STOCHASTIC MODEL PREDICTIVE CONTROL FOR MULTI-ENERGY SYSTEMS WITH HIGH PENETRATION OF ELECTRIC VEHICLES

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Abstract

Stochastic Model Predictive Control for Multi-Energy Systems with High Penetration of Electric Vehicles

Anita Aboshiogwe Aliu, PhD Thesis, October 2021

The growing adoption of electric vehicles presents an opportunity to explore the numerous benefits to network operators. For example, aggregated electric vehicles can replace peaking power plants traditionally used to satisfy peak energy demands. However, unlike other distributed energy resources, electric vehicles do not have fixed locations within single- or multi-energy systems as they can be connected to any charging station. This makes optimally coordinating their charge/discharge operations challenging, compounded when uncertainties related to electric vehicles' characteristics, availability, and charging preferences are considered. Presented is a generalised mobile storage model representing successive electric vehicles' charge/discharge operations that will utilise a charging station. The model is not restricted to a fixed number of electric vehicles and can be used to analyse the different ways charging stations are utilised in residential, commercial, and public areas. The mobile storage model extends a generalised modelling framework primarily developed for predictive control applications. Modifications are made to the entire framework for application in stochastic predictive control. The effectiveness of the modified framework is demonstrated with three representative case studies. One illustrates how the model is incorporated into the generalised framework and implemented within a deterministic energy management scheme. Results show significant cost savings when exploiting successive electric vehicles utilising a charging station. The other is used to demonstrate how uncertainties are incorporated within the generalised framework and implemented within a stochastic energy management scheme. Results show significant cost savings compared to the deterministic scheme. Finally, the last case study has a varying number of charging stations. It is used to analyse the performance of a stochastic scheme whose optimisation problem is designed to consider charge/discharge power smoothing applications. This is done to prevent damage when electric vehicles are used for ancillary services such as peak demand management. Analyses presented show the challenges in implementing the stochastic scheme in different areas.

Declaration

I, Anita Aboshiogwe Aliu, declare that this report titled, "*Stochastic Model Predictive Control for Multi-Energy Systems with High Penetration of Electric Vehicles*" and the work presented in it are my own. I confirm that:

- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Copyright Statement

In dedication to my mother: Mrs Anetu-Anne Aliu. I LOVE YOU. THANK YOU.

Acknowledgments

For his patience, guidance, knowledge and encouragement throughout the course of my PhD, I wish to express my gratitude to my supervisor ***Dr Ognjen Marjanovic****.*

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Publications

Research outputs related to this thesis include the following publications:

1. A. Aliu, O. Marjanovic, and A. Parisio, "Charge/Discharge Event Model for Electric Vehicles with Predictive Control Application", *Mediterranean Conference on Control and Automation (MED) 2021*, pp.192-197.

2. A. Aliu, O. Marjanovic, and A. Parisio, "Stochastic Energy Management Scheme for Multi-Energy Systems with Electric Vehicle Integration", *International Journal of Electrical Power & Energy Systems*. - Submitted.

Acronyms and Nomenclature

Acronyms

AS	Auxiliary Services
BEV	Battery Electric Vehicle
CCS	Combined Charging System
CEMPC	Certainty Equivalent Model Predictive Control
CHP	Combined Heat and Power
COMMES	Control-Oriented Modelling Framework for Multi-Energy Systems
DER	Distributed Energy Resources
DG	Distributed Generation
DH	District Heat
DMPC	Deterministic Model Predictive Control
DNO	Distribution Network Operator
DR	Demand Response
DSM	Demand-Side Management
ECM	Energy Conversion Model
EEZ	Energy Exchange Zone
EH	Energy Hub
EMS	Energy Management Schemes
EV	Electric Vehicle

HEMS	Home Energy Management Schemes
HEV	Hybrid Electric Vehicle
HP	Heat Pump
IDSM	Integrated Demand Side Management
LLN	Law of Large Numbers
MEA	My Electric Avenue
MEPC	Economic Model Predictive Control
MES	Multi-Energy Systems
MG	Microgrid
MILP	Mixed Integer Linear Programming
MIQP	Mixed-Integer Quadratic Programming
MPC	Model Predictive Control
p.u.	per unit
PHEV	Plug-in Hybrid Electric Vehicle
PID	Proportional-Integral-Derivative
PM	Prosumer Model
PV	Photovoltaics
RES	Renewable Energy Sources
RMPC	Robust Model Predictive Control
RTO	Real Time Optimisation
SAA	Sample Average Approximation
SAPI	Shiftable - Adjustable - Pliable - Interruptible
SG	Smart Grid
SMPC	Stochastic Model Predictive Control
SM	Storage Model

SoC State-of-Charge

TNO Transmission Network Operator

UoM University of Manchester

V2X Vehicle-to-X (X can either be Vehicle (V), Building (B) or Grid (G))

VOFEN Vision of Future Energy Networks

VPP Virtual Power Plants

WT Wind Turbines

General

n_i, n_j	Node indices
n	Energy carrier type
P_{n_i}	Power flow in/out of node n_i
$P_{(n_i \to n_j)}$	Power flow from node n_i to node n_j
$\eta_{(n_i \to n_j)}$	Conversion factor from node n_i to node n_j
$\delta_{(n_i \to n_j)}$	Binary variable associated with arc $n_i \to n_j$
$\to n_j$	Node n_j as sink node
$n_j \to$	Node n_j as source node
N_H	Prediction horizon
k	Sampling period
h	Scheduling period
π_e^{buy}	Per unit purchase price of electricity
π_e^{sell}	Per unit revenue from selling electricity
π_g^{buy}	Per unit purchase price of gas
Bi	Index set representing bi-directional arc power flow
Su	Index set representing sum nodes
Tr	Index set representing transmitter nodes
Sw	Index set representing switch nodes
T	Index set representing all terminal nodes
T^n	Index set representing all terminal nodes not connected to uncertainty sources
T^s	Index set representing all terminal nodes connected to uncertainty sources
GL	Index set representing all prosumers
GL^n	Index set representing all flexible prosumers
GL^s	Index set representing all fixed prosumers

Es	Index set representing all energy storage systems
Es^n	Index set representing all fixed storage systems
Es^s	Index set representing all mobile storage systems
$J(\cdot)$	Objective function
$P_{cost}(\cdot)$	Economic part of the objective function
$P_A(\cdot)$	Cost of the adjustable portion of prosumers
s	Scenario index
N, N'	Number of scenarios
$\boldsymbol{x}$	First-stage decision variables
$\boldsymbol{c}$	Penalty on first-stage decision variables
$\boldsymbol{w_s}$	Random or uncertain variables
$\boldsymbol{Q(x, w_s)}$	Second-stage function
$\boldsymbol{\xi}_s^+, \boldsymbol{\xi}_s^-$	Second-stage or recourse variables related to scenario s
$\boldsymbol{q}_s^+, \boldsymbol{q}_s^-$	Penalty on recourse variables related to scenario s
$P_{first}(\cdot)$	First-stage objective function
$P_{second}(\cdot)$	Second-stage objective function

Fixed and Mobile Storage

E_{n_j}	SoC of fixed storage connected to n_j
Q_{n_j}	Charging/discharging power of fixed storage connected to n_j
S_{n_j}	Standby efficiency of fixed storage connected to n_j
cd	Number of charging/discharging operations
i	Charging/discharging operation i
a	Arrival
d	Departure
δ_{n_j}	Binary variables monitoring the presence of EV connected to charging station n_j
$h^a_{EV,i}$	Arrival time of EV during charge/discharge operation i
$h^d_{EV,i}$	Departure time of EV during charge/discharge operation i
$E_{EV,i}$	SoC of EV connected to n_j during charge/discharge operation i
$E^a_{EV,i}$	Arrival SoC of EV during charge/discharge operation i
$E^d_{EV,i}$	Departure SoC of EV during charge/discharge operation i
$E_{EV,i\to n_j}$	SoC of an EV during charge/discharge operation i connected to terminal node n_j
$Q_{EV,i}$	Charging/discharging power of EV connected to n_j during charge/discharge operation i
$\pm Q_{EV,i}$	Charge/discharge power limits of EV during charge/discharge operation i
$Cap_{EV,i}$	Battery capacity of EV during charge/discharge operation i
$S_{EV,i}$	Battery efficiency factor of EV during charge/discharge operation i
$\delta_{EV,i}$	V2X capability of EV during charge/discharge operation i
W	Length of matrices containing historical data on a charging station utilisation
$\boldsymbol{T_{n_j}}$	Historical information on successive EV arrival and departure times
$\boldsymbol{SoC_{n_j}}$	Historical information on successive EV arrival and departure SoC

$\boldsymbol{Q_{n_j}}$	Historical information on successive EV maximum and minimum charge/discharge power limit
$\boldsymbol{Cap_{n_j}}$	Historical information on successive EV battery capacities
$\boldsymbol{S_{n_j}}$	Historical information on successive EV battery standby efficiencies
$\boldsymbol{\delta_{n_j}^{V2X}}$	Historical information on successive EV bidirectional capabilities

Prosumer

N_n	number of energy segment
G_m	Total generating component
$G_{y,flex,n_j}$	y^{th} flexible generating component
G_{z,fix,n_j}	z^{th} fixed generating component
L_m	Total load component
$L_{y,flex,n_j}$	y^{th} flexible load component
L_{z,fix,n_j}	z^{th} fixed load component
h_c	Scheduled time flexible prosumer comes online
$\tilde{l}_{n,u}$	baseline energy requirement of the u^{th} segment
$l_{n,u}$	actual energy consumption of the u^{th} segment
$\Delta l^+_{n,u}/\Delta l^-_{n,u}$	exceeding/curtailment slack variables relating to the amount of deviation from the nominal energy requirement of the u^{th} segment of n
$\delta^+_{n,u}/\delta^-_{n,u}$	binary variables associated with $\Delta l^+_{n,u}$ and $\Delta l^-_{n,u}$ respectively
λ^+_A, λ^-_A	Penalty and incentive for exceeding or not meeting the baseline requirement due to adjustable portion of flexible prosumer
$E_{n,u}$	total baseline energy requirement of the u^{th} segment of n
L_n	Actual energy consumption of n accounting for the contribution from all its segments
$\delta^p_{n,u}$	segment processing binary variables
$\delta^c_{n,u}$	segment complete binary variables
$\delta^w_{n,u}$	segment waiting binary variables

