the result of this case, that most of the power load demand in the smart home is consumed by PV and BESS due to their availability, which reduces dependency on the grid power. The BESS supplies power to meet the load demand, enabling the PV to have more excess energy to sell into the grid as much as possible.

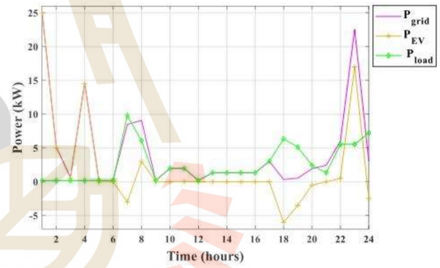


Figure. 6 The power consumption in Case B1

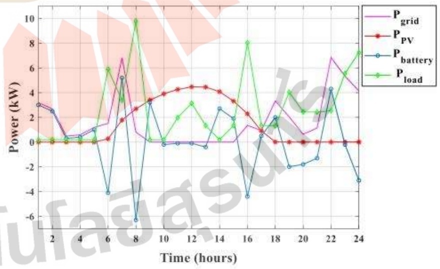


Figure. 7 The power consumption in Case B2

 DOI: 10.22266/ijies2025.0731.25

Received: April 2, 2025. Revised: May 16, 2025.

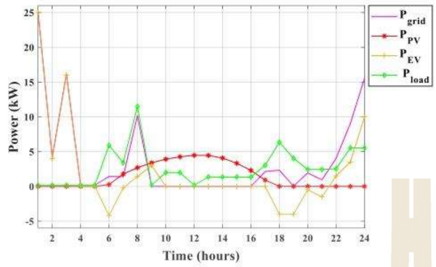


Figure. 8 The power consumption in Case B3

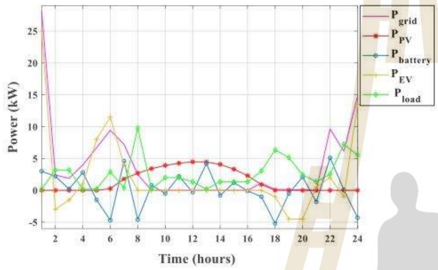


Figure. 9 The power consumption in Case B4

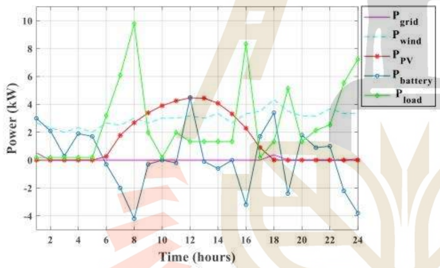


Figure. 10 The power consumption in Case B5

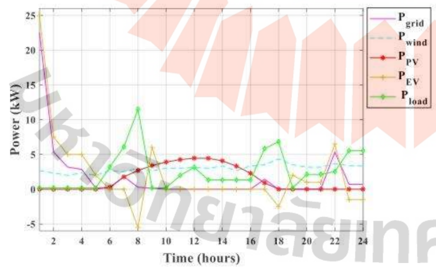


Figure. 11 The power consumption in Case B6

4.2.3 Case B3: SHIEMS with PV and V2H

In case B3, Fig. 8 displays the daily power consumption. When PV power is available and the EV departs from home, allowing the generated energy to supply the household load, reducing dependency on the grid during peak hours. With the EV absent, any excess PV energy can be sold back to the grid. When the EV returns, the EV can discharge power to minimize costs in peak hours. Conversely, EV will charge a large amount of energy from the grid in off-peak hours.

4.2.4 Case B4: SHIEMS with PV, BESS, and V2H

As a result of Case B4 shown in Fig. 9, when PV power is available and the EV departs from home, allowing the generated energy to supply the household load and charge the battery. In addition, the excess PV energy can be sold back to the grid. On the other hand, when the EV returns to charge from the grid, the battery can supplement its power to minimize costs and decrease reliance on the grid during peak hours.

4.2.5 Case B5: SHIEMS with PV, wind, and BESS

The result in this case is represented in Fig. 10. Due to the availability of two RES, the BESS charging and discharging are more flexible. Wind power assists batteries in providing power when PV power is unavailable, allowing batteries to make better decisions to minimize the strain on PV power, resulting in PV having more excess power to feed into the grid to reduce costs in households.

