School of Electrical Engineering, Computing and Mathematical Sciences

Optimal Home Energy Management System for Committed Power Exchange Considering Renewable Generations

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Author's Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made. This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

10/04/2020

Bahman Naghibi

Statement of Originality

This thesis contains three original studies which are published as two conference papers and one peer-reviewed journal article. They have been incorporated in Chapters 3 and 4.

- Naghibi, B., M.A. Masoum, and S. Deilami, 'Effects of V2H integration on optimal sizing of renewable resources in smart home based on Monte Carlo simulations.' IEEE Power and Energy Technology Systems Journal, 2018. **5**(3): p. 73-84.

- Naghibi, B. and S. Deilami. 'Non-intrusive load monitoring and supplementary techniques for home energy management.' in Power Engineering Conference (AUPEC), 2014 Australasian Universities. 2014.

- Naghibi, B. 'Data Modeling for Renewable Resources and Smart Home using Monte Carlo Simulations.' in 2019 IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe). 2019. IEEE.

The full-text version of papers are available in Appendix A followed by attribution of publications in Appendix B.

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Abstract

With the development of smart grid (SG) and demand response (DR) programs, smart homes (SHs) can play a significant role in increasing the penetration of renewable resources while improving the sustainability of the grid. This thesis addresses the complexity of SH operation and local renewable resources optimum sizing. The effect of different criteria and components of SH on the size of renewable resources and annual cost of electricity in the residential sector is investigated. The operation of SH with the optimum size of renewable resources is also evaluated to study the annual cost of SH. In addition, the effectiveness of SH with committed exchange power functionality is studied with the goal of minimising annual electricity cost while responding to DR programs.

First, background and a literature review relevant to state-of-the-art technologies and elements (such as SH optimal sizing problem, DR programs, home energy management System (HEMS), renewable distributed generation and SH enablers) are presented. Then, a modelling framework for implementing stochastic behaviour of renewable resources in optimisation problems is introduced. Wind turbine (WT), photovoltaics (PV), SH generation cost, battery charge/discharge, heating, ventilation, and air conditioning (HVAC) load and plug-in electric vehicles (PEV) charge/discharge are also modelled to be used for sizing optimisation. After that, optimum component sizing for a SH with rooftop WT, PV, battery storage system (BSS), PEV and shiftable loads by minimising annual electricity cost is introduced. A new rule-based HEMS is proposed in association with Monte Carlo simulations and particle swarm optimisation (MCS-PSO). Import and export of energy with vehicle-to-home (V2H) integration is considered along with stochastic behaviors of temperature, irradiance, wind speed, load, PEV availability and electricity rate (ER). After determining near-optimal sizes of rooftop PV, WT, and BSS, the performance of the SH operation is evaluated with the selected near-optimal renewable resources. The impacts of shiftable loads, maximum daily export energy, battery charge/discharge rates, V2H integration and, maximum WT, PV and battery capacity limits are investigated in sensitivity analysis simulations.

Following the above, a SH with committed exchange power functionality is proposed. Near-optimal sizes of rooftop PV, WT and BSS are studied for different conditions based on the proposed rule-based HEMS algorithm utilising a proposed MCS-PSO approach. Annual cost is minimised for determining near-optimal size of rooftop PV, WT and BSS for the SH with the committed power exchange. Stochastic behaviors of renewable resources and availability of PEV are considered. After determining near-optimal sizes of rooftop PV, WT and BSS, the performance of the SH operation is evaluated with the selected near-optimal renewable resources. The impacts of shiftable loads, maximum daily export energy, battery charge/discharge rates, V2H integration and maximum WT, PV and battery capacity limits are investigated in sensitivity analysis simulations. Further investigation is conducted to study the effect of various committed power exchanges to the annual cost and optimal sizes of rooftop PV, WT and BSS for the SH with shiftable load and V2H integration.

The contribution of this study is significant for policy-makers, researchers and system designers who aim to improve SG, SH, electricity tariff structures and DR programs for the residential sector, which can further increase the penetration of renewable resources.

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Dedicated to my beloved wife and my parents for their enduring support and love.

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List of Abbreviations

ABC	artificial bee colony
AMI	advanced metering infrastructure
AMR	automatic meter reading
BACnet	Building Automation and Control Network
BSS	battery storage system
CPP	critical peak pricing
DG	distributed generation
DI	decision interval
DLNA	Digital Living Network Alliance
DR	demand response
DSM	demand-side management
EE	energy efficiency
EMS	energy management systems
EPR	electricity purchase rate
ER	electricity rate
ESR	electricity selling rate
GHG	greenhouse gas
Gt	gigatonnes
H2G	home-to-grid
H2V	home-to-vehicle
HAN	home area network
HEMS	home energy management system
HVAC	heating, ventilation and air conditioning
ICT	information and communication technologies
kWh	kilowatt hour
LCOE	levelised cost of electricity (cents/kWh)

IoT	Internet of Things
MCS	Monte Carlo simulations
MG	microgrid
MCS-PSO	Monte Carlo simulations and particle swarm optimisation
NILM	non-intrusive load monitoring
NP-Hard Problem	non-deterministic polynomial-time hard problem
O&M	operation and maintenance
oBIX	Open Building Information Exchange
PC	personal computer
PEV	plug-in electric vehicle
PV	photovoltaic
RTP	real-time pricing
SCADA	supervisory control and data acquisition
SG	smart grid
SH	smart home
SHMC	smart home micro-computer
SOC	state of charge
SR	spinning reserve
TMY	typical meteorological year
TOU	time of use
UK	United Kingdom
UPnP	Universal Plug and Play
V2G	vehicle-to-grid
V2H	vehicle-to-home
WT	wind turbine

List of Symbols

i	daily time steps in MCS-PSO
j	hourly time steps in MCS-PSO
k	MCS-PSO maximum iteration number
Δt	time interval for simulations (sec)
α	electricity Reward Factor
β	electricity Penalty Factor
$B(\Delta t_j)$	available battery charge (kWh)
c_1	the cognitive parameter in PSO
c_2	the social parameter in PSO
Cap_B	capacity of battery (kWh)
Cap_{PEV}	capacity of PEV (kWh)
Cap_{PV}	capacity of PV (kW)
Cap_{WT}	capacity of WT (kW)
C_{Hour}	hourly electricity cost of SH (cents)
C_{Day}	daily electricity cost of SH (cents)
C_{Annual}	annual electricity cost of SH (cents)
$C_{d,sell}^{PEV}$	cost of discharging PEV for sell/export (cents/kWh)
D	search–space dimension for PSO and ABC
DOD	depth of discharge (%)
$E_B(\Delta t_j)$	electricity charge/discharge of battery during Δt_j (kWh)
$E_{PEV}(\Delta t_j)$	electricity charge/discharge of PEV during Δt_j (kWh)
$E_{PV}(\Delta t_j)$	energy generation by PV during Δt_j (kWh)
$E_w(\Delta t_j)$	energy generation by WT during Δt_j (kWh)
$E_{Buy}(\Delta t_j)$	electricity imported/purchased from SG during Δt_j (kWh)
$E_{Sell}(\Delta t_j)$	electricity exported/sold to SG during Δt_j (kWh)

$E_{Sell,max}$	maximum limit of daily electricity export (kWh/day)
$E_{sell}^{PEV}(\Delta t_j)$	electricity sold to SG from PEV during Δt_j (kWh)
$ER(\Delta t_j)$	electricity rate during Δt_j (cents/kWh)
$ER_{max}(DI)$	maximum electricity rate during DI (cents/kWh)
$ER_{min}(DI)$	minimum electricity rate during DI (cents/kWh)
FF	fill factor
fit_s	fitness of the candidate solution in ABC
$G(\Delta t_j)$	global horizontal irradiance during Δt_j (W/sq.m)
I_{SC}	short-circuit current (A)
$I_{SC.STC}$	short-circuit current measured under standard test conditions (A)
K_I	short-circuit current coefficient (A/°C)
K_V	open-circuit voltage coefficient (V/°C)
L_b	base load (kW)
L_s	schedulable load (kW)
L_{bu}	unpredictable load (kW)
L_{HVAC}	HVAC load (kW)
LC_{PV}	levelised cost of PV (cents/kWh)
LC_W	levelised cost of WT (cents/kWh)
LC_{PV+WT}	levelised cost of total PV+WT (cents/kWh)
LC_B	levelised cost of the battery (cents/kWh^2)
limit	prearranged number of cycles which a food source will be abandoned if does not improve in ABC
MCN	maximum cycle number in ABC
η_{PVinv}	PV system inverter efficiency
N_{PV}	number of PV modules
NCOT	nominal cell operating temperature (°C)
p_{gbest}	the global best solution in PSO
p_{id}	the local best solution in PSO

p_s	probability of choosing a food source in ABC
R_c	rate of battery charge and discharge (kW)
R_c^{PEV}	rate of PEV charge and discharge (kW)
SN	number of candidates/food sources in ABC
SOC^B	state of charge of the battery (%)
SOC^{PEV}	state of charge of PEV (%)
SOC_{arrive}^{PEV}	state of charge of PEV at arrival time (%)
$SOC_{dep,min}^{PEV}$	minimum state of charge of PEV at departure time (%)
SOC_{init}^{PEV}	initial state of charge of PEV in the start of the day (%)
$T_A(\Delta t_j)$	ambient temperature during Δt_j (°C)
$T_C(\Delta t_j)$	cell temperature during Δt_j (°C)
T_{arrive}^{PEV}	PEV arrival time (hour)
T_{dep}^{PEV}	PEV departure time (hour)
T_{ref}	PV panel temperature of 25°C at reference operating conditions
V_{ci}	cut-in wind speed (m/s)
V_{co}	cut-out wind speed (m/s)
V_{OC}	open-circuit voltage (V)
$V_{OC.STC}$	open-circuit voltage measured under standard test conditions (V)
V_r	rated wind speed (m/s)
V_w	wind speed (m/s)
w	inertia weight for PSO

Chapter 1 Introduction

1.1 Background

Concerns about greenhouse gas (GHG) emissions and electricity demand increases have dramatically increased interest in renewable energy resources over the last decades. As a result, the penetration of the grid by renewable resources has increased. With the increase of distributed generation and the intermittency characteristic of some renewable energy resources, the need for smart, efficient, balanced, economic, sustainable and secure grid has also increased.

Information and communication technologies (ICT) play an important role in the evolution of the smart grid. Demand-side management (DSM) and demand response (DR) programs are also considered important options for balancing energy generation and demand. With the development of demand response programs and new technologies, the residential sector can play a significant role in optimising grid operation.

1.1.1 Fossil CO_2 emissions

Since the start of the 21st century, reports show that global GHG emissions have increased compared to the three preceding decades. This is in part due to increased CO_2 emissions generated by emerging economies. Global anthropogenic fossil CO_2 emissions showed an increase of 1.2% in 2017 compared to 2016, reaching about 37.1 Gt. This increase was 0.4% in 2016 compared to 2015 (noting that 2016 was a leap year) [1]. Figure 1.1 shows global fossil CO_2 annual emissions in Gt CO_2/year separated by sectors. As can be seen, a large part of global CO_2 is generated by the power and transport industries. This portion can be decreased by increasing the penetration of renewable resources and plug-in electric vehicles (PEVs).

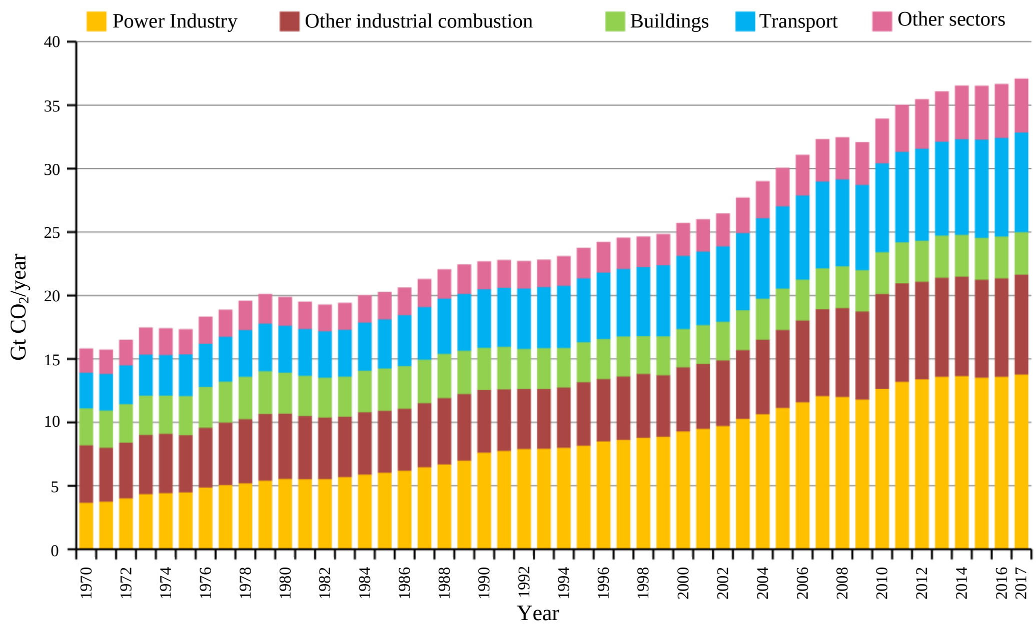


Figure 1.1. Global fossil CO_2 annual emissions (Gt CO_2/year) [1].

1.1.2 Renewable energy

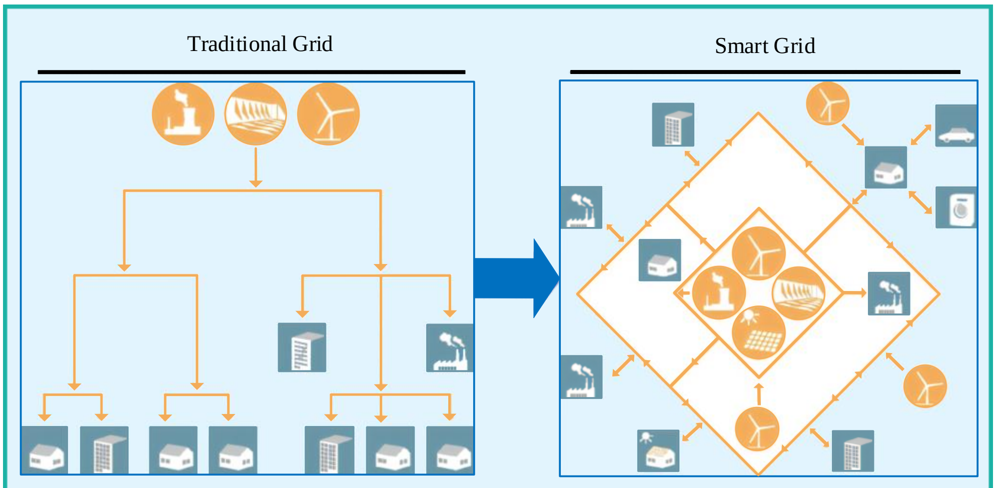
Interest in renewable energy has increased significantly over the last several decades due to the limited supply of conventional fossil fuels and their associated environmental issues. In the 1970s the threat of running out of conventional fossil fuels led to programs for expanding renewable resources, but this interest was temporary and receded again as supply increased to meet demand. However, with recognition of the link between global warming and CO_2 emissions, and the risks of using conventional fossil fuels, renewable energy has seen renewed attention. The main renewable energy systems which have been used for generating electricity are wind, solar, thermal, photovoltaics (PVs), biomass, geothermal, hydroelectric and ocean. According to [2], 25,921 km^2 of PV can generate (during one year) the equivalent energy of the United States' needs for one year. This area is less than one-quarter of the area that is covered with streets and roads in the USA. Adding other renewable resources makes it even more feasible to power the entire country using only renewable resources. However, there is a problem associated with many forms of renewable resources – namely, their intermittency characteristic.

1.1.3 Smart grid (SG)

Electrical grid efficiency needs to improve to overcome environmental and regulatory restraints and the rapid increase in demand for penetration of renewable sources [3]. According to [4], the challenges operation of the electrical grid system faces include:

- reliability, power quality and energy efficiency
- increased renewable energy resources penetration, household demand, electric cars and micro-generation
- generation and consumption uncertainty, customer awareness and short-term contracts.

Some of traditional grid issues driving the transition towards a smart grid (Figure 1.2) are listed in [5]. A brief definition of smart grid is also offered: ‘The smart grid is a suite of information based applications made possible by increased automation of the electricity grid, as well as the underlying automation itself; this suite of technologies integrates the behaviour and actions of all connected supplies and loads through dispersed communication capabilities to deliver sustainable, economic and secure power supplies’ [5].



Traditional Grid	Smart Grid
Centralized Generation	Generation Everywhere
Power Flows Downhill	Power Flows from Everywhere
Utility Controls Connections	Anyone May Participate
Behaviour: Predictable	Behaviour: Chaotic

Figure 1.2. Transition to smart grid [6].

Economic and policy-based considerations, along with new technologies – in communications, renewable generation, energy storage and computing power – as well as innovative products and services, intelligent control/monitoring, and self-healing technologies, mean that SG can [5]:

- enable consumers to choose their supply and equip them with superior information
- authorise consumers to play a role in system operation optimisation.

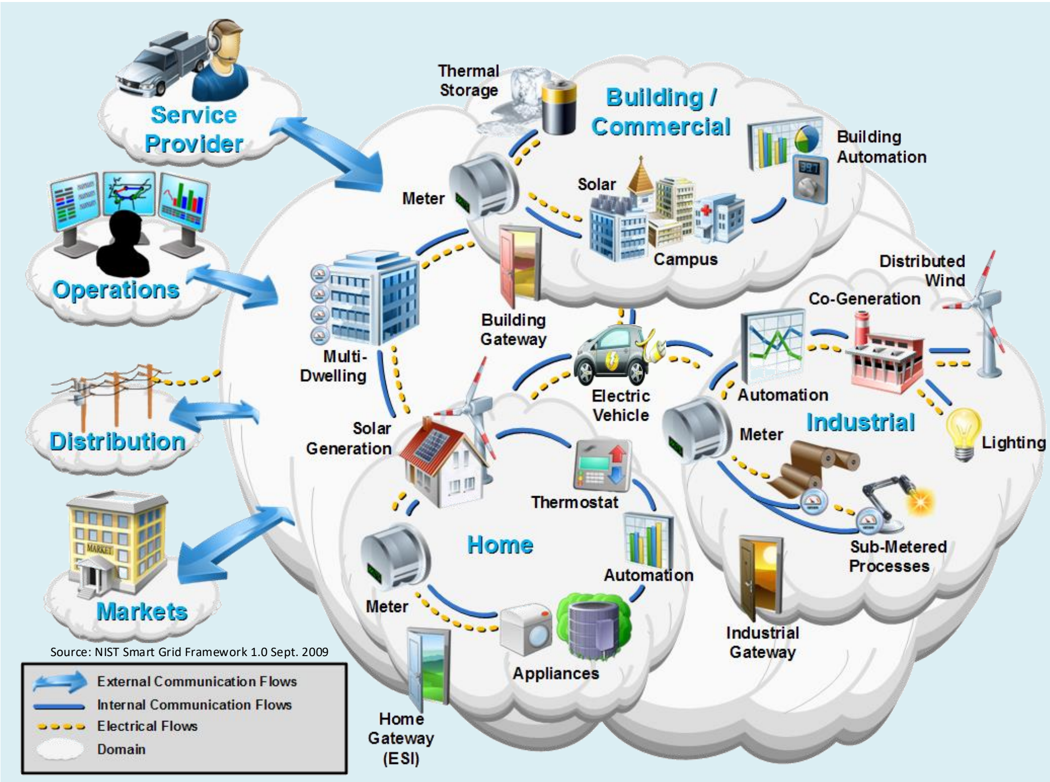


Figure 1.3. Customer domain overview in SG [7].

An overview of the customer domain in SG is shown in Figure 1.3. There are three key features in the interconnection of buildings and the smart grid [7]. The first is a distributed renewable energy strategy that enables customers to generate electricity. The second feature is demand response (DR) programs between customers and service providers. Finally, the third feature is the availability of plug-in electric vehicles (PEV) and the possibility of charging them in buildings.

The smart home (SH) can be considered as a nanogrid which can play a significant role in the transition of the grid towards a smart grid [4]. With the development of SGs and SHs, and utilisation of demand-side load management, the electrical grid is expected to have higher stability, with lower load fluctuation and operational cost (in terms of matching generation and demand) and reduced network dynamics and line losses [8]. SG can forecast electricity prices and control the energy at transmission and distribution levels by monitoring SHs' energy and environmental data [9]. Using demand-side management in the residential sector in the context of SGs and SHs appears promising, as residential energy usage is almost 40% of global primary usage [3, 10, 11].

1.1.4 Smart home

Smart homes (SHs) were introduced to improve energy efficiency, energy savings, comfort, security, safety and healthcare [12, 13]. They use artificial intelligence, communication skills, computational power, monitoring and controlling abilities to improve life experience and they can respond to residents' behaviour [14]. Also, the development of the Internet of Things (IoT), along with other information and communication technologies (ICT), makes SHs more feasible [3, 15]. According to [3], an SH is defined as 'a home which is smart enough to assist the inhabitants to live independently and comfortably with the help of technology is termed as smart home. In a smart home, all the mechanical and digital devices are interconnected to form a network, which can communicate with each other and with the user to create an interactive space'. In another definition [12], the SH is defined as 'an application that is able to automatize or assist the users through different forms such as ambient intelligence, remote home control or home automation systems' [3]. Some of fundamental characteristics of SHs are presented by [3] as follows.

- Automation: having the capability to incorporate automatic devices or execute automated functions.
- Adaptability: having the capability to learn, forecast and fulfil users' needs.
- Multi-functionality: having the capability to produce various results or carry out multiple duties.
- Efficiency: having the capability to save time and costs by carrying out functions in a suitable manner.

- Interactivity: having the capability to allow users to interact with each other.

Systems and technologies for SHs are investigated by [3]. Their advantages and disadvantages are discussed and available products on the market are introduced; these are presented in Table 1.1.

Table 1.1. Smart home technologies.

Integrated Wireless Technologies	**HEMS Products**	**SHMC Products**	**Home Automation products**
6LoWPAN	CISCO	Arduino	Control4Home automation
Blutooth	DigitalSTROM	Libelium Waspmote	Creston home automation & entertainment
EnOcean Technology	The Energy Navigator platform	BeagleBone Black	British Gas Smarter Living & energy saving-smart meters
DASH7	e-GOTHAM	Raspberry Pi	General Electric Brillion technology
GSM	Dreamwatts	Banana Pi	Panasonic smart appliance
NeuRFon ™ Netform	Energy Team's Energy Data Collector Tool		Whirlpool smart appliances
MyriaNed	Google PowerMeter		Vera smarter home control
RFID	Savant		Honda Smart Home US
UWB	SMARTHEMS™		Samsung SmartThings
Wi-Fi	EmonCMS		LG Smart Thinq™
WLAN			HomeSeer HS3, Staples Connect
Z-Wave			LonWorks, OpenHAB, Wink, Iris
ZigBee			Nexia, KNX, UPnP, iHome, WeBee

A home energy management system (HEMS) is one of the important enablers of SHs. It can be used to minimise electricity cost and increase efficiency by enabling consumers to actively control demand and generation [16]. According to [17], HEMSs can be used for:

- balancing demand and supply while managing energy flow for SHs
- planning energy production for exchanging energy with the grid.

Renewable energy generation and energy requirements in SHs are misaligned, and energy cost differs during peak and off-peak hours. HEMS can be used for managing energy, which can be facilitated with energy storage [16].

SHs can help consumers use electricity efficiently in order to decrease energy cost, peak load and GHG emissions. However, more studies are needed in the areas of DR and end-users of the SG [3].

1.2 Research scope

This thesis focuses on a committed power smart home (SH) with optimal size of renewable resources for demand response (DR) programs to facilitate penetration of renewable resources in order to reduce emissions while improving SG efficiency. SHs with various ranges of committed power are studied, which helps policy-makers understand the impact of electricity rate and electricity tariff structures on the penetration of renewable resources.

Two HEMSs – for a non-committed power SH and a committed power SH – are proposed to schedule the load and allocate the local renewable resources for the SH based on dynamic day-ahead price and incentive DR programs.

Also, the near-optimal size of renewable resources for SHs is investigated using Monte Carlo simulation and particle swarm optimisation (MCS-PSO) to increase the profit of households while increasing the penetration of renewable resources based on the DR programs.

Probabilistic behaviour of renewable resources, loads, electricity rate (ER) and availability of a plug-in electric vehicle (PEV) is considered along with household comfort preferences, SH energy generation cost and shiftable/non-shiftable loads.

1.3 Research objectives

This thesis aims to investigate the optimum sizing of renewable resources for SH with/without committed power exchange and PEV integration. SH operation is evaluated for determined near optimal sizes following a sensitivity analyses. The research objectives can be listed as follows:

1. Modelling stochastic behaviour of SH components and development of rule-based HEMS algorithms to empower households for shifting (scheduling) their shiftable loads to off-peak periods based on the DR programs.
2. Optimum sizing of SH renewable resources and investigating the impacts of shiftable loads, V2H, battery rate, maximum daily electricity export, and maximum capacities of BSS, WT and PV on optimal sizes.
3. Optimum sizing of renewable resources for SH with committed power exchange and PEV integration by utilizing proposed rule-based algorithm with MCS and PSO. Also, investigating the impacts of shiftable loads, V2H, battery rate, maximum daily electricity export, and maximum capacities of BSS, WT and PV on optimal sizes.
4. Evaluating the performance through the operation of SH with/without committed power exchange and cost evaluation with near-optimal renewable component sizes.
5. Investigating the impact of various range of committed power for the SH with shiftable loads and shiftable PEV/H2V/V2H.

1.4 Thesis structure

The outline of this thesis is shown in Figure 1.4. After this introductory chapter, the rest of this thesis is organised as follows.

- **Chapter 2:** This chapter presents an overview of the recent literature about SH components in the context of smart grid and demand response programs. A number of technologies and components that play a significant role in SHs are discussed and evaluated. Recent studies of demand-side management, renewable distributed generation, optimal sizing of renewable resources and SH enabling technologies are summarised and discussed.

- **Chapter 3:** This chapter presents data modelling and optimisation methods used for energy management and sizing optimisation in SHs. Two methods are introduced for modelling wind speed, global irradiance, temperature, power demand, and electricity rate based on yearly data by use of Monte Carlo simulation (MCS). Additionally, components of SHs, such as renewable resources and loads, are modelled to be used in the following chapters' simulations. Further, particle swarm optimisation (PSO) is presented to be used for optimum sizing of components for SHs.
- **Chapter 4:** This chapter presents optimum component sizing for an SH with rooftop WT, PV, BSS, PEV and shiftable loads by minimising annual electricity cost. A new rule-based home energy management system (HEMS) is proposed in association with MCS-PSO. Import and export of energy with V2H integration is considered along with stochastic behaviors of temperature, irradiance, wind speed, load and ER. Also, lognormal and normal probability density functions are used for projecting availability of PEV. After determining near-optimal sizes of rooftop PV, WT, and BSS, the performance of the SH operation is evaluated with the selected near-optimal renewable resources. The impacts of shiftable loads, maximum daily export energy, battery charge/discharge rates, V2H integration and maximum WT, PV and battery capacity limits are investigated in sensitivity analysis simulations. Finally the optimisation results for MCS-PSO and MCS-ABC are compared for Cases B1, B2 and B3 in Section 4.4.4.
- **Chapter 5:** This chapter presents a SH with committed exchange power functionality. Near-optimal sizes of rooftop PV, WT, and BSS are studied for different conditions based on the proposed rule-based algorithm (HEMS) with MCS-PSO. Annual cost is minimised for determining the near-optimal size of rooftop PV, WT, and BSS for the SH with committed power exchange. Stochastic behaviors of renewable resources and availability of PEV are considered. After determining near-optimal sizes of rooftop PV, WT and BSS, the performance of the SH operation is evaluated with the selected near-optimal renewable resources. The impacts of shiftable loads, maximum daily export energy, battery charge/discharge rates, V2H integration and maximum WT, PV and battery capacity limits are investigated in sensitivity analysis simulations.

Further investigation is conducted to study the effect of various committed power exchange to the optimal sizes of rooftop PV, WT and BSS for the SH with the shiftable load and V2H integration.

- **Chapter 6:** This chapter presents conclusions, contributions and future research recommendations.

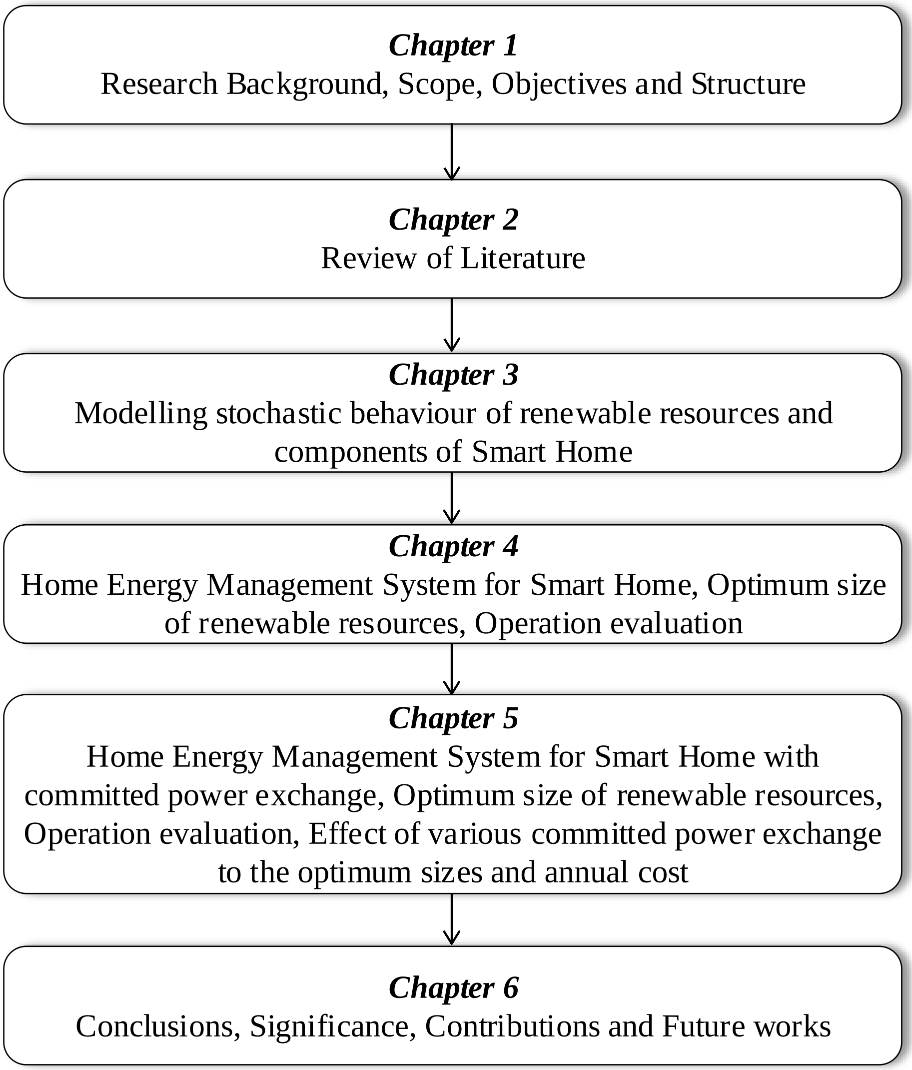


Figure 1.4. Thesis outline.

Chapter 2 Literature Review for Smart Homes

2.1 Introduction

This chapter presents an overview of recent literature about SH components in the context of smart grid and demand response programs. A number of technologies and components that play a significant role in SHs are discussed and evaluated. These technologies empower SHs and facilitate the transition of the grid towards a smart grid. Implementation of these technologies and optimal usage is important for increasing energy efficiency while reducing greenhouse gas emissions. Investigated areas are classified into four main categories.

1. Demand-side management and demand response programs
    a. Demand-side management
    b. Demand response programs
2. Renewable distributed generation
    a. PV system
    b. Wind system
    c. Electrical storage system
3. Optimal sizing of renewable resources
    a. Optimal sizing for microgrid
    b. Optimal sizing for smart home
4. Smart home enablers
    a. Power metering devices
    b. Communication network
    c. Smart appliances
    d. The Internet of Things
    e. Smart sensors
    f. Monitoring and control systems
    g. Cloud computing
    h. Home energy management system (HEMS)
    i. Energy consumption scheduling

2.2 Demand-side management and demand response programs

Demand-side management (DSM) and demand response (DR) programs are promoted in residential contexts to address residential demand increases. They seek to influence the patterns of energy consumption. DSM programs are used to influence consumers in the medium- or long-term to increase energy efficiency. However, DR is designed for short-term influence on demand by use of a control signal, such as price [4].

2.2.1 Demand-side management

Demand-side management (DSM) was introduced in 1970 [18]. It is a marketing strategy focused on technology and on utilities' and customers' needs [7]. DSM activities are defined as 'those which involve actions on the demand (i.e. customer) side of the electric meter, either directly or indirectly stimulated by the utility. These activities include those commonly called load management, strategic conservation, electrification, strategic growth or deliberately increased market share' [19]. DSM has been extended to be used for stability and reliability improvement, power system loading and system expenditures decrement [20].

DSM aims to balance demand with available supply and achieve the following goals [7, 21].

- Operational cost reduction for entire network.
- Improving consumers' participation in generation and energy management.
- Load management.
- Balancing demand and supply.
- Improving energy efficiency and conservation.
- Decreasing emissions.

DSM is categorised by [22], based on timing and the impact of the applied measures on the customer process, into four categories: (i) energy efficiency (EE); (ii) time of use (TOU); (iii) demand responses (DR); (iv) spinning reserve (SR). In addition, DSM challenges in UK are studied in [23] and the policy is reviewed by [21] after dividing DSM into three broad areas, as can be seen in Figure 2.1.

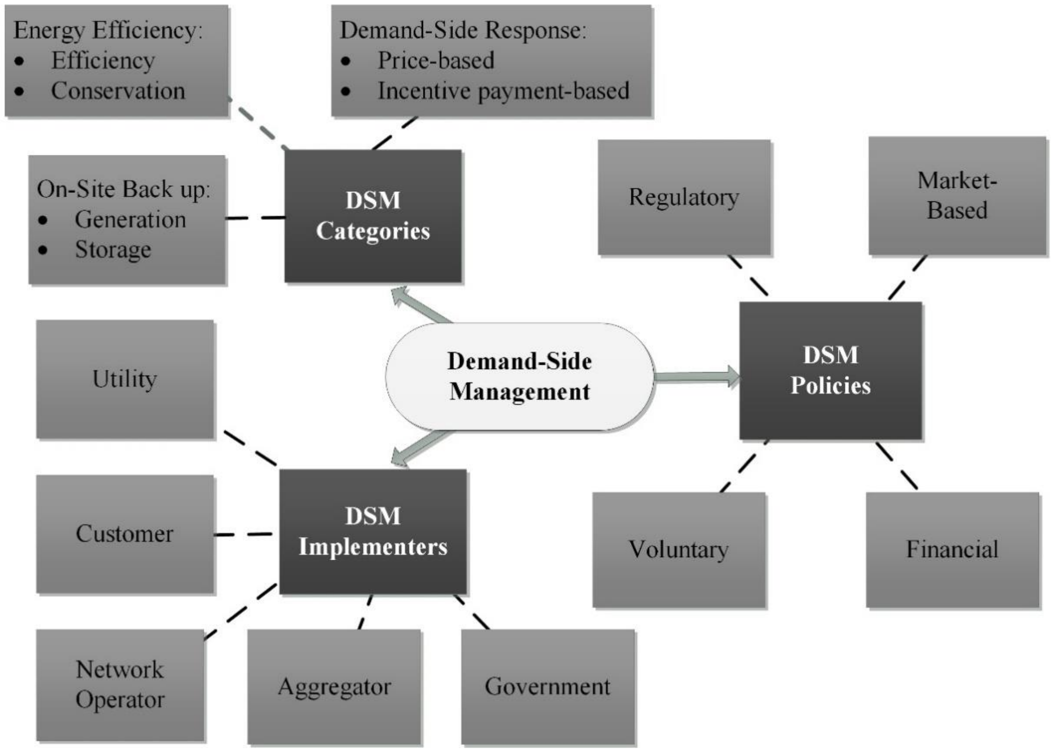


Figure 2.1. Elements of demand-side management [21].

2.2.2 Demand response programs

Utilities and aggregators use DR, which is a DSM programs, to manage power consumption. DR provides notifications to customers in order to change consumers' expected load patterns for efficiency improvement [24]. It is a cost-effective alternative (compared to adding generation resources) during demand spikes and peak times to reduce system emergencies and peak demand [25].

DR is defined as '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' [18].

There are two types of DR programs[26]:

- time-based programs
- incentive-based programs.

These two types contain fourteen DR classifications, which are described in [7] and listed in Table 2.1. In the price-based programs, price is variable and based on dynamics such as real-time pricing (RTP), critical peak pricing (CPP) and time of use (TOU) [27].

A simple type of DR is TOU, which defines several periods with different electricity prices for each period. Providers such as Ausgrid (Figure 2.2) in Sydney and Synergy in Perth, Australia, provide TOU services for motivated customers. CPP is similar to TOU pricing; however, for some days regular peak price is changed to a predetermined higher rate. This seeks to reduce customer demand when the reliability of the grid is under pressure [28]. One of the most efficient price-based programs is RTP, which reflect changes in the wholesale market and energy price changes hourly or a day ahead [7].

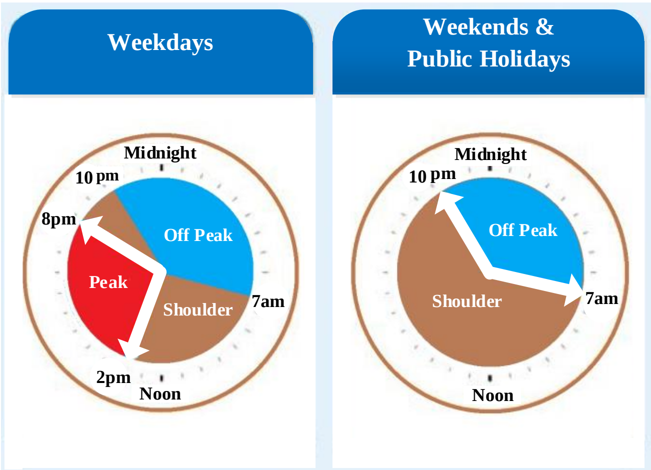


Figure 2.2. Ausgrid TOU periods [7].

In the incentive-based programs, customers receive load control signals to reduce their demand. These signals can be based on contractual agreement or incentive-based payments [29].