Chapter 1

Introduction

1.1 Background

Since the mid-20th century, observed changes from the effects of greenhouse gases have increased significantly in rate and scale, and have motivated countries to commit to the ever-increasing adaption of sustainable technologies. The *Paris Agreement*, signed in 2015, sets out a global framework to deal with greenhouse gas emissions mitigation and adaptation by limiting global warming within 1.5°C to 2°C pre-industrial levels [3]. Prior to 2015, some countries had already committed to combatting climate change: for example, UK's *Climate Change Act 2008* targets a reduction of 80% by 2015 [4], EU leaders adopted in 2014 the climate and energy framework targeting to cut emissions in the EU by at least 40% below 1990 levels by 2030 [5]. Around the world, we see efforts been made, mainly by developed countries, through the degree to which they have integrated distributed renewable energy sources (RES) and other low-carbon technologies like solar PhotoVoltaic (PV), micro-Combined Heat and Power (CHP), and domestic Heat Pumps (HP). These changes are prominent especially within the energy sector, specifically in the production of electricity and heat, which are the largest contributor to greenhouse gas emissions. According to the International Energy Agency (IEA), about 50% of CO_2 is emitted from the production of electricity and heat, with a significant amount being emitted from residential and commercial buildings, and unallocated fuel combustion of biomass and on-site heat sources (refer to Figure 1.1). The transportation sector, the second largest contributor

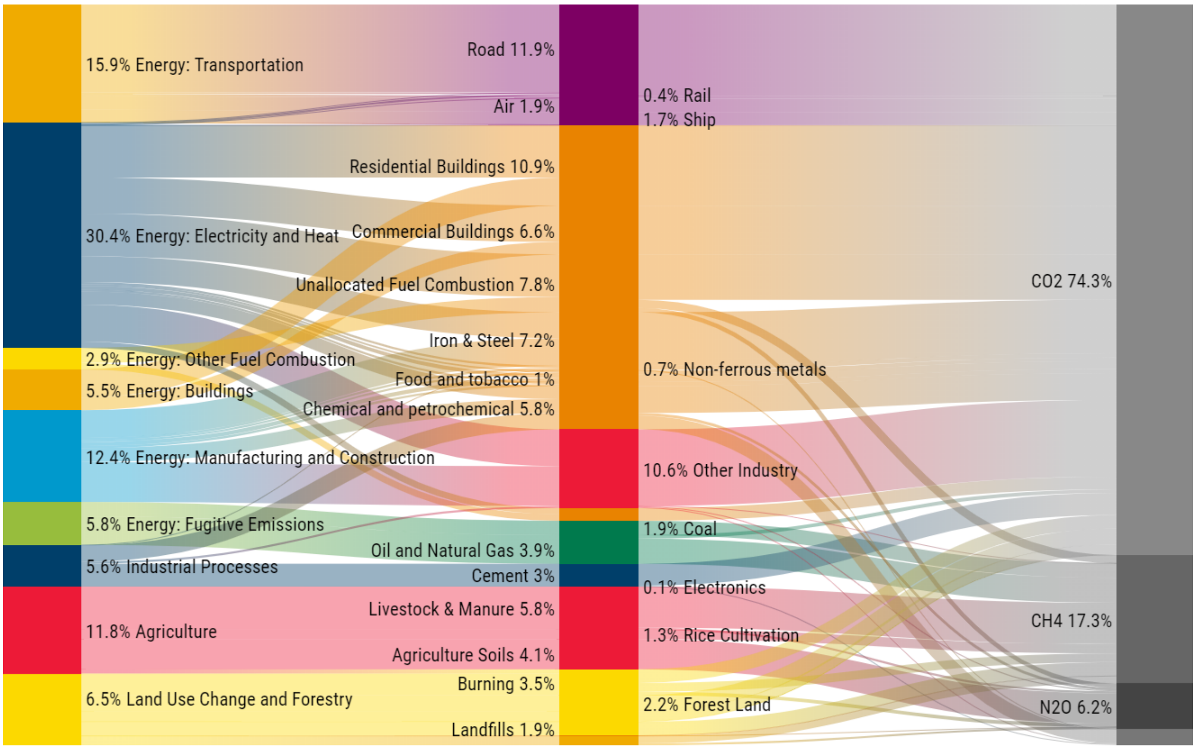

Figure 1.1: World greenhouse gas emissions in 2016 (sector | end use | gas).
Source: Climate watch, based on raw data from International Energy Agency (2018); modified by world resource institute

of greenhouse gases contributing about 20% of CO_2, has not been ignored in the efforts made to cut emissions. This is clearly seen through the adoption of Electric Vehicle (EV)s. While adopting more sustainable technologies has the potential to significantly reduce dependence on fossil fuels, it also presents a number of challenges for network operators as power generation and consumption from these devices are highly volatile and stochastic, making it particularly difficult to maintain the stability and reliability of energy networks [6].

Traditionally, power generation and consumption patterns have been relatively predictable. Generation has been done centrally, with power transferred through transmission system and into the distribution network eventually reaching end-users. The network structure has been hierarchical with unidirectional power flow. Majority of loads operate in passive-only mode with easily predictable energy demands and peaking power generators that can be readily ramped up are used to satisfy peak energy demands during certain periods. However, the integration of distributed sustainable technologies into energy networks together with end-users owning more controllable devices has resulted in non-hierarchical energy networks with bi-directional power flow. Furthermore, end-users are increasingly installing devices such as PVs and/or owning mobile storage systems, such as EVs, making control of distribution networks more challenging.

The adoption of these devices by end-users makes them not just net consumers of energy but also producers, with the term *prosumers* is used to define them as in [7] and [8]. Power generated from devices such as PVs and wind turbines can be controlled, to a certain degree, by curtailing their power output and/or utilising storage systems when energy is generated in excess. Hence, these devices have the potential to reduce the reliance on peaking power generators. However, this is more complicated if such devices are located on the end-user side since network operators do not have direct control of these devices. In addition, end-users' adoption of EVs introduces uncertainty regarding their location and energy demands, since EVs do not have fixed presence and known generation/consumption patterns within energy networks. This uncertainty has traditionally been addressed by incorporating significant levels of redundancy into the energy network. However, the current ageing and overstressed infrastructure combined with ever increasing transition from passive end-users towards more active participants, operating energy consuming assets such as EVs, means network operators face important challenges of how to maintain network reliability.

One approach of addressing these issues is straightforward network reinforcement but this is generally quite expensive and leads to assets operating below economically optimal capacity. Alternatively, the *Smart Grid* (SG) concept has been extensively researched that employs digital technology to monitor and manage the transfer of electrical power and coordinate the needs and capabilities of all assets and stakeholders within a network. However, this concept primarily focuses on electrical networks. *Demand-Side Management* (DSM) methodology facilitated by the SG concept, provide network operators with the ability to manipulate generation and demand profiles by controlling prosumers and EVs provided adequate control schemes are developed. Another alternative to addressing the aforementioned issues of present energy networks is the adoption of the *Multi-Energy Systems* (MES) concept. This concept extends the SG concept into the multi-energy domain, allowing optimal interaction between different energy vectors (e.g natural gas, heat, cooling, transport, water, etc) by exploiting the flexibility they provide. In addition, the incorporation of DSM in the MES concept brings new insights into Integrated Demand-Side Management (IDSM), a generalised concept that allows switch between different energy carriers, storage systems, prosumers and EVs.

Energy sectors have traditionally been planned and operated independently of each other. However, the adoption of the MES structure gives a holistic approach to coordinating these sectors using unified energy infrastructure. MES presents an opportunity to exploit synergies among various energy forms from Distributed Energy Resources (DERs) such as PVs, Wind Turbines (WT), CHP units, EVs and HPs. This opportunity is exploited by taking advantage of the flexibility that DERs provide to meet energy demands and assist in integrating intermittent energy generators. Such configuration of DERs is known as an Energy Hub (EH) and embracing DERs bring forth the issue of how to control the energy they generate and/or consume in a coordinated way. Most DER are permanently present within an EH and a major concern for network operators is to effectively integrate their operation into the energy network while considering the uncertain nature of some energy sources such as wind speed and solar radiation. However, EVs introduce added complexities related to accounting for uncertainties in individual EV characteristics (e.g. battery capacities, charge/discharge power limits, bidirectional energy exchange capabilities), availabilities (arrival and departure times) and owners' charging preferences (e.g. individual's choice to utilise EV bidirectional energy exchange capability, State-Of-Charge (SoC) at departure).

Similar to conventional vehicles, EVs are stationary approximately 90% of the time. Hence, they can be exploited to provided valuable services to energy network operators [9]. There is significant research interest on how EVs can interact with intermittent power generators to aid their integration into energy networks [10] and the role EV aggregators can play in deciding services, optimisation and control strategies for EVs [11]. Benefits EVs provide include the following:

- The storage capacity that EVs provide can be exploited to aid the reduction of energy generation cost within an energy network as well as minimise EVs' charging cost through the controlled interaction between EVs and intermittent energy generators.
- EVs with Vehicle-to-X (V2X) capability, where X refers to an infrastructure such as the grid, a building or another EV, has restructured EVs' role to include distributed generators, and potentially allows for EV to participate actively in electricity market by providing regulatory and spinning reserve services to system operators.

- Aggregated EVs can be utilised to provide peak demand management service to network operators, acting as distributed generators and reducing the requirement for expensive peaking generation plants traditional used to satisfy peak demands.

The expected future increase in EV numbers will be beneficial as a large number of them will be required to efficiently exploits the services they can provide to energy network operators. However, large EV numbers will pose a challenge to network operators if proper modifications and/or control of energy networks are not made to accommodate their charging/discharging operations [12,13]. Hence, their integration in energy networks has received significant interest in research communities.

1.2 Motivation

EV integration in the operation of MES has been investigated to capture the benefits EVs can potentially contribute to achieving a future sustainable energy network through various proposed control strategies. However, EVs lack of fixed presence, known location and generation/consumption patterns, which most DERs possess, makes them difficult to control and coordinate. Attempts in research to handle this difficulty and incorporate EVs in the operation of energy systems are based on relatively known mobility behaviour (e.g. when and where to charge, and energy consumed) [14–30] and investigations done within the MES context, uncertainties are typically overlooked [31]. In addition, individual owners' charging preferences are usually ignored, and proposed control schemes are mostly implementable in specific cases where an approach proposed for a case study cannot be used for another, hence lacking a systematic approach. These assumptions are reasonable when analysing schemes for EV fleets with shared schedules, private car parks or homes with individually allocated charging stations. In these cases, ownership of charging stations is known and near-full information regarding EV's mobility and charging behaviour can be obtained. However, the diverse nature of future EV ownership in addition to their different technology types as well as owners' individual utilisation, availabilities and charging preferences, will restrict the applicability of the existing approaches. Inadequacy of the existing approaches is particularly acute in the cases of public charging facilities where it is difficult to determine the different types of EVs and their owners' charging preferences that will utilise specific charging stations.