4.2.6 Case B6: SHIEMS with PV, wind and V2H

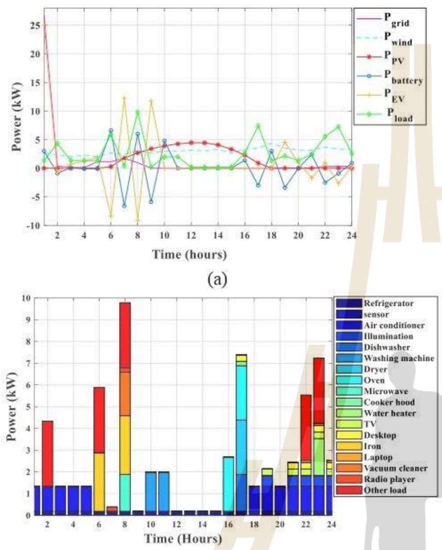
The power consumption in case B6 is presented in Fig. 11. Although the EV is a large load, the EV charging and discharging are more relaxed due to the availability of two RES. When EVs depart, wind power assists in providing power to load demand, allowing PV to have more excess power to feed into the grid to reduce household costs. In addition, wind power helps the grid charge EVs when they arrive home, and power from PV is unavailable.

4.2.7 Case B7: SHIEMS with PV, wind, BESS, and V2H

Due to the availability of two RESs, the battery charging and discharging are more flexible. The battery charges power from RESs to avoid the burden of the grid during peak hours. Batteries help discharge power when there are insufficient RESs to satisfy demand or high electricity prices. When an

Received: April 2, 2025. Revised: May 16, 2025.

EV arrives at a smart home, the EV contributes a minor amount of power to meet the load demand. EVs can consume power from the wind and batteries. The power consumption and appliance scheduling in case B7 are presented in Fig. 12.



(b)

Figure. 12 The result in Case B7: (a) The power consumption and (b) Appliances scheduling

Table 5. The electricity cost and power comparison

Cases		Energy grid usage (kWh)	Energy excess from PV (kWh)	Electricity cost (THB)
Scheduling by hybrid PSO-LP	1	113.240	-	355.364
	2	42.162	11.582	117.552
	3	94.926	17.257	273.563
	4	94.217	8.744	233.828
	5	0.608	17.941	-37.868
	6	43.514	15.870	80.906
	7	34.307	17.833	48.637
Non-Scheduling	1	140.115	-	558.578
	2	56.265	5.311	266.956
	3	137.446	8.312	481.913
	4	131.941	2.440	464.607
	5	26.551	9.430	115.799
	6	94.755	9.214	314.163
	7	91.588	6.734	295.135

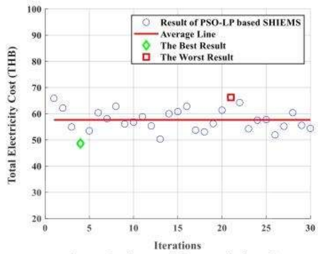


Figure. 13 The solution with 30 trials of Case B7

The results above clearly show that the SHEMS using the hybrid PSO-LP efficiently optimizes energy consumption and schedules load to avoid peak hours. Table 5 shows the daily energy consumption from the grid, energy excess from PV, and daily electricity cost in two scenarios: non-scheduling the appliance and scheduling with hybrid PSO-LP in all cases. The computation reliability of the proposed method had been verified by 30 trial runs of case B7 as shown in Fig. 13. The minimum and maximum daily cost from optimization of the SHIEMS obtained by hybrid PSO-LP is 48.637 THB/day and 66.233 THB/day, respectively. The average daily electricity cost in the optimization system is 57.640 THB. The results show that the proposed computational procedure can successfully provide stable and reliable results for SHIEMS.

4.3 The scalability of the hybrid PSO-LP

The scalability of the proposed hybrid PSO-LP based SHIEMS was considered for a larger number of appliances and extended scheduling time slots. Table 6 shows the result, which provides the feasibility of applying the proposed method in more complex SHIEMS scenarios. In addition, the proposed framework was also tested with seven days of operating conditions, as shown in Fig. 14. The result indicates that the proposed method can be effectively applied in a large time period.

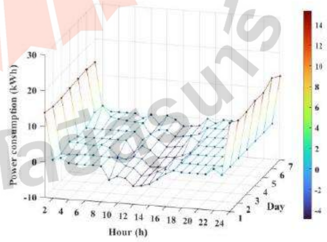


Figure. 14 The power consumption in seven days

 DOI: 10.22266/ijies2025.0731.25

Received: April 2, 2025. Revised: May 16, 2025.