Table 2.1. Demand response programs, issues, approaches and future extensions [7, 28].

Demand Response	
Incentive-Based Programs	**Time-Based Programs**
1. Direct load control [30] 2. Interruptible load [31] 3. Spinning reserves 4. Non-spinning reserves 5. Emergency demand response [32] 6. Load as capacity resource 7. Demand bidding and buyback [33] 8. Regulation service	1. Critical peak pricing [34] 2. Real-time pricing [35, 36] 3. Time-of-use pricing [37-39] 4. Critical peak pricing with control 5. Peak time rebate 6. System peak response transmission tariff
Mathematical Problems	**Mathematical Models**
Utility maximisation [40-45] Cost minimisation [46-52] Price reduction [46, 53] Renewable energy [43, 44, 54-60] Energy storage [40, 45, 58, 59, 61-71]	Utility function [40-44, 47, 48] Cost function [41, 42, 47, 48]
Approaches	**Future Extensions**
Convex optimisation [40, 41, 46] Game theory [47, 48, 69, 72-77] Dynamic programming [44, 49, 71, 78-81] Markov decision process [57, 70, 82, 83] Stochastic programming [43, 84-86] Particle swarm optimisation [45, 61, 87-90]	Coupled constraint [91, 92] Hierarchical game [93, 94] Communication impact [95, 96]

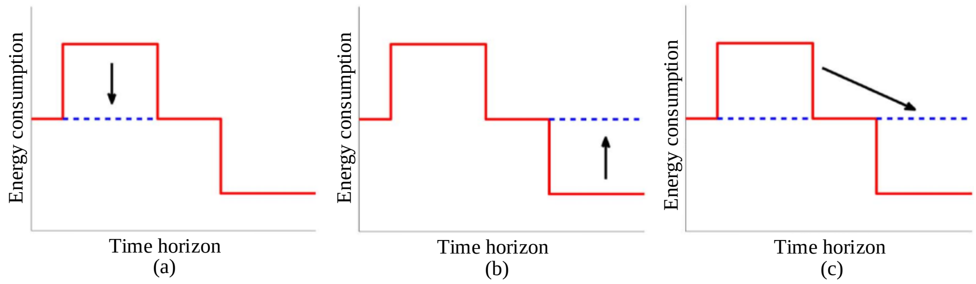


Figure 2.3. Demand response for: (a) peak shaving; (b) valley filling; and (c) load shifting [28].

For deployment of SG technologies and services, DR is one of the important areas with critical functionality [97]. It is used for peak shaving, valley filling and load shifting (Figure 2.3). Also, it brings significant economic advantages, as can be seen in Figure 2.4 [24]. DR techniques are reviewed by [98].

EMS at the end-user level is one of technologies that can be improved to further advance DR [99]. Residential DR is investigated by [100] and multi-consumption level pricing is introduced to control high-level consumer consumption. Also, a Dynamic Demand Response Controller (DDRC) is proposed by [101] to control HVAC loads with a threshold price determined by households.

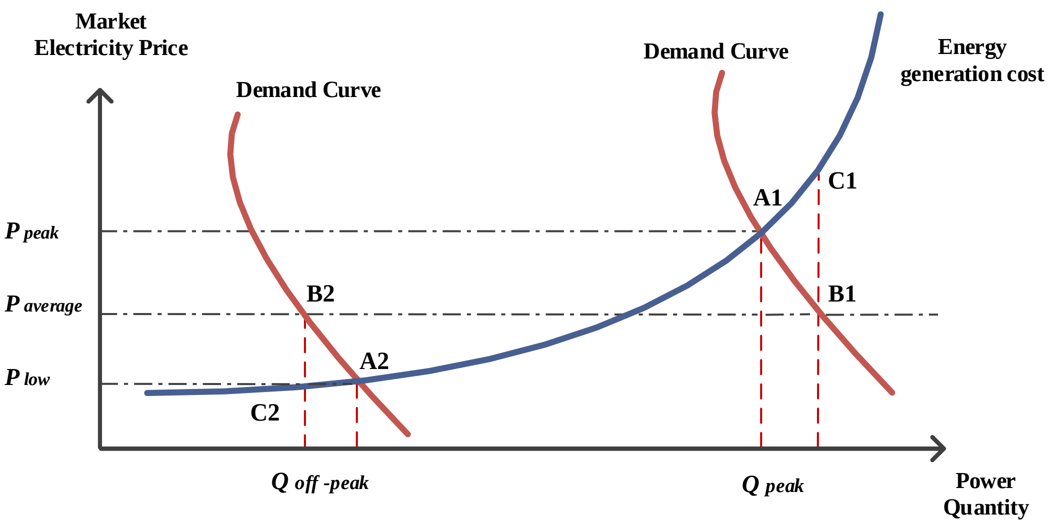


Figure 2.4. Price volatility reduction by demand response programs [7].

2.3 Renewable distributed generation

Distributed generation (DG) units are utilised in the grid to decrease power interruption along with serving customers and ensuring reliable supply. They are classified into non-renewable and renewable classes (Figure 2.5). There are several definitions of DG in the literature. ‘DG is defined as small generation units from a few kilowatts (kW) up to 50 MW and/or energy storage devices typically sited near customer loads or distribution and sub-transmission substations as distributed energy resources’ [102]. The economics of DG are reviewed in [103] and the impact of DG on power quality is studied in [104].

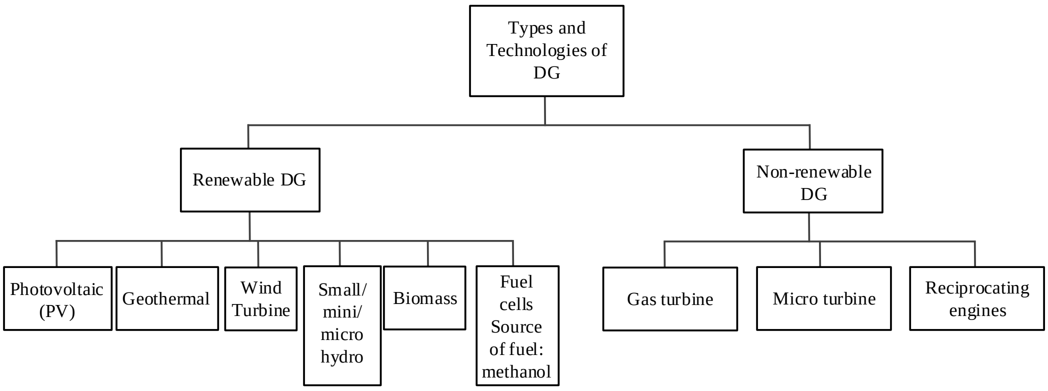


Figure 2.5. Distributed generation types and technologies [102].

Renewable DG plays an important role in the electric power system given recent developments in renewable energy technologies and the negative environmental impacts of fossil fuels. In addition, deregulation of markets and the demand for reliable power is expanding renewable DG all over the world [104]. Power utilities are utilising renewable DG in the distribution network to decentralise their power systems. This integration has environmental, technical and economic benefits, which depend on type, size and location of renewable DG units, configuration of distribution system and the technology utilised for energy conversion [102, 105]. Optimum sizing and location of renewable DG are important to achieve the maximum benefits [106]. It is predicted that 34% of global electricity will be generated by renewable resources by 2030 [102]. PV and wind systems are two renewable resources that have been widely utilised over the last few decades.

2.3.1 PV system

A PV system converts solar energy into electrical energy and includes PV cells, electronics interface, controller and associated auxiliaries. The modules' position, cell temperature and insolation are some of important factors for PV output power. Solar resources are environmentally friendly and are potential alternatives to conventional resources. Based on the demand, PV systems can be configured to produce direct or alternating current. They can be used for serving a specific demand or for peak shaving. They can also connect to the grid through feed-in and net-metering [107]. Advantages of PV systems include their low operation and maintenance costs with long service lifetimes, their being pollution free with no fuel cost, being modular and easy to install and being environmentally friendly. PV systems' penetration is expected to reach 872 GW by 2030 because of the abovementioned advantages – along with their supply security compared to oil and gas availability and price variations [102].

Solar power generation studies are reviewed by [108] and PV technologies [109] and challenges [110] are investigated in the literature. Also, PV self-consumption and improvement options are summarised by [111].

2.3.2 Wind systems

A wind system converts wind energy into electrical energy and includes blades, electronic circuit interface, gearbox, rotor, mechanical shaft and electric generator. Wind speed capacity and the height of the wind system are the important factors for wind system output power. Wind resource assessment and feasibility studies are essential to siting wind systems [112]. This can dramatically affect levelised cost of electricity (LCOE) for wind systems.

LCOE is lifecycle cost of a generation technology divided by lifetime energy production of that technology. It can be used to compare different technologies for electricity generation. LCOE depends on factors such as; initial investment, installation cost, O&M expenses, capacity, fuel cost (where relevant), interest rate, government tax subsidies, location (availability of resources) and other important metrics [102, 113].

Advantages of wind systems include no fuel cost, long lifespan of the components, low O&M costs, low installation cost, low effective cost, no greenhouse gases (GHGs) and capablity to export reactive power to the grid [114]. Some factors that need to be considered before installing a wind system are identifying a reliable demand and understanding the energy's economics; capital access; availability of the grid for grid-connected system; understanding the wind resource; and land availability. Wind system penetration has increased over recent decades due to its potential contribution to power supply. It is expected that the global installed capacity of wind energy will reach 2000 GW by 2030 [102].

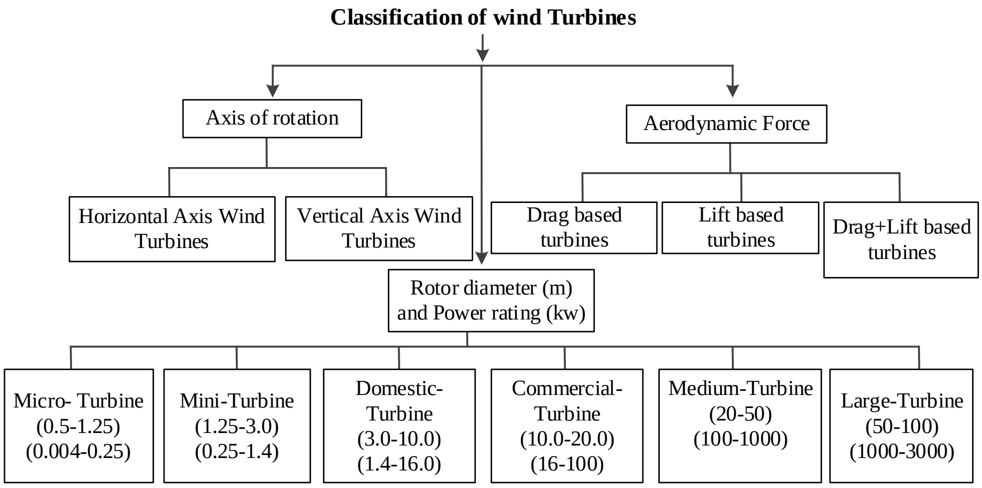


Figure 2.6. Wind turbine classification [115].

A cross-axis WT is studied in [116] and vertical axis WTs for urban usage are reviewed by [115] after classifying WTs (Figure 2.6). In addition, an unconventional power electronic interface is presented by [114] for power quality improvement of wind energy conversion system. In another study, economic, environmental and material developments for wind and solar resources coupled with electric storage systems (ESSs) are studied in [117]. Additionally, many universities in Australia and all around the world have installed PV-WT for research studies (Figure 2.7). The PV-wind hybrid system which is implemented in the National Institute of Technology (India) [118] utilizes a horizontal axis WT as illustrated in Figure 2.7 a. However, the hybrid system at Curtin University contains both horizontal and vertical axis WTs as illustrated in Figure 2.7 b.

Figure 2.7. PV-Wind hybrid [118].

2.3.3 Electrical storage system

An electrical storage system (ESS) is a process for storing electricity produced during off-peak demand, when the electricity price and demand are generally low, to be used in the future when the demand is high. ESSs play an important role in enhancing the integration of renewable resources into the grid. Some advantages of ESS are electricity cost reduction at peak period and low O&M costs, congestion reduction on the power system and reducing line losses, generation capacity reduction, ancillary services, improving power system quality, deferring investment in transmission and distribution facilities and improving power system reliability [102]. ESSs can be categorised based on the form of stored energy in the system [119].

ESS planning in the distribution network is studied in [120]. In addition, battery storage technologies and the role of battery storage systems of electric hybrid vehicles in the power system are studied in [121]. Increasing PV penetration by using energy storage technology is studied in [122]. Distributed PV generation and ESSs are studied in [123]. Residential PV-battery systems are also used for peak shaving [124] and residential voltage profile improvement [107].

With the increase of EV penetration, ESSs are also used for energy services [125]. Also, V2G technologies' impact on distribution systems and utility interfaces is studied in [126].

2.4 Optimal sizing of renewable resources

One complex problem in SG is defining the optimal capacities of distributed generations (DGs) and battery storage systems (BSSs) for grid-connected systems, which depend on many variables including probabilistic behaviours of renewable resources. Novel strategies are being used for energy management in microgrids (MGs) [127, 128], smart buildings [129] and SHs [130] after the rapid developments in SGs. For example, DR programs, rooftop PVs, PEVs and BSSs are used in SHs for peak load shaving [131]. PEV coordination in SG has been studied for peak load shaving [132], minimisation of cost and losses [133, 134] and reactive power compensation [135]. Optimal size of renewable resources will be affected by all of these novel strategies, DR programs and penetration of PEVs. For grid-connected systems, the optimum sizes of DGs and BSSs have been studied for MGs, which have a large capacity for renewable generation [133, 134] [136-138] as well as for SHs, which have a limited capacity for renewable generation [139-143].

2.4.1 Optimal sizing for microgrid

At the large scale (MGs), optimal sizing and energy management for BSS have been studied with regard to renewable energy generation and dynamic pricing of the electricity [127]. In another study, the optimal size of WT and PV for different levels of PEV penetration in residential MGs has been studied [137]. In addition, multi-criteria decision analyses are used in [138] for optimal sizing of a hybrid PV–WT system and weighting criteria techniques are used for studying its sensitivity to input profiles. Controllable loads effect on residential MGs with BSS and renewable energy generations without considering V2G has also been studied [128].

2.4.2 Optimal sizing for smart home

At the small scale (SHs), more investigations is necessary for determining optimal sizes of renewable generation and BSS, in view of factors such as H2G, V2H and DR, as well as the probabilistic behaviors of temperature, irradiance, wind speed, ER and load. Determining the optimal size of renewable generation and BSS becomes more complex when we consider these concepts. Some studies have been conducted on component sizing of SHs; however, these did not consider all types of loads and generations [139-141]. For instance, a hybrid wind–PV system with BSS is studied in [140] without consideration of PEVs and component sizing. Different residential PV and BSS sizes are evaluated in [141] from an economic point of view. DR impacts on SH component sizing for different case studies are investigated in [142] without consideration of shiftable loads and WT. Additionally, this study considers only a flat trading price, which provides no incentive for customers to accomplish peak load shaving [142]. Optimum sizes of WT and BSS in SHs are determined in [139] by adopting a stochastic approach. However, PV and V2H are not considered. Moreover, it is based on daily (not annual) cost minimisation, which may not determine an acceptable solution [143].

2.5 Smart home enablers

Penetration of SHs depends on developing and implementing new technologies that enable SHs to integrate into SGs. These technologies provide the proper infrastructure for interconnection of SHs and SGs. Some of the main enablers are discussed in the following sections.

2.5.1 Power metering devices

Around the 1980s, automatic meter reading (AMR) began to be used for collecting meter data. However, AMR systems could not be used for control messages or broadcasting command. Advanced metering infrastructure (AMI), introduced around 2005, creates a link between external information systems and AMRs via a bi-directional communication system. Figure 2.8 shows a proposed network described in [144]. Currently, smart meters are becoming ever smarter. Non-intrusive load monitoring (NILM) can be implemented in them to determine the operation of some individual loads [145-148]. This may reduce the number of sensors needing to be installed in a SH. According to [144], key features of smart meters are as follows.

- Providing consumption data for utility and consumer.
- Time-based pricing.
- Outage and failure notification.
- Net metering.
- Power quality monitoring such as: voltage, phase and current, power factor, active and reactive power.
- Load limiting for demand response purposes.
- Detecting energy theft.
- Remote command (turning on/off) operations.

- Improving environmental conditions with decreasing emissions through efficient power consumption.
- Communicating with other intelligent devices.
- Providing security [149].

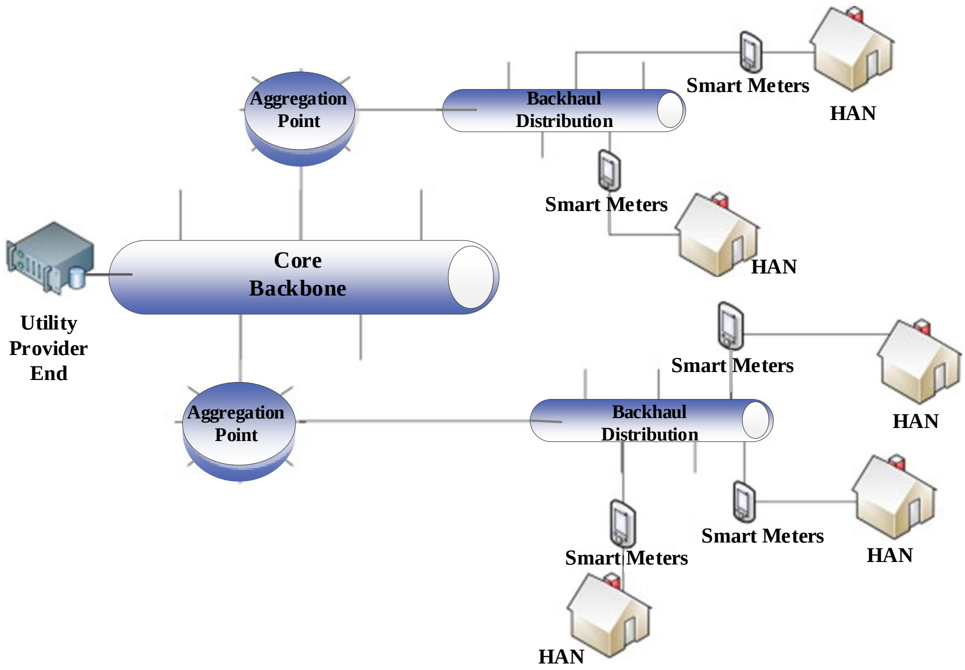


Figure 2.8. Proposed network by [144].

2.5.2 Communication network

One of the important components of SHs is the home area network (HAN). Without a HAN, it is not feasible to implement a SH. HAN was defined in 2001 as 'a network to interconnect home electronic products and systems, enabling its remote access and control and making available any content such as music, video, and other data' [150]. In another study, a HAN is defined as 'a network to connect devices capable of sending and receiving signals from other devices and applications' [10, 150]. Therefore, HANs are an important element of SHs that empower HEMS.

HANs can use a combination of wireless and wired technologies. The first technologies were wired technologies, which have low cost and can be used based on the pre-existing infrastructure of houses. Optical fibre, telephone lines, twisted pairs, coaxial cables and power lines can be used for wired HANs. However wireless technologies are expected to play an important role in HANs based on recent research and developments. WiFi and Zigbee are generic technologies, while 6LoWPAN is a new technology that optimises Internet Protocol Version 6 (IPv6) for low-power communications.

Some of the technologies and standards – such as UPnP (Universal plug and play), DLNA (Digital Living Network Alliance), LonWorks, ZigBee (a wireless BACnet), X-10, domoNet, Amigo, Project HYDRA, Home Plug and Play, oBIX (Open Building Information Exchange), Konnex and Jini – are analysed and compared in [150]. Figure 2.9 shows a classification of HAN communication technologies.

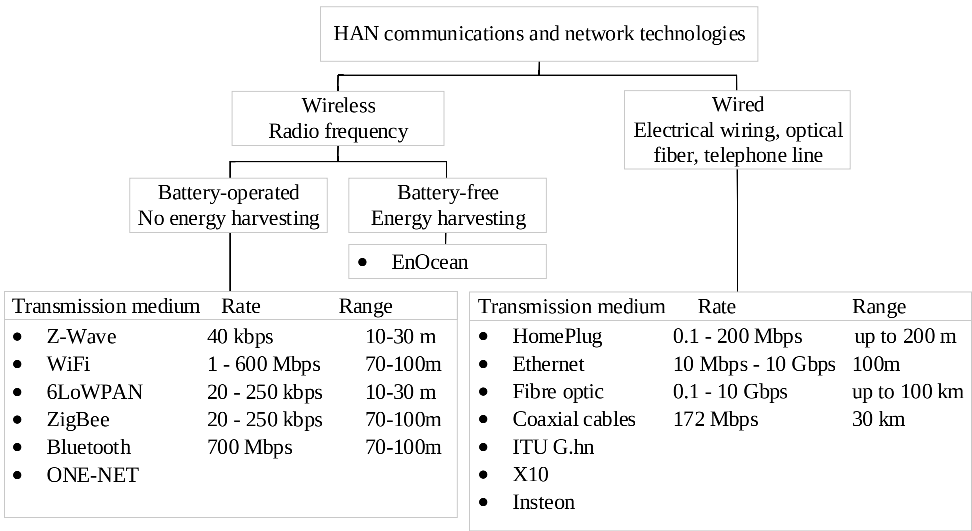


Figure 2.9. HAN medium classification [4, 150].

Important features for HAN communication technologies are [4]:

- reliability
- security
- interoperability and scalability
- total cost

- coexistence
- bandwidth and latency
- forward and backward compatibility
- power consumption

Each HAN technology is superior in some features but none of them is dominant across all features. Three of the most popular HAN technologies (WiFi, Zigbee and HomePlug) are compared in Figure 2.10.

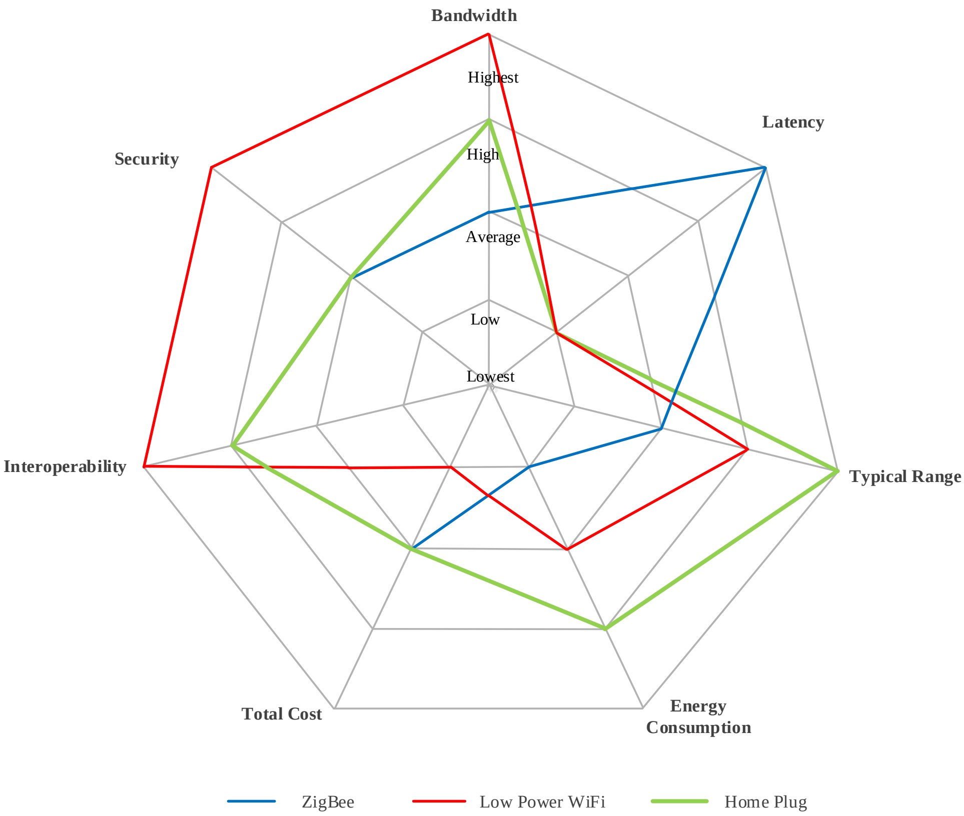


Figure 2.10. Qualitative comparison of three HAN communication technologies [151].

2.5.3 Smart appliances

Domestic devices are getting smart. They are becoming more intelligent and can communicate with HEMS to shift their operational times. They can also be controlled and monitored remotely. The demand for customer involvement in their energy use and load shifting is less because of their intelligent algorithms. Smart appliances may run less frequently or shift their operational cycle to reduce cost and/or save energy. Some common smart appliances are washing machines, dishwashers, air conditioners and refrigerators. For instance, a smart washing machine in a house with local renewable generation will operate during the high local generation period and a smart fridge can shift defrost cycles to the off-peak hours. Some smart washing machines in a pilot project in the Netherland have been tested to operate with control signals [152]. Residential customers can decrease and modify the demand if smart appliances adaptation becomes popular and widespread [4]. Smart appliances sufficiency is investigated for providing reserve services [153] and electricity demand shifting [154] in the literature. In another study, five smart appliances' flexibility potential (maximum duration of time that a specified decrease or increase of power can be realised without user comfort violation) is investigated; this can be used for defining the impact of DR [155].

2.5.4 The Internet of Things

The Internet of Things (IoT) is defined as 'an emerging global Internet-based information architecture facilitating the exchange of goods and services in global supply chain networks' [4, 156]. Several advantages of implementing IoT in intelligent electric power network are [157]:

- fewer communication protocols [158-160]
- increased adaptability, resiliency, reliability and energy efficiency [157]
- facilitation of on-demand information access and end-to-end service [161]
- advanced control over home appliances [161]
- networked operation and increased information operation capabilities [162]
- advanced sensing capabilities [163]
- reduced physical attacks (e.g. substation break-ins) by continuously monitoring the electric power network's assets in real-time [157]
- reduced natural disasters damage [164]
- increased scalability and interoperability [165].

Some challenges related to IoT – such as security, computation, power management, complexity, big data, connectivity and sensing – are discussed in [157] and some solutions are proposed. A layered architecture to apply IoT to SHs is also introduced (Figure 2.11).

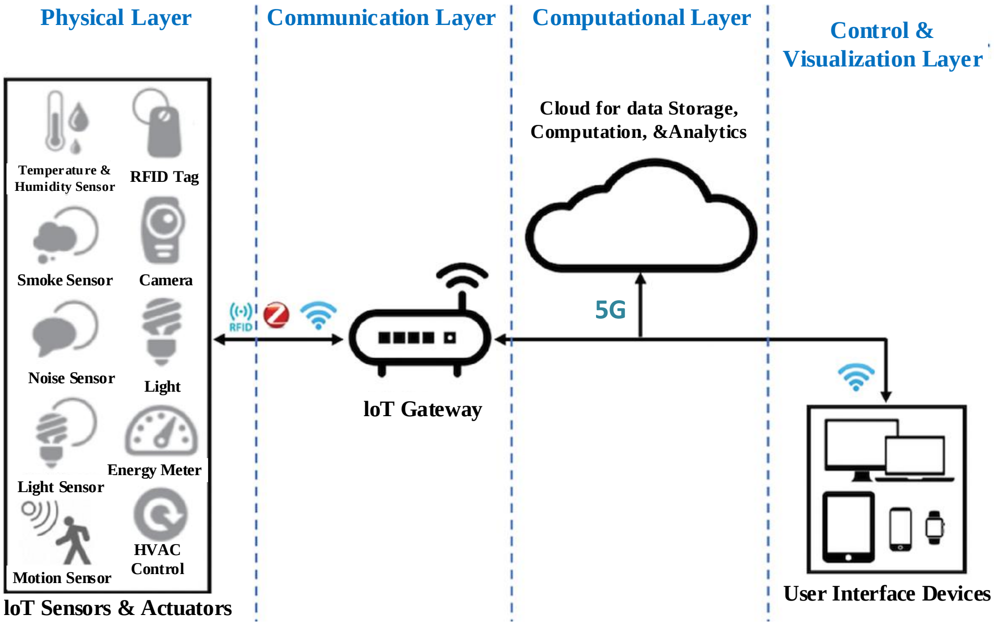


Figure 2.11. IoT architecture introduced for SHs by [157].

The IoT perspective has been accelerated by the introduction of IPv6, high-performance computers, innovative analytical tools, wireless communication technologies, clouding computing, microelectromechanical systems and radio-frequency sensors [4]. Motivations (Figure 2.12) and challenges (Figure 2.13) for SH applications based on IoT are discussed and reviewed in [166].

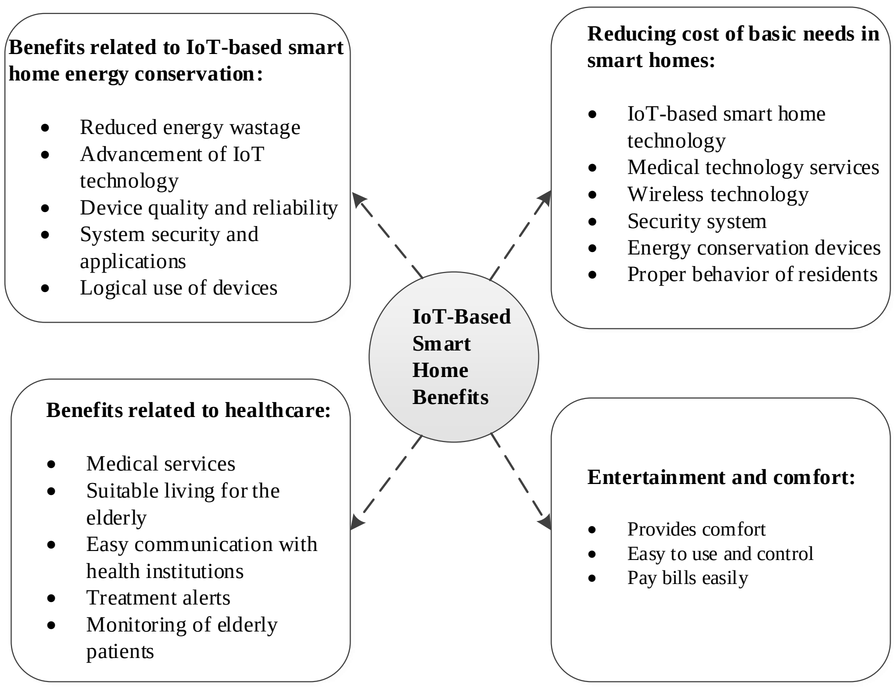


Figure 2.12. Benefits classification for SH applications based on IoT [166].

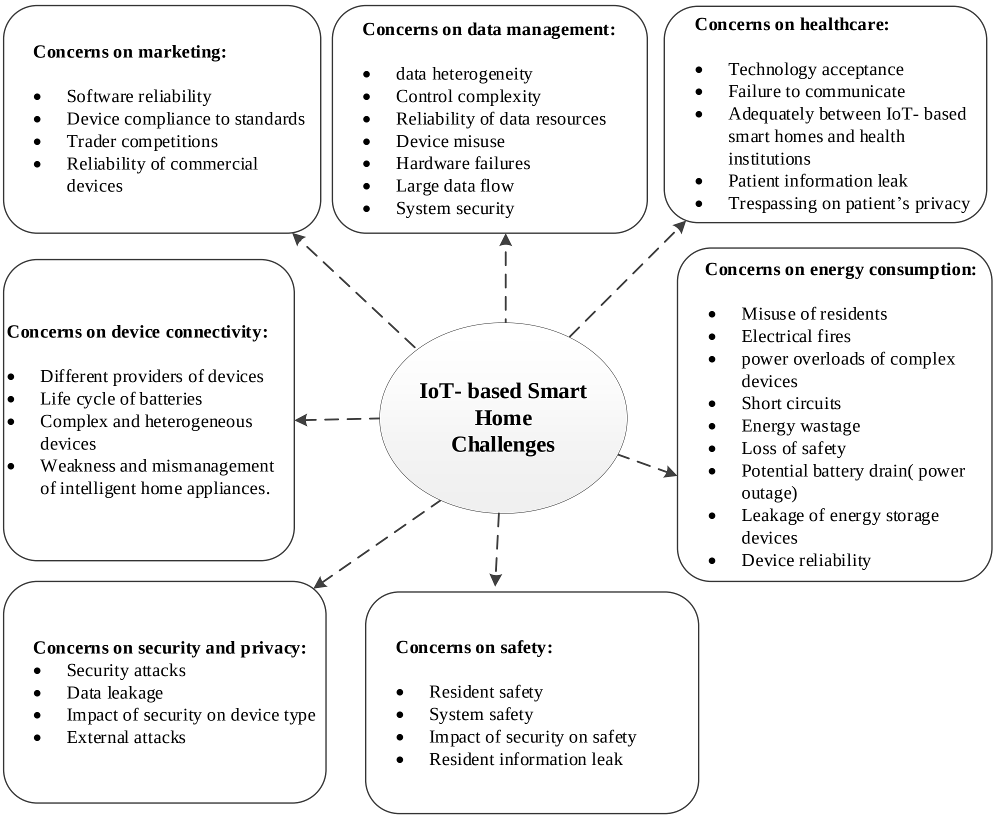


Figure 2.13. Challenges classification for SH applications based on IoT [166].

2.5.5 Smart sensors

In the last few decades the number of sensors in our world has increased dramatically. Cars, mobile phones, buildings and cities are equipped with more sensors that enable users to control devices and activate security systems. Some studies suggest that more than 30 sensors are required for SHs to have a meaningful impact.

There are a variety of sensors designed for safety, health and security. For example, ambient-assisted homes in Europe are equipped with sensors to monitor the daily routine and health of inhabitants. Sensors for detecting occupancy, temperature, light, motion, voltage and current are more appropriate for energy management purposes. They measure the parameters for different devices and at different locations of the house and send the data to a centralised system to be monitored by users. Although sensors have restrictions – such as limited storage and computations, limited ability for communication and short battery life – they can make household devices programmable, intelligent and better able to interact with inhabitants and the outside world [4]. A number of sensor technologies for SHs are reviewed by [167] and several types of IoT sensors are listed in [157]. Additionally, several studies related to intelligent sensors for the industrial IoT are compared in [168] and a smart sensor is designed and verified for this application.

2.5.6 Monitoring and control systems

Personal computers (PCs), tablets, mobile devices and web servers can be used for monitoring SH data. This monitoring system can be called a human–machine interface. For example, an embedded monitoring and automatic control system for an industrial system is demonstrated in [169].

Control systems are the brain of SHs. They can be implemented by use of micro-computers, programmable logic controllers and embedded systems or they can be cloud-based. Supervisory control and data acquisition (SCADA) is also used in large control systems [170]. Monitoring and control systems in SHs are considered components of the home energy management system (HEMS) [171], which is discussed later in this chapter.

2.5.7 Cloud computing

Along with the benefits of ICT, there are some concerns about the reliability, availability and security of SG data processing and analysis. Cloud computing can be one of the best solutions [172]. A number of studies related to cloud computing applications for SG architecture are compared in [173].

A cloud-based computing framework is proposed by [174] for big data information management in SGs. Another cloud-based framework is proposed by [175] for SHs. Cloud computing can be even more beneficial with the expansion of IoT [168], and the conjunction of cloud computing and IoT is investigated by [176] and [177] for SHs.

2.5.8 Home energy management system (HEMS)

Energy management systems (EMSs) have been used for the last several decades in the generation and transmission of the electrical power system and, more recently, in distribution systems [178]. They are used to optimise, control and monitor the demand, generation and transport of energy. Various technologies –such as Xerox systems, computer-based and software-based systems and embedded systems – are used for EMSs in the grid. EMSs, along with SCADA, enable applications such as optimal power flow, dispatcher training simulators, unit commitment, load forecasting, state estimation, and flow and contingency analysis [170].

Distribution network operation is becoming more automated with emerging SG functionalities, and households are becoming actively involved in energy markets. Because of this, home energy management systems (HEMSs) are dramatically expanding. HEMSs enable households to minimise their electricity cost and collaborate with the public grid through ancillary services, peak shaving, demand response and load shifting. HEMSs are defined as 'in-home devices or systems that monitor, control, and analyse home energy use and provide information to the occupants. These systems are to conserve energy, reduce cost and improve comfort using intelligent monitoring and control systems' [4]. They are also defined by [179] as, 'a demand response tool that shifts and curtails demand to improve the energy consumption and production profile of a house according to electricity price and consumer comfort. The HEMS can communicate with household devices and the utility, as needed, and receive external information (e.g., solar power production and electricity prices) to improve the energy consumption and production schedule of household devices. The HEMS finds the optimal operation schedule by using a scheduling algorithm, and dispatches signals appropriately.'

Residential generation integration into the SG can be facilitated by HEMSs to meet the various needs of households and to maintain the robustness and reliability of energy supply infrastructure. Some of potential interests for HEMSs among main stakeholders are given in the Table 2.2. According to [3], benefits of HEMSs include:

- greater savings for utility providers and customers.
- decreased peak loads and peak-to-average ratio
- making it possible to compare energy usage with historical data
- including local renewable energy production
- enabling households to be in a systemic context and to interconnect to the outside wold (Shaping SG).

Table 2.2. Potential interests for HEMS among stakeholders [4].

Residential users	Government	Network operators	Energy retailers	Others
Comfort	Carbon emission reduction	Demand response	Demand response	Energy services
Cost reduction	Energy efficiency measures	Asset management	HEMS products sales	HEMS sales
Social prestige	Fuel poverty alleviation	Load shifting	Customer retention	Research

Although HEMS applications are correlated, they can apply to four main areas, which are shown in Table 2.3. Customer-based HEMS applications are mostly based on customers' needs. However, network-based HEMS applications mostly focus on enhancing networks' power quality and reliability while considering customers' comfort and preferences [180-184]. Market-based HEMS applications are more focused on dynamic tariff systems for DR [46, 181, 185, 186], while service-based HEMS applications mostly concentrate on energy efficiency improvements [4].

Table 2.3. Four major areas for HEMS applications [4].

Customer-based	Network-based	Market-based	Service-based
Power monitoring and feedback	Demand response	Customer benefits	Energy provision at lowest cost
Personalisation and goal setting	Congestion management	Network operator benefits	Energy efficiency improvements
Device control	Load shifting	Retailers benefits	Customer comfort
Safety			

Various EMSs for energy savings are reviewed in [187]. In addition, centralised [188-192] and decentralised [48, 92, 193-199] EMSs for residential area through coordination of multiple SHs are studied in [200]. Modelling and complexity related to HEMSs is reviewed by [179]. There are various algorithms and approaches in the literature for EMSs, DR and scheduling. Some of them are presented in Table 2.4 with references.