To account for diverse EV ownership will require a energy network modelling approach that is easily adaptable and not restricted to specific case studies. Some aforementioned literature that incorporate EVs in the operation of energy systems have utilised the SG concept. However, the SG concept is applicable in electrical-only domain. Other approaches that have incorporated EVs in energy network operations have used the different approaches to modelling MES such as microgrid and EH concepts. However, these modelling framework are not capable of representing multi-directional energy flow required to facilitate EVs' bi-directional energy exchange with the grid. A novel modelling framework that addresses the short-falls of the aforementioned approaches to modelling energy systems is the Control-Oriented Modelling framework for MES (COMMES) in [8]. The COMMES framework is capable of representing energy converter arrangements of arbitrary complexity containing multiple energy vectors, as well as multi-directional energy flow, multi-generation and multi-mode devices. However, the existing formulation of the COMMES framework does not allow for straightforward representation of EVs charge/discharge operations.

In controlling energy networks, system operators have traditionally focused on the supply side with regards to grid management and have made control decisions based on optimisation strategies that allow for the best choice for a set of interacting variables to be determined considering system constraints. With energy users on the demand-side installing devices such as PVs, WTs and EVs, and with the inherently multi-variable nature of MES, power system operators have equally adopted optimisation strategies in making control decisions as it allows the constraints of these devices and flexibility of the MES to be accounted for. Promising optimisation strategies gaining interest in power research communities are those based on Model Predictive Control (MPC) (a.k.a. receding-horizon control). It is an attractive control approach to utilise the existing flexibility in MES as its formulation explicitly incorporates system constraints and its receding horizon strategy introduces a degree of robustness against the stochastic nature of RES and active energy users. Research has begun to embrace its stochastic formulation, especially when dealing with real-world problems because its deterministic formulation renders its robustness property inadequate. Another advantage of the COMMES framework is that is was primarily developed to be implementable within predictive control schemes and is exemplified by its implementation in deterministic MPC schemes in [8, 32, 33]. However, in addition to the inability of representing EV charge/discharge operations using the existing formulation of the COMMES framework, the framework is also not adaptable to consider uncertainties from DER. Therefore, an opportunity presents itself to modify the existing modelling framework to capture uncertainties from all energy sources, efficiently account for the complexities of integrating EV charge/discharge operations and is implementable in stochastic MPC schemes.

1.3 Aim and Objectives

The aim of this thesis is the development of a generalised model to represent the charge/discharge operation of EVs. The model should be incorporated into the novel control-oriented modelling framework for multi-energy systems hence should match the framework's modular structure. In particular, the EV representation should not be restricted to specific EV characteristics, availabilities and owner's charging preferences nor should a fixed number of EVs be imposed. The entire framework should be adaptable to consider uncertainties from generation and demand sources, including EV related uncertainties. In order to meet this aim, the following objectives have been identified:

- Develop and identify a suitable model for representing EV charge/discharge operation i.e. an approach that is not limited to specific EV characteristics (battery capacities, charge/discharge power limits, bidirectional energy exchange capabilities), EV availabilities (arrival and departure times) and EV owners' charging preferences (individual's choice to utilise EV bidirectional energy exchange capability, State-Of-Charge (SoC) at departure) as well as not restricted to a fixed number of EVs and can consider multiple uses of a charging station.

- Modify the novel COMMES framework to incorporate a representation of mobile storage devices that matches the COMMES modular structure.

- Investigate and identify part of the modified COMMES framework that need to be adapted to uncertainties from generation and demand energy sources.

- Develop and identify suitable methods to predict future uncertainties related to EV characteristics, availabilities and owner's charging preferences in order that stochastic predictive control schemes can be tested using the modified COMMES framework.

1.4 Contribution

To the best of the author's knowledge, no formalised systematic approach to mobile storage modelling for control applications has yet been proposed that is not restricted by the number of mobile storage devices. In order to address this, the model of mobile storage device is developed based on the utilisation of charging stations. This approach allows driver's decide to participate in bidirectional energy exchange once they connect their vehicle to a charging station if the charging station has bidirectional energy exchange capabilities. The contributions of the thesis can be summarised as follows:

- Provision of a model representation of successive EVs charge/discharge operations based on the utilisation of charging stations instead of directly modelling a fixed number of EVs, which is the approach employed in most literature. The model structure facilitates the representation of individual EV characteristics and availabilities and allows their owners to set desired charging preferences before a charge/discharge operation begins.

- Incorporation of the aforementioned representation of successive EV charge/discharge operation model in a novel generalised COMMES framework. The inclusion of the EV charge/discharge model extends the COMMES framework to capture mobile storage devices that are not always permanent in MES. While alternative representation of EV charge/discharge model have been proposed within the MES context, they lack a modular structure as they are focused on fixed EV numbers and a reasonable understanding of their utilisation can be obtained.

- Proposal of a modification to the novel COMMES framework to consider the stochastic nature of EVs by addressing uncertainties related to EV characteristics, availabilities and owners charging preferences as well as fixed generation and loads. The proposed modification facilitates forecasts of EV needs to be generated and is applicable in the analysis of EV utilisation within residential, commercial, and public areas. While alternative approaches exist that facilitate the forecast of EV charge/discharge patterns, they are based on individual EV utilisation within specific areas and allow only one EV charge/discharge operation per charging station to be considered.

- A mechanism for updating current and estimate of future EV charging/discharging operations to facilitate online control applications by continuously monitoring and assessing EV presence, energy level and associated uncertainties, within the MES. The mechanism considers the random behaviours and inter-temporal constraints between successive EV charging/discharging operations.

1.5 Thesis Outline

The remainder of this thesis is organised in the following way:

Chapter 2: Review of the literature relevant to the topics discussed in this thesis is presented.

Chapter 3: Preliminary topics of the COMMES framework, stochastic programming and MPC are discussed, to support their application in later chapters.

Chapter 4: The generalised representation of mobile storage charge/discharge model proposed in this thesis is discussed in this Chapter. In addition, a deterministic model predictive control scheme is designed and a case study is presented to demonstrate how the mobile storage model is incorporated into the COMMES framework.

Chapter 5: Formal modifications to the COMMES framework is presented in this chapter. In particular, discussions on how uncertainty sources affect the three components of the COMMES framework is presented together with how uncertainties related to EV characteristics, availabilities and charging preferences are incorporated into the mobile storage model. In addition, a stochastic energy management scheme is developed and another case study is provided to demonstrate the modifications to the COMMES framework.

Chapter 6: Computational considerations of EV utilising charging stations in residential, commercial and public areas are analysed. A general electrical-only system with a number of charging stations is used to demonstrate the computational challenges in the different areas. The stochastic EMS is designed with the added functionality to smoothing the charge/discharge power flow of EVs.

Chapter 7: Concluding remarks to the thesis and some promising direction for future work are presented.

Chapter 2

Literature Review

This chapter presents a review of existing literature that informed the development of the mobile storage model and control scheme proposed in this thesis. In particular, approaches in literature on modelling, aggregating and controlling the charge/discharge operations of EVs within single- and multi-energy networks are explored.

It is highlighted in Chapter 1 that unlike EVs, most DERs are permanently present within energy networks. To further illustrate this, Figure 2.1 shows a schematic of a MES containing different DERs. It provides a helpful example of various technologies and energy vectors that can exist within a MES. Energy sources shown on the left in Figure 2.1 contain different technologies that provide input energy to the MES. Electrical energy sources come from generation plants and renewable technologies. Gas is supplied from the natural gas network, and the heat source is from the district heating system. The right box contains energy prosumers made of aggregated fixed and/or flexible technologies that individually either consume or produce energy. Fixed technologies have a constant generation or consumption pattern that can not be manipulated when the device is in operation. Conversely, the generation or consumption pattern of flexible technologies can be manipulated to achieve specific objectives, such as a specific demand profile during peak periods. Washing machines, dryers and dishwashers are examples of flexible consumers, while computers and TVs are examples of fixed consumers. Renewable technologies are examples of fixed generators while petrol generators are examples of flexible generators. Conversion technologies such as transformer, CHP, boiler and heat exchanger are in the central box. These technologies convert input energy vectors from energy sources into the output vectors supplied to energy prosumers and storage. EVs are better categorised as storage devices rather than energy prosumers during their charge/discharge operations because they simultaneously perform the function of both energy consumers and producers. However, as EVs are not always connected to the energy network, charging stations are shown in Figure 2.1 instead as they are equipment EVs utilise to recharge their batteries.