Table 6. The scalability of hybrid PSO-LP in Case B7

Number of appliances	Time slots	Total cost (THB)	Runtime (sec)
18	24	48.637	4910.30
36	24	148.35	17626.62
18	168	250.45	27984.26

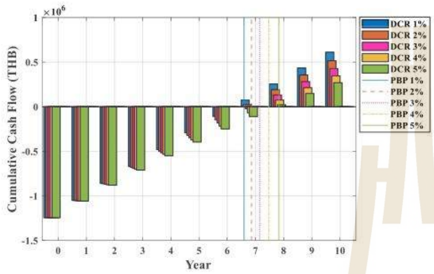


Figure. 15 Cumulative cash flow over 10 years

4.4 Economic impact of the proposed SHIEMS

In this study, the total initial investment for this project is estimated to be approximately 1,245,000 THB, which includes the 10 kWh BESS, a 5kW rooftop solar PV system, a vertical-axis wind turbine (VAWT), and a 50 kWh EV. Based on the projected annual energy savings of approximately 196,082 THB. Using a discount rate (DCR) of 5%, the present value (PV) of these savings over 10 years is estimated at 1,514,058 THB. Consequently, the Net Present Value (NPV) of the project is about 269,058 THB and a return on investment (ROI) of approximately 21.6% over 10 years. Since both the NPV and ROI are positive, this indicates that the investment is economically viable under the system conditions. Figure. 15 presents the cumulative cash flow over 10 years and payback period (PBP) with the DCR 1% to 5%.

5. Conclusion

The proposed method effectively provides optimal appliance scheduling and improves smart home energy management, leading to a decrease in daily electricity costs. The proposed SHIEMS can supervise the load appliances in selecting their power consumption from various energy resources through a TOU-based demand response system. The BESS and V2H can charge when renewable energy sufficiently meets the load consumption and discharge when renewable energy is insufficient to satisfy load demands or during peak hours. The simulation results demonstrate that the proposed hybrid PSO-LP-based SHIEMS effectively minimizes daily electricity costs for prosumers by 16.48% compared to the non-scheduling. Additionally, the proposed framework maximizes PV electricity sales for prosumers by 17.941 kWh and minimizes energy usage from the grid by 0.608 kWh, which helps alleviate the grid burden during peak hours.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization and methodology, 1st and 2nd authors; software, 1st author; validation, 1st and 2nd author; formal analysis, investigation, resources, data curation, 1st and 2nd authors; writing—original draft preparation, 1st author; writing—review and editing, 1st and 2nd authors; visualization, 1st author; supervision, 2nd author.

Acknowledgments

We would like to express our heartfelt appreciation to the Suranaree University of Technology for their invaluable support in the completion of this research.

References

[1] J. Y. Lee, and S. G. Choi, "Linear programming based hourly peak load shaving method at home area", In: *Proc. of 16th International Conference on Advanced Communication Technology*, Pyeong chang, Korea (South), pp. 310-313, 2014.

[2] F. Blaabjerg-Y. Yang-D. Yang, and X. Wang, "Distributed power-generation systems and protection", In: *Proc. of the IEEE,* vol. 105, No. 7, pp. 1311-1331, 2017.

[3] I. Javid-A. Chauhan-S. Thappa-S. Verma-Y. Anand-A. Sawhney-V. Tyagi, and S. Anand, "Futuristic decentralized clean energy networks in view of inclusive-economic growth and sustainable society", *Journal of Cleaner Production,* Vol. 309, pp. 127304, 2021.

[4] F. Y. Melhem-O. Grunder-Z. Hammoudan, and N. Moubayed, "Optimal residential load scheduling model in smart grid environment", In: *Proc. of 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*, Milan, Italy, pp. 1-6, 2017.

Received: April 2, 2025. Revised: May 16, 2025.

[5] Y. Farzambehboudi-O. Erdinç-A. R. Boynue-L. Ucun, and M. AliÖz, "Economic impact analysis of load shifting in a smart household", In: *Proc. of 2018 International conference on smart energy systems and technologies (SEST)*, Seville, Spain, pp. 1-5, 2018.

[6] P. Du, and N. Lu, "Appliance commitment for household load scheduling", *IEEE transactions on Smart Grid,* Vol. 2, No. 2, pp. 411-419, 2011.

[7] P. Palensky, and D. Dietrich, "Demand side management: Demand response, intelligent energy systems, and smart loads", *IEEE transactions on industrial informatics,* Vol. 7, No. 3, pp. 381-388, 2011.