Table 2.4. Some methods in the literature for EMSs, DR and scheduling.

Methods and approaches	**Ref.**
Mixed Integer Multi-Time Scale Stochastic Optimisation	[201]
Adaptive Neural Fuzzy Inference System	[202]
Artificial Neural Network	[203, 204]
Bayes Theorem	[205]
Binary Particle Swarm Optimisation	[90, 206]
Clustering	[207]
Contextual Energy Resource Management Methodology	[208]
Different Evolution And PSO (PSO-DE Algorithm)	[209]
Dinkelbach Method	[210]
Domotic Effects Enforcement And Boolean Satisfiability Problem	[211]
Fuzzy TOPSIS Approach	[212, 213]
Game Theory (GT) Approach	[48, 214]
Genetic Algorithm	[215-219]
Greedy Iterative Algorithm And Walrasian Equilibrium Theory	[220]
Nondominated Sorting Genetic Algorithm-II And Grey Relational Analysis	[221]
Hill-Climbing Heuristic Method	[222]
Integer Linear Program	[223]
Vickrey-Clarke-Groves Mechanism	[42]
Knapsack	[224, 225]
Lagrangian Dual Approach	[226]
Linear Regression Modelling	[227]
Linear Programming	[228]
Mixed-Integer Linear Programing	[180, 229-231] [232] [233]
Mixed-Integer Nonlinear Programming	[234, 235]
Moving Window Algorithm	[236]

Methods and approaches	Ref.
Multiagent Coordination Algorithm	[237]
Multi-Period Joint Energy Scheduling Algorithm	[238]
Multi-Time Scale And Multi-Stage Stochastic Optimisation Framework	[239]
Mutation Particle Swarm Optimisation	[240]
Naive Bayes Classifier (NBC) And Hidden Markov Model (Machine Learning)	[241]
Newton's Method	[242]
Particle Swarm Optimisation	[89, 243, 244]
Polyblock Approximation Algorithm	[245]
Q-Learning	[246] [247]
Semi Markov Model	[248]
Stochastic Dynamic Programming	[249]
Tabu Search	[250]
Token Bucket Algorithm	[251]
Traversal-And-Pruning Algorithm	[252]
Two-Horison Algorithm	[253]

2.5.9 Energy Consumption Scheduling

Complex algorithms for HEMSs are created because of DR programs [101, 181, 216, 224, 225, 254-259], modern ICTs [183, 201, 228, 242, 256] and distributed energy generation [16, 48, 89, 260-262] in residential sectors. Scheduling problems [146, 263-265] are one optimisation problem, along with other categories [7] such as household problems [181, 255, 266], distributed generation problems [89, 257] and pricing problems [46, 48, 267].

There are diverse operation conditions for various appliances which should be considered in scheduling methods. A particular number of timeslots will be determined for the duration of time horizon planning approach. Then, optimisation techniques can be used to allocate the timeslots to the operations of various appliances and determine which operation should start/finish in each timeslot. Sequential order of tasks and the number of shiftable timeslots are the other factors that need to be considered. Appliances operations are different. For example, various tasks must be taken in order for a washing machine to fulfil a job. Appliances load commitment in an allocated timeslot has been considered in [51, 256, 268] as an important factor. In another study, household appliances scheduling for a stand-alone system is investigated by [269]. Also, operation scheduling of distributed energy resources is investigated in [270].Some of scheduling and optimisation approaches for residential are summarised in Table 2.5 [7].

Table 2.5. Scheduling and optimisation for residential sector.

Optimisation Method	**Optimisation Objective**	**DRP**	**Ref.**
• Particle swarm optimisation • Monte Carlo simulation	• Cost minimisation	Real-Time	[271] [272]
• Particle swarm optimisation • Monte Carlo simulation	• Cost minimisation	N/A	[273]
• Particle swarm optimisation • Monte Carlo simulation	• Cost minimisation	TOU	[274]
• Monte Carlo simulation • Decision tree	• Cost minimisation • Energy usage efficiency	TOU	[275]
• Pattern search-based optimisation with sequential Monte Carlo simulation	• Cost minimisation • Reliability satisfaction	N/A	[276]
• Particle swarm optimisation • Binary particle swarm optimisation	• Cost minimisation	TOU	[277]
• Particle swarm optimisation	• Cost minimisation • Emission reduction	Real-Time	[278]
• Agent-based particle swarm optimisation	• Energy saving • Comfort maximisation • Voltage support	Real-Time	[279]
• Particle swarm optimisation	• Cost minimisation • Comfort maximisation	TOU	[280]
• Particle swarm optimisation	• Cost minimisation	N/A	[240]

Optimisation Method	**Optimisation Objective**	**DRP**	**Ref.**
• Quadratic binary particle swarm optimisation	• Cost minimisation	Real-Time & TOU	[281]
• Particle swarm optimisation	• Cost minimisation • Comfort maximisation	Real-Time & TOU & Load curtailment	[282]
• particle swarm optimisation	• Cost minimisation	TOU	[283]
• Mixed Integer Linear Programming • heuristic allocation algorithm	• Cost minimisation • Maximisation of scheduling preferences • Maximisation of climatic comfort	TOU	[284]
• particle swarm optimisation	• Maximising comfort level	N/A	[285]
• particle swarm optimisation	• Saving energy • cost minimisation	N/A	[269]
• Linear Programming • Offline and Online stochastic scheduling	• minimise the monetary expense of the customer	Day-ahead pricing	[228]
• Scenario-based Stochastic optimisation • Mixed integer linear programming	• Minimising the electricity bill in different time slots	Real-time pricing	[256]
• Linear programming	• Utility maximisation and cost minimisation	Real-time pricing	[41]
• Linear Programming	• Minimising energy cost and maximising the consumer utility	Real-time pricing	[286]
• N/A	• N/A (Energy cost and comfort as constraint)	Time varying price	[181]
• Combinatorial optimisation (First fit decreasing height) • Earliest deadline first scheduling algorithm	• Peak load shaving	N/A	[183]
• Particle Swarm Optimisation	• Determine the distributed energy resources operation schedules (maximise the end-users' net benefits)	TOU and CPP	[89]

Optimisation Method	Optimisation Objective	DRP	Ref.
• Linear sequential Optimisation	• Minimising the energy cost	Real-time pricing (day-ahead)	[51]
• Linear programming	• Minimising the payment and inconvenience functions	Time-varying price	[268]
• Mixed integer programming	• Minimising the payment and interruption cost at the time of outage occurrence	TOU	[287]
• Linear programming	• Minimising energy to the grid and maximising the energy to grid	Day-ahead pricing	[288]
• Linear programming	• Cost minimisation • Maximising the financial gain for selling energy to grid	Dynamic pricing scheme	[289]
• Linear programming	• Utility maximisation (or welfare maximisation) and cost minimisation	Real-time pricing	[40]
• Convex programming with $L1$ regularisation	• Minimising the total cost of energy and the users' dissatisfaction	Real-time pricing	[290]

Use of stochastic optimisations is promising for power system uncertainty modelling and renewable energy applications particularly for capturing uncertainty behaviour of renewable energy systems [291] [292]. One of popular methods for modelling uncertainty of data is MCS [293, 294]. Because MCS is considered as a time consuming method [292], meta-heuristic methods can be used for reducing the computational expense of optimisations [291]. Meta-heuristic methods such as PSO are considered quick compared to "Mathematical programming methods" for complex scheduling problems [240] [295]. In addition, hybridization of PSO is suggested by [296] for solving complex and intricate problems. Therefore, there are many studies which have used MCS-PSO to solve complex problems especially when uncertainty of data needs to be considered [272-274, 295, 297-300].

2.6 Conclusion

In this chapter, the most important technologies and elements related to SHs and end users of the SG are identified and reviewed, with a focus on the most relevant recent investigations.

With the development of new technologies, SH penetration is increasing. SHs and new technologies are changing people's lifestyles. Adopting SH technology can improve lifestyle, comfort and safety, and lead to a cleaner environment and energy savings. Uptake also facilitates the transition of the grid towards a smart grid.

With the merging of new technologies in the SG, new factors need to be considered in the interaction of SHs and the SG. EMSs and sizing of renewable resources should be updated by considering new technologies and using the full capacity of new technologies to provide the best benefit and service to energy users and energy providers.

In the next chapter, components and data modelling for SHs, along with the optimisation and approaches used in this thesis, are explained.

Chapter 3 Data Modelling and Optimisation for SHs[1]

3.1 Introduction

The penetration of solar generation, wind turbine, battery storage systems (BSSs) and plug-in electric vehicles (PEVs) in the smart grid (SG) and smart homes (SHs) has increased rapidly in the last few decades. As a consequence, there is a need to model the associated data for studies into demand response (DR) programs, energy management systems (EMSs), load scheduling and optimal sizing of renewable resources for SHs. There are many complex problems in SG and SHs that need to be solved by robust algorithms. Some popular optimisation algorithms which can be used for solving these problems are summarised at the end of this chapter.

Determining the optimum size of renewable energy is explored here for both SHs with a small capacity for renewable generation [139, 140, 143] and microgrids with a large capacity for renewable generation [127, 128, 138]. However, for the studies in the concept of SG and distributed generation (DG), it is important to consider the probabilistic behavior of wind speed, irradiance, temperature, load, electricity rate (ER) and availability of PEVs. Monte Carlo simulation (MCS) can be used to model the probabilistic behavior of these data. MCS can be used along with optimisation algorithms to find optimal solutions, and especially for finding the optimal size of renewable resources for SHs, which is explained in the sections 4.3 and 5.3 in following chapters. Two approaches are investigated for modelling data based on MCS in sections 3.3.1 and 3.3.2 and the second approach is chosen for the simulations in chapters 4 and 5.

[1] This chapter is mainly extracted from published papers [301] and [143] (Appendix A).

This chapter starts with a description of SH components. Renewable resources such as PV, WT and BSS, along with coordinated PEV, are described. This will be followed by a description of data modelling for SHs. Two methods of implementing MCS with hourly probability distributions and daily data sampling are investigated in sections 3.3.1 and 3.3.2. MCS with daily data sampling is chosen for data modelling in the following chapters, after comparison of section 3.3.3. Finally, optimisation methods are summarised, and particle swarm optimisation (PSO) is precisely described to begin preparation for its use in the following chapters.

3.2 Smart home components and modellings

Figure 3.1 shows the electricity flow for a grid-connected SH with rooftop PV, WT, BSS and PEV with the possibility of importing and exporting energy considering dynamic electricity pricing.

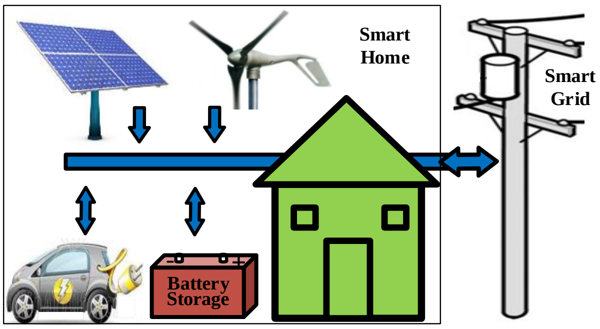


Figure 3.1. Electricity flow between SH and SG [143].

3.2.1 Wind turbine system model

The WT output energy E_W during time interval Δt_j is calculated based on the wind speed [302]:

$$E_W(\Delta t_j) = \begin{cases} Cap_{WT}\left(\dfrac{V_w(\Delta t_j) - V_{ci}}{V_r - V_{ci}}\right)\Delta t & V_{ci} \le V_w(\Delta t_j) \le V_r \\ Cap_{WT}.\Delta t & V_r \le V_w(\Delta t_j) \le V_{co} \\ 0 & otherwise \end{cases} \quad (3.1)$$

where $V_w(\Delta t_j)$, V_{ci}, V_{co} and V_r denote wind speed, cut-in, cut-out and rated wind speed (m/s), respectively.

3.2.2 PV system model

The rooftop PV output energy E_{PV} during Δt_j depends on the open-circuit voltage and short-circuiting current [136, 138]:

$$E_{PV}(\Delta t_j) = N_{PV} V_{OC}(\Delta t_j) I_{SC}(\Delta t_j) \eta_{PVinv}. FF(\Delta t_j) \tag{3.2}$$

where:

$$V_{OC}(\Delta t_j) = V_{OC.STC} + K_V\big(T_C(\Delta t_j) - T_{ref}(\Delta t_j)\big) \tag{3.3}$$

$$I_{SC}(\Delta t_j) = \{I_{SC.STC} + K_I\big[T_C(\Delta t_j) - T_{ref}(\Delta t_j)\big]\}\tfrac{G(\Delta t_j)}{1000} \tag{3.4}$$

$$T_C(\Delta t_j) = T_A(\Delta t_j) + \frac{NCOT - 20}{800} G(\Delta t_j) \tag{3.5}$$

where *NCOT*=45°C, $T_{ref}\big(\Delta t_j\big)$=25°C, $V_{OC}(\Delta t_j)$ is open-circuit voltage (V), $I_{SC}(\Delta t_j)$ is short-circuit current (A), $T_C(\Delta t_j)$ is cell temperature (°C), $T_A(\Delta t_j)$ is ambient temperature during Δt_j, $I_{SC.STC}$ and $V_{OC.STC}$ are the PV module short-circuit current (A) and open-circuit voltage (V) measured under standard test conditions, K_V is open-circuit voltage coefficient (V/°C), K_I is the short-circuit current coefficient (A/°C) and $G(\Delta t_j)$ is global irradiance during Δt_j (W/sq.m) [136].

3.2.3 Cost of renewable energy generation

The renewable generation cost is included in the total electricity cost using the concept of levelised cost of electricity (LCOE) by calculating levelised cost of electricity for a PV-WT system (LC_{PV+Wt}) at each Δt_j as a function of LC_{PV} and LC_W:

$$LC_{PV+WT}\big(\Delta t_j\big) = \begin{cases} \dfrac{LC_{PV} + LC_W}{2} & E_{PV}\big(\Delta t_j\big) + E_W\big(\Delta t_j\big) = 0 \\ \dfrac{E_{PV}(\Delta t_j) \times LC_{PV} + E_W(\Delta t_j) \times LC_W}{E_{PV}(\Delta t_j) + E_W(\Delta t_j)} & otherwise \end{cases} \tag{3.6}$$

where levelised cost of electricity for PV (LC_{PV}) and levelised cost of electricity for WT (LC_W) are determined by dividing PV and WT total costs (including the initial investment, installation, maintenance and operation costs) by their total lifetime energy production [113, 139]. They depend on SH location, wind speed, solar radiation, PV/WT size, type, availability and cost. The cost of battery is considered separately by including its levelised cost LC_B in the formulation of SH electricity cost (Eq. (4.3)).

3.2.4 Battery charge and discharge conditions

BSS is used for storing renewable energy during off-peak load hours and releasing it during high-demand periods as well as trading with the grid by importing/ exporting electricity when the Electricity rates (ERs) are low/high. However, the charge and discharge permissions for trading are limited as follows [139].

- To increase battery lifetime, decision intervals (DIs) are defined as the periods with two consecutive intersections of LC_{PV+WT} (Δt_j) (Eq. (3.6)) and $ER(\Delta t_j)$ profiles (Figure 3.2).
- There is permission for only one charge/discharge action during each DI at the extreme minimum/maximum point of ER, as illustrated in Figure 3.2.

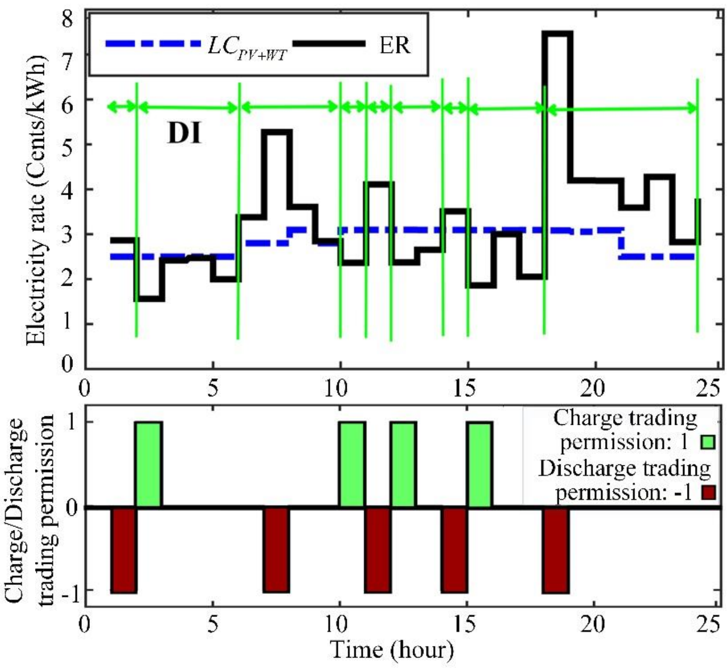


Figure 3.2. Decision intervals (DIs) and charge/discharge trading permissions.

The battery state of charge is limited to be between minimum (SOC_{min}^{B}) and maximum (SOC_{max}^{B}) state of charge of the battery and there are limitations for BSS operation during demand supply and power trade. The following constraints are considered for charging and discharging the battery:

$$\begin{cases} \left|E_B(\Delta t_j)\right| < R_c \times \Delta t \\ -E_B(\Delta t_j) < DOD \times Cap_B \\ B(\Delta t_j) < Cap_B \\ SOC_{min}^{B} \leq SOC^{B}(\Delta t_j) \leq SOC_{max}^{B} \end{cases} \tag{3.7}$$

where $R_c = 0.2 \times Cap_B$ (R_c is rate of battery charge/discharge (kW) and Cap_B is capacity of battery (kWh)) and DOD=85% [139]. DOD is depth of discharge (%), $E_B(\Delta t_j)$ is electricity charge/discharge of battery during Δt_j (kWh) and $B(\Delta t_j)$ is available battery charge during Δt_j (kWh).

3.2.5 PEV charge and discharge conditions

The charge/discharge (H2V/V2H) control of PEV is similar to the battery operation (Section 3.2.4) with additional variables, constraints, and conditions. The additional variables (T_{arrive}^{PEV}, T_{dep}^{PEV}, SOC_{arrive}^{PEV} and $SOC_{dep,min}^{PEV}$) are modelled based on their probability density functions of Eqs. (3.8)–(3.11) (Figure 3.3) and are subject to Eqs. (3.12)–(3.13). T_{arrive}^{PEV}, T_{dep}^{PEV}, SOC_{arrive}^{PEV} and $SOC_{dep,min}^{PEV}$ denote PEV arrival time (hour), PEV departure time (hour), state of charge of PEV at arrival time (%) and minimum state of charge of PEV at departure time (%), respectively. Based on the data set given in [303], it was recommended in [257] that the PEV's arrival and departure times follow normal distributions with the means of 6 pm and 7 am and standard deviations of 2 hours. In addition, SOC_{arrive}^{PEV} is related to SOC_{dep}^{PEV} and daily travel distance. Daily travel distance was modelled in [304] with a log-normal distribution with a mean of 32 miles and standard deviation of 24 miles. We considered that the minimum acceptable departure SOC for PEV follows a normal distribution with the mean of 80% and standard deviation of 20%. Also, we assumed that the daily travel distance and period which PEV is out of the house during the weekends is 50% less than the weekdays.

$$T_{arrive}^{PEV} \sim N(\mu_{PEV_a}, \sigma_{PEV_a}) \tag{3.8}$$

where $\mu_{PEV_a} = 18$, $\sigma_{PEV_a} = 2$ and $12 \le T_{arrive}^{PEV} \le 24$.

$$T_{dep}^{PEV} \sim N(\mu_{PEV_d}, \sigma_{PEV_d}) \tag{3.9}$$

where $\mu_{PEV_d} = 7$, $\sigma_{PEV_d} = 2$ and $5 \le T_{dep}^{PEV} \le 12$.

$$SOC_{arrive}^{PEV} \sim SOC_{dep}^{PEV} - lnN(\mu_{SOC_a}, \sigma_{SOC_a}) \tag{3.10}$$

where $\mu_{SOC_a} = 3.66$ and $\sigma_{SOC_a} = 0.42$.

$$SOC_{dep,min}^{PEV} \sim N(\mu_{SOC_d}, \sigma_{SOC_d}) \tag{3.11}$$

where $\mu_{SOC_d} = 80$ and $\sigma_{SOC_d} = 20$.

$$T_{dep}^{PEV} < T_{arrive}^{PEV} \tag{3.12}$$

$$SOC_{arrive}^{PEV} < SOC_{dep}^{PEV} \tag{3.13}$$

Note that based on PDFs of Figure 3.3, T_{dep}^{PEV} and T_{arrive}^{PEV} are around 7:30am and 6pm while $SOC_{dep,min}^{PEV}$ and SOC_{arrive}^{PEV} are about 80% and 65% of the total PEV battery capacity [257, 303, 304].

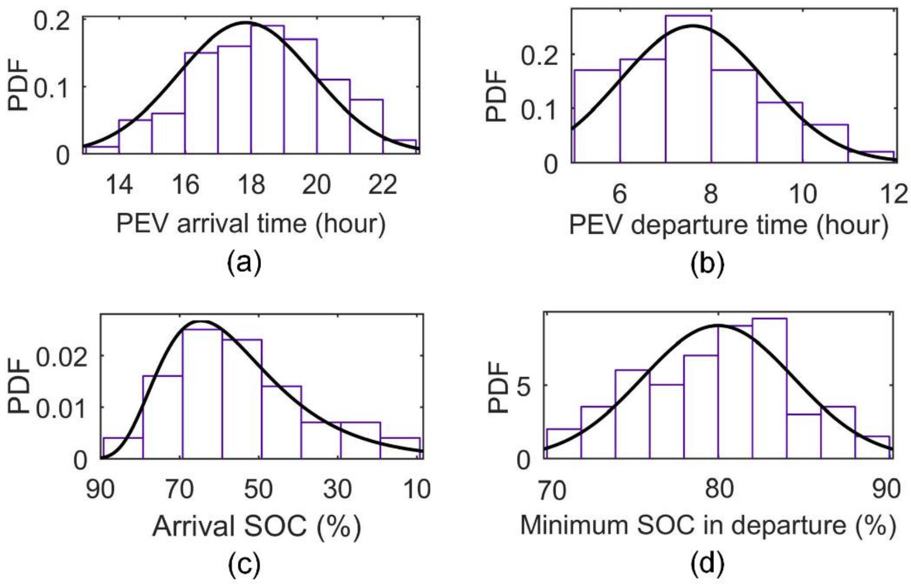


Figure 3.3. Probability density functions (PDFs) for the PEV.

Additional conditions for H2V and V2H operations are:

- Period 1 (before 5 am): PEV will be first charged from the renewable resources and then from the SG until it reaches at least $SOC^{PEV}_{dep,min}$. PEV is not allowed to be discharged from 1am to 5 am (Eq. (3.17)).
- Period 2 (5 am to T^{PEV}_{dep}): PEV can be discharged (according to Table 4.2) until it reaches $SOC^{PEV}_{dep,min}$ (Eqs. (3.14) and (3.17)).
- Period 3 (T^{PEV}_{dep} to T^{PEV}_{arrive}): No charge and discharge actions since PEV is not at SH (Eq. (3.15)).
- Period 4 (after T^{PEV}_{arrive}): PEV charging and discharging are allowed (according to Table 4.2) subject to Eqs. (3.16)–(3.17).

$$SOC^{PEV}_{dep,min} \leq SOC^{PEV}(\Delta t_j) \leq SOC^{PEV}_{max} \ \ \forall j \in [5, T^{PEV}_{dep}] \tag{3.14}$$

$$SOC^{PEV}(\Delta t_j) = 0 \quad \forall \, j \in [T^{PEV}_{dep}, T^{PEV}_{arrive}) \tag{3.15}$$

$$SOC^{PEV}_{min} \leq SOC^{PEV}(\Delta t_j) \leq SOC^{PEV}_{max} \ \ \forall \, j \notin \left[T^{PEV}_{dep}, T^{PEV}_{arrive}\right] \tag{3.16}$$

$$\begin{cases} \left|E_{PEV}(\Delta t_j)\right| \leq R^{PEV}_c \times \Delta t & \forall \, j \\ E_{PEV}(\Delta t_j) < Cap_{PEV} & \forall \, j \end{cases} \tag{3.17}$$

where at the beginning of each day, SOC^{PEV}_{init} (initial state of charge of PEV in the start of the day (%)) is assumed to be equal to its last value in the previous day. SOC^{PEV}_{min}, SOC^{PEV}_{max}, $E_{PEV}(\Delta t_j)$, R^{PEV}_c and Cap_{PEV} denote minimum state of charge of PEV (%), maximum state of charge of PEV (%), electricity charge/discharge of PEV during Δt_j (kWh), rate of PEV charge/discharge (kW) and the capacity of PEV (kWh), respectively. Figure 3.4 shows an example of PEV charging and discharging operations during a typical day where the departure and arrival times are 9 am and 5 pm, respectively. Other PEV parameters are listed in Table 3.1 ($C^{PEV}_{d,sell}$ denotes cost of discharging PEV for sell/export (cents/kWh)).

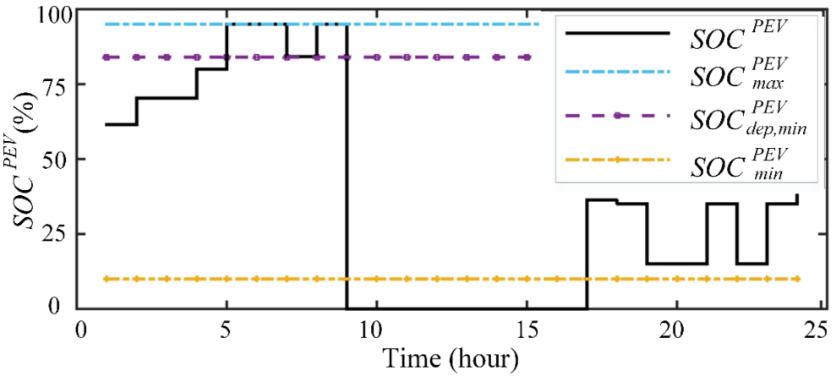


Figure 3.4. PEV State of Charge (SOC) during a typical day.

Table 3.1. Input parameters for PEV.

Parameter	Cap_{PEV} [kWh]	R_c^{PEV} [kW]	$C_{d,sell}^{PEV}$ [cents/kWh]	SOC_{max}^{PEV} [%]	$SOC_{dep,min}^{PEV}$ [%]	SOC_{min}^{PEV} [%]
Value	50	12	0.3	95	80	10
Associated Eq.	(3.17)	(3.17)	(4.3)	(3.14) and (3.16)	(3.14)	(3.16)

3.2.6 HVAC load

The proposed model for calculating the heating, ventilation, and air conditioning load $L_{HVAC}(\Delta t_j)$ is based on the occupancy, ambient temperature (T_A) and electricity rate (ER). There is a correlation between occupancy and load consumption [305]. Therefore, at each hour, the SH is assumed to be occupied if at least one of the following conditions holds.

- Base load (L_b) is higher than the average of L_b.
- PEV is at the SH and L_b is higher than 80% of the L_b average.
- The time is between 1 am and 5 am.

If the SH is unoccupied, $L_{HVAC}(\Delta t_j)$ is considered to be zero; otherwise, it is obtained from Table 3.2 and is subject to Eq. (3.18). The maximum $L_{HVAC}(\Delta t_j)$ is assumed to be 2 kW for the SH and it is limited to 1 kW during the early morning hours:

$$\begin{cases} 0 \leq L_{HVAC}(\Delta t_j) \leq 1 & \forall j \in [1,5) \\ 0 \leq L_{HVAC}(\Delta t_j) \leq 2 & \forall j \in [5,24] \end{cases} \quad (3.18)$$

Table 3.2. Heating, ventilation, and air conditioning (HVAC) loads of SH.

	$T_A(\Delta t_j)$ Conditions (°C)		
Conditions	$18°C \leq T_A(\Delta t_j) \leq 26°C$	$12°C \leq T_A(\Delta t_j) < 18°C$ Or $26°C < T_A(\Delta t_j) \leq 32°C$	$T_A(\Delta t_j) < 12°C$ Or $32°C < T_A(\Delta t_j)$
$\boldsymbol{ER_{max}(DI)}$	0 kW	0 kW	0.5 kW
Usual ER	0 kW	0.5 kW	1 kW
$\boldsymbol{ER_{min}(DI)}$	0 kW	1 kW	2 kW

3.3 Data modelling

MCS can be used for random generation of the input data for renewable energy simulations. MCS is used in the literature to model the stochastic behavior of renewable resources. In this section, two methods for implementing MCS are introduced and described along with their characteristics. One of the methods for generating data is the use of probability distributions. Probability distributions for wind speed, global irradiance, temperature, power demand, and electricity rate in every hour are determined. The other method is data sampling, which can be based on real yearly data or typical meteorological year (TMY) data, which are classified seasonally or monthly. These two methods are described and compared in this section [301].

3.3.1 Modelling wind speed, irradiance, temperature, load and electricity rate based on yearly data using probability distributions for Monte Carlo simulations

For modelling these sources of data, we can use their probability distributions in each hour (when the simulation interval is considered to be one hour). First, we need to determine these probability distributions for each hour for each set of data using their TMY or yearly historical data. Then we can use these probability distributions to generate hourly data for simulations and optimisations.

3.3.1.1 Determine probability distributions for yearly data in every hour

Probability distributions of wind speed, global irradiance, temperature, power demand, and electricity rate are determined for every hour of the day. For each of these sources of data in every hour/interval, at least one specific probability distribution is defined.

3.3.1.1.1 Wind speed probability distribution

Wind speed for each hour is fitted to a probability distribution. One year's hourly historical data at a 10-metre elevation from McCook, Nebraska [306], are utilised and indicate that a Weibull distribution is the best for describing data in each hour. Therefore, there are 24 probability distributions with 24 shape and scale parameters. In other words, for each hour there are one shape parameter and one scale parameter. These probability distributions are described by Eq. (3.19). Two of Weibull distributions are demonstrated for 9am and 2pm in Figure 3.5.

$$V_w(\Delta t_j) \sim WEIB(A_{w\,j}, B_{w\,j}) \quad \forall\, j \in \{1,2,3,\ldots,24\} \tag{3.19}$$

with $A_{w\,j}$ and $B_{w\,j}$ illustrated in Table 3.3.

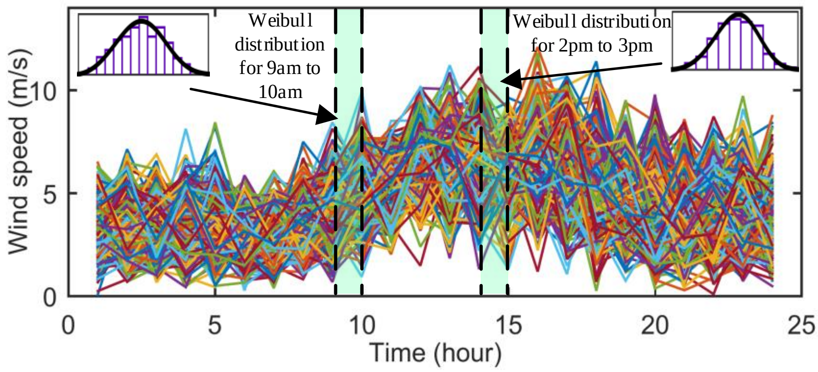


Figure 3.5. Wind speed data modelling by hourly probability distributions.

3.3.1.1.2 Irradiance probability distribution

Global horizontal irradiance data for each hour are fitted to one or two probability distributions. One year's data for McCook, Nebraska, in 2014 from [307] are collected and fitted to 14 probability distributions, which are demonstrated in Figure 3.6.

Hourly normalised data from 10:00 to 17:00 are best fitted to eight beta distributions, which are described by Eq. (3.20). For other hours, data are zero or a fraction of data is fitted to Weibull or lognormal distributions, as described by Eqs. (3.21) and (3.22).

$$G(\Delta t_j) \sim Beta(\alpha_{G\,j}, \beta_{G\,j}) \quad \forall\, j \in \{10,11,12,\dots,17\} \tag{3.20}$$

$$G(\Delta t_j) \sim WEIB(A_j, B_j) \quad \forall\, j \in \{9,18\} \tag{3.21}$$

$$G(\Delta t_j) \sim lnN(\mu_{G\,j}, \sigma_{G\,j}) \quad \forall\, j \in \{8,19,20\} \tag{3.22}$$

with $\alpha_{G\,j}$, $\beta_{G\,j}$, A_j, B_j, $\mu_{G\,j}$ and $\sigma_{G\,j}$ illustrated in Table 3.3.

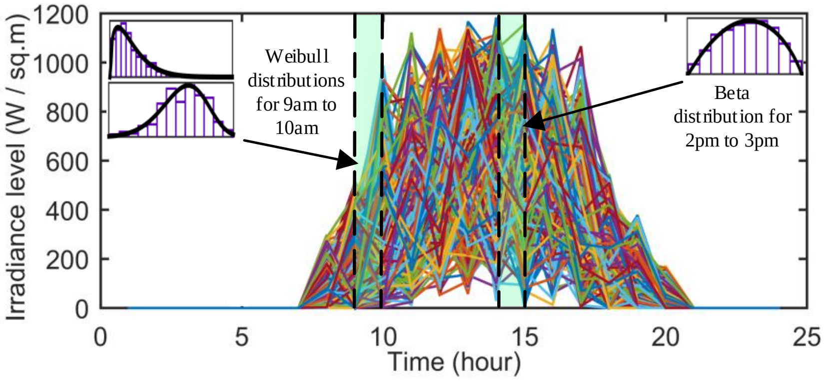


Figure 3.6. Irradiance data modelling by hourly probability distributions.

3.3.1.1.3 Temperature probability distribution

Temperature data for each hour are fitted to two probability distributions. One year data for McCook, Nebraska, in 2014 from [307] are utilised and indicate that normal and lognormal distributions are the best to describe data in each hour. For each hour the data are best fitted to two normal distributions, except for 15:00 and 16:00 which are fitted to both normal and lognormal distributions. Therefore, Eqs. (3.23) and (3.24) can be used for generating temperature data as are demonstrated in Figure 3.7.

$$T_A(\Delta t_j) \sim N(\mu_{t\,j}, \sigma_{t\,j}) \quad \forall\, j \in \{1,2,\dots,14,17,\dots,24\} \tag{3.23}$$

$$T_A(\Delta t_j) \sim lnN(\mu'_{t\,j}, \sigma'_{t\,j}) \quad \forall\, j \in \{15,16\} \tag{3.24}$$

with $\mu_{t\,j}$, $\sigma_{t\,j}$, $\mu'_{t\,j}$ and $\sigma'_{t\,j}$ illustrated in Table 3.3.

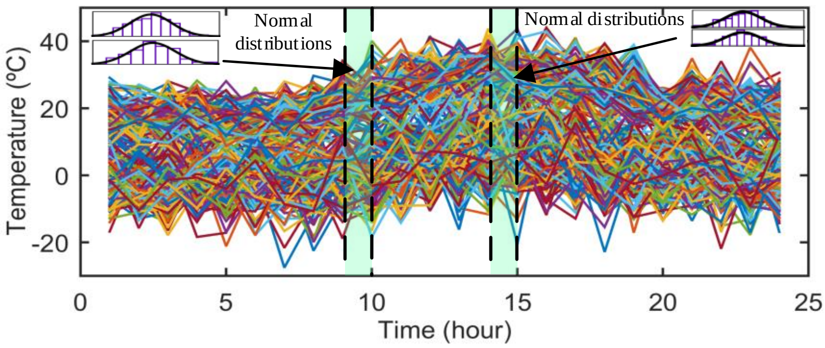


Figure 3.7. Temperature data modelling by hourly probability distributions.

3.3.1.1.4 Load probability distribution

The predetermined (not schedulable) load of a US home that is considered as base load, L_b and includes lighting, freezers, refrigerators, water heaters, microwave, ovens etc.[139, 308] for each hour is fitted to a normal distribution which is described by Eq. (3.25) and shown in Figure 3.8.

$$L_b(\Delta t_j) \sim N(\mu_{l\,j}, \sigma_{l\,j}) \quad \forall\, j \in \{1,2,3,\ldots,24\} \tag{3.25}$$

with $\mu_{l\,j}$ and $\sigma_{l\,j}$ illustrated in Table 3.3.

Schedulable load, (L_s) and unpredictable load, (L_u) should be modelled separately (Section 4.2.1). The models for HVAC and electric vehicle are described in the previous sections (Sections 3.2.5 and 3.2.6).

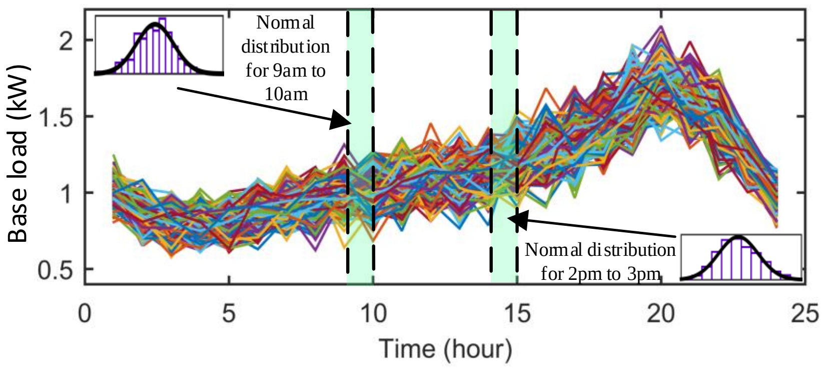


Figure 3.8. Base load data modelling by hourly probability distributions.

3.3.1.1.5 Electricity rate probability distribution

Electricity rate for each hour is fitted to a probability distribution. One year's hourly historical data from Ameren utility [309] is utilised and indicates that normal and lognormal distributions are the best for describing data in each hour. Therefore, there are 24 probability distributions which are described by Eqs. (3.26) and (3.27). One year data are generated and showed in Figure 3.9.

$$ER(\Delta t_j) \sim N(\mu_{r\,j}, \sigma_{r\,j}) \qquad \forall\, j \in \{1,2,\dots,6\} \cup \{22,23,24\} \tag{3.26}$$

$$ER(\Delta t_j) \sim lnN(\mu'_{r\,j}, \sigma'_{r\,j}) \qquad \forall\, j \in \{7,8,\dots,21\} \tag{3.27}$$

with $\mu_{r\,j}$, $\sigma_{r\,j}$, $\mu'_{r\,j}$ and $\sigma'_{r\,j}$ illustrated in Table 3.3.