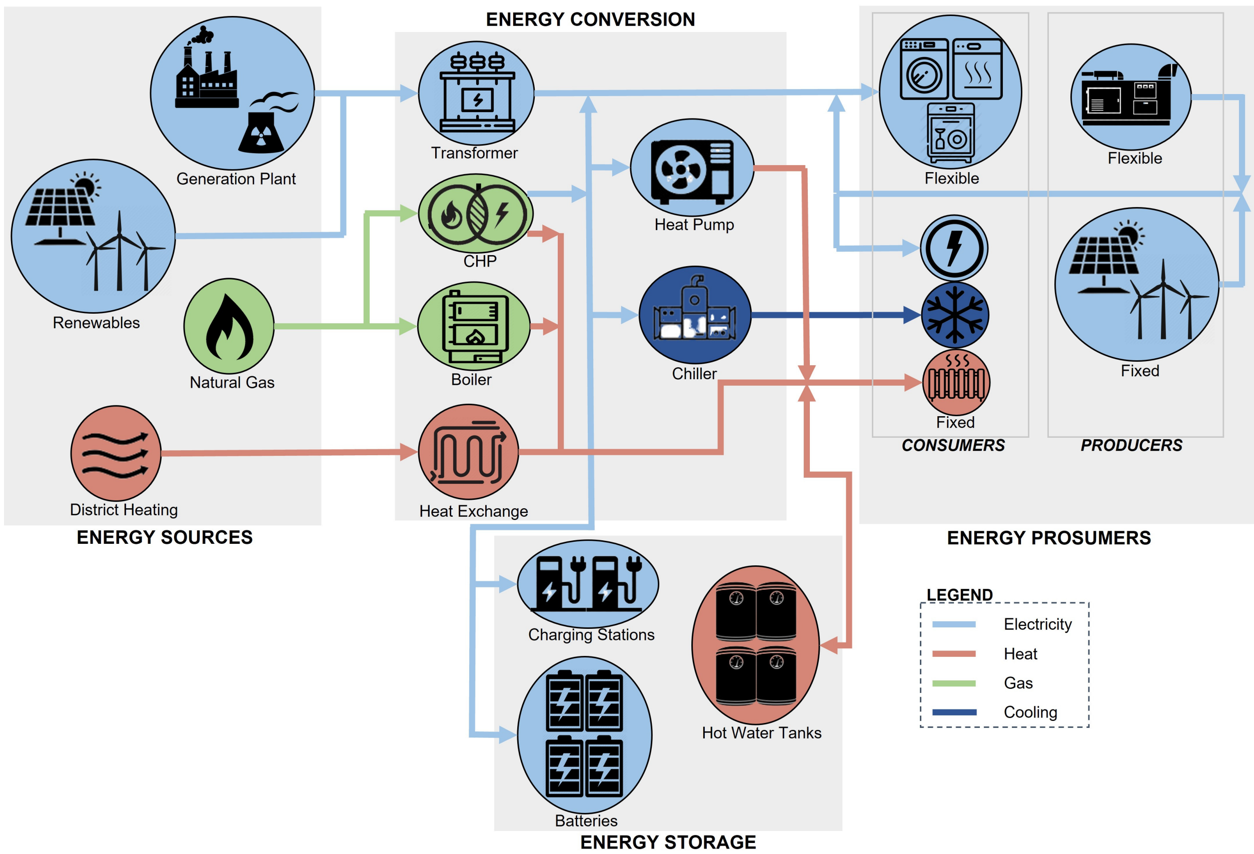

Figure 2.1: Schematic of a multi-energy system

This chapter is organised as follows: The review begins in Section 2.1 with an overview of EVs and the role they play in energy networks. This is followed by a review of the different ways EV battery dynamics have been modelled to facilitate the development of EMS in Section 2.2. Then a review of aggregation concepts relevant to MES modelling in Section 2.3 and works related to IDSM that incorporate EVs in Section 2.4. Overview of EV Sharing Communities and EV aggregators are presented in Sections 2.5 and 2.6 respectively. Finally in Section 2.7, a review of literature addressing coordination of EV utilised in residential, commercial and public areas are presented.

2.1 Electric Vehicles in Energy Networks

One contribution in this thesis is the incorporation of a model representing the charge/discharge operation of mobile storage systems in the novel MES modelling framework in [8] without exact knowledge of the number and type of EVs that will utilise charging stations in the network. Unlike conventional vehicles that use internal combustion engines for propulsion, EVs use electric motors for the same purpose. The fuel sources for conventional vehicles (e.g. petrol and diesel) are stored in tanks located in fuelling stations. Their operation is independent of the operation of energy grids. However, EVs require electricity to recharge their onboard battery to meet their energy needs. Recharging an EV requires it to be plugged into a charging station that is connected to the energy grid. As such, EVs are added devices in energy networks, and knowledge on their types, energy requirements and understanding of their energy needs must be known by network operators. Attempts in literature to coordinate the charge/discharge operation of EVs assume reasonable understanding of how they are utilised [7, 14–16, 18–20, 31, 34–37]. In addition, EV numbers are assumed fixed and possible multiple utilisation of charging stations is ignored. As will be proven in Chapter 4, the benefits of accounting for multiple uses of a charging station within an energy network without exact knowledge of EV numbers will be highlighted. However, a discussion is first presented on EV types, how their charge/discharge operations have been modelled in literature and their impact on future energy networks.

The term EV is generally used to refer to vehicles such as an electric car, electric motorcycle, electric bus, electric train, electric van, and electric truck. EVs have been in existence since the mid-19th century [38]. Their increased adoption in the turn of the 21st century is due to an increased focus on renewable energy and the potential reduction of the transportation sector's impact on climate change and other environmental issues. With the benefits that accompany large-scale adoption of EVs, there are concerns on how to optimally coordinate EVs' charge/discharge operation without negatively impacting the energy grid.

2.1.1 Role of Electric Vehicles in Energy Networks

Future energy networks are projected to comprise a significant number of devices whose power generation/consumption are highly stochastic. EVs are one of the most promising to aid the integration of intermittent and non-dispatchable energy sources such as wind and solar. However, significant penetration of EVs into energy grids will result in large charging loads and will make managing the energy grid difficult for network operators. Highlighted in [10] is that EVs' role in energy network and the benefits they could provide to network operators are mostly focused around four core factors: **cost**, **efficiency of supply**, **emission reduction** and **user comfort**. Some ways **cost** considerations have been addressed are:

- Operational cost minimisation where DERs within single- or multi-energy systems are leveraged in the formation of optimisation problems using generic mathematical methodologies such as non-linear programming and mixed-integer linear programming (MILP) (e.g. [14, 17, 18, 23, 39, 40]).
- Reduction of electricity generation cost from conventional non-RES sources by exploiting the storage capacity EVs provide to aid RES integration in energy networks (e.g. [17,24]).
- Profit maximisation for aggregators that coordinate charging of EVs by leveraging their storage capacity and availabilities to provide ancillary services to network operators (e.g. [23, 28, 36, 40, 41]).
- EV charging cost minimisation by scheduling EV charging operation either when energy costs are cheap, RES generation is in excess or non-controllable energy demands are low(e.g. [15, 16, 23, 34, 42, 43]).
- Minimisation of congestion, investment expenses and transmission cost to avoid redundant capacity been installed in energy network through appropriate charging and discharging control of EVs (e.g. [9, 40, 44]).

Maximising the use of intermittent RES generation, minimising power losses and optimising energy dispatch are ways EVs have been utilised to ensure the **efficiency of supply**. These objectives have also been considered in literature that addresses cost regarding EVs' role in energy networks. Literature exploring charging EVs less from conventional non-RES generation and exploiting their storage flexibility to aid efficient utilisation of RESs address **emission reduction** as such approaches aid curtailing carbon footprint derived from purchasing energy from non-RES generation sources. Approaches in [14, 24, 34, 39] are examples were emissions have been considered. EV **user comfort**s are usually considered in research by modelling the stochastic nature of EV availabilities and energy demands obtained from understanding their utilisation patterns [9,18,20,24,26,34,43,45]. These models are used to estimate EVs' charging demand and when EVs will be available to network operators.

2.1.2 Open Issues

There are numerous benefits EV can possibly contribute to energy networks. However, issues have yet to be addressed on how EVs can be effectively exploited and integrated into energy networks. Major issues are:

1. **Feasibility of bi-directional power flow**

   Bi-directional energy flow between EVs and an infrastructure, generally referred to as V2X, will facilitate EV's role in providing ancillary (such as regulatory and reserve) and storage services and help fix power imbalances in energy networks. However, a large number of EVs have to be aggregated to achieve this. V2X envisions EVs as distributed generators that can inject power back to another entity such as an EV, a building or the energy grid. Numerous literature have explored the benefits of exploiting EVs' V2X capabilities [16, 18, 19, 23, 24, 28, 36, 40, 41]. Presently, only a few EVs have bi-directional power flow capabilities (e.g. the Nissan Leaf and the Mitsubishi Outlander) and these capabilities are not yet fully exploited in control strategies implemented by Distribution Network Operators (DNO)s. As EV adoption continues to increase, and with possible technological advancement for them to all have bi-directional power flow capabilities, control strategies for coordinating their charge/discharge operations will be more complicated. In addition, it will be increasingly challenging to account for the uncertainty in EV owners deciding not to participate in V2X through their EVs have bi-directional capabilities.

2. **EV charge/discharge coordination and information flow**

   Understanding how EVs are utilised and when they will be available to the energy network is key to coordinate their charge/discharge operations efficiently. However, such knowledge is difficult to obtain as EV utilisation is highly stochastic as they are based on drivers' schedules. Attempts to address this are seen in the EV coordination scheme that assumes information flows between EVs and an aggregator/network operator [23, 24]. However, the challenge with such schemes is that when EVs are widely adopted, it will be challenging to coordinate information flow between EVs and aggregators that manage charging stations in different locations EVs will use over time. Predominant alternatives are approaches that utilise historical EV data to estimate the availabilities and energy levels of EVs within a network [16, 18, 19, 35, 45, 46]. Critical assumptions made are that EVs that utilise the charging stations are known, fixed, and charge mainly once over a certain period. However, with the projected growth in EV number over the coming years, it will be expected that charging stations in certain areas will be utilised multiple times over certain periods, drawing parallels to how fuelling stations are utilised today. Hence, these approaches are applicable in specific cases such as sharing schemes where EVs are used for work-related trips or shared within a community, as EV utilisation in these cases can be easily estimated.

3. **Holistic markets and opportunities**

Traditionally, large power plants are compensated for ramping up/down power generation to help maintain supply-demand balance in classical passive energy networks. With current power systems adapting more RESs and DGs, the energy network is being transformed to one with less inertia. This transformation limits the extent large power plants can aid supply-demand balance. Methods mostly researched on how to compensate new active players in energy networks that would help the balancing process are DSM strategies employing incentive or price-based programs [47–49]. These strategies are quite difficult to implement, requiring two-way communication between prosumers and network operators, and are more challenging when EVs are incorporated. Compared to other devices owned by prosumers, EVs lack of fixed presence and known charge/discharge operation profile makes leveraging the flexibility they provide difficult for network operators. In addition, network operators have to consider the owner's charging preference and charge/discharge rate as a function of incentives provided to EV owners. Most investigation into compensation provided to EV owners involved in DSM strategies are done considering individual EV ownership [18, 19, 34, 46], EV sharing schemes [16, 27, 28] or EV aggregators [24, 27, 41, 42, 50]. Compensation to EVs is facilitated through optimal charging strategies, EV involvement in providing peak power to electrical networks from their V2X capability and provision of ancillary services to power systems operators through their interactions with aggregators. However, restrictions are placed on EV types, their mobility and numbers considered in most literature. Hence, limiting their applicability in scenarios where EVs are of diverse nature and their numbers are not exactly known.

2.2 Electric Vehicle Battery Dynamics and Driving Pattern

Models and control strategies developed in literature that incorporate the charge/discharge operation of EVs require battery models that accounts for EVs' SoC and an understanding of how EVs are utilised to extract information on EV characteristics, availabilities and owner's charging preferences. The next subsections explain how these factors have been considered in research.

2.2.1 Types and Battery Model Representation

EV types generally refer to Hybrid Electric Vehicle (HEV), Plug-in Hybrid Electric Vehicle (PHEV) and Battery Electric Vehicle (BEV). HEV runs on a combination of conventional combustion engine and electric propulsion system to achieve better fuel economy or better performance than a conventional vehicle. The onboard battery of a HEV does not require an external power source to recharge. Rather, the battery charges using the petrol engine while the vehicle is in motion. Similarly, PHEV runs on both petrol and electricity. However, unlike HEV, the on-board battery of a PHEV recharges when the EV i plugged into a charging station. A BEV runs exclusively on electricity provided by the onboard battery. A BEV's battery recharges when the vehicle is plugged into a charging station using the EV charging cable. In this thesis, EVs are referred to PHEV and BEV only.