[8] H. A. Özkan, "Appliance based control for home power management systems", *Energy,* Vol. 114, pp. 693-707, 2016.

[9] A. Agnetis-G. De Pascale-P. Detti, and A. Vicino, "Load scheduling for household energy consumption optimization", *IEEE Transactions on Smart Grid,* Vol. 4, No. 4, pp. 2364-2373, 2013.

[10] D. Ren-H. Li, and Y. Ji, "Home energy management system for the residential load control based on the price prediction", In: *Proc. of 2011 IEEE Online Conference on Green Communications*, NJ, USA, pp. 1-6, 2011.

[11] D. Kanakadhurga, and N. Prabaharan, "Demand response-based peer-to-peer energy trading among the prosumers and consumers", *Energy Reports,* Vol. 7, pp. 7825-7834, 2021.

[12] T. Logenthiran-D. Srinivasan, and T. Z. Shun, "Demand side management in smart grid using heuristic optimization", *IEEE transactions on smart grid,* Vol. 3, No. 3, pp. 1244-1252, 2012.

[13] K. Ma-T. Yao-J. Yang, and X. Guan, "Residential power scheduling for demand response in smart grid", *International Journal of Electrical Power & Energy Systems,* Vol. 78, pp. 320-325, 2016.

[14] W. Piawises, and K. Chayakulkheeree, "Smart Home Energy Management Algorithm for TOU-Based Demand Response", In: *Proc. of 2024 12th International Electrical Engineering Congress (iEECON)*, Pattaya, Thailand, pp. 1-5, 2024.

[15] K. C. Sou-J. Weimer-H. Sandberg, and K. H. Johansson, "Scheduling smart home appliances using mixed integer linear programming", In: *Proc. of 2011 50th IEEE conference on decision and control and European control conference*, Orlando, FL, USA, pp. 5144-5149, 2011.

[16] H. Zhu-Y. Gao-Y. Hou-Z. Wang, and X. Feng, "Real-time pricing considering different type of smart home appliances based on Markov decision process", *International Journal of Electrical Power & Energy Systems,* Vol. 107, pp. 486-495, 2019.

[17] T. Pamulapati-R. Mallipeddi, and M. Lee, "Multi-objective home appliance scheduling with implicit and interactive user satisfaction modelling", *Applied Energy,* Vol. 267, pp. 114690, 2020.

[18] Z. Yahia, and A. Pradhan, "Multi-objective optimization of household appliance scheduling problem considering consumer preference and peak load reduction", *Sustainable Cities and Society,* Vol. 55, pp. 102058, 2020.

[19] P. Pawar-S. Sampath-T. Ghosh, and K. Vittal, "Load scheduling algorithm design for smart home energy management system", In: *Proc. of 2018 IEEE 7th international conference on power and energy (PECon)*, Kuala Lumpur, Malaysia, pp. 304-309, 2018.

[20] F. A. Qayyum-M. Naeem-A. S. Khwaja-A. Anpalagan-L. Guan, and B. Venkatesh, "Appliance scheduling optimization in smart home networks", *IEEE Access,* Vol. 3, pp. 2176-2190, 2015.

[21] I. Ullah-N. Javaid-Z. A. Khan-U. Qasim-Z. A. Khan, and S. A. Mehmood, "An incentive-based optimal energy consumption scheduling algorithm for residential users", *Procedia Computer Science,* Vol. 52, pp. 851-857, 2015.

[22] I. Yahyaoui-F. Tadeo-H. Rocha, and R. Fiorotti, "Optimal load scheduling of a smart home supplied by a photovoltaic grid-connected plant", *IFAC-PapersOnLine,* Vol. 51, No. 28, pp. 292-296, 2018.

[23] R. El Makroum-A. Khallaayoun-R. Lghoul, and M. Chraibi, "A Linear Programming Based Load Scheduling System Considering Dynamic Pricing and Renewable Energy", In: *Proc. of 2021 12th International Renewable Engineering Conference (IREC)*, Amman, Jordan, pp. 1-5, 2021.

[24] R. El Makroum-A. Khallaayoun-R. Lghoul-K. Mehta, and W. Zörner, "Home Energy Management System Based on Genetic Algorithm for Load Scheduling: A Case Study Based on Real Life Consumption Data", *Energies,* Vol. 16, No. 6, pp. 2698, 2023.

[25] T. Dang, and K. Ringland, "Optimal load scheduling for residential renewable energy integration", In: *Proc. of 2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm)*, Tainan, Taiwan, pp. 516-521, 2012.