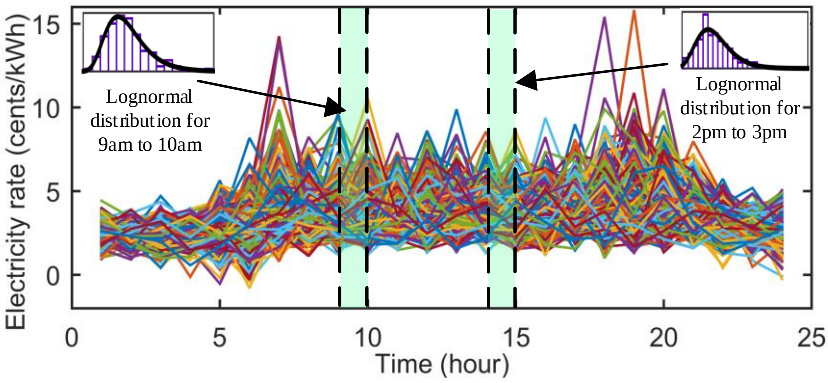


Figure 3.9. Electricity rate data modelling by hourly probability distributions.

Table 3.3. Parameters of hourly probability distribution functions for wind speed, global irradiance, temperature, base load and ER.

Hour	**Wind Speed (Eq. 19)**		**Global Irradiance* (Eqs. 20–22)**		**Temperature** (Eqs. 23–24)**				**Base load (Eq. 25)**		**Electricity Rate (Eq. 26–27)**	
j	A_w	B_w	α_G, A, μ_G	β_G, B, σ_G	μ_t	σ_t	μ'_t	σ'_t	μ_l	σ_l	μ_r, μ'_r	σ_r, σ'_r
1	3.78	3.07	N/A	N/A	-0.4	6.3	18.4	4.4	1.00	0.07	2.47	0.66
2	4.06	2.70	N/A	N/A	-0.5	6.3	18.1	4.2	0.85	0.07	2.45	0.57
3	3.64	2.93	N/A	N/A	-1.0	6.0	17.3	4.4	0.80	0.08	2.46	0.67
4	3.99	2.61	N/A	N/A	-1.6	5.8	16.5	4.5	0.80	0.07	2.44	0.67
5	3.76	2.41	N/A	N/A	-1.6	5.8	16.1	4.3	0.80	0.08	2.59	1.02
6	3.28	3.10	N/A	N/A	-1.9	5.7	15.6	4.4	0.86	0.08	2.95	1.24
7	3.44	2.92	N/A	N/A	-2.0	5.7	16.1	4.7	0.90	0.08	1.23	0.48
8	4.19	3.47	4.33	1.15	-2.0	5.9	17.6	5.3	0.95	0.09	1.21	0.35

Hour	Wind Speed (Eq. 19)		Global Irradiance* (Eqs. 20–22)		Temperature** (Eqs. 23–24)				Base load (Eq. 25)		Electricity Rate (Eq. 26–27)	
9	4.59	3.25	88.9,377	1.2,5.3	-0.7	6.4	20.3	5.6	1.00	0.09	1.26	0.35
10	5.62	3.84	1.20	3.58	1.6	7.0	23.1	5.5	1.00	0.10	1.29	0.37
11	5.95	4.78	1.65	2.90	4.0	7.5	25.6	5.2	1.06	0.10	1.28	0.34
12	7.42	5.14	1.91	2.31	5.8	7.7	27.2	5.1	1.10	0.10	1.28	0.34
13	7.33	4.51	1.92	1.89	7.0	7.8	28.2	5.1	1.09	0.11	1.26	0.32
14	7.17	4.00	2.00	1.86	8.4	8.2	29.4	4.8	1.14	0.10	1.25	0.29
15	6.84	5.03	1.99	2.09	8.1	8.2	3.4	0.2	1.20	0.11	1.22	0.32
16	7.27	3.69	2.01	2.78	7.9	8.3	3.4	0.2	1.28	0.11	1.23	0.32
17	7.09	3.53	1.69	3.63	6.6	8.2	28.2	4.8	1.34	0.11	1.30	0.31
18	6.02	2.62	307.58	1.61	4.6	7.9	26.8	5.0	1.45	0.12	1.35	0.37
19	5.22	2.87	4.95	0.82	2.9	7.2	24.6	5.2	1.59	0.13	1.37	0.41
20	4.74	2.19	4.31	0.90	1.4	7.3	19.5	3.3	1.67	0.13	1.34	0.38
21	4.28	2.33	N/A	N/A	1.5	6.8	21.5	4.6	1.65	0.12	1.25	0.33
22	4.66	2.56	N/A	N/A	0.9	6.6	20.6	4.6	1.49	0.13	3.08	0.86
23	4.52	2.51	N/A	N/A	0.2	6.4	19.7	4.6	1.20	0.08	2.79	0.80
24	4.50	2.49	N/A	N/A	-0.2	6.3	18.9	4.6	0.99	0.07	2.72	0.85

* $\mathrm{G}(\Delta \mathrm{t}_8) < 300, \mathrm{G}(\Delta \mathrm{t}_{18}) < 550, \mathrm{G}(\Delta \mathrm{t}_{19}) < 380, \mathrm{G}(\Delta \mathrm{t}_{20}) < 180$, $\mathrm{G}(\Delta \mathrm{t}_8) = \mathrm{G}(\Delta \mathrm{t}_{19}) = 0$ with a probability of 1/3. $\mathrm{G}(\Delta \mathrm{t}_9) = \mathrm{G}(\Delta \mathrm{t}_{18}) = 0$ with a probability of 1/5. $\mathrm{G}(\Delta \mathrm{t}_{20}) = 0$ with a probability of 2/3. Global irradiance data between 10 am to 5 pm are normalised and divided by 1200.

** Temperature <45 °C and probability of choosing (μ_{t_j},σ_{t_j}) or (μ'_{t_j},σ'_{t_j}) is 1/2.

3.3.1.2 Utilise probability distributions to model input data in each hour

For every hour/interval, data can be generated based on their probability distributions. These probability distributions can be used to apply MCS for sizing optimisation or electricity management simulations in that location. It should be mentioned that, because PEV is modelled based on daily PDFs and there is no sign of the relationship between PEV availability and different seasons/months of the year, these PDFs can be used in the second method as well.

3.3.2 Daily data modelling for wind speed, irradiance, temperature, load and electricity rate using data sampling for Monte Carlo simulations

Repeated random sampling can be used to generate MCS input data for simulations to model uncertainties associated with the data. These data intervals can be per hour, per minutely etc. depending on available data, and can be chosen based on simulation purposes. These repeated data samples can be chosen from TMY data or real historical data. However, these data need to be classified based on seasons or months of the year. For example, it is not practical to choose an irradiance sample from winter and to then choose a wind speed sample from summer for the same day simulation data, because wind speed, irradiance, temperature, load and electricity rate data are correlated. In other words, for each day, data sampling should be collected from similar databases based on the season (or month) of the year. In addition, daily sampling instead of hourly/interval sampling will make it possible to consider the correlation of every interval value with their prior interval value more precisely during each day [301].

3.3.3 Comparison of two methods for MCS data modelling

Use of probability distributions as given in section 3.3.1 is a good way to model the probabilistic behavior of renewable resources. However, there are two noteworthy matters that should be considered for simulation purposes. First, the correlation between wind speed, irradiance, temperature, load and electricity rate should be considered in order to improve this method. Second, the correlation between every interval value and the prior interval value is not considered precisely (i.e. generated data fluctuation is high). Although there is an inherent correlation between every interval value and the prior interval value, which is generated with probability distributions in section 3.3.1, these correlations might be insufficient for some sensitive simulations. One of the two following options can be used to improve the first method.

1. Prediction or classification methods can be used for determining correlated databases and for defining or predicting the next interval value.
2. Defining probability distributions for every season (or every month) of data (instead of yearly data) separately. Therefore, for each interval for every season (or month) for every database, we will have at least one probability distribution. Although there will be an inherent correlation between every interval with the prior interval value, prediction, or classification methods might be used for improvement.

The second method given in section 3.3.2, which is based on data sampling, considers the correlation between databases and data intervals more precisely. Also, it is less expensive in terms of computing resources. Therefore, the second method is used in the following chapters for data modelling of the simulations to determine the optimum capacity of renewable resources for the SH.

3.4 Optimisation

There are three common approaches to solving optimisation problems: mathematical optimisation, heuristic methods and meta-heuristic searches. Mathematical optimisation can solve many optimisation problems. However, these methods are relatively expensive for some difficult problems. Mathematical optimisation includes the following.

- Linear programming problems: these are simple problems, and objectives are affine functions of constraints.
- Quadratic programming problems: these are similar to linear programming problems; however, they have a quadratic objective and they can be solved in polynomial time if the objective is positive definite. Although they are comparably simple, they will be an NP-hard problem if the objective is indefinite.
- Convex programming problems: these are more complex than linear and quadratic problems. They have concave inequality and linear equality constraints along with a convex objective function. Convex problems convergence is guaranteed if they have a solution.

- Dynamic programming problems: these solve the sub-problems after subdividing large complex problems. They store the solutions for sub-problems and solve the problems recursively.
- Mixed integer linear programming problems: these have integer variables along with other unknown variables and usually are NP-hard. However, some can be solved by algorithms such as the cutting-plane method and branch-and-bound.
- Mixed integer nonlinear programming and nonlinear programming problems: it can be extremely challenging to solve these problems, and there is no guarantee of find the solution (if any solution exists).

Heuristic and meta-heuristic functions are introduced for solving difficult problems which are impossible or expensive to solve with mathematical approaches. They can be used to find quick and approximate solutions for many difficult problems.

Heuristic methods are knowledge-based methods that use certain rules to determine approximate solutions. They are well-designed and useful for decreasing computational effort.

Meta-heuristic searches may find a near-optimal solution by making few or no assumptions. Many of these algorithms – such as particle swarm optimisation, genetic algorithms and evolutionary algorithms – converge near a solution within a search space by using massive population sizes which navigate semi-randomly. These methods are used widely to solve optimisation problems, and they can usually find good solutions by searching a wide set of possible solutions. They are less expensive compared to mathematical methods [179].

Table 3.4. Optimisation methods.

Mathematical Optimisation	**Meta-Heuristic Search**	**Heuristic Method**
Linear programming	Immune clonal selection programming	Mix of optimisation and heuristics
Dynamic programming	Particle swarm optimisation	Artificial neural networks
Convex programming	Tabu search	State-queueing model

Mathematical Optimisation	Meta-Heuristic Search	Heuristic Method
Quadratic programming	Genetic algorithm	Backtracking-based method
Mixed integer linear programming	Evolutionary algorithms	Constraint optimisation by broadcasting
Mixed integer nonlinear programming		Markov decision processes
		TOPSIS

Meta-heuristic methods are one of the best approaches for solving continuous and combinatorial problems [240, 310-312]. For solving many multi-objective and nonlinear optimisation problems in research, meta-heuristic methods are preferred because of reliability, availability, cost and performance optimisation [296, 313-315].

PSO is a meta-heuristic methods that has been extensively used for optimisation problems in the literature. There are more than 1779 applications of PSO introduced in the literature. PSO is recognised as one of the most suitable tools for various optimisation problems compared to other meta-heuristic and evolutionary algorithms, such as genetic algorithms [316, 317]. In another research study, three different meta-heuristic optimisation methods are compared for real-time-application optimisation in HEMS. Evaluation results demonstrated that PSO performance was better than Tabu search (TS) and simulated annealing (SA) [318].

3.4.1 Particle swarm optimisation (PSO)

Particle swarm optimisation (PSO) is used in the simulations to minimise the annual cost of the SH (Eq. (4.4)). PSO is one of the most appropriate AI approaches, making it possible to find a near-global solution for multi-dimensional problems. It works by choosing a population of candidate solutions. These candidate solutions (particles) move around the search space based on a few formulae to find the best solution. This technique was introduced by Kennedy and Eberhart in 1995 based on a simplified version of social systems in nature, such as a bird flock behavior [319].

The steps for the PSO algorithm are as follows.

1. Initialise PSO parameters such as a total number of iterations, size of swarm or population etc.
2. Initialise particles randomly in the problem space. Each particle has a position (Eq. (3.28)) and velocity (Eq. (3.29)) in D dimensional space, which can be represented as follows:

$$X_i = [X_{i1}, X_{i2}, .., X_{iD}] \tag{3.28}$$

$$V_i = [V_{i1}, V_{i2}, .., V_{iD}] \tag{3.29}$$

3. Evaluate the objective function fitness (Eq. (3.30)) for each particle, which can be represented as follows:

$$F_i = f(X_{i1}, X_{i2}, .., X_{iD}) \tag{3.30}$$

4. Obtain personal best position (p_{id}) and global best position (p_{gbest}). The best position obtained by a particle itself up to the current iteration is called personal best position and shown with p_{id}. In each iteration p_{id} is obtained by comparing the fitness value of the current position with the last p_{id} and will be updated if the current position is better. For the first iteration the p_{id}will be same as the first position (X_i). The best position among all personal best positions is called global best position (p_{gbest}).
5. In each iteration, velocity (Eq. (3.31)) for each particle updates as follows:

$$V_i^{t+1} = w \times V_i^t + c_1 \times rand_1 \times \left({p_{id}}_i^t - X_i^t\right) + c_2 \times rand_2 \times \left(p_{gbest}^t - X_i^t\right) \quad (3.31)$$

where w is inertia weight and V_i^t is the velocity for particle *i* at iteration *t*, c_1 and c_2 are acceleration coefficients, $rand_1$ and $rand_2$ are random numbers between (0,1), ${p_{id}}_i^t$ is the best position for particle *i* at iteration *t*, X_i^t is the position for particle *i* at iteration *t*, p_{gbest}^t is the global best position at iteration *t*, and V_i^{t+1} is the velocity for particle *i* at iteration *t+1*.

6. Each particle position (Eq. (3.32)) updates in each iteration as follows:

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (3.32)$$

7. Evaluate the fitness of each particle to obtain personal best positions and global best position.
8. Repeat the process until the convergence criteria are met.

The velocity is limited to V_{max}. Each particle is pulled toward p_{id} and p_{gbest} positions with stochastic acceleration terms which are controlled by acceleration coefficients [319, 320]. Figure 3.10 shows the flowchart for the PSO algorithm.

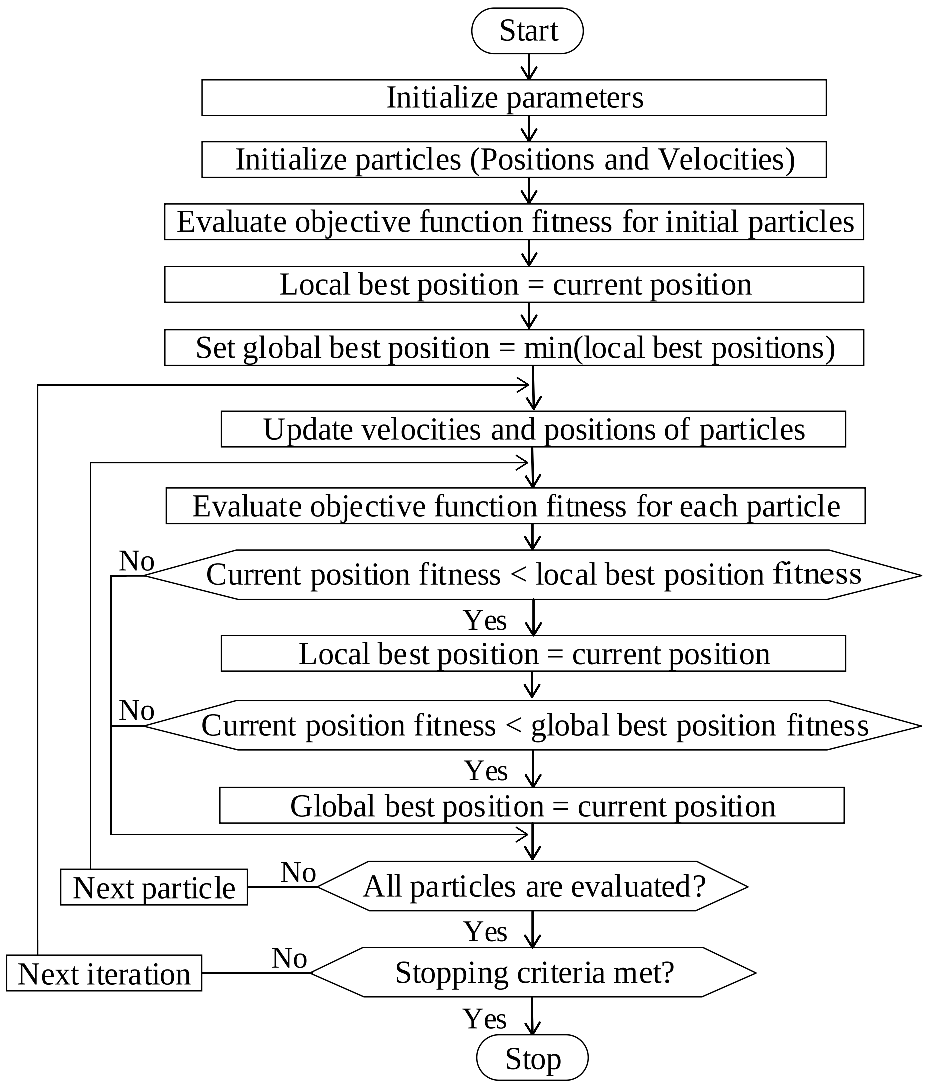


Figure 3.10. PSO algorithm.

PSO is hybridised with MCS in the following chapters for solving optimisation problems while considering the probabilistic behaviour of input data. In the following chapters, the second approach given in section 3.3.2 is used for implementing MCS and hybridisation of MCS-PSO is further explained.

3.5 Conclusion

In this chapter, SH components and renewable resources are modelled and will be used for optimisations and simulations in the following chapters. Furthermore, two methods for MCS simulations are introduced. The first method is based on probability distribution for generating data and the second on data sampling that allows us to generate data relating to the correlation between databases and data intervals more precisely. Therefore, the second approach given in section 3.3.2 is chosen for further simulations in the following chapters. Finally, PSO optimisation is described and will also be used in the following chapters for optimisations.

Chapter 4 Optimal Sizing of Renewable Resources in Smart Homes[1]

4.1 Introduction

In this chapter, the annual electricity cost of a SH with rooftop PV, WT, BSS, PEV and shiftable loads is minimised by performing optimal component sizing using Monte Carlo simulations and particle swarm optimisation (MCS-PSO) in association with a new rule-based home energy management system (HEMS) considering import and export of energy with V2H integration. The stochastic behaviors of wind speed, irradiance, temperature, load and ER are considered while the availability of PEV is projected using normal and lognormal probability density functions. Performance of the proposed approach is evaluated by SH operation and cost calculations with near-optimal component sizes. Simulations and sensitivity analyses are performed to investigate the impacts of shiftable loads, V2H integration, battery charge/discharge rates, maximum daily export energy, maximum PV, WT and battery capacity limits as well as the possibility of eliminating BSS for further reductions in annual cost and levelised cost of electricity (LCOE). Finally the optimisation results for MCS-PSO and MCS-ABC are compared for Cases B1, B2 and B3 in Section 4.4.4.

4.2 Data modelling for wind speed, irradiance, temperature, load and ER

Annual data are used to implement MCS and perform near-optimal component sizing of the SH in Section 4.3.

[1] This chapter is mainly extracted from published paper [143] (Appendix A).

4.2.1 Input data

The typical meteorological year (TMY) data [307] for wind speed, global horizontal irradiance and ambient temperature are used along with ER [308, 309] from McCook, Nebraska. Also, the predetermined (not schedulable) load of a home in the United States is considered as the base load (L_b) [139, 308]. It includes lighting, freezer, refrigerator, water heater, microwave and oven loads. Schedulable and unpredictable loads (L_s, L_u) are also modelled along with the L_b. Five types of schedulable loads are considered (Table 4.1). L_u is considered to be less than 5% of L_b and to change randomly based on a uniform distribution. Schedulable loads can be shifted to the cheapest ER hours in their DIs while HVAC and PEV are considered separately, as explained in the previous chapter.

Table 4.1. Schedulable loads (L_s).

Appliance	Usage Frequency	Working Cycle (Hours)	Total Energy (kWh)
Dishwasher	Every day	2	1.2
Clothes Dryer	Twice a week	1	1.1
Washing Machine	Twice a week	1	0.5
Iron	Once a week	1	1
Electric Oven	Once a week	1	2

4.2.2 Monte Carlo simulation (MCS)

Repeated random sampling is used to obtain numerical results since there are uncertainties associated with the inputs. The TMY information and annual data for wind speed, irradiance, temperature, load and ER are used as the input data for MCS. These data are separated into four seasons in order to keep the most closely correlated data in the same databases. Everyday input data are generated based on daily data sampling from the associated season databases. In addition, daily data sampling (instead of hourly) is used to consider the dependency and high correlation of hourly data to their prior values. This method makes it possible to apply a combination of MCS with PSO optimisation and determine the near-optimal WT, PV and BSS capacities, as explained in Section 4.3.

4.3 Proposed MCS-PSO for optimal component sizing and operation of SH with H2V and V2H integrations

This section will first introduce the new rule-based HEMS and then incorporate it into the proposed MCS-PSO for near-optimal component sizing (Figure 4.1) and operation (Figure 4.2) of the SH.

4.3.1 Proposed rule-based HEMS with coordinated PEV and BSS charging and discharging operations

The proposed HEMS (Table 4.2) considers day-ahead electricity prices to coordinate charging/discharging activities of BSS and PEV based on renewable generation and loads to reduce the daily cost of SH electricity consumption. Charge and discharge costs and constraints (Sections 3.2.4–3.2.5) are considered in the simulations. In addition, the net renewable generation surplus is stored in the battery and PEV for future demands and electricity trading. This is done based on the proposed seven HEMS rules of Table 4.2.

At each interval (Δt_j), the proposed HEMS satisfies the following trading and power flow constraints.

$$E_{Sell}(\Delta t_j) < E_{Sell,max} \tag{4.1}$$

$$L_b(\Delta t_j) + L_s(\Delta t_j) + L_u(\Delta t_j) = E_{Buy}(\Delta t_j) - E_{Sell}(\Delta t_j) - E_B(\Delta t_j) - E_{PEV}(\Delta t_j). \tag{4.2}$$

4.3.2 Proposed MCS-PSO for optimal component sizing of SH

One of the best options for solving the nonlinear SH component-sizing problem is a meta-heuristic optimisation technique such as PSO. As explained in the previous chapter, PSO starts with a population of random candidate solutions (particles) within the problem space. In each iteration, particles move toward the best global (p_{gbest}) and the best local (p_{id}) solutions. PSO updates p_{gbest} and p_{id} at the end of each iteration until it arrives at a sufficiently good fitness or reaches the maximum iteration number. The particle acceleration rates toward p_{id} and p_{gbest} locations are controlled by the cognitive parameter (c_1) and social parameter (c_2), respectively. Moreover, an inertia weight coefficient (w) is used for better control of the exploration and exploitation in PSO.

Table 4.2. Operation rules of proposed rule-based HEMS with consideration of shiftable loads and v2h to minimise the annual cost of SH.

Rule	HEMS Rule-Based Instruction
1	Acquire initial SOCs for PEV and BSS from the previous day.
2	Determine DIs (according to the instructions of Section 3.2.4 and Figure 3.2) and move all shiftable loads to the cheapest ER hours.
3	Schedule PEV to be charged until 5 am (Section 3.2.5).
4	At each iteration considering Eqs. (4.1)–(4.2), use the following priorities to supply the SH loads from: i) renewable resources, ii) battery, iii) PEV and iv) SG.
5	At each DI considering Eqs. (4.1)–(4.2), sell/purchase electricity at the extreme maximum/minimum point of ER to discharge/charge the: i) PEV and ii) battery.
6	At each iteration, sell the surplus electricity to satisfy Eqs. (4.1)–(4.2).
7	Update initial SOCs of PEV and BSS for the next day.

The proposed MCS-PSO is executed to minimise the annual electricity cost of the SH and determine the near-optimal sizes of PV, WT, and BSS (Figure 4.2). For each Δt_j of the day, the electricity cost is calculated as:

$$\begin{aligned} C_{Hour}(\Delta t_j) = {} & LC_W . E_W(\Delta t_j) + LC_{PV} . E_{PV}(\Delta t_j) \\ & + LC_B . Cap_B . \Delta t + C_{d,sell}^{PEV} . E_{sell}^{PEV}(\Delta t_j) + E_{Buy}(\Delta t_j) \\ & \times ER(\Delta t_j) - E_{Sell}(\Delta t_j) \times ER(\Delta t_j) \end{aligned} \tag{4.3}$$

where the electricity purchase rate (EPR) and the electricity selling rate (ESR) are assumed to be equal to the ER. For the selected SH located in McCook (Nebraska, USA), LC_W=3.5 cents/kWh [139] and LC_{PV}=4.1 cents/kWh [113] while a reduction of 1.0 cent/kWh is also considered for the carbon capture cost [321, 322], and it is assumed that $C_{d,sell}^{PEV} = 0.3$ cents/kWh and $LC_B = 0.3$ cents/kWh/h [139].

The objective function for PSO is the minimisation of the SH annual cost of electricity:

$$Min\ C_{Annual} = \sum_{i=1}^{365} C_{Day}(i) \tag{4.4}$$

$$C_{Day} = \sum_{j=1}^{24} C_{Hour}(\Delta t_j) \tag{4.5}$$

The simulations' convergence was ensured by a detailed analysis of PSO behavior based on different parameters. The selected PSO parameters for the simulations are presented in Table 4.3. For improving the effectiveness of MCS, an inertia weight of 0.2 is used to limit particle's velocity. The selected upper boundaries for PV, WT and BSS are based on physical limitations of the SH. Also, $E_{Sell,max}$ depends on the physical limitations and utilities contracts' flexibility. For the simulations of this chapter, $E_{Sell,max}$ is considered to be always less than the average base load of the SH. Figure 4.1 shows the proposed MCS-PSO algorithm for determining near-optimal size of PV, WT and BSS.

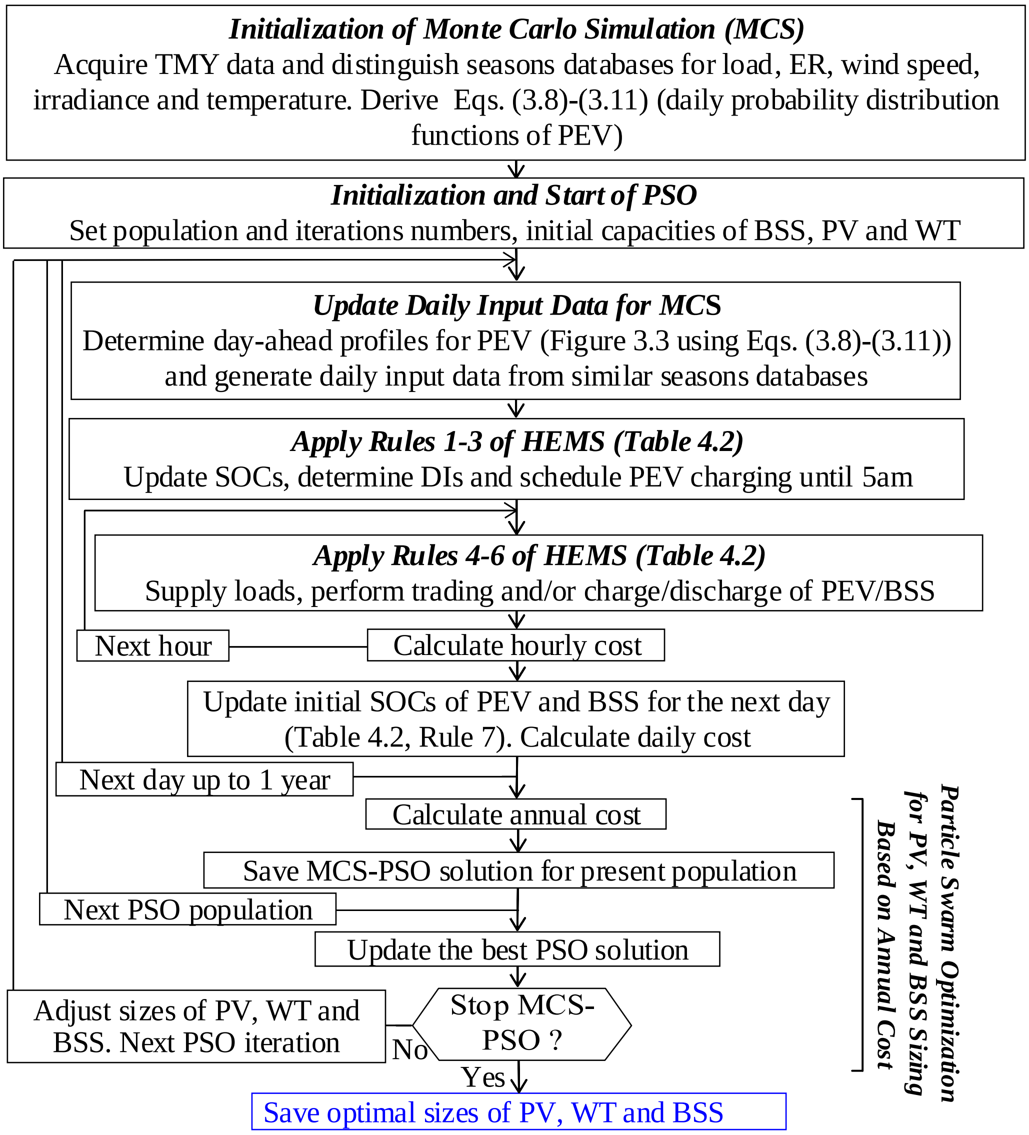


Figure 4.1. Proposed MCS-PSO algorithm for optimal sizing of PV, WT, and BSS to minimise annual electricity cost of SH.

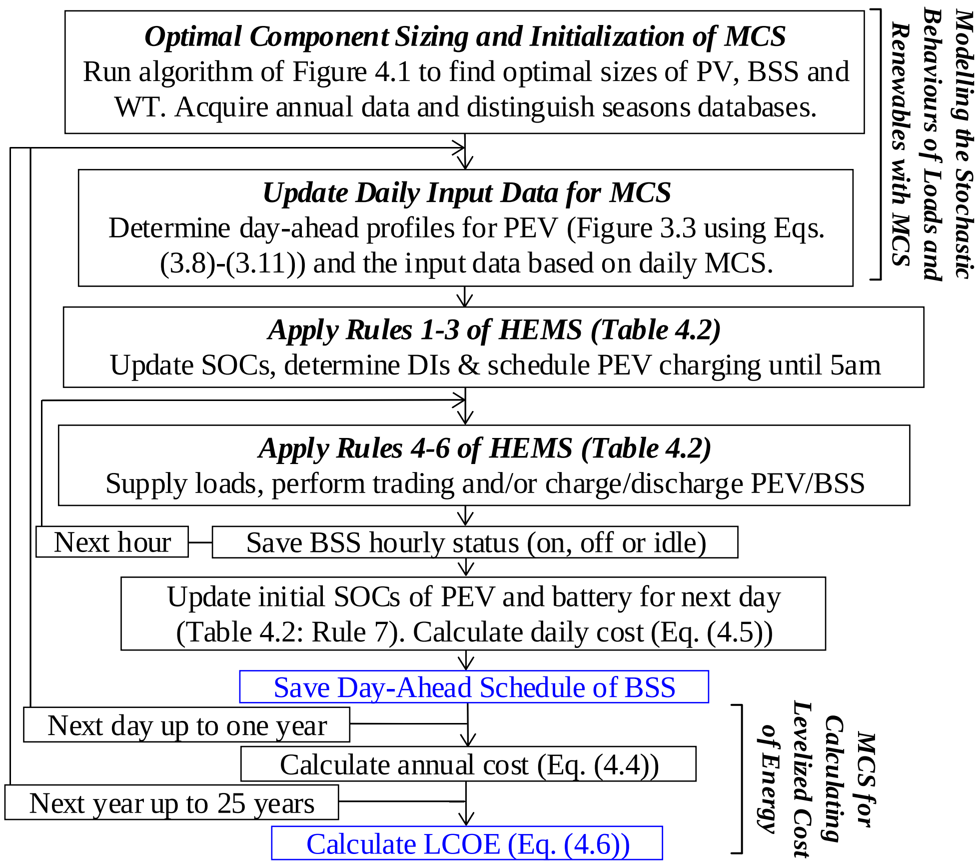


Figure 4.2. Proposed algorithm for SH operation to determine day-ahead BSS schedules, annual cost (Eq. (4.4)) and LCOE (Eq. (4.6)).

Table 4.3. Input parameters for PSO.

Parameter	**Particles**	***K***	***D***	c_1	c_2	***w***	**Boundaries**		
							PV	**WT**	**BSS**
Value	50	1000	3	1	1	0.2	[0,15]	[0,5]	[0,30]

4.3.3 Operation of SH

After determining the near-optimal component sizes (Figure 4.1), the proposed algorithm of Figure 4.2 can be used for SH operation and day-ahead scheduling of BSS. The algorithm can also be used for the calculation of annual cost (Eqs. (4.4)–(4.5)) and the LCOE over the lifetime of renewable resources [113, 139]:

$$LCOE_{SH} = \frac{\sum cost\ over\ life\ time}{\sum suplied\ demand\ over\ life\ time} \tag{4.6}$$

where the lifetime of PV and WT is assumed to be 25 years and battery life is eight years with the maximum of 2000 cycles [323].

4.4 Simulations results

Simulations are performed first to determine the near-optimal component sizes of the SH shown in Figure 3.1 with the proposed PSO-MCS algorithm of Figure 4.1 and then to investigate its operation and performance with the proposed algorithm of Figure 4.2. Simulations results (Figures. 4.3–4.8) are summarised in Table 4.4.

The optimal component sizes, annual cost, annual cost reduction and the LCOE (Eq. (4.6)) are determined and compared for two operating conditions: without (Table 4.4; rows 5–8) and with (Table 4.4; rows 9–12) the WT. For each case, the impacts of shiftable loads (Cases A2 and B2), H2V and V2H integrations (Cases A3 and B3), as well as the effect of eliminating BSS altogether (Cases A4 and B4) are investigated. For the base case operation (without PV, BSS and WT), the annual cost is $848, and the LCOE is 3.21 cents/kWh (Table 4.4; row 4).

4.4.1 Optimal sizing of PV and BSS without WT to minimise annual cost of household electricity

This section does not consider WT and determines the near-optimal sizes of PV and BSS as well as the corresponding annual and levelised costs for operating conditions with and without shiftable loads and V2H integration (Table 4.4, Cases A1–A3). In addition, the possibility of eliminating BSS altogether is also investigated in Case A4.

Table 4.4. Summary of simulation results (Figures. 4.3–4.8) for optimal component sizing (Figure 4.1) and operation (Figure 4.2) of SH.

Simulated Case Studies			Optimal Component Sizing of SH (Proposed MCS-PSO Algorithm of Figure 4.1) using Daily Monte Carlo Generated Data					Operation of SH (Algorithm of Figure 4.2) using Optimal Component Sizes and Daily Monte Carlo Generated Data		
			Input Variables		Optimal Component Sizes					
			$E_{Sell,max}$ [kWh/day]	R_c [kWh/hour]	Cap_{PV} [kW]	Cap_B [kWh]	Cap_{WT} [kW]	**Annual Cost [$]**	**Annual Cost Reduction [%]**	**LCOE (Eq. (4.6)) for 25 Years [cents/kWh]**
Base Case: SH without PV, BSS, and WT			N/A	N/A	N/A	N/A	N/A	848	N/A	3.21
Case A: SH with PV, PEV and BSS (Figures. 4.3–4.5)	A1	Nonshiftable Loads, PEV (H2V only)	50	10	10.73	10.27	N/A	718	15.3	2.72
	A2	Shiftable Loads, PEV (H2V only)	50	7	11.11	7.37	N/A	696	17.9	2.64
	A3	Shiftable Loads, PEV (H2V and V2H)	50	3	9.85	0.79	N/A	634	25.2	2.40
	A4	Case A3 without BSS	50	N/A	9.88	0	N/A	636	25.0	2.41
Case B: SH with PV, PEV, BSS and WT (Figures. 4.6–4.8)	B1	Nonshiftable Loads, PEV (H2V only)	50	10	6.40	10.60	4.83	710	16.1	2.68
	B2	Shiftable Loads, PEV (H2V only)	50	10	6.21	9.42	5	687	19.0	2.60
	B3	Shiftable Loads, PEV (H2V and V2H)	50	8	0.08	6.25	5	612	27.8	2.31
	B4	Case B3 without BSS	50	N/A	0	0	5	615	27.5	2.32

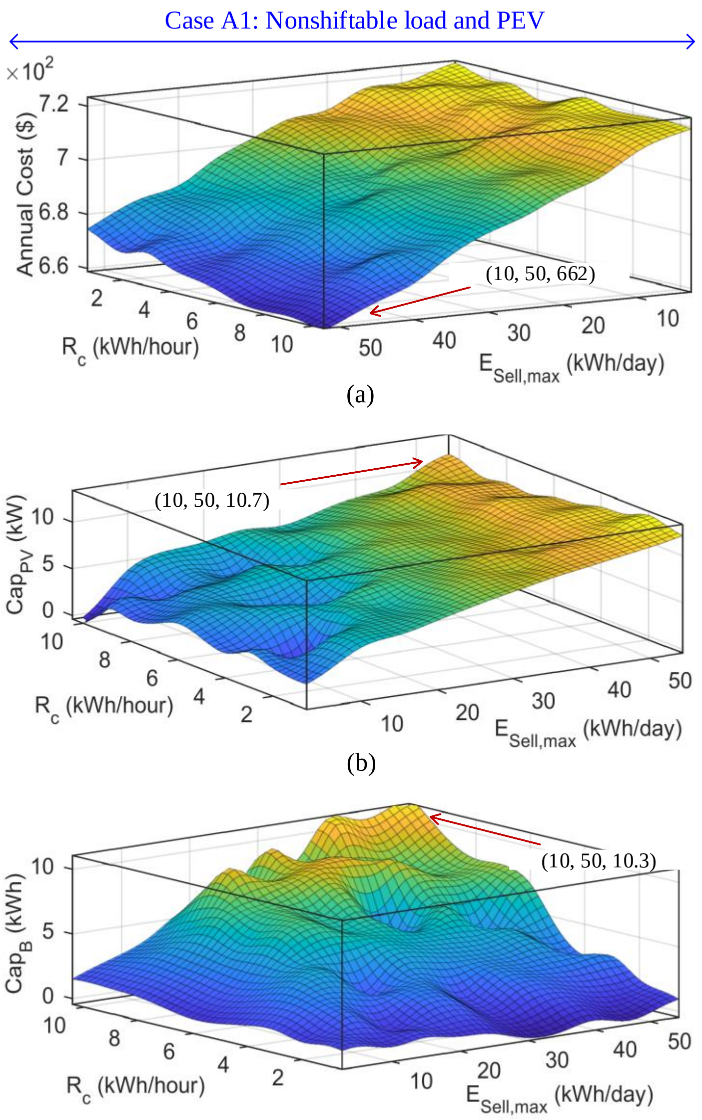


Figure 4.3. Case A1 (nonshiftable loads and PEV). The sensitivity of MCS-PSO solution (Figure 4.1) to battery charge/discharge rate and maximum daily export limit. Arrows show near-optimal solutions for the annual cost ($662), PV (10.73 kW), and battery (10.27 kWh) sizes.