Literature that has incorporated coordinating EV charge/discharge operations together with other DERs within energy networks have generally modelled EV in two ways. One is the aggregated EV charge/discharge power model with a set limitation on the sum of charging/discharging powers of connected EVs [51] or aggregated EV charge/discharge powers required to track a reference power pattern [40]. The second and most used model is the charge level model, which focuses on modelling the SoC of an EV's battery during its charge/discharge operation. There are generally three approaches used to model EV charge/discharge operation in literature. However, there is an evolutionary progression pattern when analysing the different EV models such that they are mutually inclusive. This thesis describes the three models as flexible load model, lossy flexible load model and state-space model.

1. **Flexible load model**

   Using the exact knowledge of the amount of energy EVs will require for their trips and their scheduled charge time, control schemes in [14,20,31,34,43,52] have modelled EVs as flexible loads. This model does not allow exploitation of EVs that have bi-directional capabilities, and the model is generally expressed as

$$\sum_{t=h_{ini}}^{h_{end}-1} P^{+}_{EV,i} = E_{EV,i,ded} = E_{EV,i,end} - E_{EV,i,ini} \tag{2.1}$$

$$0 \leq P^{+}_{EV,i} \leq \overline{P}^{+}_{EV,i} \tag{2.2}$$

   Where $P^{+}_{EV,i}$ is the charging power which accumulates over the period EV i is connected to the network. The accumulated power is set equal to the EV's energy demand $E_{EV,i,ded}$. The time when the EV charging process starts is denoted as h_{ini} and the time the charging process ends is denoted as h_{end}. The initial and final SoC of EV i are denoted as $E_{EV,i,ini}$ and $E_{EV,i,end}$ respectively.

2. **Lossy flexible load model**

   Lossy flexible load model refers to EVs modelled as flexible loads with added consideration of charging losses. This model has been utilised in [19,36,46] and can be generally expressed as

$$E_{EV,i,min} \leq E_{EV,i,ini} + \eta_{chg,i} \sum_{t=h_{ini}}^{h_{end}-1} \delta_{chg,i} P^{+}_{EV,i} = E_{EV,i,end} \leq E_{EV,i,max} \tag{2.3}$$

$$\delta_{chg,i} = \begin{cases} 1, & \text{if EV } i \text{ is available} \\ 0, & \text{otherwise} \end{cases} \tag{2.4}$$

   Where $E_{EV,i,min}$ and $E_{EV,i,max}$ in (2.3) are respectively the minimum and maximum limits that constrain the SoC of EV i during the charging process. Losses during the charging process of EV i are considered using the efficiency factor $\eta_{chg,i}$. The binary variable $\delta_{chg,i}$ monitors the presence of EV i. The multiplication of this variable by the charging power $P^{+}_{EV,i}$

ensures that (2.3) is only implementable when an EV is connected to the energy network. However, when $\eta_{chg,i} = 0$, (2.3) collapses to the equality constraint $E_{EV,i,ini} = E_{EV,i,end}$. This gives the illusion that the EV remains connected to the charging station when the required SoC is reached.

3. **State-space model**

The state-space model representation of the charge/discharge operation of an EV is the most generic as the previous three models can be derived from it. It is mainly used when a realistic representation of charging stations utilisation is required. No information about the EV is unknown by the network or charging station operator when the EV departs, or its charge/discharge process is finished. The model is generally expressed as

$$\begin{aligned} E^{t+1}_{EV,i} = E^{t}_{EV,i} + \eta_{chg} P^{+}_{EV} - \frac{P^{-}_{EV}}{\eta_{dischg}} \qquad & \forall t \in (h_{ini} : h_{end}] \\ E^{t}_{EV,i} = E_{EV,int} \qquad & at\ t = h_{ini} \\ E^{t}_{EV,i} = E_{EV,end} \qquad & at\ t = h_{end} \end{aligned} \tag{2.5}$$

$$\begin{aligned} & \delta_{chg} + \delta_{dischg} \leq 1 \\ & P^{+}_{EV} - \delta_{chg} \overline{P}^{+}_{EV} \leq 0 \\ & P^{-}_{EV} - \delta_{dischg} \overline{P}^{-}_{EV} \leq 0 \end{aligned} \tag{2.6}$$

Examples where this model has been implementation, are in [9, 15, 16, 18, 23, 24, 35, 39, 41]. Some have implemented (2.5) and (2.6) without exploiting the bi-directional capabilities of EVs. Energy losses during an EV's discharging process are represented using the binary variable δ_{dischg}. The discharging power is denoted as P^{-}_{EV}. The charging/discharging process of an EV begins at h_{ini} with a SoC of $E_{EV,ini}$ and ends at h_{end} with a SoC of $E_{EV,end}$ usually set by the driver or set to charge fully. Constraint (2.6) is implemented to prevent simultaneous charging and discharging of the connected EV. The state-space model is in operation only within the period $h_{end} - h_{ini}$, after which the SoC of the EV is unknown and is of no concern to the network operator.

Literature that has utilised the three models assume that multiple uses of a charging station or multiple recharging of an EV do not occur. Control schemes are mainly designed considering fixed EV numbers of specific types. However, as exponential growth in EV adoption is projected to increase in the next decade, multiple recharge operations of an EV at a private charging station or multiple utilisation of a public charging station will become a common occurrence. Hence, proposed control schemes that modelled EVs using the three models mentioned above limit their applicability in real-world scenarios. Therefore, an opportunity presents itself for further development of a generic EV charge/discharge operation model that captures the multiple utilisation of charging stations by EVs within energy networks.

2.2.2 Electric Vehicle Driving Patterns

To design an adequate control scheme for energy systems requires an understanding of the system use case. This approach influenced research in DSM, as an understanding of fixed technologies through the collection and analyses of generator and demand data and the operation of flexible technologies through integrating user preference on devices operation, influenced the performance of proposed control scheme and the incentive structure in DSM strategies. The energy system use case has also been considered in proposed EMSs that have incorporated EV charge/discharge operation. The use case considered in designing such EMS is generally based on whether the EVs are recharged using charging stations in a residential, commercial or public energy network. Defining the use case requires an understanding of EVs' characteristics, availability and owners charging preferences. These factors are highly stochastic and need to be known by the network operator to adequately exploit the flexibility EVs may provide to the energy network.

Highlighted in Chapters 1, is that network operators view EVs differently from other devices that exist within an energy network. Specifically, they are viewed as non-permanent end-user devices in energy networks. Especially in commercial and public energy networks where it isn't easy to know which EV will utilise a specific charging station and if they will choose to participate in bi-directional energy exchange all the time. This has lead researchers to investigate, analyse and model EVs based on their driving patterns to better plan and operate energy networks to incorporate better the uncertainties they introduce. EMSs that have incorporated EVs mostly estimate their utilisation:

1. Assuming a typical EV users driving schedule follow specific probability distribution.

2. EV utilisation is estimated from information data collected from driving survey or trials.

Where an EV driving schedule follow a specific probability distribution, the EV information required to design the EMS are mostly extracted from either uniform distributions as in [16, 23, 41, 42] and/or normal distribution as in [17, 24, 35, 37, 41, 43, 51]. Chi-square distribution has also been used in [16]. These distributions are mostly arbitrary and do not match realistic EV utilisation. Information on a group of EVs in the aforementioned literature is mostly extracted from the same probability distribution. To obtain EV utilisation information under real-world conditions, some researchers have extracted information from data collected from individual EV utilisation and used it to validate proposed control schemes. The EMS proposed in [7] utilised data from a Hunan travel survey conducted in China, and EMS proposed in [18–20] utilised data collected from EVs utilising charging stations on UCLA campus.

A critical piece of information not included in the EV data utilised in most literature is the multiple uses of a charging station over certain periods. Highlighted in Section 2.1, is that accounting for this is essential, especially when charging stations are utilised multiple times in commercial and public areas like how fuelling stations are utilised today. At the time of writing, only data from the "My Electric Avenue" project led by EA technology in collaboration with the UK DNO Scottish and Southern Energy Network [53] includes the number of times charging stations are utilised. To the best of the author's knowledge, this data is the only one that includes multiple utilisation of a charging station together with EVs' start time and initial and final SoC. Hence, it is used to validate the stochastic EMS proposed in Chapter 5.

2.3 Multi-Energy Systems Modelling

Similar to research addressing the charge/discharge coordination of EVs, research in MES are based on the same four core factors: **cost**, **efficiency**/security **of supply**, **emission reduction** and social acceptance, which includes **user comfort**. Research in MES addresses the issue of affordability, reliability, and sustainability of energy networks using this four factors termed the energy *'quadrilemma'* in [54]. However, balancing the different dimensions of the quadrilemma poses a challenge. Part is the lack of a detailed MES modelling framework capable of representing synergy between different energy sectors and integrating of DERs, which can be used to highlight potential benefits and possible drawbacks of energy systems integration. Modelling MES has generally been approached using the MicroGrid (MG), Virtual Power Plant (VPP) or Energy Hub (EH) concepts. The CIGRÈ C6.22 Working Group [55] defines MGs as:

Electricity distribution systems containing loads and DERs (such as distributed generators, storage devices, or controllable loads) that can be operated in a controlled, coordinated way either while connected to the main power network or while isolated.

In [56], a VPP is described as:

A flexible aggregation of DERs (including MGs) that are coordinated in an optimal way, are capable to play in the energy market, and offer services in the same way as conventional large-scale power plants.

Both the MG and VPP concepts constrain application to single-carrier energy system, specifically in the electricity domain. Compared to both, the EH has been favourable and has drawn the attention of power and energy systems research communities. The EH focuses beyond the electrical networks by providing a framework in which synergies among various energy forms can be optimally exploited. It was initially proposed within the vision of future energy networks (VOFEN) project [57] with focus set on the long-term evolution of energy networks (around 50 years). The project identified three key features expected of future energy networks: multi-carrier system, non-hierarchical structure, and hub network, intended to be achieved using the greenfield approach. This involves neglecting restrictions imposed by existing systems and developing a new system structure from scratch with the aim of achieving hidden optima that might exist behind present system structures [58]. First modelled in [59], the EH is described from a system point of view to represent:

A part or a unit of mixed energy carrier power system providing basic features of input and output, conversion and storage of different energy carriers.

It has been used extensively to model and analyse MES in numerous studies and has been applied to address concerns of optimal operation [60, 61], planning and investment [62, 63] and reliability assessment [64, 65]. Figure 2.2 shows an example of an EH. Models developed using the EH framework have acceptable representations; however they assume unidirectional power flow. In addition, the framework does not represent all possible combination of energy flow, assumes that losses only occur in conversion devices and require parameters that describe the splitting or combination of energy carriers.