[26] M. Qais-K. Loo-H. M. Hasanien, and S. Alghuwainem, "Optimal Comfortable Load

Received: April 2, 2025. Revised: May 16, 2025. 407

Schedule for Home Energy Management Including Photovoltaic and Battery Systems", *Sustainability,* Vol. 15, No. 12, pp. 9193, 2023.

[27] K. M. Tsui, and S.-C. Chan, "Demand response optimization for smart home scheduling under real-time pricing", *IEEE Transactions on Smart Grid,* Vol. 3, No. 4, pp. 1812-1821, 2012.

[28] E. Shirazi, and S. Jadid, "Optimal residential appliance scheduling under dynamic pricing scheme via HEMDAS", *Energy and Buildings,* Vol. 93, pp. 40-49, 2015.

[29] M. B. Rasheed-N. Javaid-A. Ahmad-Z. A. Khan-U. Qasim, and N. Alrajeh, "An efficient power scheduling scheme for residential load management in smart homes", *Applied Sciences,* Vol. 5, No. 4, pp. 1134-1163, 2015.

[30] A. Kapoor, and A. Sharma, "Optimal charge/discharge scheduling of battery storage interconnected with residential PV system", *IEEE Systems Journal,* Vol. 14, No. 3, pp. 3825-3835, 2019.

[31] A. C. Duman-Ö. Güler-K. Deveci, and Ö. Gönül, "Residential load scheduling optimization for demand-side management under time-of-use rate", In: *Proc. of 2018 6th International Istanbul Smart Grids and Cities Congress and Fair (ICSG)*, Istanbul, Turkey, pp. 193-196, 2018.

[32] A. U. Rehman-Z. Wadud-R. M. Elavarasan-G. Hafeez-I. Khan-Z. Shafiq, and H. H. Alhelou, "An optimal power usage scheduling in smart grid integrated with renewable energy sources for energy management", *IEEE Access,* Vol. 9, pp. 84619-84638, 2021.

[33] X. Hou-J. Wang-T. Huang-T. Wang, and P. Wang, "Smart home energy management optimization method considering energy storage and electric vehicle", *IEEE Access,* Vol. 7, pp. 144010-144020, 2019.

[34] P. Singh-N. Tayal-Y. P. Verma, and B. Singh, "Optimum scheduling of residential appliances along with the management of distributed energy resources using mixed integer linear programming", In: *Proc. of 2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, Bombay, India, pp. 1-6, 2019.

[35] P. Singh-S. Dhundhara-Y. P. Verma, and N. Tayal, "Optimal battery utilization for energy management and load scheduling in smart residence under demand response scheme", *Sustainable Energy, Grids and Networks,* Vol. 26, pp. 100432, 2021.

[36] B. Chreim-M. Esseghir, and L. Merghem-Boulahia, "LOSISH—LOad Scheduling In Smart Homes based on demand response: Application to smart grids", *Applied Energy,* Vol. 323, pp. 119606, 2022.

[37] D. Kanakadhurga, and N. Prabaharan, "Smart home energy management using demand response with uncertainty analysis of electric vehicle in the presence of renewable energy sources", *Applied Energy,* Vol. 364, pp. 123062, 2024.

[38] M. E. A. MEA, "Household's Solar Project", Thailand, 2023. Available online at: https://www.mea.or.th/other-services/electricity-producers/ (Accessed 20 October 2024).

[39] A. Y. Saber, and G. K. Venayagamoorthy, "Plug-in vehicles and renewable energy sources for cost and emission reductions", *IEEE Transactions on Industrial Electronics,* Vol. 58, No. 4, pp. 1229-1238, 2010.

[40] M. E. A. MEA, "Tariff Calculation: Type 1 Residential Service", Thailand, 2023. Available online at: https://www.mea.or.th/our-services/tariff-calculation/other/ (Accessed 20 October 2024).

BIOGRAPHY

Ms. Wilawan Piawises received her B.Eng. degree in Electrical Engineering with First Class Honors from Suranaree University of Technology, Thailand, in 2023. She is currently pursuing her M.Eng. degree in Electrical Engineering at the same institution.

During her undergraduate studies, she completed an internship in the maintenance department, where she was involved in basic electrical equipment inspection and assisted with PLC programming tasks. She also worked as a teaching assistant in an electrical circuits laboratory, supporting students in hands-on experiments.

Her current research focuses on smart home energy management systems, with an interest in optimization techniques and renewable energy integration. She has some experience in MATLAB programming and algorithm development for energy system applications.