In Case A1, the schedulable loads (Table 4.1) and PEV are considered to be nonshiftable, and there is no V2H integration. The near-optimal sizes of PV and BSS are determined based on a range of different R_c and $E_{Sell,max}$ values for the SH (Figure 4.3). As expected, there are different solutions for different operating conditions. However, the minimum yearly cost is achieved when $E_{Sell,max}$ is 50 kWh/day, R_c is 10 kWh/hour and the capacities of PV and battery are 10.73 kW and 10.27 kWh, respectively. This near-optimal solution for Case A1 offers an annual cost reduction of 15.3% (Table 4.4).

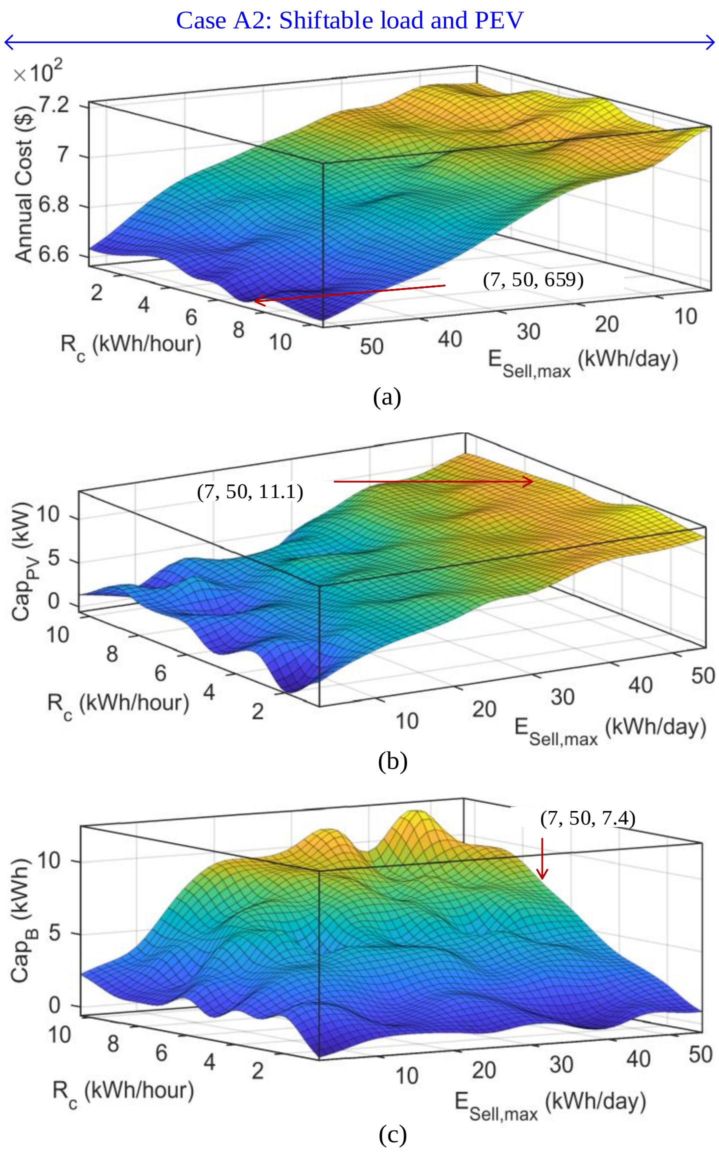


Figure 4.4. Case A2 (shiftable loads and shiftable PEV/H2V). The sensitivity of MCS-PSO solution (Figure 4.1) to battery charge/discharge rate and maximum daily export limit. Arrows show near-optimal solutions for the annual cost ($659), PV (11.11 kW), and battery (7.37 kWh) sizes.

In Case A2, the schedulable loads (L_s in Table 4.1, which are less than 2% of the total load) are considered to be shiftable and there is no V2H integration. The near-optimal sizes of PV and BSS are determined based on a range of different R_c and $E_{Sell,max}$ values for the SH (Figure 4.4). As with Case A1, there are different solutions. However, the minimum yearly cost is attained when $E_{Sell,max}$ is 50 kWh/day, R_c is 7 kWh/hour and the capacities of PV and battery are 11.11 kW and 7.37 kWh, respectively. This near-optimal solution for Case A2 can produce a 17.9% annual cost reduction (Table 4.4).

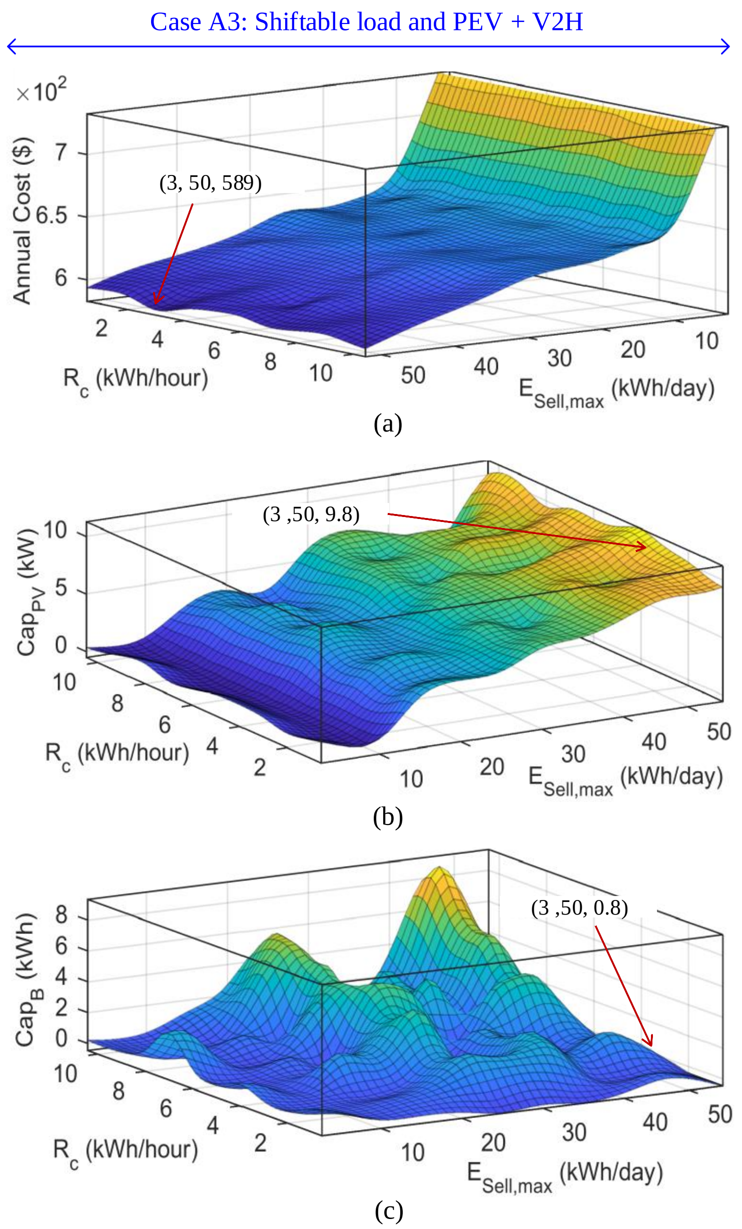


Figure 4.5. Case A3 (shiftable loads and shiftable PEV/H2V/V2H). The sensitivity of MCS-PSO solution (Figure 4.1) to battery charge/discharge rate and maximum daily export limit. Arrows show near-optimal solutions for the annual cost ($589), PV (9.85 kW) and battery (0.79 kWh) sizes.

In Case A3, both schedulable loads and V2H integration are considered. As with Cases A1–A2, the near-optimal sizes of PV and BSS are determined based on a range of different R_c and $E_{Sell,max}$ values (Figure 4.5). The minimum yearly cost corresponding to 25.2% annual cost reduction (Table 4.4) is reached when $E_{Sell,max}$, R_c, PV and battery ratings are 50 kWh/day, 3 kWh/hour, 9.85 kW and 0.79 kWh, respectively.

According to the summarised results of Table 4.4 (rows 5–8), for the SH with optimal sizes of PV and BSS:

- Introduction of PV and BSS will reduce the annual cost by 15.3% while the LCOE reduces from 3.21 to 2.72 cents/kWh (Table 4.4; rows 4 and 5).
- Scheduling of shiftable loads by the proposed HEMS (Table 4.2) will provide greater savings with an annual cost reduction of 17.9% and LCOE of 2.64 cents/kWh (Table 4.4; row 6).
- Integration of V2H will further reduce the optimal sizes of PV and BSS to 9.85kW and 0.79kWh while the annual cost reduction and LCOE are also improved to 25.2% and 2.40 cents/kWh, respectively (Table 4.4; row 7).
- The proposed battery-less configuration (Table 4.4, Case A4) looks very promising as well, with a 25% reduction in the annual cost. Comparing the results of Cases A1 and A4, LCOE is improved from 2.72 to 2.41 cents/kWh.

4.4.2 Optimal sizing of PV, WT, and BSS to minimise annual cost of household electricity

The impacts, benefits, and limitations of introducing WT are investigated in Cases B1–B4. They are similar to Cases A1–A4 with the inclusion of WT. Near-optimal sizes of PV, WT, and BSS are determined for a range of R_c and $E_{Sell,max}$ values as shown in Figures. 4.6–4.8. For Case B1, the minimum yearly cost is achieved when $E_{Sell,max}$ is 50 kWh/day, R_c is 10 kWh/hour and the capacity of PV, WT and battery are 6.40 kW, 4.83 kW and 10.60 kWh, respectively (Figure 4.6). This near-optimal solution for Case B1 can create a 16.1% annual cost reduction (Table 4.4). Note that the solution for Case B2 offers a more significant annual cost reduction of 19.0% (Table 4.4 and Figure 4.7 with $E_{Sell,max}$=50 kWh/day, R_c=10 kWh/hour, PV=6.21 kW, WT=5 kW and BSS=9.42 kWh). While the most attractive solution with an annual cost reduction of 27.8% (Table 4.4) is for Case B3 with $E_{Sell,max}$=50 kWh/day, R_c=8 kWh/hour, PV=0.08 kW, WT=5 kW and BSS=6.25 kWh (Figure 4.8).

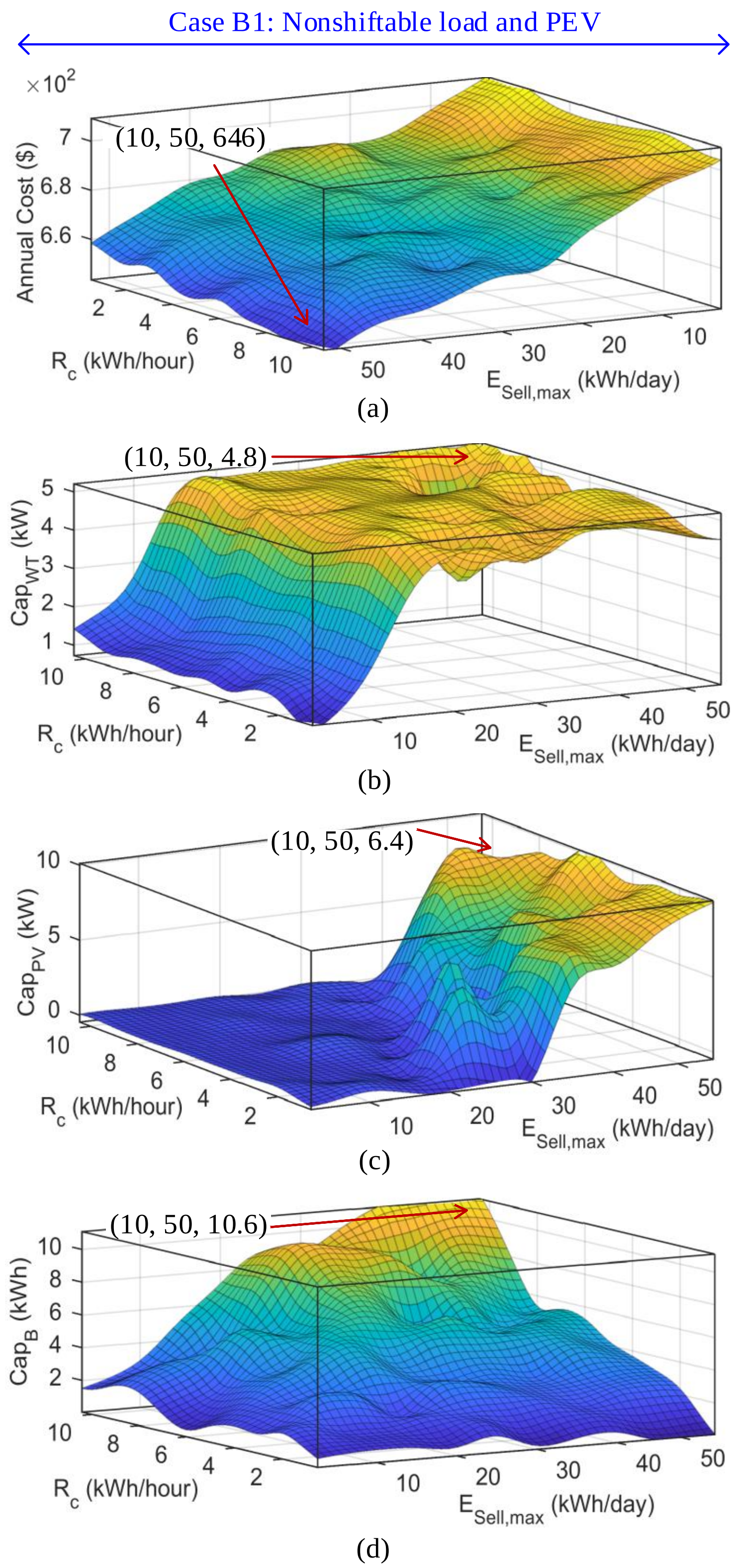


Figure 4.6. Case B1 (nonshiftable loads and PEV). The sensitivity of MCS-PSO solution (Figure 4.1) to battery charge/discharge rate and maximum daily export limit. Arrows show near-optimal solutions for annual cost ($646), WT (4.83 kW), PV (6.40 kW) and battery (10.60 kWh) sizes.

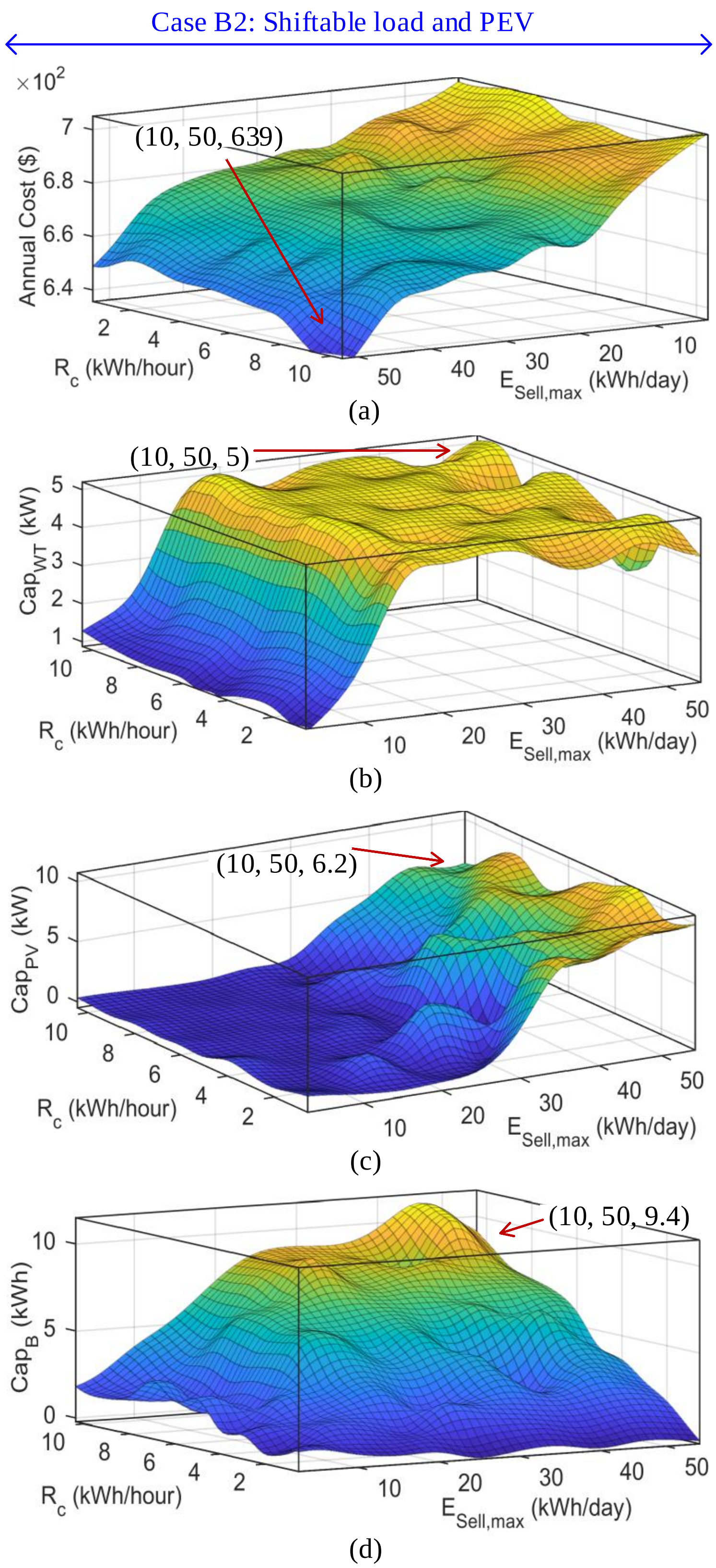


Figure 4.7. Case B2 (shiftable loads and shiftable PEV/H2V). The sensitivity of MCS-PSO solution (Figure 4.1) to battery charge/discharge rate and maximum daily export limit. Arrows show near-optimal solutions for the annual cost ($639), WT (5 kW), PV (6.21 kW), and battery (9.42 kWh) sizes.

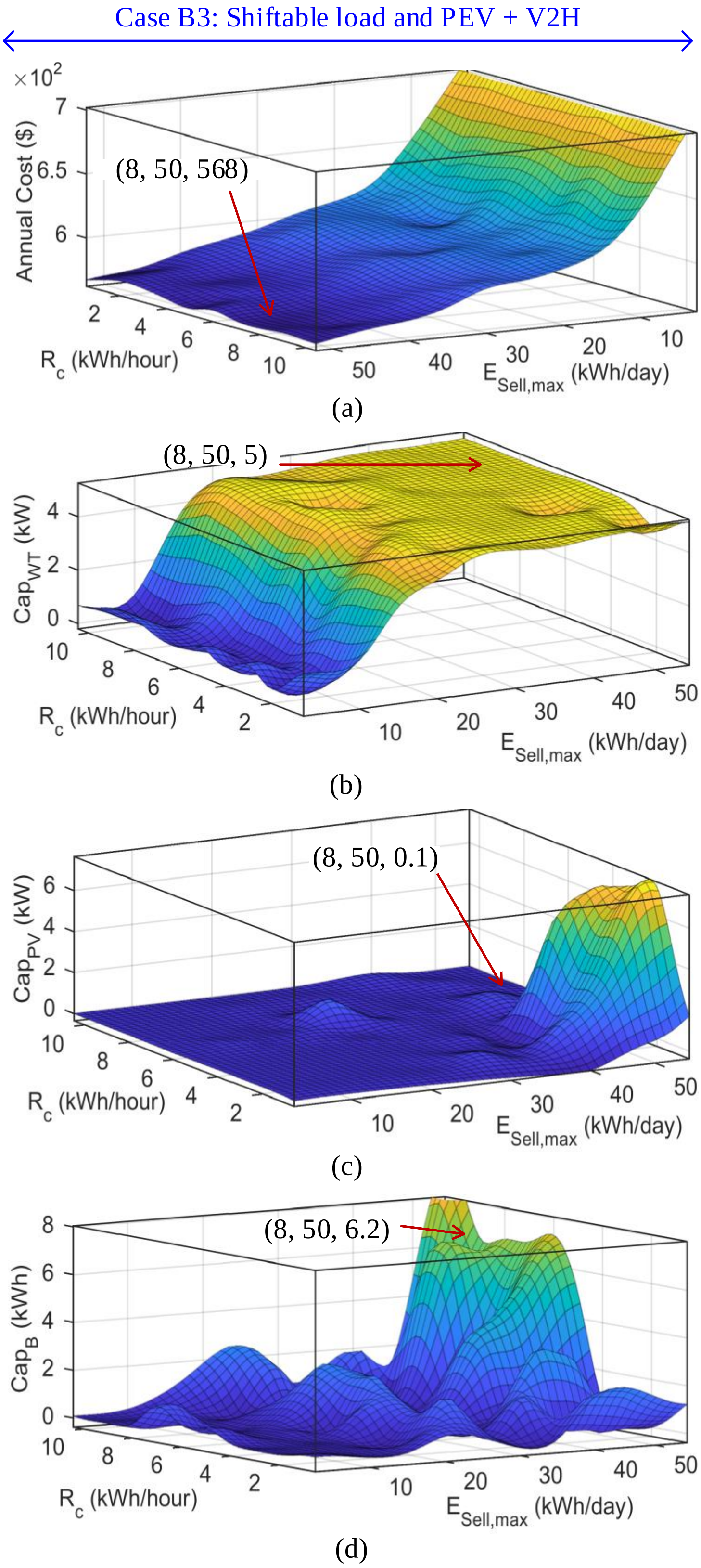


Figure 4.8. Case B3 (shiftable loads and shiftable PEV/ H2V/V2H). The sensitivity of MCS-PSO solution to battery charge/discharge rate and maximum daily export limit. Arrows show near-optimal solutions for annual cost ($568), WT (5 kW), PV (0.08 kW) and battery (6.25 kWh) sizes.

Comparison of simulations results in Table 4.4 (rows 5–12) for Cases A1–A4 and B1–B4 reveals further improvements in annual cost and LCOE for all simulated scenarios. For example:

- According to Table 4.4 (column 10), there are further reductions in the annual costs from 15.3%, 17.9%, 25.2% and 25.0% (without WT; rows 5–8) to 16.1%, 19.0%, 27.8% and 27.5% (with WT; rows 9–12).
- There are also reductions in LCOE from 2.72, 2.64, 2.40, and 2.41 cents/kWh (without WT; Table 4.4: column 11; rows 5–8) to 2.68, 2.60, 2.31, and 2.32 cents/kWh (with WT; Table 4.4: column 11; rows 9–12).
- The proposed battery-less configuration (Table 4.4, Case B4) looks even more attractive compared to Case A4 since the annual cost reduction and LCOE are further improved from 25.0% to 27.5% and from 2.41 cents/kWh to 2.32 cents/kWh, respectively.

4.4.3 Impacts of load shifting on BSS operation

For the SH considered in this study, the schedulable loads (L_s) are about 2% of the total household load (Table 4.1). Figure 4.9 demonstrates the impacts of shifting L_s on the BSS operation. The consumption, generation and, SOC of BSS before and after shifting L_s to the cheapest ER hours in their corresponding DIs are shown in Figure 4.9.a and Figure 4.9.b, respectively. In this particular study, shifting of the schedulable loads did not result in significant impacts on the battery consumption, generation and SOC.

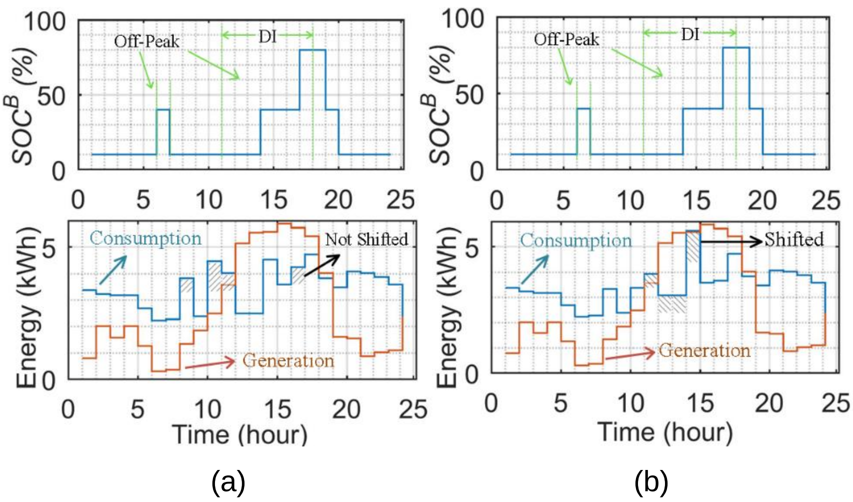


Figure 4.9. Consumption, generation and SOC for BSS in SH; (a) before shifting the schedulable loads, (b) after shifting the schedulable loads.

4.4.4 Comparing MCS-PSO results with MCS-ABC

In this section, Artificial Bee Colony (ABC) is utilized in conjunction with MCS to evaluate MCS-PSO results for three most complex Cases of B1, B2 and B3. Simulation results are compared in Table 4.5.

Artificial Bee Colony (ABC) is one of the stochastic optimisation methods which is proposed by Karaboga [324] and its performance is examined and compared with other heuristic algorithms such as PSO [325-333]. A food source position, indicates a potential solution in ABC algorithm and the fitness/quality of this solution is defined based on the amount of food source in that position. There are three categories of bees in this algorithm. First category is called employed bees which go to the food source based on their memories from their last visit and local information. Second category is onlookers which are waiting to choose food sources based on employed bees information. Third category is called scouts which search randomly for new sources. In ABC algorithm, onlookers and employed bees are responsible for exploitation of the search space and scouts are responsible for exploration. Also a greedy selection process is utilized in each cycle for memorizing food source position based on the comparison of fitness of the new solution and the previous solution [325].

First step in this algorithm is generating initial population of solutions. Each solution (x_s) is a three dimensional vector. In other words, each solution or food source position consists of 3 numbers which represent size of BSS, PV and WT in our simulations. Number of onlooker bees or employed bees are equal to number of population (*SN*) which is considered to be 50 in this section simulations. Two other control parameters in ABC are maximum cycle number (*MCN*) and the value of *limit* which are considered to be 3000 and 300 in our simulations. The number of *limit* is defined in ABC to abandon a food source if it cannot be improved further during that prearranged number of cycles. If a food source is abandoned, then the scout will discover a new food source based on the following equation:

$$x_s^d = x_{min}^d + rand(0,1)(x_{max}^d - x_{min}^d) \tag{4.7}$$

where $d \in \{1, 2, \dots, D\}$ and D is equal to 3 in this section simulations.

After initialisation, these solutions will be populated for each cycle and the position of the employed bees will be changed based on the local information and fitness value of the new solutions. Every employed bee in each cycle modifies her position to check if the fitness value improves. If it is improved then, memorises the new position/solution, otherwise, remembers the previous one. However, each onlooker bee will get the information from employed bees after their population in each cycle completed. She will choose a food source based on the employed bees information. Probability of choosing food sources (p_s) with higher fitness value is higher when an onlooker bee chooses her position [325]. This probability is defined as follows:

$$p_s = \frac{fit_s}{\sum_{n=1}^{SN} fit_n} \tag{4.8}$$

where fit_s and SN are fitness of the candidate solution and the number of candidates/food sources respectively. Fitness of the candidate solution is calculated as follows:

$$fit_s = \frac{1}{1 + C_{Annual_s}} \tag{4.9}$$

where C_{Annual_s} is our objective function which is the annual cost of electricity for candidate x_s (Eq. (4.4)).

Each candidate population in ABC is determined from the old food position based on the following equation:

$$v_{sd} = x_{sd} + \varphi_{sd}(x_{sd} - x_{nd}) \tag{4.10}$$

where n, d and φ_{sd} are chosen randomly along with $d \in \{1, 2, \dots, D\}$ and $n \in \{1, 2, \dots, SN\}$. In addition, n is always different from s. Also, φ_{sd} is always between -1 and 1 [325].

Table 4.5. Simulation results for comparing MCS-PSO with MCS-ABC for Cases B1, B2 and B3.

Simulated Case Studies			**Optimal Component Sizing of SH, using Daily Monte Carlo Generated Data along with PSO and ABC optimisations**					**Operation of SH (Algorithm of Figure 4.2) using Optimal Component Sizes and Daily Monte Carlo Generated Data**		
			Input Variables		**Optimal Component Sizes**			**Annual Cost [$]**	**Annual Cost Reduction [%]**	**LCOE (Eq. (4.6)) for 25 Years [cents/kWh]**
			$E_{Sell,max}$ [kWh/day]	R_c [kWh/hour]	Cap_{PV} [kW]	Cap_B [kWh]	Cap_{WT} [kW]			
Case B: SH with PV, PEV, BSS and WT	B1: Nonshiftable Loads, PEV (H2V only)	$B1_{MCS-PSO}$	50	10	6.40	10.60	4.83	710	16.1	2.68
		$B1_{MCS-ABC}$	50	10	6.91	10.69	4.71	691	18.6	2.61
		Differences %	-	-	7.97	0.85	-2.48	-2.68	15.53	-2.61
	B2: Shiftable Loads, PEV (H2V only)	$B2_{MCS-PSO}$	50	10	6.21	9.42	5.00	687	19.0	2.60
		$B2_{MCS-ABC}$	50	10	6.11	9.40	4.64	688	18.9	2.60
		Differences %	-	-	-1.61	-0.21	-7.20	0.15	-0.53	0.00
	B3: Shiftable Loads, PEV (H2V and V2H)	$B3_{MCS-PSO}$	50	8	0.08	6.25	5.00	612	27.8	2.31
		$B3_{MCS-ABC}$	50	8	0.00	6.68	5.00	612	27.8	2.31
		Differences %	-	-	-100	6.88	0.00	0.00	0.00	0.00

For Case B1, based on the MCS-ABC, near-optimal sizes of PV, battery, and WT are 6.91 kW, 10.69 kWh and 4.71 kW which was determined by MCS-PSO to be 6.40 kW, 10.60 kWh and 4.83 kW respectively. In other words, MCS-ABC results for PV and battery are 7.97% and 0.85% higher and for WT, it is 2.48% lower. Also, annual cost, annual cost reduction and LCOE are determined to be $691, 18.6% and 2.61 cents/kWh which was determined by MCS-PSO to be $710, 16.1% and 2.68 cents/kWh respectively. In other words, MCS-ABC results for annual cost and LCOE are 2.68% and 2.61% lower and annual cost reduction is changed from 16.1% to 18.6% for Case B1 (Table 4.5; rows 4-6).

For Case B2, based on the MCS-ABC, near-optimal sizes of PV, battery, and WT are 6.11 kW, 9.40 kWh and 4.64 kW which was determined by MCS-PSO to be 6.21 kW, 9.42 kWh and 5 kW respectively. In other words, MCS-ABC results for PV, battery and WT are 1.61%, 0.21% and 7.20% lower. In addition, annual cost, annual cost reduction and LCOE are determined to be $688, 18.9% and 2.60 cents/kWh which was determined by MCS-PSO to be $687, 19.0% and 2.60 cents/kWh respectively. It can be seen that, the differences were lower than 1% for annual cost, annual cost reduction and LCOE in Case B2 (Table 4.5; rows 7-9).

For Case B3, based on the MCS-ABC, near-optimal sizes of PV, battery, and WT are 0 kW, 6.68 kWh and 5 kW which was determined by MCS-PSO to be 0.08 kW, 6.25 kWh and 5 kW respectively. In other words, MCS-ABC results for PV is changed from 0.08 kW to 0 kW and for battery is changed from 6.25 kWh to 6.68 kWh, which is 6.88% higher, and for WT it is equal for both methods. Also, annual cost, annual cost reduction and LCOE are determined to be $612, 27.8% and 2.31 cents/kWh which was determined by MCS-PSO to be $612, 27.8% and 2.31 cents/kWh respectively. It can be seen that, the differences were almost 0.00% for annual cost, annual cost reduction and LCOE in Case B3 (Table 4.5; rows 10-12).

Although the near-optimal solutions are slightly different for MCS-ABC and MCS-PSO, they are close to each other as expected. It should be noted that the maximum cycle number in ABC optimisation was three times more than PSO to make sure the near-optimal solution is achieved.

4.5 Sensitivity analyses

Detailed sensitivity analyses are performed for Cases A1–A3 and B1–B3 to investigate impacts of the maximum daily electricity export ($E_{Sell,max}$) and the rate of battery charge/discharge (R_c) as well as the maximum capacity limits for PV, WT and BSS. These are a number of parameters that significantly affect the optimal sizes of PV, WT and BSS for the SH. Based on the detailed sensitivity simulations presented in Table 4.4 and Figures 4.3–4.8:

- Increasing the maximum daily electricity export will: i) decrease the annual cost and increase the PV size for all cases, ii) increase the WT size up to an upper limit, iii) increase the BSS size for Cases A1–A2 and B1–B2. This happens because the SH is able to export more electricity.
- Increasing the rate of battery charge and discharge will: i) reduce annual cost and slightly decrease the PV size for Cases B1–B2, and ii) significantly increase the BSS size for Cases A1–A2 and B1–B2. This happens because BSS is able to charge/discharge faster.
- Inclusion of WT in addition to PV will: i) reduce the annual cost for Cases B1–B3, ii) decrease the PV size, particularly for Case B3.

4.6 Conclusion

This chapter performs:

i. optimum sizing of rooftop PV, WT, and BSS for the SH with PEV using a proposed rule-based algorithm with MCS and PSO (Figure 4.1)

ii. performance evaluation through the operation of the SH and cost calculations with near-optimal component sizes (Figure 4.2)

iii. sensitivity analyses on the impacts of maximum daily electricity export, rate of battery charge and discharge, as well as the maximum capacities of PV, WT and BSS on their optimum sizes (Table 4.4 and Figures. 4.3–4.8)

iv. comparing the results of MCS-PSO with MCS-ABC for Cases B1, B2 and B3 (Table 4.5).

The main conclusions are as follows.

- Introduction of PV and BSS will provide significant annual cost reduction (over 15%) and LCOE from 3.21 to 2.72 cents/kWh, while the inclusion of WT will provide an additional reduction in annual cost (over 16%) and LCOE to 2.68 cents/kWh (Table 4.4; rows 4, 5 and 9).
- Consideration of V2H decreases initial investment (by reducing component sizes), annual cost (over 25.2% and 27.8% without and with WT) and LCOE to 2.40 and 2.31 cents/kWh without and with WT (Table 4.4; rows 7 and 11).
- It may be a good option to eliminate BSS altogether in SHs that have renewable resources and PEVs with V2H integration. This battery-less configuration results in annual cost and LCOE reductions (Table 4.4; rows 8 and 12).
- Based on the sensitivity analyses (Figures. 4.3–4.8), further reductions in LCOE are possible by increasing PV, WT and BSS sizes; however, there may be limitations associated with the initial investment, maximum daily electricity export, battery charge, and discharge rate as well as space requirements for installations of rooftop PV and WT.

Chapter 5 Optimal Sizing of Renewable Resources for Smart Home with Committed Exchange Power Functionality

5.1 Introduction

In this chapter, committed exchange power functionality is considered for the SH. Then, near-optimal sizes of rooftop PV, WT, and BSS are studied for different conditions based on the proposed rule-based algorithm (HEMS) with MCS and PSO (Figure 5.1). Annual cost is minimised for determining near-optimal size of rooftop PV, WT and BSS for the committed power SH. Stochastic behaviors of renewable resources and availability of PEV are considered the same as in the previous chapter. After determining near-optimal sizes of rooftop PV, WT and BSS, the performance of the SH operation is evaluated with the selected near-optimal renewable resources. The impacts of shiftable loads, maximum daily export energy, battery charge/discharge rates, V2H integration and maximum WT, PV and battery capacity limits are investigated in sensitivity analyses of Sections 5.4.1 and 5.4.2. Further investigation is conducted in Section 5.4.3 to study the effect of various committed power exchange to the optimal sizes of rooftop PV, WT and BSS for the SH with the shiftable load and V2H integration.

5.2 Data modelling for temperature, irradiance, wind speed, load and ER

Similarly to the previous chapter, MCS is used to model annual data for performing a near-optimal component sizing of the SH with a committed exchange power capability in Section 5.3.

5.2.1 Input data

Input data in this chapter simulations are same as for the previous chapter and are explained in Section 4.2.1. Similar annual data is used for ambient temperature, global horizontal irradiance, wind speed, ER and base load while PEV, HVAC, L_u and L_s (Table 4.1) are modelled separately, as in the last chapter. However, a committed power export is considered for the SH in this chapter during peak time hours (7pm, 8pm and 9pm).

5.2.2 Monte Carlo simulation (MCS)

As in the previous chapter, MCS is used to model probabilistic behaviour of input data. At the same time, the correlation between different data is considered along with the correlation between each interval and the previous interval in each database. Correlation between different data is considered by separating data into four databases based on four seasons and generating data separately for each season. Also, correlation between each interval and the prior interval is considered by use of daily data sampling. These methods make it possible to model probabilistic behaviour of input data to be used in optimisation algorithms, as described in the next section.

5.3 Proposed MCS-PSO for optimal component sizing and operation of SH with H2V and V2H integrations and committed power exchange functionality

In this section, we introduce the new rule-based HEMS with a committed power exchange functionality. We then integrate it into the proposed MCS-PSO to execute near-optimal component sizing (Figure 5.1) and operation (Figure 5.2) for the SH with a committed power exchange functionality.

5.3.1 Proposed rule-based HEMS with committed power exchange, coordinated PEV and BSS charging and discharging operations

The new HEMS is proposed to consider committed power exchange functionality (Table 5.1). Hourly day-ahead electricity prices are considered along with predefined hours for the SH to export predetermined power to the grid. EPR and ESR for the committed power SH are different compared to other SHs during the predefined committed hours, which can be defined based on the utility contracts and agreements. This proposed HEMS will export the committed power to the grid in the predetermined hours, which in this chapter are considered to be during peak time hours (7pm, 8pm and 9pm). It also decreases the daily cost of SH electricity bills by using renewable generations and coordinating BSS charge/ discharge activities and PEV. Constraints are considered along with charge and discharge costs (Sections 3.2.4–3.2.5) in the simulations. Furthermore, battery and PEV are utilised to store surplus renewable generation for future demands and electricity trading. This new HEMS is based on the proposed rules in Table 5.1.