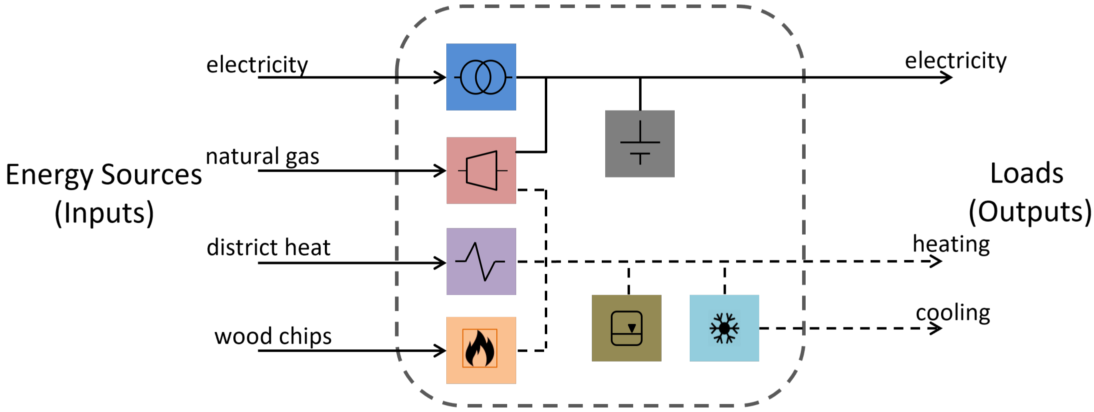

Figure 2.2: An energy hub containing a transformer, CHP, boiler, battery and hot water storage (Redrawn from [1])

Within the EH, a forward conversion matrix is used to connect inputs to outputs. This limits the extent to which DERs such as EVs, PVs and fixed storage systems on the demand-side can be exploited as reversed direction of energy flow from outputs to inputs can not be represented. Although the EH has significantly aided research in MES, to effectively analyse optimal performance of multi-carrier energy systems, it is necessary to develop a more detailed modelling framework of a multi-carrier energy system that address the EH short fall. Still employing a system point of view with the use of graph and network theory, a novel approach to modelling EH is presented in [66] that addresses the limitation of the original EH framework by accommodating bi-directional power flow and placing a distinction between input and output terminals. In addition, a more detailed description of the model of multi-carrier energy system is presented as:

A representation of energy delivery system by multiple energy carriers which associates power load or embedded generation, energy transmission/distribution infrastructure as well as devices suitable for: energy conversion between particular carriers, transformation of energy parameters and energy storage.

However, it is argued in [67] that by allowing varying ratios between the output branches of the multi-terminal converters such as CHPs that outputs more than one energy carrier at varying ratios, the approach does not represent physical energy converters or embedded generation as these ratios should be fixed. This augment implies that the EH model presented in [66] does not fully represent the description of the model of multi-carrier energy system defined within. The authors in [67] then presents a new MES modelling framework to address the shortfalls in [1] and [66]. Further development of the framework are presented by the same authors in [8, 32, 33], extending the original EH framework and presenting a novel COMMES framework. This new framework eliminates the need for parameters that describe the splitting or combination of energy carriers and the need for varying ratios of output branches of multi-terminal converters. The assumption that losses within EH occur only in conversion devices is relaxed as this approach considers losses through energy distribution and transmission network. Significantly, the prosumer characteristics introduced enables explicit consideration of DSM, not considered in [59, 66], by allowing controllable and uncontrollable embedded generation and/or load devices that may be owned by end-users. The different combinations of the four flexible prosumer characteristics introduced can be used to model individual controllable devices linked to user comfort and preferences. Resulting models using the COMMES framework maintain an accurate representation of physical converter devices and are well suited for software implementation.

A shortfall of the aforementioned MES modelling frameworks is that they exclude the representation of mobile technologies such as EVs that will connect to energy networks. These MES modelling frameworks, although developed from a system point of view, assume that the location of aggregated technologies are fixed with their location known and reasonable understanding of their generation/demand pattern known by network operators. EVs do not fit these assumptions as they can connect to any charging station within an energy network at any time, and their charge/discharge patterns depend on their characteristics, availabilities and owners' charging preference. Increase adoption of EVs means network operators need to consider new large loads, and with the concept of V2X, EVs can act as distributed generators or storage systems that can be exploited by network opertors. Given these reasons, an opportunity presents itself to provide a MES modelling framework that addresses the short fall of the aforementioned studies. Specifically, provide a modelling framework that includes a model representation of mobile storage systems that is adaptable in any topological order and has a systemic approach that can be seamlessly integrated in a model of single- and multi-carrier energy system. Although technologies are not modelled in detail using the COMMES framework and power flow are mainly characterised using real power and conversion efficiency as with the original EH framework, to the best of the author's knowledge, COMMES is the only modelling framework that gives a holistic view of MES that enables DSM strategies to be exploited. Hence, it is the framework used in this thesis.

2.4 Integrated Demand-Side Management

DSM aims to redefine the approach of balancing power supply and demand by exploiting flexible generators/loads owned by end-users. Research on DSM implementation has been focused on electrical power systems; this is justifiable as demand for electrical energy is significantly large compared to other energy forms as shown in Figure 1.1, and is projected to increase in future. As discussed in Section 1.1, the move to de-carbonize all energy sectors and exploits synergies between various energy forms has influenced research thinking to explore MES. The core concept of MES brings new insights for DSM under a generalised concept called integrated demand-side management (IDSM) [68]. The ability to switch between different energy carriers or storage systems and conversion technologies, integrated with different smart technologies, create more flexibility in IDSM strategies and improves the reliability of MES. In [49], it is highlighted that research and engineering projects on IDSM have widely been investigated in the past decade with most of the existing studies focusing on the optimal operation of MES considering demand response (DR). A key issue discussed in [49] about existing studies is that they do not provide precise models to represent multi-energy consumption for accurate implementation of IDSM. The COMMES framework [8], to the extent of its development, addresses this issue. Specifically, the set of fundamental flexible prosumer model characteristics introduced allows individual end-user devices to be modelled. This is achieved by combining four flexible model characteristics to represent a full range of IDSM flexibility considering specific device operation and user comfort. End-user devices such as washing machines, dryers and dimmable lights can be modelled using the flexible prosumer models presented in [8]. However, as already mentioned in Section 2.2, the current structure of the COMMES framework can not be used to represent a generalised charge/discharge operation of EVs.

Despite the benefits EVs provide over conventional vehicles and their impact on distribution grids [10–12], research on a holistic approach on their integration in DSM has been ignored. Literature that has addressed EV integration in DSM or IDSM are tailored to specific case-studies with EVs charging schedule defined or estimated from EV driving patterns. An argument can be made that accounting for uncertainties regarding EV characteristics, availabilities and charging preferences are contributing factors as to why a systematic approach addressing the coordination and aggregation of EV charge/discharge operation, weather integrated in DSM strategies or not, is yet to be developed. One approach used to address EV integration in DSM take the view of coordinating EVs owned by individuals utilising buildings in residential or commercial areas [14, 15, 31]. In these cases, understanding of specific EV drivers' schedules are obtained assuming EVs are used for specific tasks. This makes estimating their characteristics, availabilities and charging preferences trivial. Another approach is to exploit concerns on the operational and maintenance costs associated with individual EV ownership, to propose EV sharing schemes focused on EV utilised by individuals in a residential and business setting [16, 27, 69]. Some have gone further to proposed coordination schemes that investigate how EVs can be integrated into energy networks on a large-scale employing EV aggregator and exploring the services they can provide to EV owners and network operators [36]. However, the aforementioned studies exploring EV sharing schemes and EV aggregators, model EVs based on the case study considered, and for simplicity, the operation of other controllable devices within the network are excluded.

2.5 Electric Vehicle Sharing Communities

An increasing number of EVs connecting to the energy grid has raised concerns about the ageing grid infrastructure and how grid limits can be maintained while coordinating EV charge/discharge operations. In addition, the operational cost involved in owning and maintaining EVs are becoming significant concerns [27]. As such, EV sharing schemes have emerged mainly in residential [27, 28] and commercial [16, 18, 69, 70] sectors to give individuals the opportunity to utilise EVs without bearing the operational and maintenance cost associated with owning it.

Although government stimulus and subsidies have been driving forces influencing EV adoption, EVs are still quite expensive for individuals to own. EV sharing schemes employ a system where a group of people make reservations, and an aggregator is responsible for coordinating EV charging and reservations. Some proposed in literature are in [16, 18, 27, 28]. However, a significant amount of sharing schemes has been implemented in countries around the world. To help reduce operation cost, Autolib' was an EV sharing company in France that provided affordable subscription service to specific private EV owners to charge their vehicles at most twice a day at designated Autolib' stations [70]. The German company Share Now provides car-sharing services to subscribers across 16 cities in Europe that completely eliminates the need for individual EV ownership by providing EV fleet to be rented [69]. Some other companies that provide similar services are BlueSG in Singapore and the pilot program between Kandi Technologies and Hangzhou, China.

The aforementioned EV sharing schemes cater mostly to residential and commercial areas, with a focus on providing EVs with sufficient charge levels drivers can use and coordinating EV charging in specific locations. However, it is still unclear how EV availabilities and user reservations can be synchronised with times when DNOs will require them to provide ancillary service or at times when their storage capacities will be required by RES suppliers. There seems to be more promise with commercial fleets where EV are strictly used for work-related trips or by individuals in a community. In such approaches, EV availabilities are easily estimated based on drivers daily activities and the locations where the EVs charge can be determined. As such, there is increasing interest in addressing how small EV fleet can be coordinated, especially with local RES [16, 18, 27, 28].

2.6 Electric Vehicle Aggregators

Large-scale integration of EVs either through aggregating individual EVs or EV fleets/sharing community ultimately means new loads to electric utilities, and undesirable congestions and voltage problems may exist in distribution network during their charging process [71]. In addition, coordinating EV charge/discharge operations together with RES in energy networks compounds the problem. As a result, smart charging solutions, including V2X, are needed to make EVs not only loads but also assets to network operators. To facilitate this, EV aggregators have been widely proposed to act as an intermediary between EV fleets and network operators as an alternative to small communities bearing the responsibility of coordinating their EV fleets [11]. Alternative names to EV aggregators used in literature are EV fleet operators, EV VPPs, EV charging service providers and EV service providers [11]. EV aggregators take advantage of smart metering infrastructure that enable two-way communication between them and individual EVs. This enables EV aggregators to develop an understand of EV drivers' schedule and use that information to inform network operator when EV are available to provide ancillary services. EV aggregators usually operate without considering RES generation technologies. Instead they focus on coordinating EVs and providing services to network operators and RES suppliers [11]. For transmission network operators (TNO), a large poll of EVs can be used to provide frequency regulatory services. EVs are also attractive alternatives to large generators with high prices as the large EV pool size compensates for stochastic variations in EV availabilities and guarantees larger regulation power per vehicle [72]. Aggregators can also help DNO prevent grid congestion (i.e. reduce peak load and power losses) as employed in [73, 74] and voltage regulation as in [75, 76].