It should be mentioned that the following power flow and trading constraints are satisfied by the proposed HEMS at each interval (Δt_j):

$$L_b(\Delta t_j) + L_s(\Delta t_j) + L_u(\Delta t_j) = E_{Buy}(\Delta t_j) - E_{Sell}(\Delta t_j) - E_B(\Delta t_j) - E_{PEV}(\Delta t_j). \quad (5.1)$$

$$E_{Sell}(\Delta t_j) < E_{Sell,max} \quad (5.2)$$

5.3.2 Proposed MCS-PSO for optimal component sizing of SH with committed power exchange functionality

A combination of MCS and PSO is used to solve the component-sizing problem for the committed power SH. As mentioned in the previous chapter, PSO is one of the best meta-heuristic optimisation techniques for solving this kind of nonlinear problem. MCS is also used to consider the probabilistic behaviour of renewable resources. PSO starts with a random candidate solutions for particles, which are size of WT, PV and BSS within the problem space. In each iteration, p_{gbest} and p_{id} are calculated based on the proposed HEMS and particles move toward these best solutions. These best solutions will be updated in each iteration until PSO reaches the maximum iteration number or reaches a sufficiently good fitness. PSO parameters such as c_1, c_2 and w are adjusted based on this problem to control particle acceleration rates toward best solutions and better exploitation and exploration.

Table 5.1. Operation rules for minimising annual cost of SH with V2H, shiftable loads and committed exchange power functionality.

Rule	Instructions for Rule-Based HEMS with the committed power exchange functionality
1	Acquire the time (intervals/hours) and the amount of power that SH is committed to export. Also reward(α) and penalty(β) factors for these hours Eq. (5.4).
2	Based on the previous day, acquire initial SOCs for BSS and PEV.
3	Schedule shiftable loads to the hours with the cheapest ER based on DIs (as explained in Section 3.2.4 and Figure 3.2).
4	Schedule PEV for early morning to be charged before 5 am (Section 3.2.5).
5	Schedule BSS before 5 am to have enough charge for committed power hours (before 5 am; charging is first from renewable resources and then from SG during cheapest hours same as PEV which is described in Section 3.2.5).
6	At each interval, if there is a commitment for exporting power then; 1-export the amount of power which is committed for that interval to SG (this can be from: first; renewable resources second; battery and third; PEV) 2-suply the load from: first; renewable resources second; battery and third; PEV 3-expensive penalty(β) applies if there is shortage to export and supply the load Eq. (5.4).
7	At each interval if there is no commitment, then supply the SH loads with the following preferences: 1-renewable resources, 2-battery, 3-PEV and 4-SG with consideration of Eqs. (5.1)–(5.2).
8	Except for the committed power hours, at each DI; purchase/sell electricity at the extreme minimum/maximum point of the ER considering Eqs. (5.1)–(5.2) to charge/discharge PEV and Battery.
9	Surplus electricity will be sold to SG at each interval to satisfy Eqs. (5.1)–(5.2) except for the committed power hours which all renewable resources will be used to deliver the committed power and supply the loads.
10	At the end of the day, initial SOCs for BSS and PEV will be updated for the next day.

The proposed MCS-PSO is used for defining near-optimal sizes of WT, PV and BSS (Figure 5.1) for the committed power SH while minimising the annual cost of electricity.

Electricity cost for each Δt_j of the day when there is no committed power exchange during that interval, is calculated as follows:

$$\begin{aligned} C_{Hour}\left(\Delta t_j\right) = LC_{PV}.E_{PV}\left(\Delta t_j\right) + LC_W.E_W(\Delta t_j) \\ + C_{d,sell}^{PEV}.E_{sell}^{PEV}\left(\Delta t_j\right) + LC_B.Cap_B.\Delta t \\ + ER\left(\Delta t_j\right) \times E_{Buy}\left(\Delta t_j\right) - ER\left(\Delta t_j\right) \times E_{Sell}\left(\Delta t_j\right). \end{aligned} \quad (5.3)$$

Electricity cost for each Δt_j of the day when there is committed power exchange during that interval, is calculated as follows:

$$\begin{aligned} C_{Hour}\left(\Delta t_j\right) = LC_{PV}.E_{PV}\left(\Delta t_j\right) + LC_W.E_W(\Delta t_j) \\ + C_{d,sell}^{PEV}.E_{sell}^{PEV}(\Delta t_j) + LC_B.Cap_B.\Delta t + \beta \times \\ ER(\Delta t_j) \times E_{Buy}(\Delta t_j) - \alpha \times ER(\Delta t_j) \times E_{Sell}(\Delta t_j), \end{aligned} \quad (5.4)$$

where the ESR and EPR are assumed to be equivalent to the ER. However, for the committed power exchange hours there are two factors that are considered in Eq. (5.4) as reward (α) and penalty (β) factors. Reward and penalty factors for the simulations are assumed to be α =3 and β =10. Other parameters, such as LC_W, LC_{PV}, $C_{d,sell}^{PEV}$, LC_B, are same as in the previous chapter.

The objective function for the optimisation is to minimise the annual electricity cost of the SH:

$$C_{Day} = \sum_{j=1}^{24} C_{Hour}(\Delta t_j) \quad (5.5)$$

$$Min\ \ C_{Annual} = \sum_{i=1}^{365} C_{Day}(i) \quad (5.6)$$

PSO behaviour is analysed carefully by using different parameters to secure the convergence of simulations. An inertia weight of 0.2 is considered to enhance the effectiveness of MCS by limiting the particles' velocity. Table 5.2 shows the PSO parameters selected for simulations. Upper boundaries for WT, PV and BSS are selected according to SH physical restrictions. In addition, $E_{Sell,max}$ can be determined based on utilities contracts' adaptability and physical restrictions. As in to the previous chapter, it is chosen to be less than the SH average base load. Figure 5.1 illustrates the algorithm (MCS-PSO) for the committed power SH to determine near-optimal size of WT, PV and BSS.

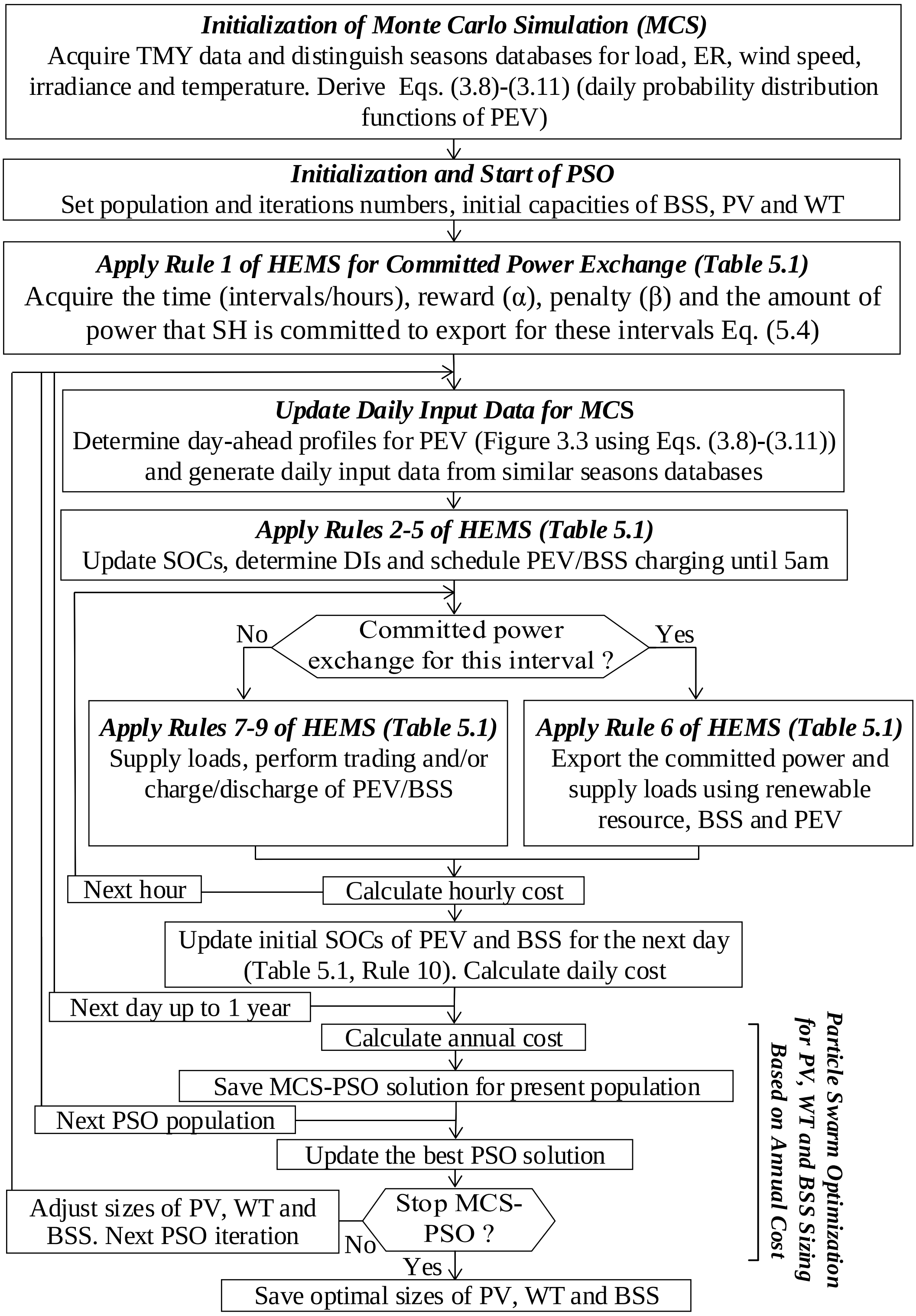


Figure 5.1. Proposed algorithm (MCS-PSO) for SH with committed power exchange functionality to determine near-optimal size of WT, PV and BSS.

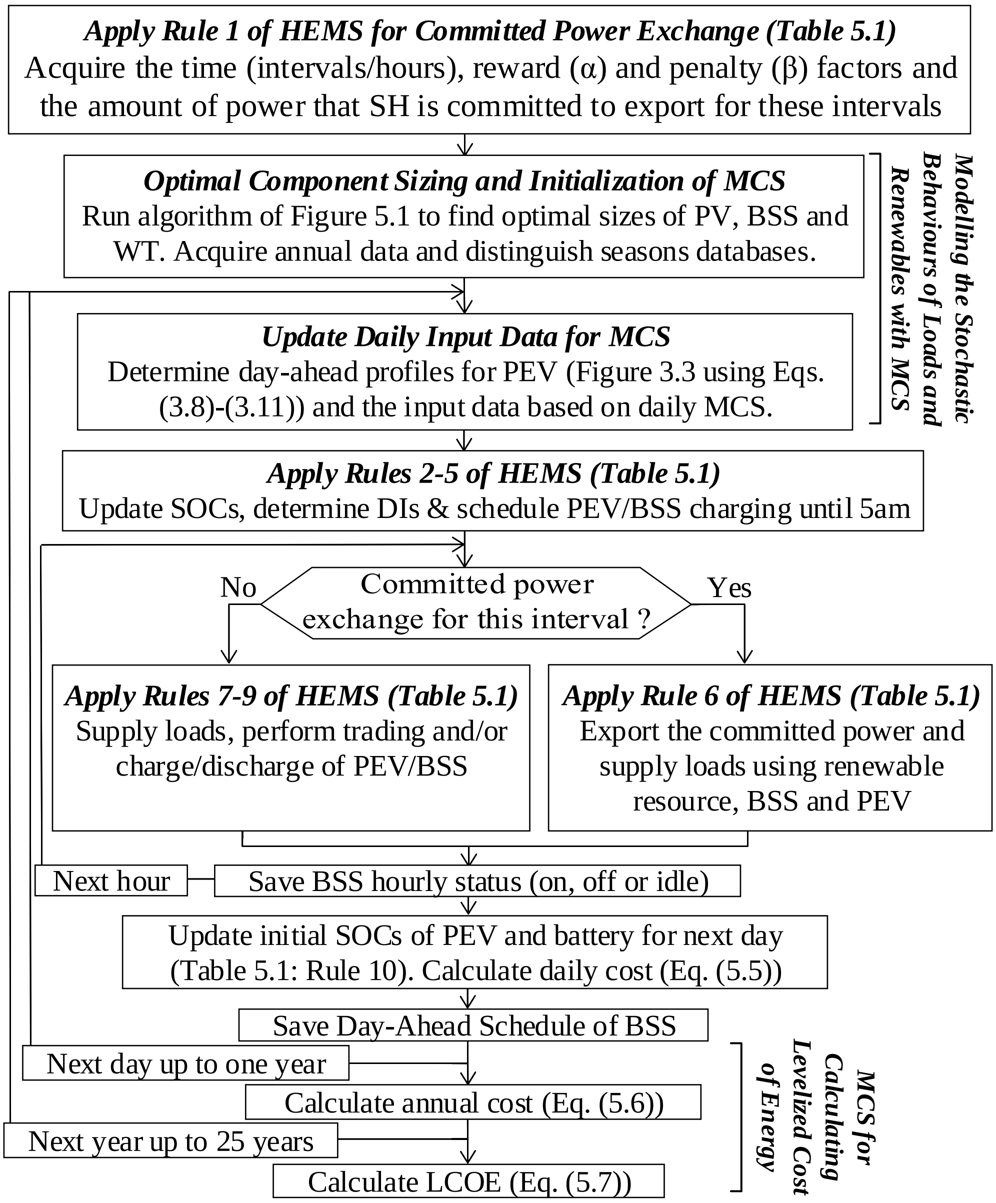


Figure 5.2. Proposed operation algorithm for SH with committed power exchange functionality to determine BSS day-ahead schedules, annual cost (Eq. (5.6)) and LCOE (Eq. (5.7)).

Table 5.2. PSO input parameters.

Parameter	**Particles**	K	D	c_1	c_2	w	**Boundaries**		
							PV	**WT**	**BSS**
Value	60	1200	3	1	1	0.2	[0,40]	[0,5]	[0,40]

5.3.3 Operation of SH with committed power exchange functionality

The SH with committed power exchange functionality exports the committed power during the agreed time (intervals/hours) to SG. In this chapter it is assumed that the SH is committed to export power during peak hours (7pm, 8pm and 9pm). In Sections 5.4.1 and 5.4.2, it is assumed that the SH is committed to export 5kWh to SG in each hour during peak hours (Figures 5.3–5.8). Committed power parameters used for simulations of Figures 5.3–5.8 are presented in Table 5.3.

Table 5.3. Committed power parameters and assumptions.

Parameter	**Committed hours [hour]**	**Committed power for each hour [kWh]**	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$
Value	7pm, 8pm, 9pm	5	3	10
Associated Figs.	5.3–5.17	5.3–5.8	5.3–5.17	5.3–5.17

For operation of the committed power SH and BSS day-ahead scheduling, the algorithm in Figure 5.2 is proposed to be used after finding the near-optimal sizes of PV, WT and BSS (Figure 5.1). This algorithm is also utilised for calculating the annual cost (Eq. (5.6)) and the LCOE over the renewable resources' lifetime [113, 139] for the committed power SH:

$$LCOE_{SH} = \frac{\sum cost\ over\ life\ time}{\sum suplied\ demand\ over\ life\ time} \tag{5.7}$$

where WT and PV lifetime is considered to be 25 years and the lifetime of battery is considered to be eight years with the maximum cycles of 2000 [323].

5.4 Simulations results for SH with committed power exchange

First, the near-optimal sizes of PV, WT and BSS are determined by use of the proposed MCS-PSO algorithm (Figure 5.1) for the committed power SH (for various cases of $E_{Sell,max}$ and R_c). Then, its performance and operation are investigated by the proposed algorithm in Figure 5.2. Simulations results of Figures 5.3–5.8 and 5.9–5.17are summarised in Table 5.4 and Table 5.5 respectively.

For the next two sections of this chapter, it is assumed that the SH is committed to export power during 7pm, 8pm and 9pm (peak hours in this case) and 5kWh for each hour (Figures 5.3–5.8). Electricity reward (α) and penalty (β) factors are assumed to be 3 and 10 during this period for finding component sizes of PV, WT and BSS.

For different operating conditions, the optimal component sizes, annual cost, annual cost reduction and LCOE (Eq.(5.7)) are resolved and compared. In the next section, the SH is without WT (Table 5.4; rows 5–8). For Section 5.4.2, WT is considered as well (Table 5.4; rows 9–11). For each of these cases, the impacts of shiftable loads (Cases A2 and B2), and integration of H2V/V2H are investigated. The effect of eliminating BSS for Case A3 is also investigated (Case A4).

In Section 5.4.3, Case B3 is repeated for the SH with various export power commitments to evaluate the effect of committed power exchange to the optimal sizing (Figure 5.1) and operation (Figure 5.2) of the SH (Table 5.5). It should be mentioned that annual cost for the base case operation (without power committed exchange, PV, WT and BSS) is $848 and the LCOE is 3.21 cents/kWh, as presented in Table 5.4 (row 4).

5.4.1 Optimal sizing of PV and BSS without WT for the SH with committed power exchange to minimise annual cost of household electricity

In this section's simulations, WT is not considered and the near-optimal sizes of PV and BSS are determined for the committed power SH. It is assumed that the SH is committed to export power during 7m, 8pm and 9pm (peak hours) at 5kWh for each hour (Figures. 5.3–5.5). Electricity reward (α) and penalty (β) factors are assumed to be 3 and 10 during this period.

Different operating conditions are investigated with and without shiftable loads and V2H integration to find near-optimal sizes by use of the MCS-PSO algorithm (Figure 5.1). Then, annual cost and LCOE are evaluated by the algorithm of Figure 5.2 for these cases (Table 5.4, Cases A1–A3). Furthermore, elimination of BSS is also studied in Case A4.

In the first case (Case A1), PEV and schedulable loads (Table 4.1) are examined as nonshiftable and V2H integration is not considered. Based on a range of different $E_{Sell,max}$ and R_c values, near-optimal sizes of PV and BSS are determined for the committed power SH (Figure 5.3). As can be seen from Figure 5.3, for various operating conditions there are different solutions. However, the minimum annual cost is achieved when R_c is 10 kWh/hour, $E_{Sell,max}$ is 50 kWh/day and the capacities of PV and battery are 16.20 kW and 32.95 kWh, respectively. The best achieved annual cost for Case A1 is $1294, which does not offer any annual cost reduction. After running the operation algorithm of Figure 5.2 for various ranges of α, we found that in order to achieve an annual cost reduction we need to increase α to almost 7 for Case A1 (Table 5.4).

In the second case (Case A2), PEV and schedulable loads (Table 4.1) are examined as shiftable and V2H integration is not considered. Based on a range of different $E_{Sell,max}$ and R_c values, near-optimal sizes of PV and BSS are determined for the committed power SH (Figure 5.4). As can be seen from Figure 5.4, for various conditions there are different solutions. However, the minimum annual cost is achieved when R_c is 10 kWh/hour, $E_{Sell,max}$ is 45 kWh/day and the capacities of PV and battery are 11.69 kW and 30.92 kWh, respectively. The best achieved annual cost for Case A2 is $1260, which again does not offer any annual cost reduction. After running the operation algorithm of Figure 5.2 for various ranges of α, we found that in order to produce an annual cost reduction we need to increase α to almost 7 for Case A2 (Table 5.4).

In the third case (Case A3), PEV and schedulable loads (Table 4.1) are examined as shiftable and V2H integration is also considered. Based on a range of different $E_{Sell,max}$ and R_c values, near-optimal sizes of PV and BSS are determined for the committed power SH (Figure 5.5). As can be seen from Figure 5.5, for various conditions there are different solutions. However, the minimum annual cost is achieved when R_c is 3 kWh/hour, $E_{Sell,max}$ is 50 kWh/day and the capacities of PV and battery are 11.44 kW and 6.98 kWh, respectively. The best achieved annual cost for Case A3 is $505. After running the operation algorithm of Figure 5.2, an annual cost reduction of 24.2% is achieved with this near-optimal solution for Case A3 (Table 5.4).

Table 5.4. Summary of simulation results (Figures 5.3–5.8) for optimal component sizing (Figure 5.1) and operation (Figure 5.2) of SH with the committed power exchange.

Case Studies Simulations			**Optimal Component Sizing of SH with Committed Power Exchange (5kWh for each hour during 7pm, 8pm and 9pm (α =3 and β =10)), utilising Daily Monte Carlo Data Generation (Proposed MCS-PSO Algorithm of Figure 5.1)**					**Operation of SH with Committed Power Exchange (Algorithm of Figure 5.2) utilising Optimal Component Sizes and Daily Monte Carlo Data Generation**					
			Input Variables		**Optimal Component Sizes**			**α =3 and β =10**			**α =7 and β =10**		
			$E_{sell,max}$ [kWh/day]	R_c [kWh/hour]	Cap_{PV} [kW]	Cap_B [kWh]	Cap_{WT} [kW]	**Annual Cost [$]**	**Annual Cost Reduction [%]**	**LCOE (Eq. (5.7)) for 25 Years [cents/kWh]**	**Annual Cost [$]**	**Annual Cost Reduction [%]**	**LCOE (Eq. (5.7)(4.6)) for 25 Years [cents/kWh]**
Base Case: SH without Committed Power Exchange, PV, BSS, and WT			N/A	N/A	N/A	N/A	N/A	848	N/A	3.21	848	N/A	3.21
Case A: SH with Committed Power Exchange, PV, PEV and BSS (Figures. 5.3–5.5)	A1	Nonshiftable Loads, PEV (H2V only)	50	10	16.20	32.95	N/A	1409	N/A	5.33	757	10.7	2.86
	A2	Shiftable Loads, PEV (H2V only)	45	10	11.69	30.92	N/A	1397	N/A	5.25	843	0.5	3.17
	A3	Shiftable Loads, PEV (H2V and V2H)	50	3	11.44	6.98	N/A	643	24.2	2.43	174	79.5	0.65
	A4	Case A3 without BSS	50	N/A	13.70	0	N/A	732	13.7	2.77	579	31.7	2.18
Case B: SH with Committed Power Exchange, PV, PEV, BSS and WT (Figures. 5.6–5.8)	B1	Nonshiftable Loads, PEV (H2V only)	50	10	11.18	31.10	5	1285	N/A	4.86	629	25.8	2.38
	B2	Shiftable Loads, PEV (H2V only)	50	10	8.48	29.41	5	1267	N/A	4.78	705	16.9	2.66
	B3	Shiftable Loads, PEV (H2V and V2H)	45	4	9.19	0	4.95	571	32.7	2.16	186	78.1	0.70

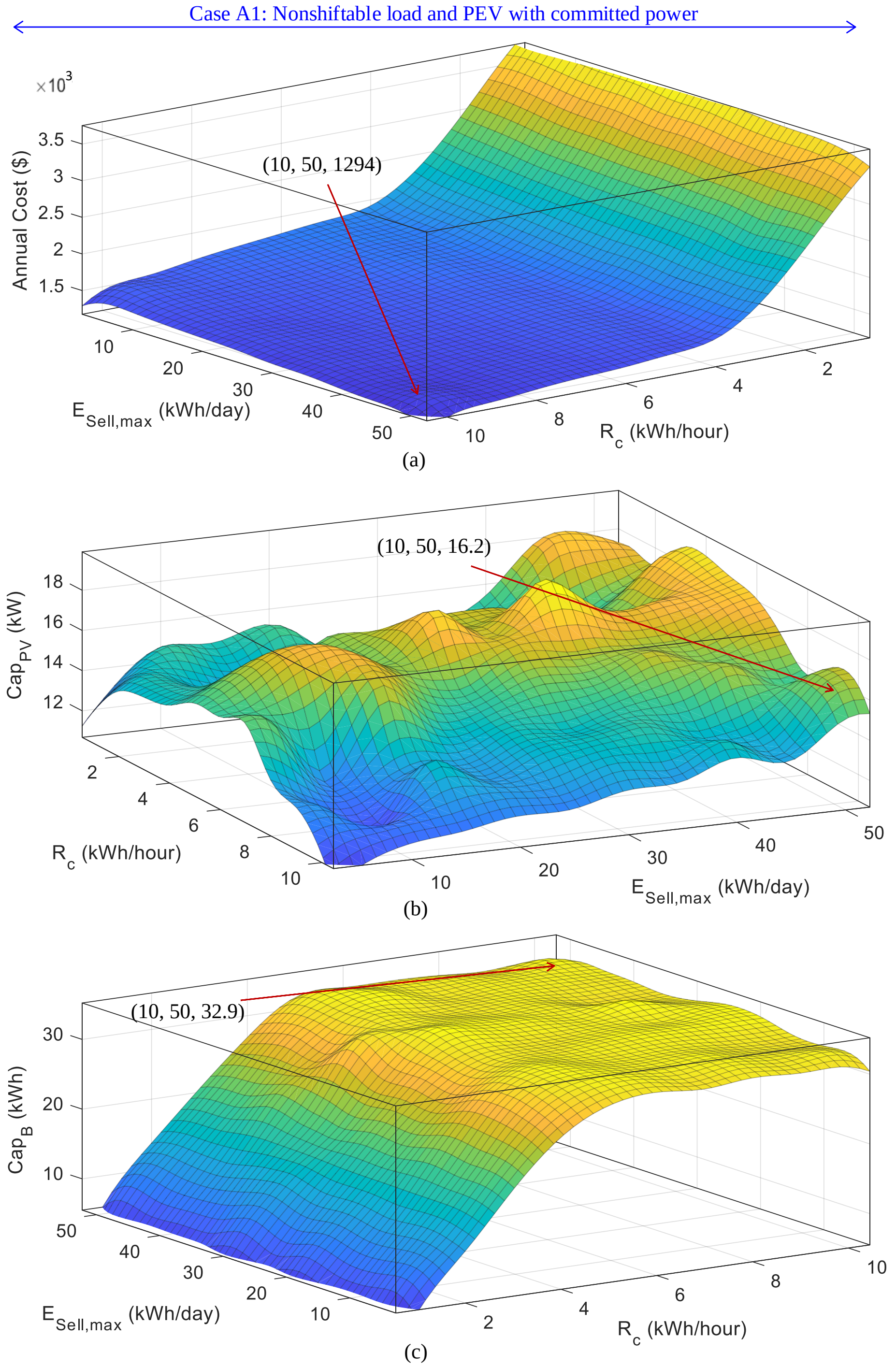


Figure 5.3. Case A1 (nonshiftable loads and PEV with committed power exchange). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($1294), PV (16.20 kW), and battery (32.95 kWh) sizes.

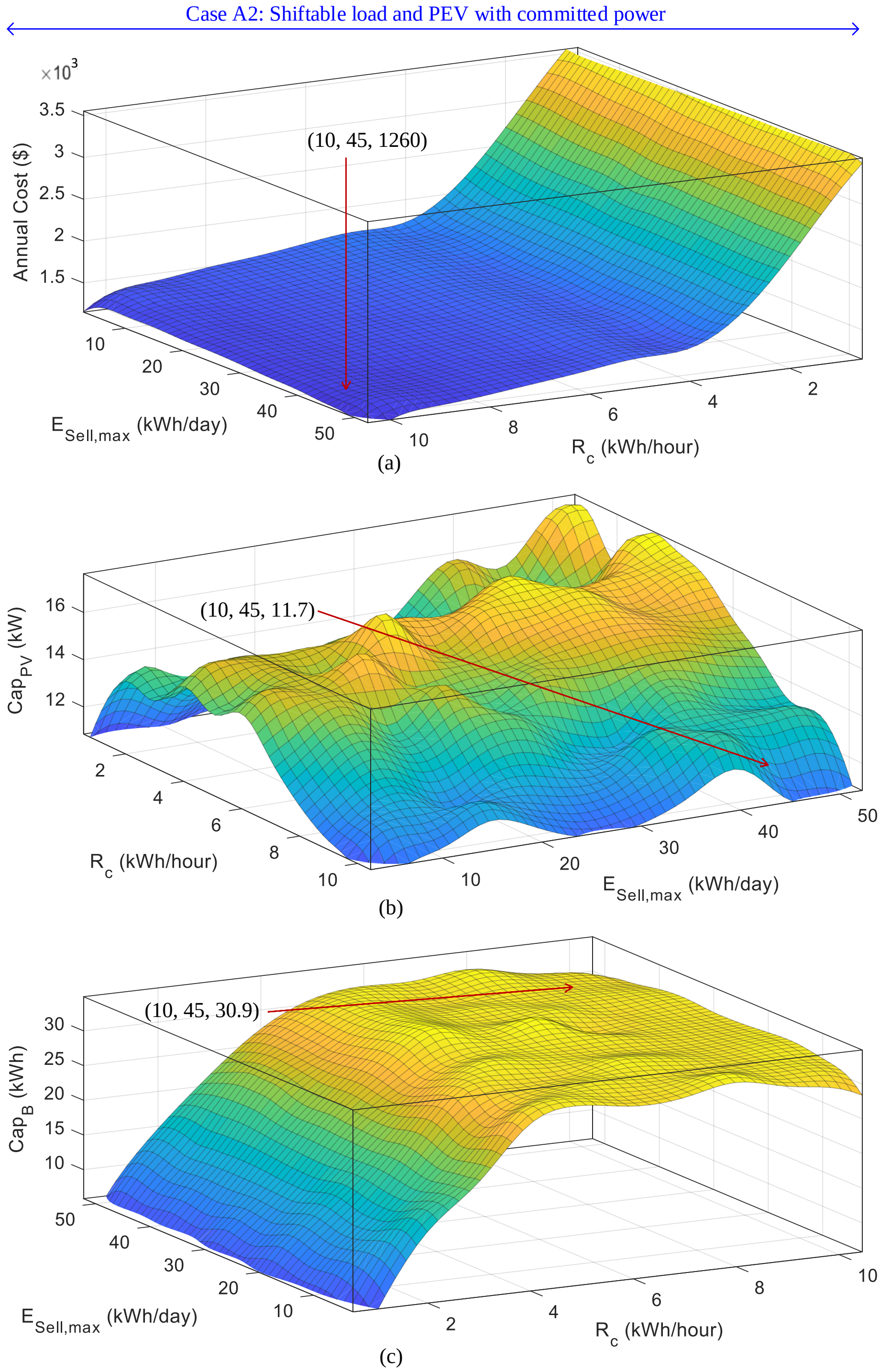


Figure 5.4. Case A2 (shiftable loads and shiftable PEV/H2V with committed power exchange). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($1260), PV (11.69 kW), and battery (30.92 kWh) sizes.

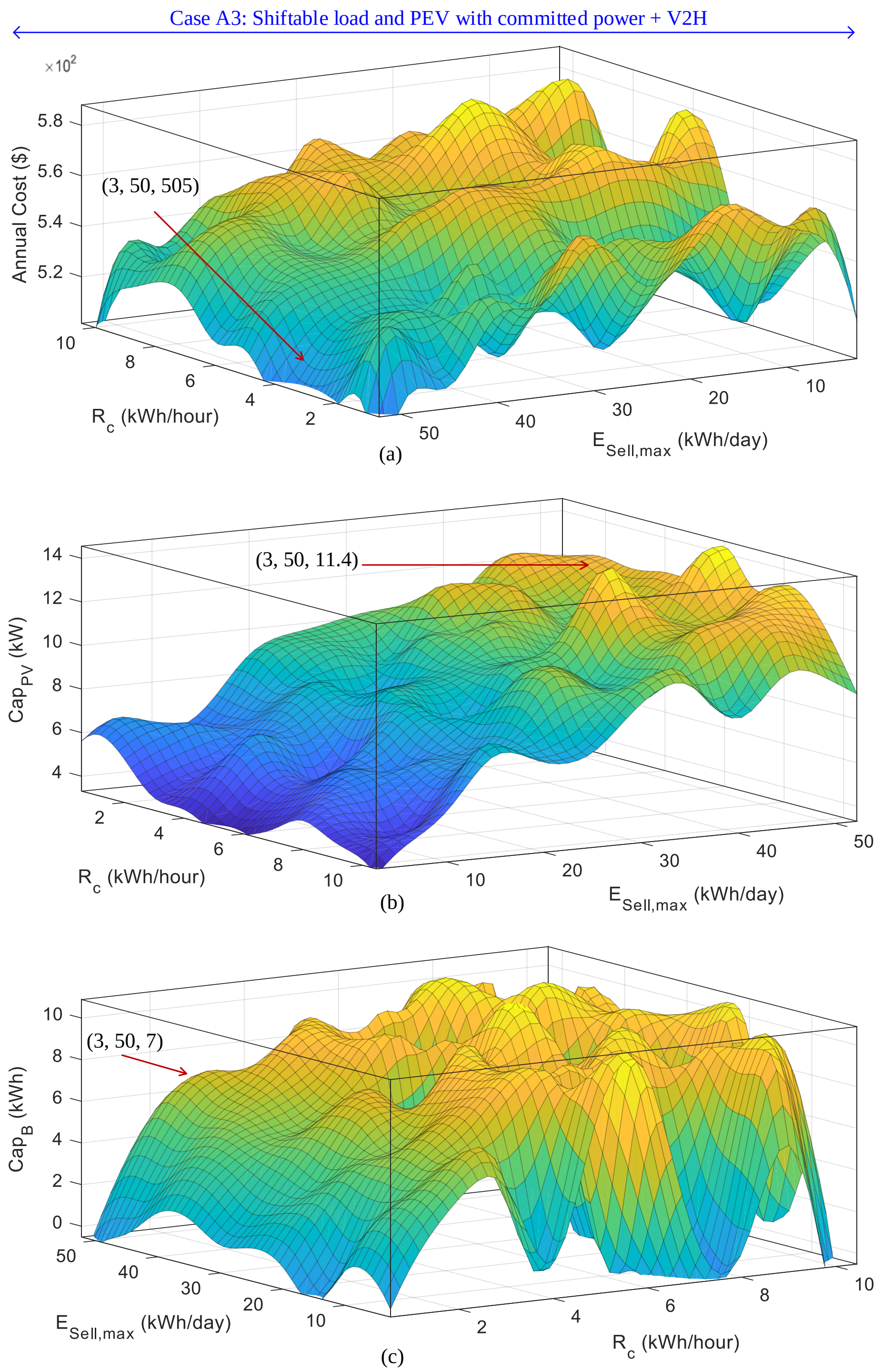


Figure 5.5. Case A3 (shiftable loads and shiftable PEV/H2V/V2H with committed power exchange). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($505), PV (11.44 kW), and battery (6.98 kWh) sizes.

Based on the simulations shown in Table 5.4 (rows 5–8), for the committed power SH with near-optimal sizes of PV and BSS:

- Introduction of PV and BSS is not sufficient to reduce the annual cost for Case A1 and we need to increase α to almost 7 for this case. (It should be mentioned that these sizes are near optimal when α =3.)
- Although shiftable load scheduling reduced the annual cost compared to Case A1, it is not sufficient and we need to increase α to almost 7 for this case to produce an annual cost reduction.
- Integration of V2H decreased the near-optimal sizes of PV and BSS to 11.44kW and 6.98kWh. It also rapidly reduced the annual cost for the committed power SH. Annual cost reduction and LCOE for Case A3 were 24.2% and 2.43 cents/kWh, respectively (Table 5.4; row 7).
- The proposed battery-less arrangement of Case A4 (Table 5.4) reduced the annual cost and LCOE to 13.7% and 2.77 cents/kWh, which is also promising but not as much as Case A3.
- Choosing α=3 for the committed power SH (Eq.(5.4)) created an annual cost reduction for Cases A3 and A4 of 24.2% and 13.7% (Table 5.4).

5.4.2 Optimal sizing of PV, WT, and BSS for the SH with committed power exchange to minimise annual cost of household electricity

In this section's simulations, WT is also considered and the near-optimal sizes of PV, WT and BSS are determined for the committed power SH. It is assumed that the SH is committed to export power during 7pm, 8pm and 9pm (peak hours) at 5kWh for each hour (Figures. 5.6–5.8). Electricity reward (α) and penalty (β) factors are assumed to be 3 and 10 during this period (as in the previous section).

As in the previous section, operating conditions are investigated with and without shiftable loads and V2H integration to find near-optimal sizes by using the MCS-PSO algorithm (Figure 5.1). Then, annual cost and LCOE are evaluated using the algorithm in Figure 5.2 for these cases (Table 5.4, Cases B1–B3).

Cases B1–B3 are similar to Cases A1–A3 but with consideration of WT to investigate the impacts, limitations and benefits of WT inclusion. For a range of $E_{Sell,max}$ and R_c values, near-optimal sizes of WT, PV, and BSS are determined, as demonstrated in Figures 5.6–5.8. The minimum annual cost for Case B1 is attained when R_c is 10 kWh/hour, $E_{Sell,max}$ is 50 kWh/day and the capacities of WT, PV and battery are 5 kW, 11.18 kW and 31.10 kWh, respectively (Figure 5.6). The best achieved annual cost for Case B1 is $1177, which does not offer any annual cost reduction for these conditions; α should be at least equal to 6 to produce an annual cost reduction. This near-optimal solution (for α=3) can generate a 25.8% annual cost reduction (Figure 5.2) for Case B1 if we choose α=7 (Table 5.4).

The minimum annual cost for Case B2 is attained when R_c is 10 kWh/hour, $E_{Sell,max}$ is 50 kWh/day and the capacities of WT, PV and battery are 5 kW, 8.48 kW and 29.41 kWh, respectively (Figure 5.7). The best achieved annual cost for Case B1 is $1144, which does not offer any annual cost reduction for these conditions; α should be at least equal to 6 for achieving annual cost reduction. This near-optimal solution (for α=3), can produce a 16.9% annual cost reduction (Figure 5.2) for Case B2 if we choose α=7 (Table 5.4).

The minimum annual cost for Case B3 is attained when R_c is 4 kWh/hour, $E_{Sell,max}$ is 45 kWh/day and the capacities of WT, PV and battery are 4.95 kW, 9.19 kW and 0 kWh, respectively (Figure 5.8). The best achieved annual cost for Case B3 is $379, which makes this the most attractive case among Cases A1–A3 and B1–B3. After running the operation algorithm in Figure 5.2, an annual cost reduction of 32.7% is achieved with this near-optimal solution for Case B3 (Table 5.4).

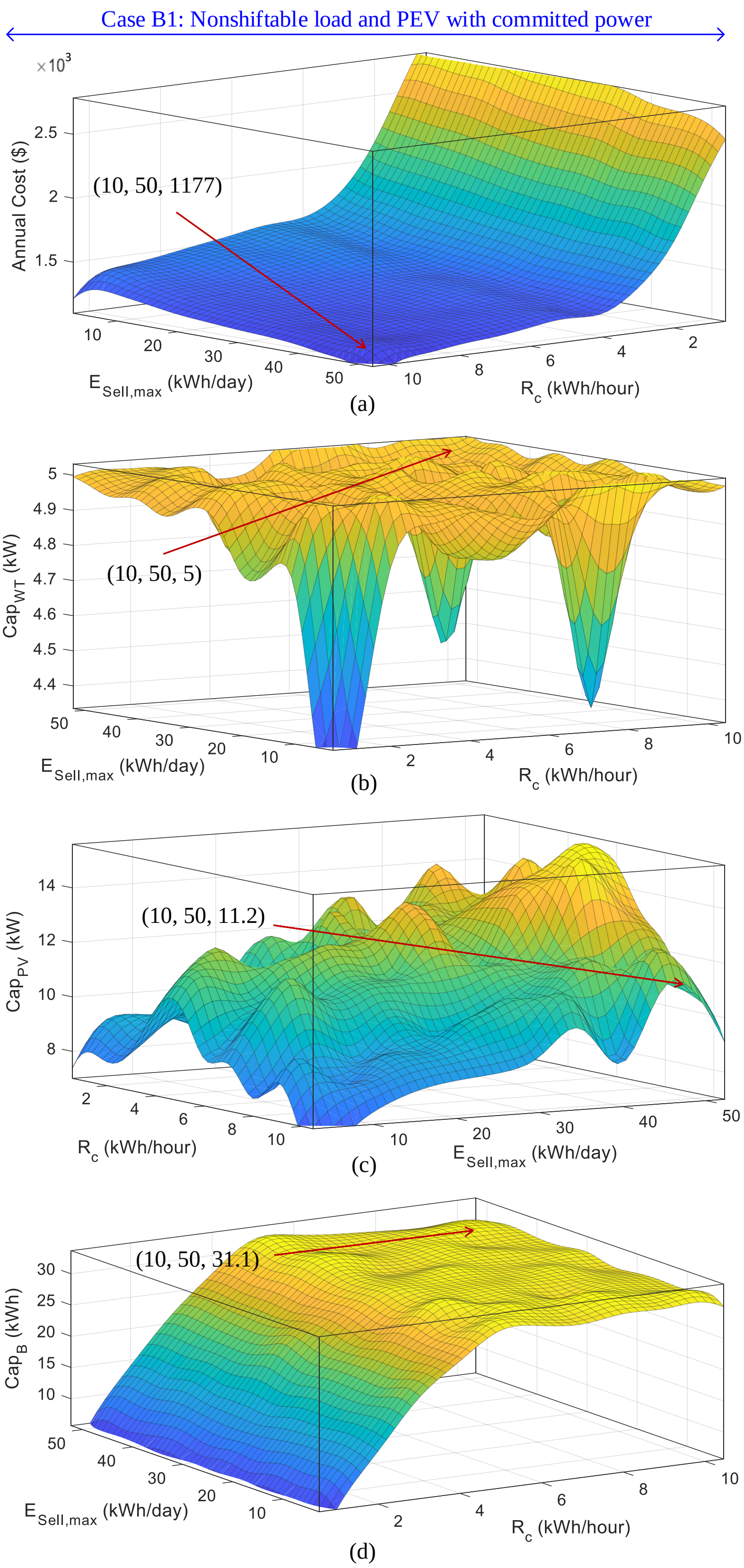


Figure 5.6. Case B1 (nonshiftable loads and PEV with committed power exchange). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($1177), WT (5 kW), PV (11.18 kW), and battery (31.1 kWh) sizes.

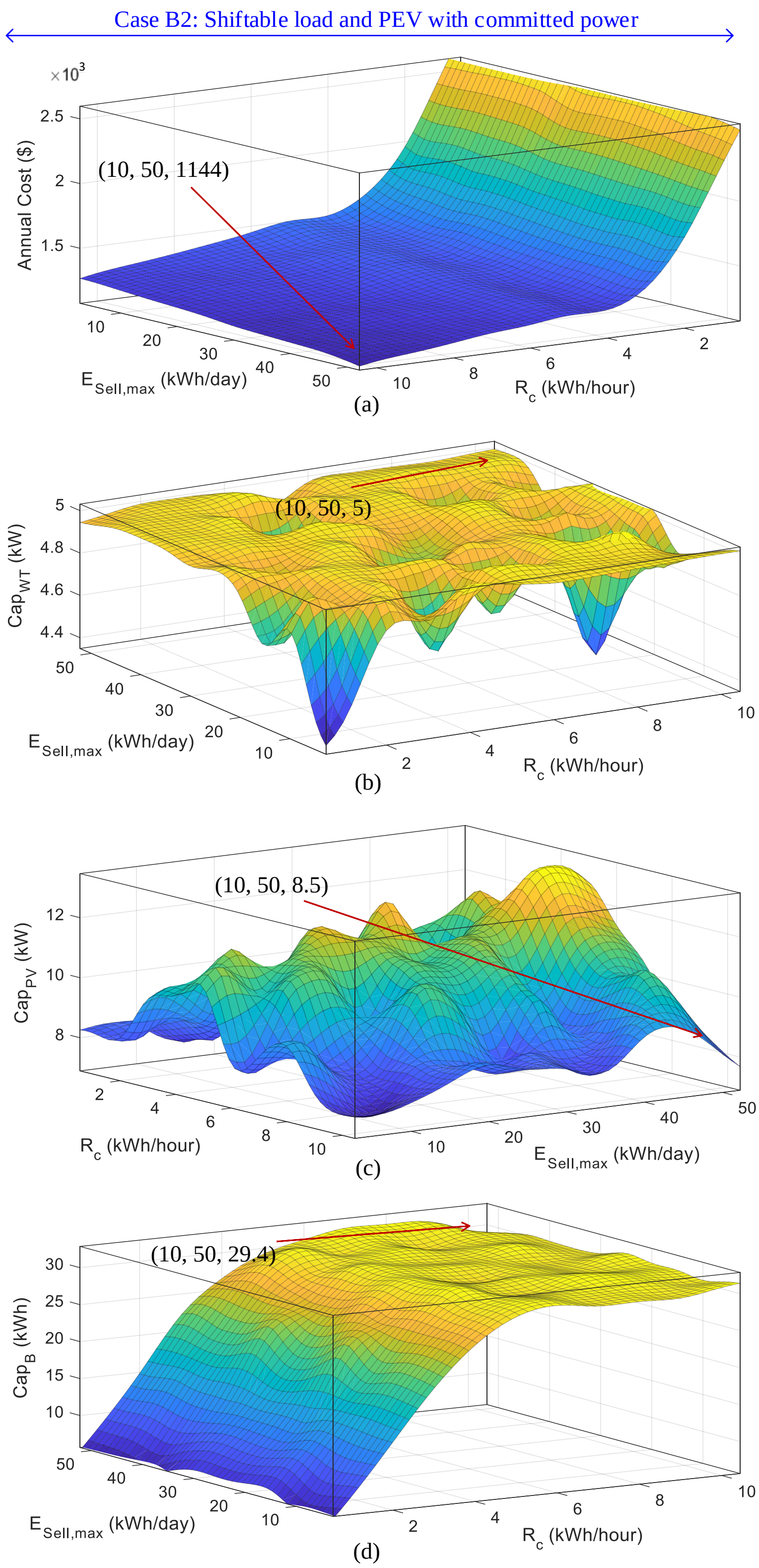


Figure 5.7. Case B2 (shiftable loads and shiftable PEV/H2V with committed power exchange). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($1144), WT (5 kW), PV (8.48 kW), and battery (29.41 kWh) sizes.

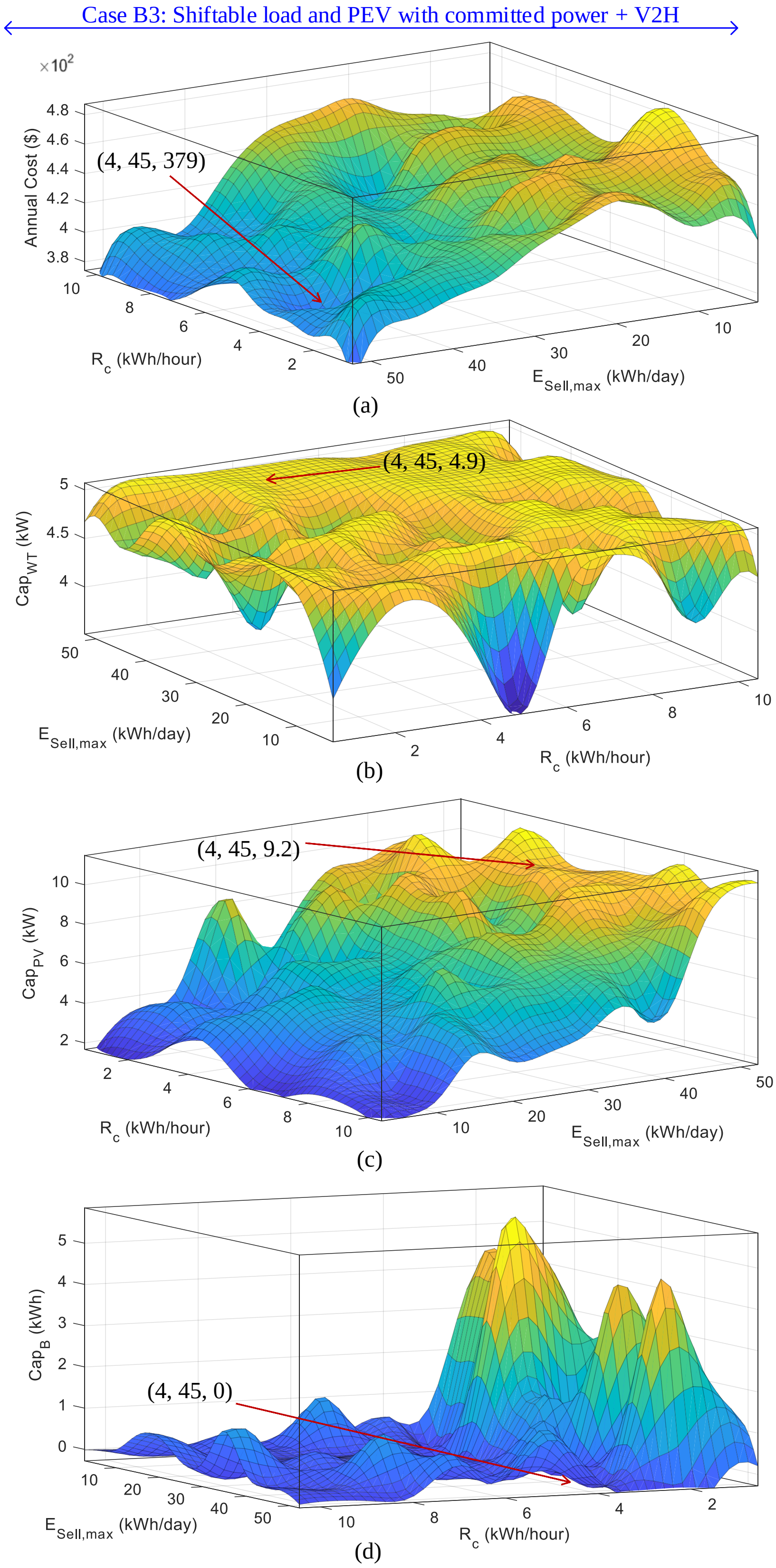


Figure 5.8. Case B3 (shiftable loads and shiftable PEV/H2V/V2H with committed power exchange). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($379), WT (4.95 kW), PV (9.19 kW), and battery (0 kWh) sizes.

Comparing Cases A1–A3 and B1–B3 simulations – which are summarised in Table 5.4 (rows 5–11) – reveals additional improvements/reduction in annual cost and LCOE for all cases when WT is added to the committed power SH. For example:

- According to Table 5.4, annual cost (column 9) and LCOE (column 11) are reduced for Cases A1–A3 (without WT; rows 5–7) when WT is added (Cases B1–B3; rows 9–11) to the committed power SH.
- Selected parameters for the committed power SH (such as α=3) can bring annual cost reductions for Cases A3, A4 and B3 of 24.2%, 13.7% and 32.7%, respectively.
- With the consideration of WT for SH, near-optimal sizes of PV and BSS are reduced along with annual cost for all cases (Table 5.4).
- Adding WT to Case A3 has given us a battery-less configuration (Case B3) as a near-optimal solution (Table 5.4) with the annual cost reduction of 32.7%.

5.4.3 Effect of committed power exchange to the optimal size of PV, WT, and BSS for the SH

In this section's simulations, further investigation is conducted to study the effect of committed power exchange on the optimal size of PV, WT and BSS. Conditions are same as for Case B3. For all cases in this section (Case C1–C10), PEV and schedulable loads (Table 4.1) are examined as shiftable and V2H integration is considered. Also, electricity reward (α) and penalty (β) factors are assumed to be 3 and 10 during committed power hours (as in previous sections). However, various committed power export is considered for each case during the three peak hours (7pm, 8pm and 9pm).

For each case, the near-optimal sizes of PV, WT and BSS are determined by use of the proposed MCS-PSO algorithm (Figure 5.1) for the committed power SH (for various cases of $E_{Sell,max}$ and R_c); then, the performance and operation of the SH are investigated by the proposed algorithm in Figure 5.2. Simulations results of Figures. 5.9–5.17 are summarised in Table 5.5.

Table 5.5. Summary of simulation results (Figures. 5.9–5.17) for evaluating the effect of committed power exchange to the optimal sizing (Figure 5.1) and operation (Figure 5.2) of SH.

Case Studies Simulations			**Optimal Component Sizing of SH with Committed Power Exchange (5kWh for each hour during 7pm, 8pm and 9pm (α =3 and β =10)), utilising Daily Monte Carlo Data Generation (Proposed MCS-PSO Algorithm of Figure 5.1)**					**Operation of SH with Committed Power Exchange (Algorithm of Figure 5.2) utilising Optimal Component Sizes and Daily Monte Carlo Data Generation**		
								α =3 and β =10		
			Input Variables		**Optimal Component Sizes**					
			$E_{Sell,max}$ [kWh/day]	R_c [kWh/hour]	Cap_{PV} [kW]	Cap_B [kWh]	Cap_{WT} [kW]	**Annual Cost [$]**	**Annual Cost Reduction [%]**	**LCOE (Eq. (5.7)) for 25 Years [cents/kWh]**
Base Case: SH without Committed Power Exchange, PV, BSS, and WT			N/A	N/A	N/A	N/A	N/A	848	N/A	3.21
Case C: SH with Committed Power Exchange, PV, PEV, BSS and WT with Shiftable Loads, H2V and V2H. Various committed power export is considered for various cases for each hour during peak hours (7pm, 8pm and 9pm). (Figures. 5.9–5.17)	C1	1kWh	50	1	8.68	0.08	5	922	N/A	3.49
	C2	2kWh	45	8	10.42	0	4.63	844	0.5	3.19
	C3	3kWh	45	10	9.15	0.01	5	751	11.4	2.84
	C4	4kWh	45	9	9.59	0.17	5	657	22.5	2.48
	C5*	5kWh	45	4	9.19	0	4.95	571	32.7	2.16
	C6	6kWh	30	8	7.10	0	5	509	40.0	1.92
	C7	7kWh	50	5	10.43	1.2	5	398	53.1	1.50
	C8	8kWh	50	3	10.04	5.29	4.99	269	68.3	1.02
	C9	9kWh	35	3	8.29	6.25	5	235	72.3	0.89
	C10	10kWh	50	4	8.62	8.61	4.61	143	83.1	0.54

*)Figures for Case C5 (which are same as Case B3) are not shown in this section as they are demonstrated in the previous section (Figure 5.8).

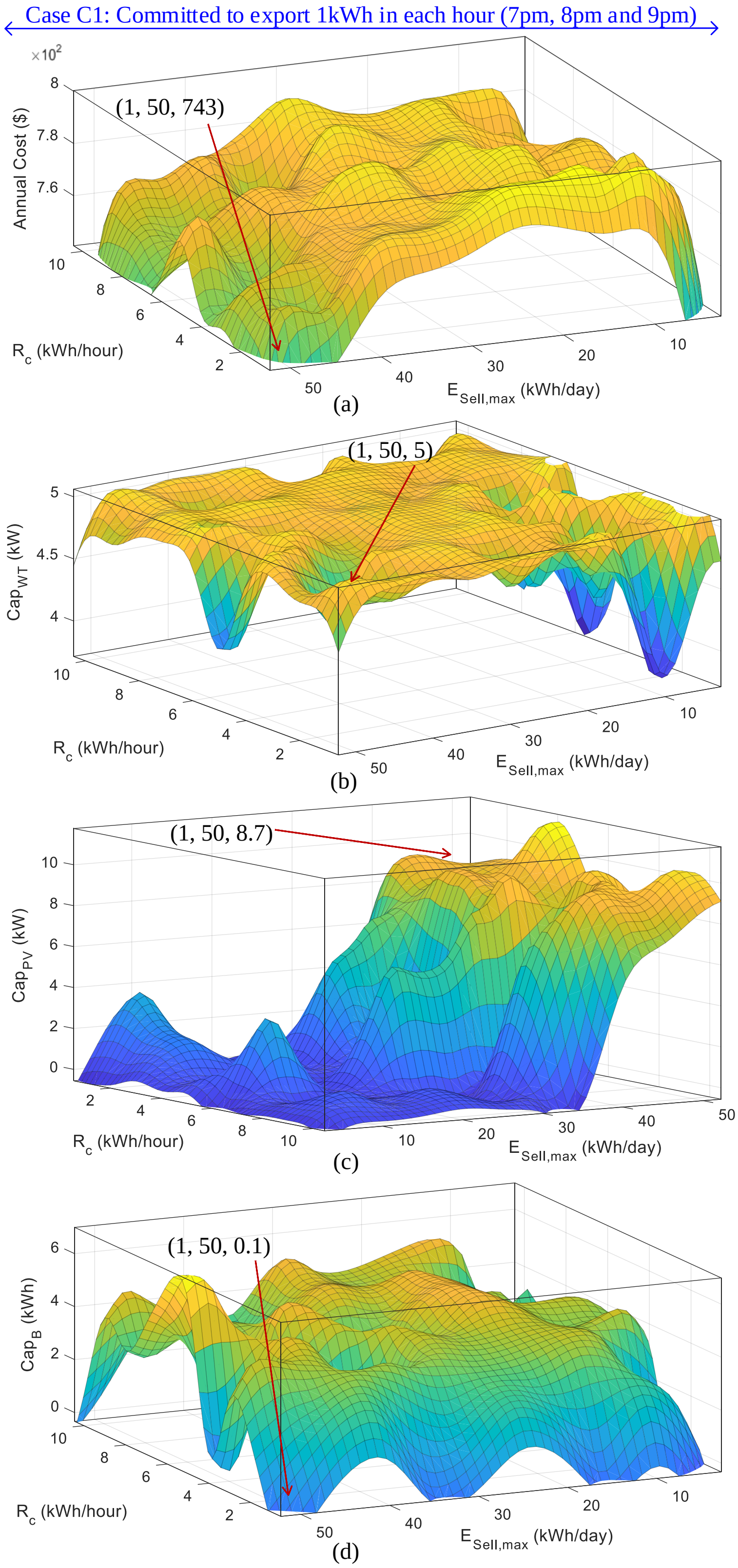


Figure 5.9. Case C1 (shiftable loads and shiftable PEV/H2V/V2H with 1kWh committed power exchange in each hour during 7pm, 8pm and 9pm). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($743), WT (5 kW), PV (8.68 kW), and battery (0.08 kWh) sizes.

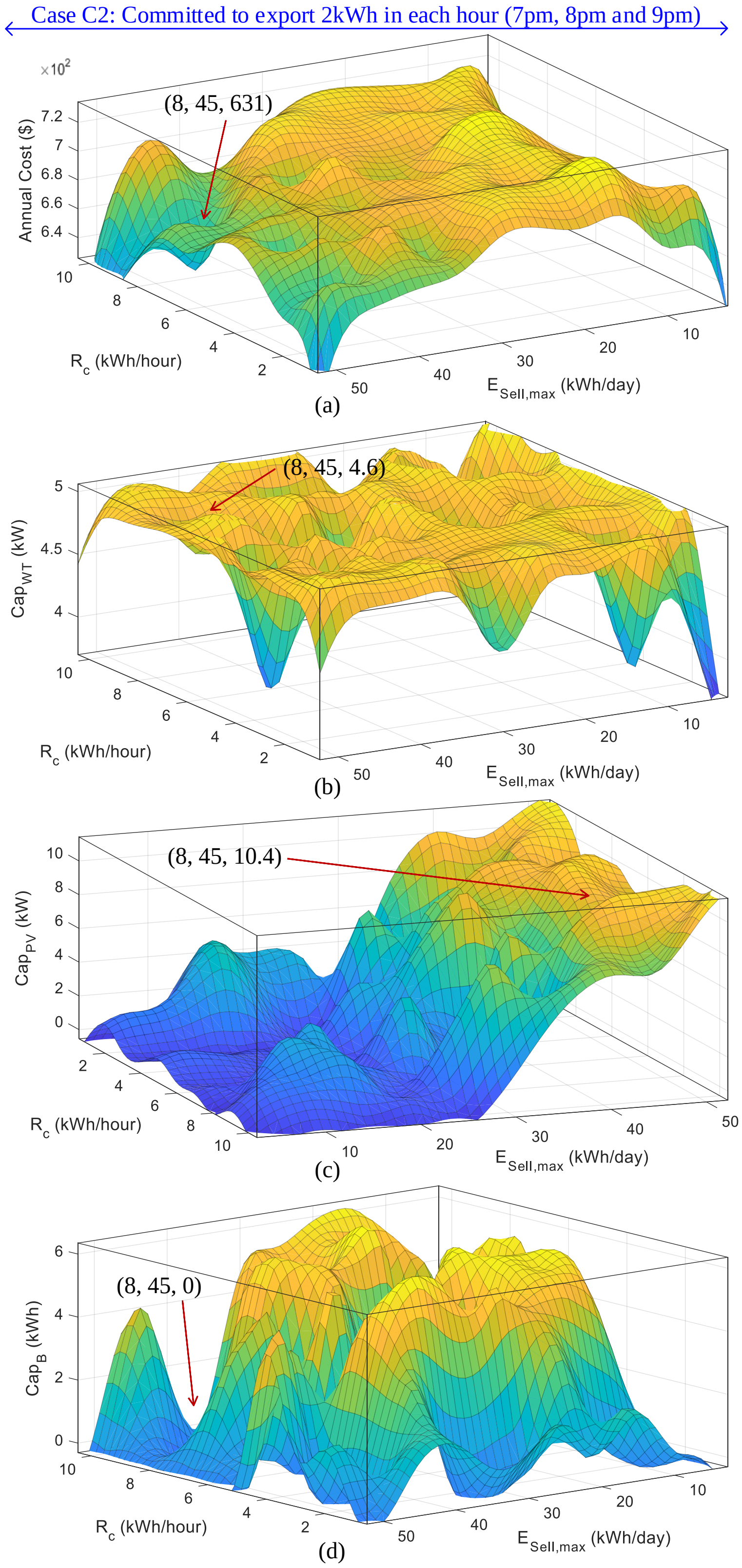


Figure 5.10. Case C2 (shiftable loads and shiftable PEV/H2V/V2H with 2kWh committed power exchange in each hour during 7pm, 8pm and 9pm). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($631), WT (4.63 kW), PV (10.42 kW), and battery (0 kWh) sizes.

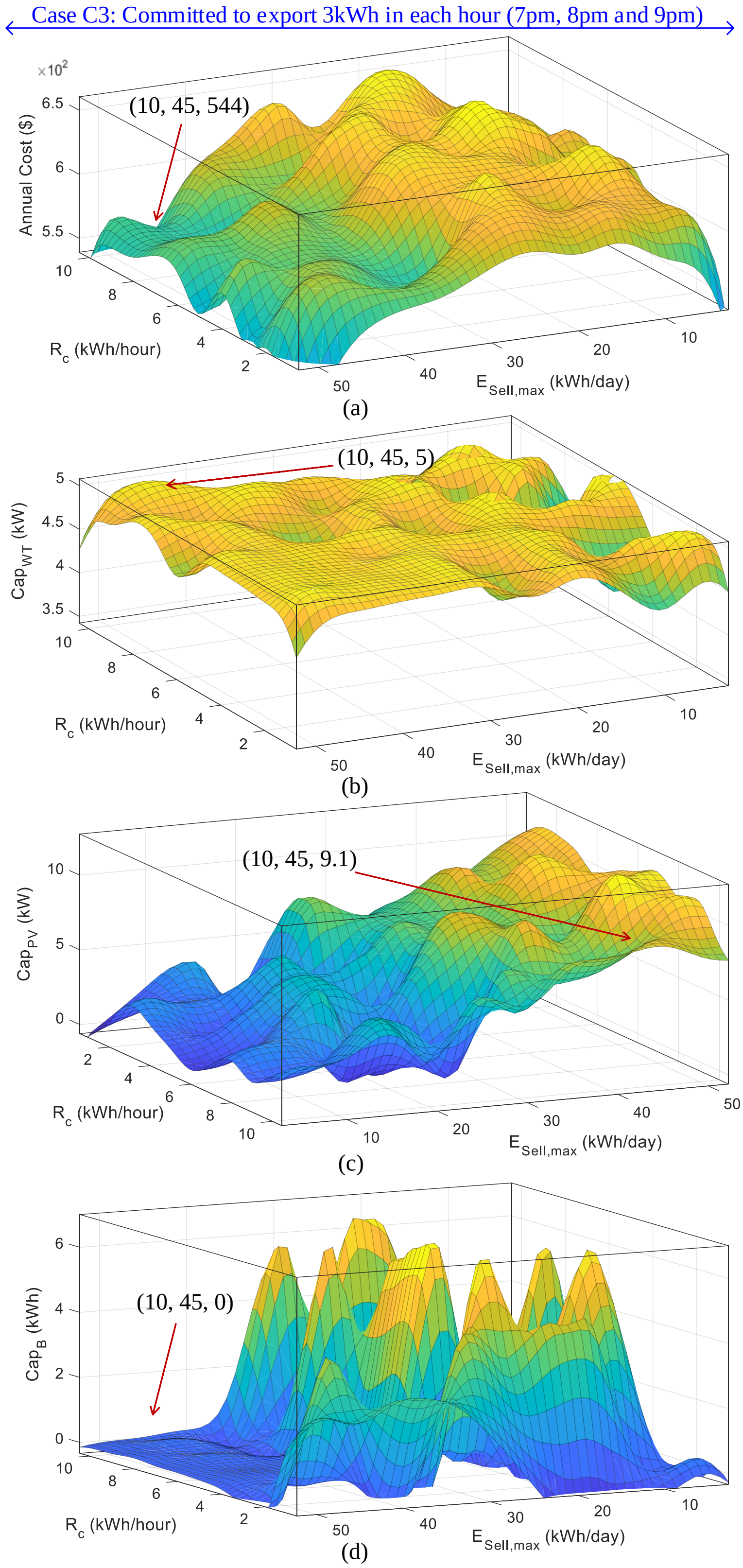


Figure 5.11. Case C3 (shiftable loads and shiftable PEV/H2V/V2H with 3kWh committed power exchange in each hour during 7pm, 8pm and 9pm). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($544), WT (5 kW), PV (9.15 kW), and battery (0.01 kWh) sizes.

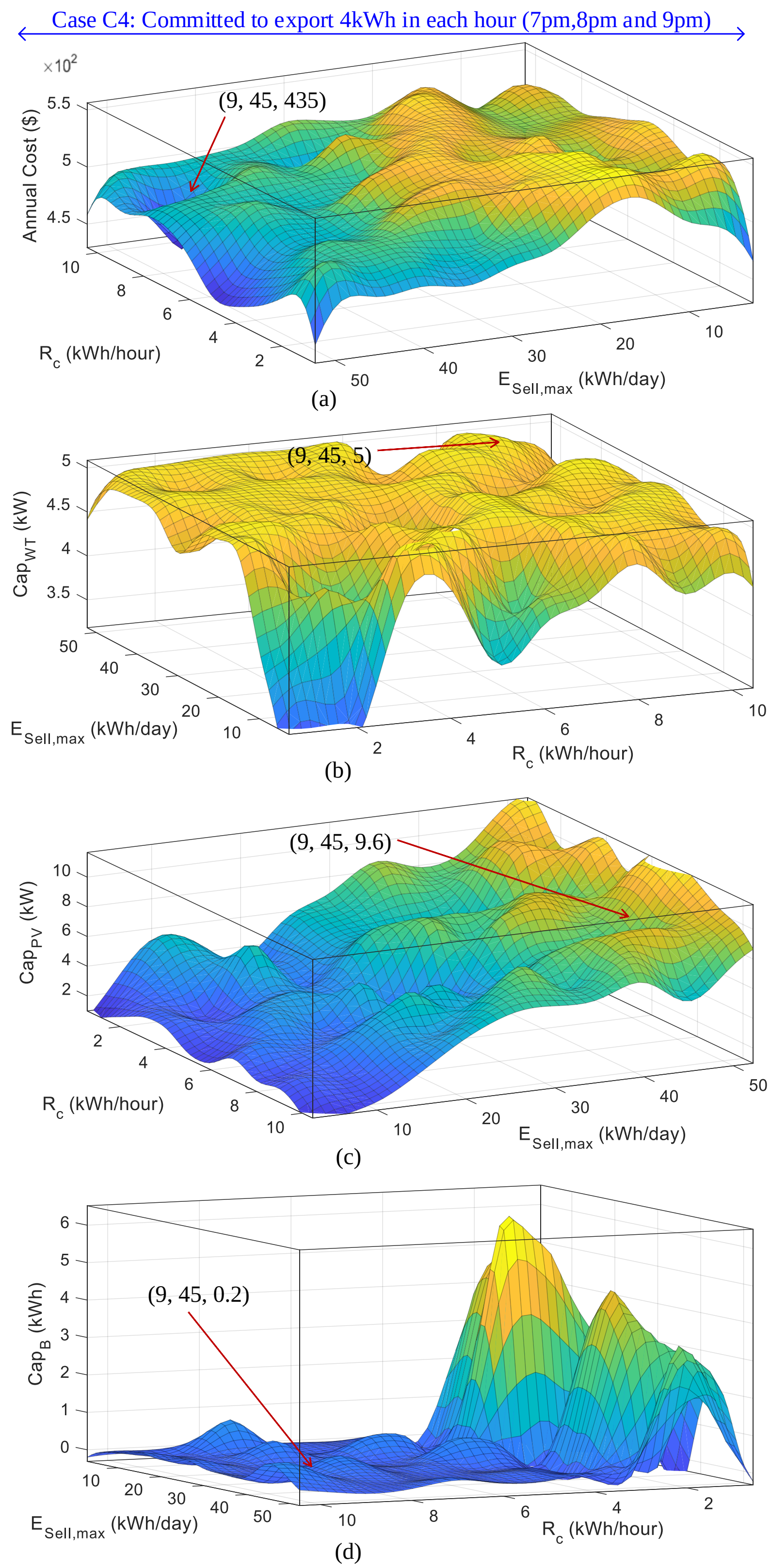


Figure 5.12. Case C4 (shiftable loads and shiftable PEV/H2V/V2H with 4kWh committed power exchange in each hour during 7pm, 8pm and 9pm). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($435), WT (5 kW), PV (9.59 kW), and battery (0.17 kWh) sizes.

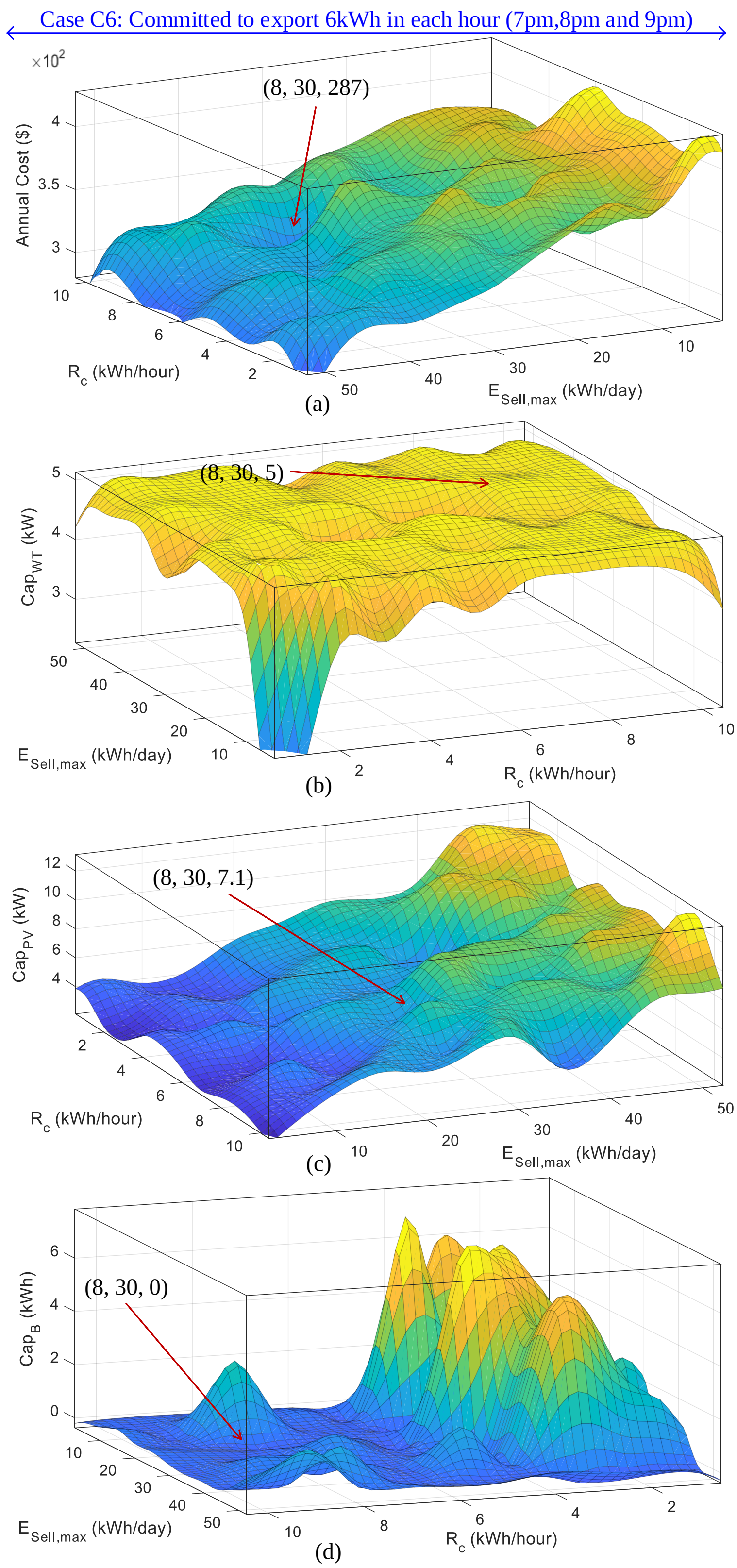


Figure 5.13. Case C6 (shiftable loads and shiftable PEV/H2V/V2H with 6kWh committed power exchange in each hour during 7pm, 8pm and 9pm). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($287), WT (5 kW), PV (7.10 kW), and battery (0 kWh) sizes.

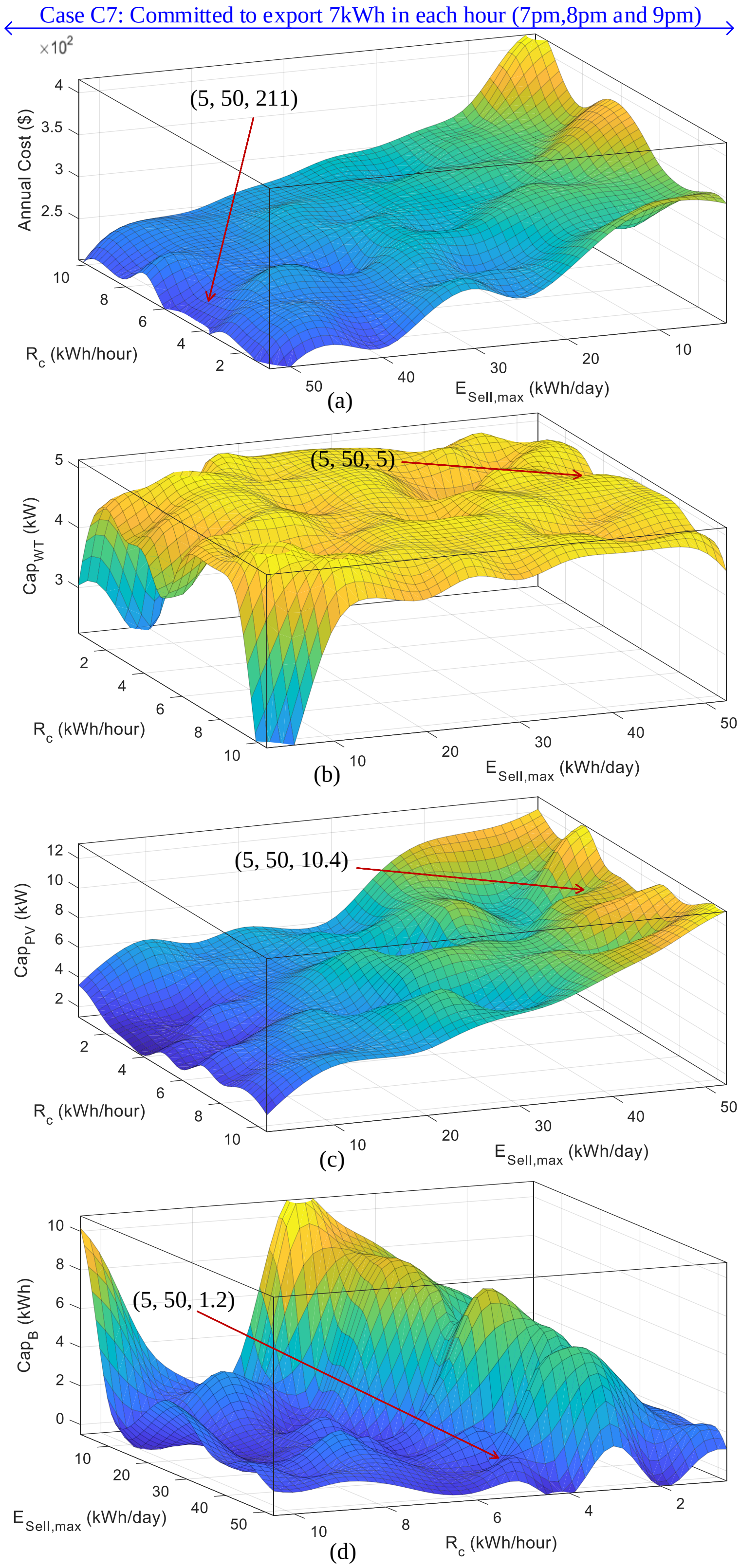


Figure 5.14. Case C7 (shiftable loads and shiftable PEV/H2V/V2H with 7kWh committed power exchange in each hour during 7pm, 8pm and 9pm). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($211), WT (5 kW), PV (10.43 kW), and battery (1.2 kWh) sizes.