The impact of using large-scale EVs to aid RES generation integration has been investigated using the Denmark and Dutch power systems [77, 78]. Results in [77] indicate that exploiting V2G from EVs allows integrating much higher levels of wind and reduces national emissions. The study in [78] concluded that an increase from 4GW to 10GW is possible if around 1 million EVs are connected to the Dutch network. Aggregators can facilitate these benefits by taking advantage of smart metering infrastructure to obtain information about EV driving patterns. This approach will indirectly handle uncertainties regarding EV availabilities and energy demands. However, both investigations assume that all EVs either participate in V2X or not and the impact of multiple utilisation of charging stations was not investigated. Nevertheless, several obstacles are still present, mainly concerning the spatial and temporal stochasticity of the power demand of EVs and the charging stations they will utilise to recharge their batteries. The current opinion in scientific literature is that existing energy networks and EV management systems are not yet ready to support large penetration of EVs [50].

2.7 Management of Electric Vehicle Charge/Discharge Operations

Developing EMS that coordinate EVs' charge/discharge operation is significantly influenced by EVs' characteristics, availabilities, and charging preferences that utilise charging stations within an energy network. The predictability of these factors vary and are different when EV are recharged in residential, commercial and public areas. These factors are easier to predict in residential areas than others, as EV owners will likely have their individual charging stations installed on their property. In this case, EVs that utilise particular charging stations are known, their respective availabilities easily estimated from drivers routine, and EV owners charging preferences will likely be consistent. EVs utilising charging stations connected to office buildings are example cases in commercial areas. Here, EVs are usually owned by the building occupants or are EV fleet owned by a business. Hence, their characteristics and availabilities can be easily estimated from commuters daily routine or work-related trips in the case of EV fleets owned by a company. Charging stations in commercial areas are not individually allocated to or owned by particular drivers. However, their utilisation can be easily estimated, and some can be utilised multiple times over certain periods. In public places such as off-road parking and parking lots, it will be challenging to determine a pattern of how charging stations are utilised. Charging stations can be utilised by EVs from anywhere. In addition, charging stations can be operated multiple times over a certain period, and there will be inconsistencies in EV owners' charging preferences. However, it can be assumed that charging station utilisations are based on EV owners whose daily routine involves visiting places where these charging stations are located. Hence, although EV characteristics, availabilities and charging preferences will be highly stochastic, a pattern of charging station utilisation can be obtained.

The following three sections review literature proposed that incorporate EV charge/discharge operations in EMS and is applicable to residential, commercial, and public areas. To the best of the authors' knowledge, this is the best way to present a clear review of attempts to coordinate EV charge/discharge operations. In addition, these literature assume that all EVs either participate in V2X or not and that multiple utilisation of charging stations by the same or different EVs over time is not considered.

2.7.1 Management in Residential Areas

An assumption usually made in EMS that incorporates the charge/discharge operation of EVs in DSM strategies is that the characteristics of EVs and their respective availabilities are known precisely. Strategies presented in [14,15,31,79] model EVs based on this assumption. In [14,31] EVs are modelled as flexible loads in the network. The two EVs considered in [31] demand the same amount of energy and are scheduled to charge over specific time periods. In [14], the energy demand of the 8 EVs are estimated from their travel distance and energy consumption. In addition to EV characteristics and availabilities, the SoC at arrival and departure of the 2 EVs incorporated in the home energy management system (HEMS) in [15] are provided, making estimating energy demand over the EVs'charge/discharge period easy. In [79], the aggregated EV charge/discharge profile is required to follow a general V2G/G2V profile, indirectly setting the specific amount of energy consumed by each EV. However, EVs are not restricted to predefined schedules in reality, and energy consumed by EVs during different charging sessions will vary.

EVs utilised in residential areas have small uncertainty regarding their characteristics, availabilities and charging preferences. As stated previously, individual EVs will likely be owned by the resident, and their availabilities will be highly dependent on residents' daily schedules. In addition, most will likely participate in V2X, especially if EVs are charged overnight. Some management schemes have attempted to account for and capture these uncertainties. In [39], a collaborative evaluation of dynamic-pricing and peak power limiting-based DR strategies is presented. Results show significant cost reduction when the proposed strategies are combined with the willingness of EV drivers to charge their EVs with lower prices and the storage capacity of fixed storage are exploited. However, to address EV related uncertainties, a two-way energy transaction between end-users and the utility is assumed. In the optimal scheduling model proposed for a regional multi-energy prosumer in [7], EVs' charge period and initial SoC are estimated from data collected from the Hunan household travel survey. However, unrealistic assumptions are made about EVs considered as they are all the same type and have the same charge period and initial battery SoC. Some researchers have directly considered EV related uncertainties in the development of EMS in residential areas. A robust approach is presented in [34] to design a DSM strategy for EV charging based on MPC. The approach considers a worst-case scenario by setting a boundary on the maximum possible charging loads to consider possible unknown charging requests by EV drivers. As uncertainties are often considered to have a probabilistic nature in real-world systems [80], an optimal charging/discharging control strategy that considers uncertainties of EV start charging time and initial SoC is proposed in [9]. EV-related uncertainties are sampled from the same uniform distribution. Three control modes are evaluated, and an aggregator is used to coordinate the interaction between EVs and the DNO considering operational costs and system constraints. A similar approach is used in designing the optimal bidding strategy for an EV aggregator participating in the day-ahead energy and regulation markets [41]. However, the strategy is proposed for night residential charging as EV drivers are more willing to participate in V2X when charging their EVs overnight, and their respective driving patterns are more easily predictable.

2.7.2 Management in Commercial Areas

Beyond residential areas and as EVs are adopted widely, EVs can be parked and charged in commercial areas such as office buildings. In addition, EVs could be part of a fleet managed by a business and used to perform work-related activities. As such, the degree of uncertainty regarding charging station utilisation will be more significant compared to those located in residential areas. Some researchers have made attempts to incorporate more uncertainty regarding EVs in their proposed schemes. However, some assumptions made restrict their approaches to be well suited to coordinate EV charge/discharge operations for specific case studies in commercial areas.

In [36], the control scheme proposed allows EV owners in the dutch market to provide regulating and reserve power to the grid. The authors classify EV drivers into three user types: resident, commuter and resident-commuter. It is assumed that the drivers have consistent travel patterns, and EVs are only utilised during weekdays. However, because of the restrictions on travel patterns and the days EVs can be used, the proposed approach is more suited to EV fleets used specifically for commutes to offices as their availabilities are quite long. Other EMSs well suited to manage EV fleet are the scheme proposed in [46] that incorporates battery swapping stations for aggregated EVs, the power source sizing strategy proposed in [37] that considers the characteristics of EVs, and the scheduling scheme in [51] that integrates RES were most EVs are available to the microgrid between 7 am and 5 pm. However, it is quite unclear how individual EVs impact the control schemes proposed in the aforementioned literature as results are presented based on aggregated EV charging powers and/or SoC. The scheduling scheme proposed in [35] for EVs that charge at home and the office captures some EV related uncertainties. However, only uncertainties in EV availabilities are considered. In addition, similar to the schemes proposed in [37, 46, 51], EVs'SoC are aggregated with limits set between 0.3 and 1 units.

EMS proposed by authors in [16, 18–20] are based on EV randomly projected driving schedule. The schemes incorporate individual EV characteristics and availabilities, and decides each EV's charging/discharging strategy separately. The stochastic DSM proposed for a commercial building in [18] is validated using data collected from the UCLA charging network that contains EVs' arrival and departure times (availabilities) and energy demands. The two-stage stochastic approach is used to optimise day-ahead transactions considering the uncertain nature of renewable generations, loads and EVs. The same data is used to validate the scalable and privacy-preserving DSM for a distribution grid proposed in [19] and the predictive scheduling framework for EVs in [20]. These proposed schemes are well suited to work commuters who charge their EVs at the office, stay connected over long periods, and all decide to participate in V2X. In addition to incorporating uncertainties relating to individual EV characteristics and availabilities, the EMS proposed in [16] to analyse the interaction between PV and EVs allows EV drivers to opt-in or out from the management scheme. However, EVs considered are of the same type and are used only for work-related trips.

2.7.3 Management in Public Areas

It can be expected that the utilisation of charging stations in public areas will be similar to the utilisation of fuelling pumps by conventional vehicles with combustion engines. Coordinating the charge/discharge operations of EVs that utilise public charging stations is quite challenging. It is challenging because the degree of uncertainty regarding estimating the characteristics, availabilities and charging preferences of EVs utilising charging stations in public areas is more significant than in residential and commercial areas. Some researchers have proposed control schemes that seem well suited to coordinating EVs' charge/discharge operations utilising public charging stations. However, assumptions made in the development of proposed techniques limit their applicability to specific cases.

The scheduling scheme in [23] requires EV owners to submit their arrival time, parking duration and minimum SoC at departure to an intelligent parking lot operator through a mobile application. This requirement reduces the difficulty of handling uncertainties related to charging station utilisation in public places. However, the approach fails to consider EVs not meeting their defined schedule in real-time and limitations in coordinating communication between individual EV drivers and parking lot operations on a large scale. In [43], an optimal bidirectional charging control strategy is proposed for a public parking facility. The control strategy employs a two-stage approach to decide day-ahead energy price and EV charging profiles. Then in real-time, coordinate individual EV charging so that aggregated charging profiles follow the optimal profiles determined in the first-stage. A similar approach is used in [24] to design a two-stage economic operation for a microgrid. Estimate of EV availabilities and initial SoC are drawn from a probability distribution. It is assumed a set number of EVs will plug into specific charging stations when they arrive. An MPC-based strategy is implemented to accommodate uncertainty brought on by the real-time variability of EV parking behaviours. An MPC-based approach is also adopted in the power dispatch method proposed in [17] to accommodate EV related uncertainties. However, the number of EVs charging can vary but are limited. In [42], a local optimal scheduling scheme is designed for groups of EV. EV arrival times, charging periods, and initial SoC are estimated from uniform distributions to help estimate each EVs' charging power. Then in real-time, each EVs' charging power is updated using a sliding window.