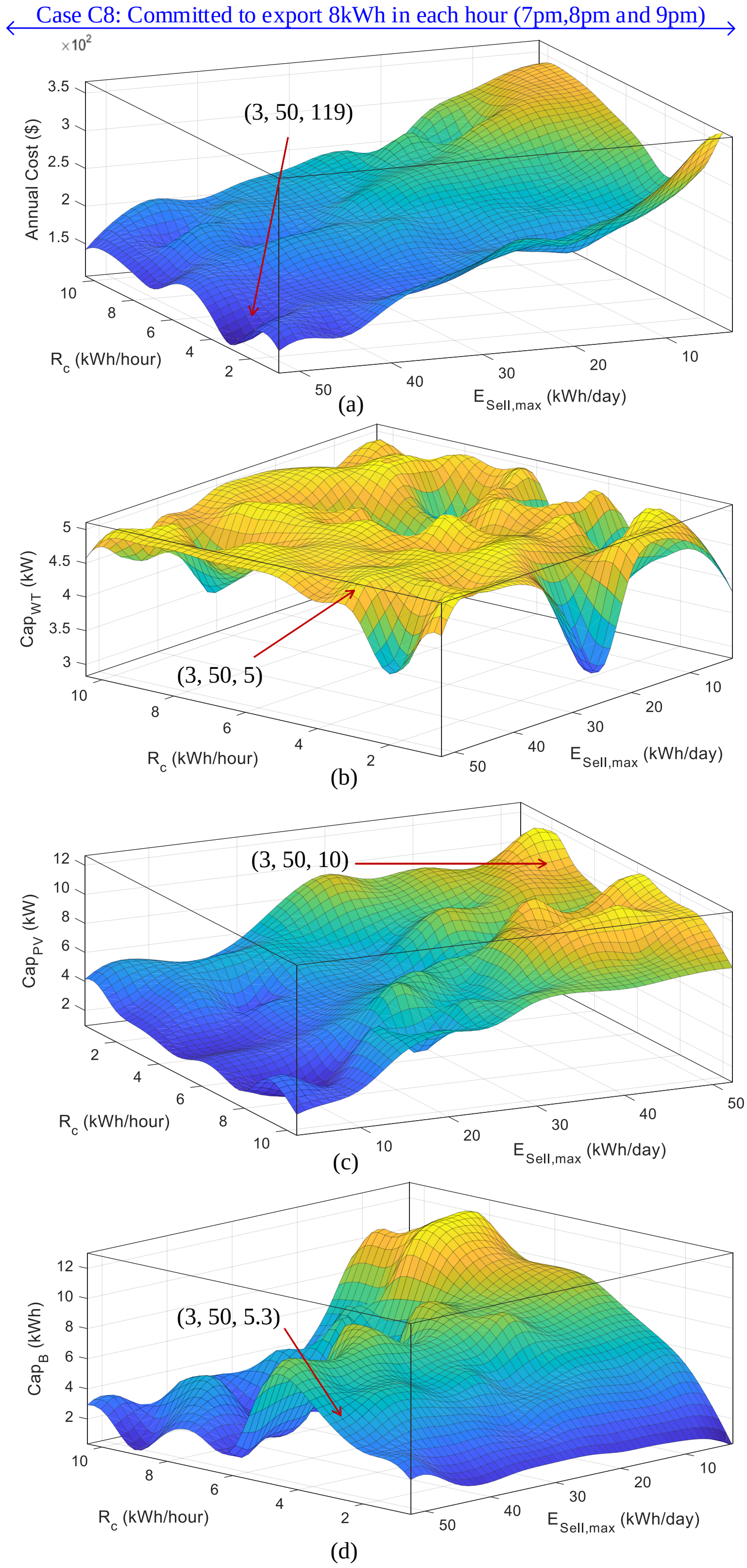


Figure 5.15. Case C8 (shiftable loads and shiftable PEV/H2V/V2H with 8kWh committed power exchange in each hour during 7pm, 8pm and 9pm). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($119), WT (4.99 kW), PV (10.04 kW), and battery (5.29 kWh) sizes.

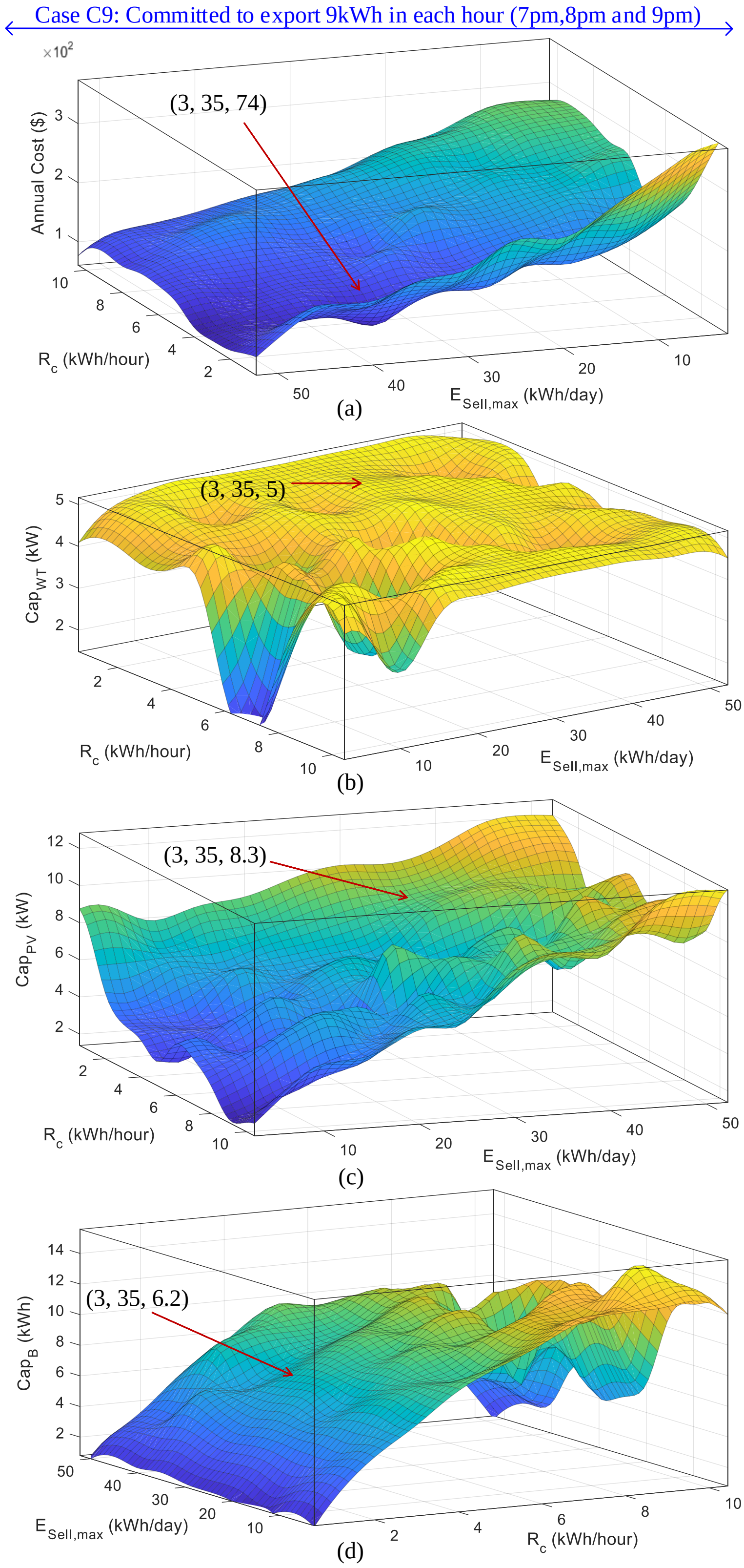


Figure 5.16. Case C9 (shiftable loads and shiftable PEV/H2V/V2H with 9kWh committed power exchange in each hour during 7pm, 8pm and 9pm). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($74), WT (5 kW), PV (8.29 kW), and battery (6.25 kWh) sizes.

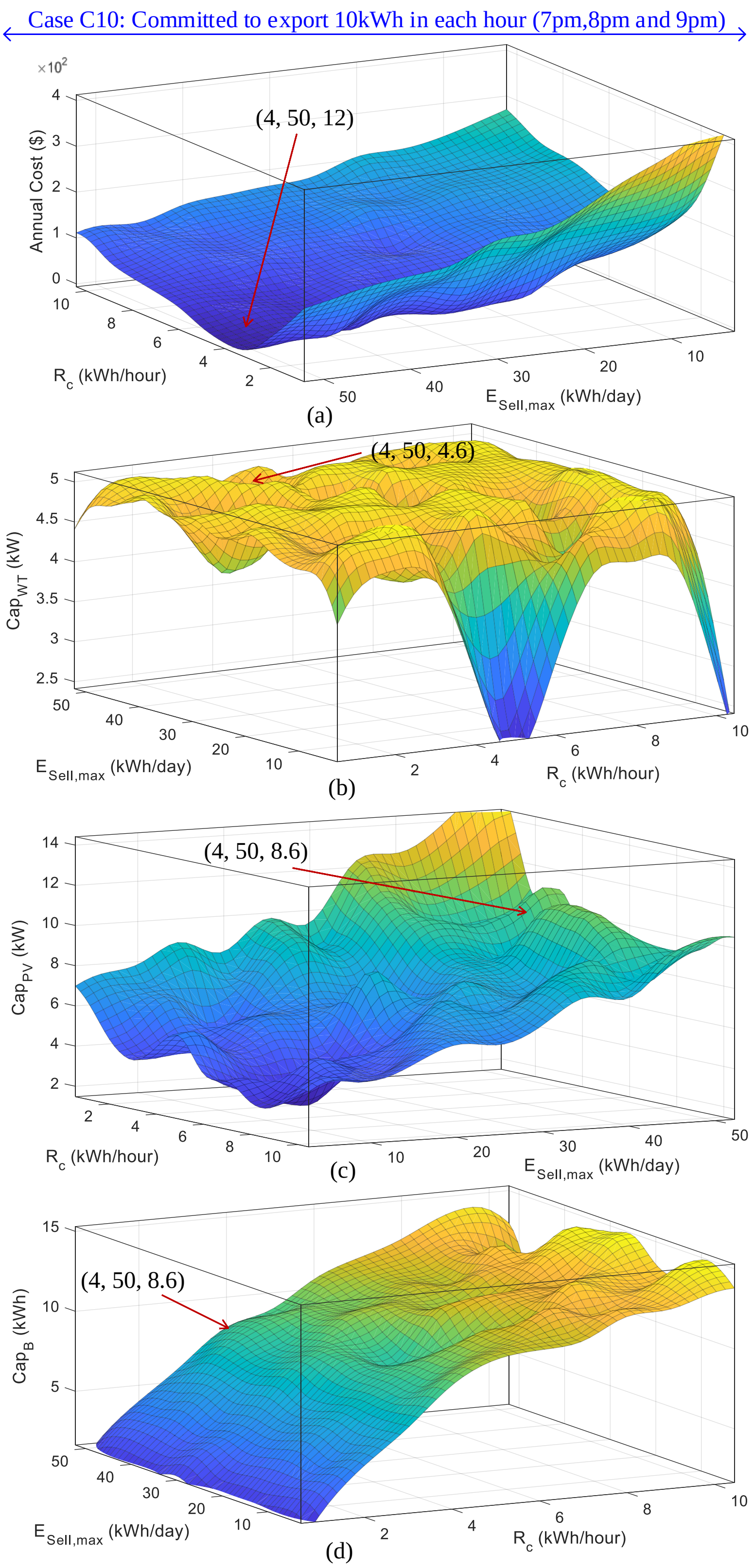


Figure 5.17. Case C10 (shiftable loads and shiftable PEV/H2V/V2H with 10kWh committed power exchange in each hour during 7pm, 8pm and 9pm). The MCS-PSO sensitivity (Figure 5.1) to maximum daily export limit and battery charge/discharge rate for SH with committed power exchange. Near-optimal solutions are demonstrated with arrows for the annual cost ($12), WT (4.61 kW), PV (8.62 kW), and battery (8.61 kWh) sizes.

Sensitivity analyses are performed for the selected solution of Case C7 to investigate the annual cost reduction for this case (PV=10.43kW, WT=5kW and BSS=1.2kWh) based on various electricity reward factors (α), as illustrated in Figure 5.18. As can be seen, with the decrease of α from 3 to 0.8, the annual cost reduction decreased from 53.1% to almost 0% and it is not economically beneficial for the SH to engage in the proposed DR if α is less than 0.8. In addition, for α=1 (i.e. ESR during committed power is equal to ER), the annual cost reduction is 5.13%, which is economically beneficial for the SH. However, it is not a sufficient incentive to encourage the SH to participate in this committed power program. Therefore, α should be at least 1.5 for this SH with committed power functionality (Case C7) to achieve at least 22% annual cost reduction.

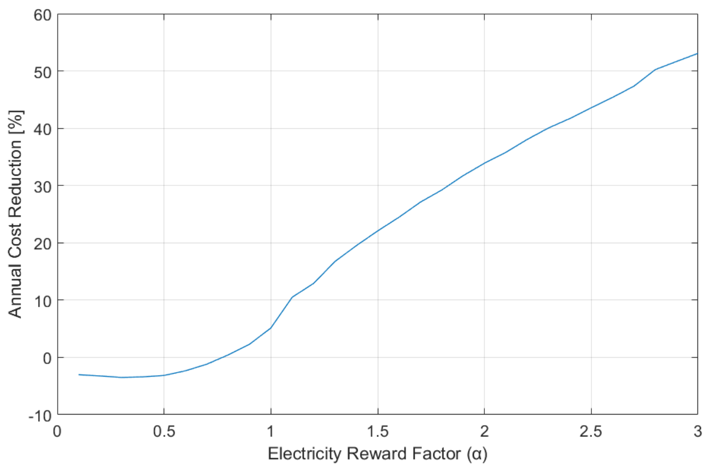


Figure 5.18. Annual cost reduction for Case C7 based on various electricity reward factors.

Based on this section's simulations (which are summarised in Table 5.5), for a committed power SH with near-optimal sizes of PV, WT and BSS:

- Introduction of a SH with the committed export power functionality reduced annual cost for Case C2 to Case C10 in comparison with the base case.
- With the increase of committed power export during peak hours (7pm, 8pm and 9pm), the annual cost of the SH is decreased.
- Near-optimal size of BSS was almost 0 kWh for Cases C1 to C6. However, after Case C6 with the increase of committed power export during peak hours (7pm, 8pm and 9pm), the near-optimal size of BSS is increased (Cases C7–C10).

- For almost all cases, the size of PV is increased with the increase of the maximum daily export limit.

5.5 Sensitivity analyses

Impacts of the battery charge/discharge rate (R_c), maximum daily electricity export ($E_{Sell,max}$) and the maximum capacity limits for WT, PV and BSS are studied for Cases A1–A3, B1–B3 and C1–C10 through a comprehensive sensitivity analysis.

Optimal sizes of WT, PV and BSS for the SH with committed power exchange functionality can be significantly affected by a number of parameters. According to the Table 5.4 (Cases A1–A3, B1–B3) and comprehensive sensitivity simulations of Figures. 5.3–5.8:

- Increasing the maximum limit for daily electricity export ($E_{Sell,max}$) for the committed power SH will reduce the annual cost and slightly increase the size of PV for almost all cases.
- Increasing the battery charge/discharge rate (R_c) for the committed power SH will decrease annual cost for Cases A1–A2 and B1–B2. (This was a dramatic decrease when R_c increased from 1kWh/hour to 5kWh/hour in these cases.) It also dramatically increase the size of BSS for Cases A1–A2 and B1–B2 because of the faster battery charge and discharge ability. However, we did not see this dramatic increase for the size of BSS when R_c increased from 5kWh/hour to 10kWh/hour in these cases.
- Considering WT in addition to PV and BSS will decrease the annual cost for the committed power SH in Cases B1, B2 and B3 and will reduce the size of PV.

More investigation is conducted for case B3 with various ranges of committed power for Cases C1–C10 (Case C5 is same as Case B3). According to Table 5.5 and comprehensive sensitivity simulations of Figures. 5.9–5.17:

- There is a cost reduction for Cases C2–Case C10 in comparison with the base case. Also, with the increase of committed power export, cost reduction is increased.

- For the cases with low committed power export, the near-optimal size of BSS was almost 0 kWh. However, with the increase of committed power export, the near-optimal size of BSS is increased for Cases C7–C10. For Case C10, the near-optimal size of BSS was 8.61kWh.
- Size of PV is increased by increase of maximum daily export limit for almost all cases.

5.6 Conclusion

This chapter performs:

i. Optimum sizing of rooftop WT, PV and BSS for a SH with committed power exchange and PEV integration using a proposed rule-based algorithm with MCS and PSO (Figure 5.1).

ii. Evaluating the performance through the operation of the SH with committed power exchange and cost evaluation with near-optimal component size (Figure 5.2).

iii. Investigating the impact of $E_{Sell,max}$, R_c, maximum capacities of WT, PV and BSS on their optimum sizes (Table 5.4 and Figures. 5.3–5.8).

iv. Investigating the impact of various range of committed power for the SH with shiftable load and shiftable PEV/H2V/V2H (Table 5.5 and Figures. 5.9–5.17).

The major conclusions are as follows.

- Introducing PV and BSS to the committed power SH (with α=3 and β=10) with shiftable load and V2H integration will provide significant annual cost reduction (over 24%) and LCOE from 3.21 to 2.43 cents/kWh for Case A3, while the inclusion of WT will provide an additional reduction in annual cost (over 32%) and LCOE to 2.16 cents/kWh for Case B3 (Table 5.4; rows 4, 7 and 11).
- Introducing PV and BSS to the committed power SH (with α=3 and β=10) without V2H integration will not provide annual cost reduction (Cases A1–A2 and B1–B2) and we need to increase α in order to get cost reduction.

- Consideration of V2H for the committed power SH (with α=3 and β=10) reduces initial investment by reducing the size of PV and BSS. In addition, it reduces annual cost (over 24% and 32% without and with WT, respectively) and LCOE to 2.43 and 2.16 cents/kWh without and with WT, respectively (Table 5.4; rows 7 and 11).
- Eliminating BSS for the committed power SH (with α=3 and β=10) with shiftable load, V2H integration and renewable resources may be a good option. As can be seen for Case A4, battery-less configuration reduces LCOE and annual cost (Table 5.4; row 8). This is more promising in Case B3 when WT is also considered for the SH. The near-optimal size of BSS for Case B3 is 0kWh (Table 5.4; row 11).

Chapter 6 Conclusion

SHs can be beneficial to energy consumers and providers if appropriate DR programs are in place. The effect of different components of SHs on the size of renewable resources and annual cost of electricity is investigated in this thesis. The operation of a SH with the optimal size of renewable resources is also evaluated to study the annual cost of SH. In addition, the effectiveness of SHs with committed power functionality is studied with the aim of minimising annual electricity cost while responding to DR programs. This study can help policy-makers establish better electricity tariff structures and DR programs for the residential sector. With appropriate implementation of SHs and DR programs, it is possible to further increase the penetration of renewable resources. The conclusions and the significance of each chapter are described in the following section.

6.1 Conclusions and significance

This thesis presented a comprehensive literature survey on state-of-the-art technologies and elements that play significant role in the SH in the SG context. A number of studies closely related to this research were reviewed in Chapter 2.

Investigated areas were classified into four categories. The first category was demand-side management and demand response programs. The second category was renewable distributed generation. PV systems, wind systems and electrical storage systems were described under the second category. The third category was optimal sizing of renewable resources, which included optimal sizing for microgrids and for SHs. The final category was SH enablers, which included: (i) power metering devices; (ii) communication network; (iii) smart appliances; (iv) the Internet of Things; (v) smart sensors; (vi) monitoring and control systems; (vii) cloud computing; (viii) home energy management system (HEMS) and; (ix) energy consumption scheduling.

Data modelling and optimisation methods used for energy management and sizing optimisation in SHs were presented in Chapter 3. Two modelling approaches were introduced to consider stochastic behaviour of wind speed, global irradiance, temperature, power demand, and electricity rate based on yearly data and use of Monte Carlo simulation (MCS). Also, components of SHs were modelled to be used in the following chapters' simulations. Particle swarm optimisation (PSO) was also introduced as a method to be used for optimum sizing of components for SHs.

The work in Chapter 3 is significant because it introduced a modelling framework for implementing stochastic behaviour of renewable resources in optimisation problems. New models were also proposed for SH generation cost, HVAC load and PEV charge/discharge algorithms.

Chapter 4 focused on HEMS and the optimisation problem for SHs. Optimum component sizing for a SH with rooftop WT, PV, BSS, PEV and shiftable loads by minimising annual electricity cost was presented in Chapter 4. A new rule-based HEMS was proposed in association with Monte Carlo simulations and particle swarm optimisation (MCS-PSO). Import and export of energy with V2H integration was considered along with stochastic behaviors of temperature, irradiance, wind speed, load and ER. Additionally, normal and lognormal probability density functions were used for projecting availability of PEV. After determining near-optimal sizes of rooftop PV, WT and BSS, the performance of the SH operation was evaluated with the selected near-optimal renewable resources. The impacts of shiftable loads, maximum daily export energy, battery charge/discharge rates, V2H integration and maximum PV, WT and battery capacity limits were investigated in sensitivity analysis simulations.

The contributions in Chapter 4 are notable, with a new rule-based HEMS algorithm proposed for a SH with rooftop PV, WT, BSS and PEV to empower households to shift (schedule) their shiftable loads to off-peak periods based on the day-ahead and dynamic electricity price. Additionally, optimum sizing of SH renewable resources (including rooftop PV/BSS or rooftop PV/WT/BSS) was studied utilising the proposed MCS-PSO approach. In addition, the effect of shiftable loads, V2H, battery charge/discharge rate, maximum daily electricity export, and maximum capacities of WT, PV and BSS on optimal sizes of renewable resources were investigated. Finally, the SH operation was evaluated based on the proposed algorithm and near-optimal renewable component sizes.

A SH with committed exchange power functionality was proposed in Chapter 5. Near-optimal sizes of rooftop PV, WT and BSS were studied for different conditions based on the proposed HEMS utilising the proposed MCS-PSO approach. Annual cost was minimised for determining the near-optimal size of rooftop PV, WT and BSS for the SH with committed power exchange. Stochastic behaviors of renewable resources and availability of PEV were considered. After determining near-optimal sizes of rooftop PV, WT and BSS, the performance of the SH operation was evaluated with the selected near-optimal renewable resources. The impacts of shiftable loads, maximum daily export energy, battery charge/discharge rates, V2H integration and maximum PV, WT and battery capacity limits were investigated in sensitivity analysis simulations. Further investigation was conducted to study the effect of various committed power exchanges to the optimal sizes of rooftop PV, WT and BSS for the SH with the shiftable load and V2H integration.

There are significant contributions in Chapter 5, too. It offers an insight into the renewable resources sizing problem and the effect of DR programs on renewable resources penetration in the residential sector, along with the economic profits/costs for households. This chapter focused on a SH with committed exchange power to investigate the savings households can achieve by participating in incentive-based DR programs along with price-based DR programs. The findings can assist stakeholders and service providers in establishing better electricity tariff structures and DR programs for the residential sector to increase the overall benefits for energy producers and consumers while increasing the penetration of renewable resources and decreasing GHG emissions.

6.2 Contributions

In terms of contributions made, this thesis has:

1. Proposed a modelling framework for implementing stochastic behaviour of renewable resources in optimisation problems.
2. Proposed a new algorithm for PEV charge/discharge to coordinate SHs for engaging DR programs.

3. Proposed a rule-based HEMS algorithm for a SH with rooftop PV, WT, BSS and PEV to empower households to shift (schedule) their shiftable loads to off-peak periods based on dynamic day-ahead electricity price and minimising electricity cost.
4. Proposed a new approach for finding optimum size of renewable resources (including PV, WT and BSS) for SHs based on annual cost minimisation by use of a proposed rule-based algorithm and MCS-PSO.
5. Conducted sensitivity analysis simulations to illustrate the effect of shiftable loads, V2H, battery charge/discharge rate, maximum daily electricity export, and maximum capacities of WT, PV and BSS on optimal sizes of renewable resources for a SH engaged in price-based DR programs.
6. Evaluated the SH operation based on the proposed algorithm and near-optimal renewable component sizes.
7. Proposed a rule-based HEMS algorithm for a committed power SH with rooftop PV, WT, BSS and PEV to empower households to engage in both price-based and incentive-based DR programs.
8. Determined the near-optimal size of rooftop WT, PV and BSS for a SH with committed power exchange and PEV integration using the proposed rule-based algorithm with MCS and PSO.
9. Evaluated the operation of SH with committed power exchange based on the proposed algorithm and near-optimal renewable component sizes.
10. Conducted sensitivity analysis simulations to illustrate the effect of shiftable loads, V2H, battery charge/discharge rate, maximum daily electricity export, and maximum capacities of WT, PV and BSS on optimal sizes of renewable resources for a SH with committed power exchange functionality.
11. Evaluated the impact of various ranges of committed power exchange on the electricity cost and renewable resources size of the SH with shiftable load and shiftable PEV/H2V/V2H. This can assist stakeholders and service providers in establishing better electricity tariff structures and DR programs for the residential sector to increase the overall benefits for energy producers and consumers.

6.3 Future work

Smart homes have many different aspects to be investigated in the context of SGs. With the development of new technologies – ICT, IoT, smart appliances, renewable resources technologies, cloud computing, data security, smart meters – DR programs and various government policies, along with the building characteristics, social and psychological behaviour of residents, there are many variable to investigate, particularly when the stability and reliability of the SG can be related to these subjects.

This research proposed a home energy management system for a SH in a residential environment along with a modelling framework for implementing stochastic behaviour of renewable resources in optimisation problems. The optimal size of renewable resources and operation was also studied for this SH along with the effect of DR programs on the size of renewable resources and operation of the SH.

There are some areas and directions which have been identified for further research, as follows.

1. Implementing machine learning techniques and forecasting methods in HEMS in order to monitor, analyse and predict both SH consumers' and devices' behaviour (including renewable resources) along with energy providers and DR programs. This will assist HEMS in better scheduling shiftable loads and better allocating renewable resources in response to DR programs.
2. Investigating the effect of implementation of machine learning techniques and forecasting methods in HEMS on the optimal size of renewable resources and operation of SHs along with the possibility of introducing new DR programs to the industry.
3. Modelling a virtual plant that includes a number of SHs, and then studying the optimum size of renewable resources and the effect of different DR programs on the operation and optimal size of renewable resources for this virtual plant.
4. Evaluating the effect of other DR programs on the operation and optimal sizing of renewable resources for SHs. SH operation cost and sizing problems can be studied in the concept of different DR programs, which may be beneficial for some individual and special consumers.

5. Investigating the implementation of scheduling algorithms for each appliance that consumes electricity in a SH. Each appliance can be considered separately to be modelled and scheduled based on its specific algorithm. Then a supervisory algorithm can be applied to minimise household electricity cost while maintaining desired comfort level.
6. Implementing advanced scheduling algorithms for HVAC load management to investigate its effect on the size of renewable resources for SH and annual cost of electricity for households.
7. Investigating the utilisation of SH for ancillary supports to the grid such as injecting reactive power to the grid based on the local renewable resources and BSS.
8. Implementing various optimisation algorithms instead of a rule-based algorithm for operation of SHs in the sizing problem. This can be followed by investigating the effect of these algorithms on the size of renewable resources for SHs. Additionally, the effect of various DR programs on the annual cost and the size of renewable resources for the SH can be evaluated with those algorithms.
9. With the expansion of ICT infrastructure and SHs, machine learning and data-mining technologies can be utilised to extract new rules and criteria from SHs' big data in order to improve rule-based algorithms (for HEMS or individual devices) and DR programs.

This chapter concludes the thesis by presenting a review of the thesis's significance, contributions and proposed solutions. Finally, some issues for further investigation identified during this research are listed in the future work.

Appendix A – Full Text of Publications

IEEE Power and Energy Technology Systems Journal

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Effects of V2H Integration on Optimal Sizing of Renewable Resources in Smart Home Based on Monte Carlo Simulations

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ABSTRACT This paper investigates optimal sizing of rooftop PV, wind turbine (WT), and battery storage system (BSS) in smart home (SH) with a plug-in electric vehicle (PEV) considering vehicle-to-home (V2H) and home-to-grid operations. The proposed idea is to use a rule-based home energy management system (HEMS) along with the Monte Carlo simulations and particle swarm optimization to find the optimal sizes of renewable resources and BSS by minimizing the annual cost of household electricity. The probabilistic behaviors of wind speed, irradiance, temperature, load and electricity rate, as well as the availability of PEV are considered for the input data generation. Detailed simulations and sensitivity analyses are performed to investigate the impacts of shiftable loads, V2H integration, battery charge/discharge rates, designated maximum daily export energy and maximum PV, and WT and battery capacity limits on the annual and levelized costs of electricity. Our analyses reveal the possibility of eliminating BSS altogether in SH with PEV with some reduction in annual electricity cost.

INDEX TERMS Smart home, smart grid, rooftop PV, wind, battery storage, optimal sizing, PEV, H2G, V2H.

NOMENCLATURE

A. ACRONYMS

BSS	Battery Storage System
DG	Distributed Generation
DI	Decision Interval
DR	Demand Response
ER	Electricity Rate
H2G	Home-to-Grid
H2V	Home-to-Vehicle
HEMS	Home Energy Management System
HVAC	Heating, Ventilation, and Air Conditioning
LCOE	Levelized Cost of Electricity (cents/kWh)
MCS	Monte Carlo Simulations
MG	Microgrid
MCS-PSO	Monte Carlo Simulations and Particle Swarm Optimization
PEV	Plug-in Electric Vehicle
PV	Photovoltaic
SG	Smart Grid
SH	Smart Home
SOC	State of Charge
TMY	Typical Meteorological Year
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home
WT	Wind Turbine

B. INDICES, PARAMETERS AND VARIABLES

i	Daily time steps
j	Hourly time steps
k	MCS-PSO maximum iteration number
Δt	Time interval for simulations (sec)
$B(\Delta t_j)$	Available battery charge (kWh)
c_1	Cognitive parameter in PSO
c_2	Social parameter in PSO

Data Modeling for Renewable Resources and Smart Home using Monte Carlo Simulations

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Abstract- **This paper introduces the use of Monte Carlo simulations (MCSs) for modeling stochastic behavior of wind speed, irradiance, temperature, load and electricity rate (ER) as well as the availability of PEV. Two methods are introduced. Probability distributions and their parameters are described in the first method which can be use in the future researches. Second method is introduced for MCS to consider the correlation between different databases and the correlation of each interval value with their prior interval value. Recommendations are provided for the first method in the future studies.**

Keywords*- Monte Carlo simulation, renewable generation, data modeling, smart home, smart grid.*

I. Introduction

Penetration of solar generation, wind turbine, battery storage systems (BSSs) and plug-in electric vehicles (PEVs) in smart grid (SG) is increased rapidly in the last few decades. As a consequence, the need for energy management systems, demand response (DR) programs, load scheduling and smart homes (SHs) is increased. A number of research studies have addressed these matters. For energy management in microgrids [1], [2] and in buildings [3], [4] modern network management strategies is used. For peak shaving [5], minimization of cost and losses [6], [7] and for reactive power compensation [8] PEV coordination is used. Determining optimum size of renewable energy is studied for both smart homes with small capacity of renewable generation [4], [9], [10] and microgrids with large capacity of renewable generation [1], [2], [11]. For the studies in the concept of SG and distributed generations (DGs), it is important to consider the probabilistic behavior of wind speed, irradiance, temperature, load, electricity rate (ER) and availability of Plug-in Electric Vehicle (PEV). Monte Carlo Simulation (MCS) can be used to model the probabilistic behavior of these data. MCS have been used along with optimization algorithms for finding optimal solutions specially, for finding optimal size of renewable resources for SH [4].

In this paper, two methods for implementing MCS are introduced and described along with their characteristics. First method is based on probability distributions. Probability distributions for wind speed, global irradiance, temperature, power demand and electricity rate in every hour is determined. Also, availability of PEV is modeled based on daily probability distributions. Recommendations are provided for improve of this method in the future studies. Second method is based on data sampling and considers correlation between databases and data intervals.

This work was supported by Curtin University and the Australian Government Research Training Program Scholarship.

II. Data Modelling

MCS can be used for random generation of the input data for renewable energy simulations. MCS is used in the literature to model the stochastic behavior of renewable resources. One of the methods for generating data is use of probability distributions. The other method is data sampling that can be based on real yearly data or typical meteorological year (TMY) data, which are classified seasonally or monthly.

A. Modelling Wind Speed, Irradiance, Temperature, Load and Electricity Rate based on Yearly Data using Probability Distributions for Monte Carlo Simulations

For modelling these sources of data, we can use their probability distributions in each hour (in this study simulation interval considered to be one hour). First, we need to determine these probability distributions for each hour for each data using their TMY or historical yearly data. Then we can use these probability distributions to generate hourly data for simulations and optimizations.

1) Determine probability distributions for yearly data in every hour:

Probability distributions of wind speed, global irradiance, temperature, power demand and electricity rate are determined for every hour of the day. For each of these sources of data in every hour/interval, at least one specific probability distribution is defined.

a) Wind speed probability distribution

Wind speed for each hour is fitted to a probability distribution. One year hourly historical data at 10-meter elevation from McCook, Nebraska [12] are utilized and found that Weibull distribution is the best for describing data in each hour. Therefore there are 24 probability distributions with 24 shape and scale parameters which are described by (1) and shown in Fig. 1 a.

$$V_w(\Delta t_j) \sim \mathrm{WEIB}(A_{w_j}, B_{w_j}) \quad \forall\, j \in \{1,2,3,\dots,24\} \qquad (1)$$

Which A_{w_j} and B_{w_j} are illustrated in Table I.

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Non-Intrusive Load Monitoring and Supplementary Techniques for Home Energy Management

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***Abstract*- The emerging smart grid technologies and rapid installations of smart meters is encouraging many consumers to implement home energy management systems (HEMSs) in order to decrease their electric utility bills and increase the efficiency of energy consumption. Intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM) are two approaches in the literature for appliance load monitoring (ALM) that make it possible for HEMSs to optimize energy utilization. However, most researchers have addressed NILM as the more practical option. In this paper, three basic methods for NILM are presented and supplementary techniques for improving the accuracy of NILM are discussed and compared. In addition, future research directions and challenges are highlighted.**

***Index Terms*- Non-intrusive load monitoring, load identification, load disaggregation, smart home and smart grid.**

I. Introduction

The global rapid growth of economic development has dramatically increased electricity energy demands over the last few years. In order to meet this emerging growth, most electric utilities are upgrading their traditional power grids to more sophisticated and self-healing smart grid technologies. It is now possible to monitor and manage residential and commercial buildings and control their electricity energy demands on real-times bases in order to reduce the overall grid efficiency. To do this, power utilities have formulated demand response (DR) programs to merge smart houses with the smart grid. In a smart house, home energy management system (HEMS) can be used to control and coordinate smart appliances, electric vehicles (EVs) and renewable energy resources such as rooftop PV systems and rooftop wind turbines [1-2].

In a smart house, HEMS interacts with all appliances which are connected together with a communication network and performs appliance load monitoring (ALM) to use the energy more efficiently, manage the demand curve and reduce the cost of energy for consumers [1-35]. This can be done using:

- Intrusive load monitoring (ILM) techniques that are relatively accurate but require more equipment and resources.
- Non-intrusive load monitoring (NILM) approaches which are more practical with acceptable accuracy.

The ILM based methods are accurate but relatively expensive and more complicated. For example, they require at least two sensors for every appliance. On the other hand, NILM based approaches have recently attracted more attentions and research focuses as they are more practical for smart grid and house applications. An attractive advantage is that NILM only requires one meter for every building.

This paper discusses NILM methods and gives a survey on supplementary techniques that may be used to improve its performance and accuracy. The remainder of this paper is organized as follows. In Section II, three basic methods of NILM are presented and their characteristics are compared. Section III presents a survey on supplementary techniques that can be utilized for improving the accuracy of NILM followed by the conclusions.

II. Non-Intrusive Load Monitoring (NILM) Methods

NILM is an attractive way to identify individual appliances and determine their energy consumption and operating schedules. Table I presents the main types of appliances that can be identifies by NILM based methods [2]:

- Type-I: ON/OFF appliances with two states such as toaster and usual lamp.
- Type-II: Finite State Machines (FSM) or multi-state appliances such as washing machine and stove burner with repeatable switching pattern.
- Type-III: Continuously Variable Devices (CVD) with no fixed pattern of states such as dimmer lights and power drill.
- Type-IV: Permanent Consumer Devices (PCD) which are active constantly for a long period such as telephone sets and hardwired smoke detector.

Table II presents the most common input data for appliance identification in NILM along with their related reference numbers.

The NILM methods for analyzing the measured data are based on one of the following three main approaches:

1) Steady-state analysis [3-5, 18-20].
2) Transient-state analysis [6, 20-23].
3) Non-traditional appliance features [2-3, 24-27].

The main differences in these analysis approaches for NILM applications are in the way they detect the changes in load identification [20]. The first approach considers stable modes (states) of appliances while the second approach mainly concentrates on the transitional state of appliances power consumption behavior [2]. The last method is based on non-traditional appliance features which is introduced by [21] and pays more attention to the working style and operation of appliances. This section presents detailed analyses and comparison of the above-mentioned data analysis approaches for NILM applications.

Appendix B – Attribution of Publication

Naghibi. B, Masoum. M.A.S, Deilami. S. "Effects of V2H Integration on Optimal Sizing of Renewable Resources in Smart Home based on Monte Carlo Simulations", IEEE Power and Energy Technology Systems Journal.

	conception & design	acquisition of data & method	data conditioning & manipulation	analysis & statistical method	interpretation & discussion	Final Approval
Bahram Naghibi	x	x	x	x	x	x
I acknowledge that these represent my contribution to the above research output. Signed.						
Professor Mohammad Masoum	x				x	x
I acknowledge that these represent my contribution to the above research output. Signed. Nov. 24, 2018						
Sara Deilami	x				x	x
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	conception & design	acquisition of data & method	data conditioning & manipulation	analysis & statistical method	interpretation & discussion	Final Approval
Bahman Naghibi	x	x	x	x	x	x
I acknowledge that these represent my contribution to the above research output. Signed						
Sara Deilami					x	x
I acknowledge that these represent my contribution to the above research output. Signed 22/01/2020						

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