Naturally, the expectation is that charging stations in public areas will be utilised by EVs with different characteristics, availabilities and charging preferences as these charging stations are not owned by or allocated to specific drivers. In addition, multiple utilisation of charging stations are expected over certain periods. The aforementioned studies do not consider these factors as the proposed control strategies accommodate specific EV numbers, which are assumed to charge once over a certain period. In addition, individual EV charging preferences are not considered as all EVs in each literature either participate in V2X or not.

2.8 Chapter Summary

The literature reviewed in this chapter has highlighted the opportunity within the field of EV charging/discharge coordination within single- and multi-energy systems (with a control oriented emphasis). A summary of this chapter is presented below:

- In Section 2.1, EVs role is energy networks is discussed based on the energy *'quadrilemma'* which are guidelines to aid efficient coordination EV charging/discharge operations within any energy network. However, it is highlighted that major issues still have to be addressed as existing approaches do not offer a systematic way to incorporate EV Charge/discharge operation in energy networks.
- EV types and how EV battery model have been modelled in literature are discussed in Section 2.2. Also discussed is how estimates of EV characteristics, availabilities have been extracted from EV utilisation data and used to validate EMSs in literature.
- In Section 2.3, the EH concept together with microgrid and VPP concepts are discussed as popular approaches to the modelling of MES. However, it is highlighted that these concepts do not readily offer a generalised approach to modelling MES. In particular, the EH concept does not allow representation of bi-directional energy flow, while the microgrid and VPP concepts are constrained to single-carrier energy systems. The novel COMMES framework readily address the shortfalls in these concepts how it is not readily suited to represent EV charge/discharge operations.
- Three major concepts utilised in proposed EMS that have incorporated EV charge/discharge operation are explored in Section 2.4, 2.5 and 2.6. As end-users are major adopters of EVs, a brief discussion IDSM strategy is presented in Section 2.4. Concerns regarding ageing grid infrastructure, and the operational and maintenance cost involved in owning EVs lead researchers to explore the concept of EV sharing communities discussed in Section 2.5. In Section 2.6, the concept of EV aggregator is discussed. EV aggregators are viewed as attractive intermediary between EVs and network operators that can aid coordinating large EV fleets to help limit undesirable grid congestions and voltage problems. However,

it is highlighted that research that have explored these concepts propose EV management schemes that are applicable in specific cases.

- Review of EMS that have incorporated EV charge/discharge operations in single- and multi-energy systems is presented in Section 2.7. The review is presented based on proposed EMS applicability in residential, commercial and public areas. A clear distinction is made between EMS applicability in these areas based on the degree of uncertainties related to individual EV characteristics, availabilities and charging preferences. Hence, an opportunity presents itself for the development a systematic approach to incorporate EV charge/discharge operations in energy network operations that is not applicable to specific cases.

Chapter 3

Preliminaries

This chapter provides discussion on topics that are prevalent in and influenced the remainder of this thesis. Section 3.1 presents an overview of the original COMMES framework. The stochastic programming approach employed to address uncertainties from generation and demand sources in this thesis is introduced in Section 3.2. The MPC methodology used to demonstrate modifications to the original COMMES framework is discussed in Section 3.3. Finally, the software tolls and added extensions used are presented in Section 3.4.

3.1 Control-Oriented Modelling Framework for MES

As highlighted in Chapter 1, one of the contribution in this thesis is the extension of the novel COMMES framework to include a representation of mobile storage systems. The COMMES framework was originally developed as a unified modelling framework capable of representing energy converter topologies of arbitrary complexity containing multiple energy vectors [33]. The framework can incorporate the full range of flexible sources within MES and is capable of representing multi-directional energy flow, multi-generation and multi-mode devices as well as a wide range of controllable prosumers and energy storage devices. COMMES can be used to model single- and multi-energy systems, and is not limited by spatial boundaries. The COMMES framework extends the EH concept initially introduced in [59] and models DERs of various energy carriers within EH under three components: the Energy Conversion Model (ECM), the Prosumer Model (PM) and the Storage Model (SM). A schematic of a single EH

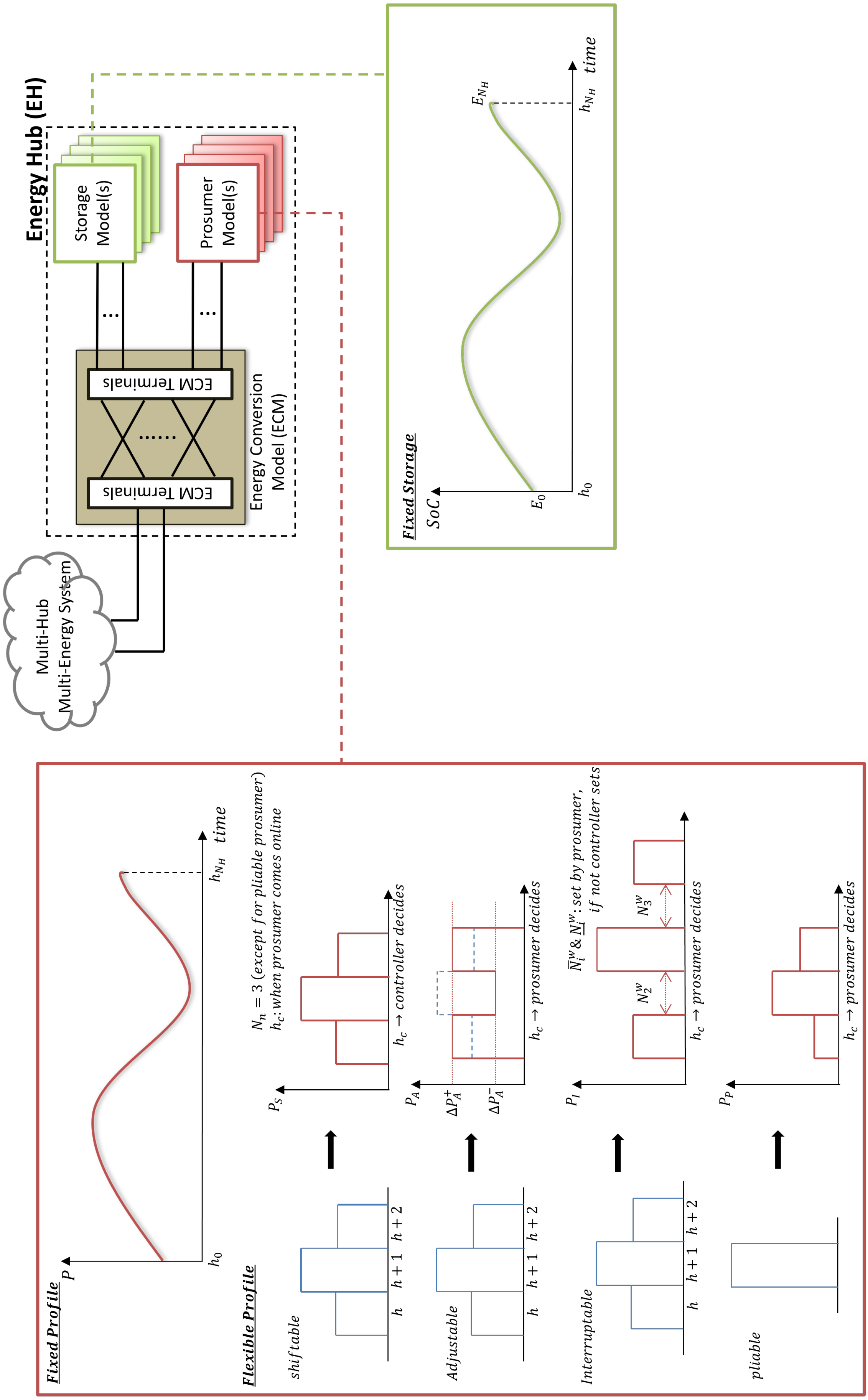

Figure 3.1: An illustrative overview of COMMES framework

is depicted within the overview of COMMES framework shown in Figure 3.1. The next three subsections explains these three components and has been extracted from [33]. For further background, the reader is referred to [33], and references therein.

3.1.1 Energy Conversion Model

Assume the topology of the EH within Figure 3.1 is shown in Figure 3.2. Within the EH, an ECM is used to describe the flow, conversion and splitting of energy carriers. An ECM representation is based on graph theory, is fully characterised by the set of nodes it contains and the associated arcs that provide mutual interconnections between the nodes, with each node associated with an energy carrier [33]. The ECM graph representation of the EH shown in Figure 3.2 is shown in Figure 3.3.

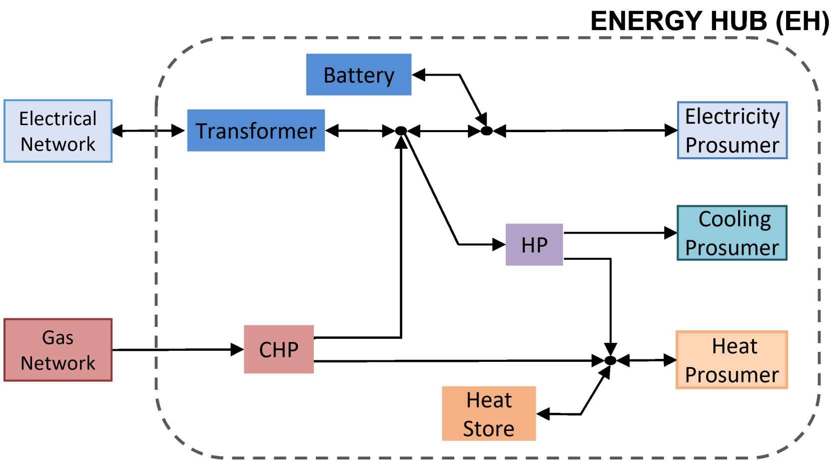

Figure 3.2: Example energy hub topology

$P_{(n_i \to n_j)} \geq 0$ represents power flow from node n_i to node n_j by means of a connecting arc. n represents an energy carrier and j, i represent corresponding node indices. Each arc has an associated efficiency factor $\eta_{(n_i \to n_j)}$ that affects the amount of power arriving at the receiving node. Set of sink nodes that n_j connects to is denoted as $I_{n_j \to}$ and set of source nodes that connects to n_j is denoted as $I_{\to n_j}$. Nodes within the ECM belongs to one of the following: *sum*, *transmitter*, *switch* and *terminal nodes*. Sum nodes describe the splinting and combination of an energy carrier. The power balance at a sum node is given by:

$$\sum_{i \in I_{\to n_j}} P_{(n_i \to n_j)}(k)\eta_{(n_i \to n_j)} - \sum_{k \in I_{n_j \to}} P_{(n_j \to n_k)}(k) = 0 \tag{3.1}$$

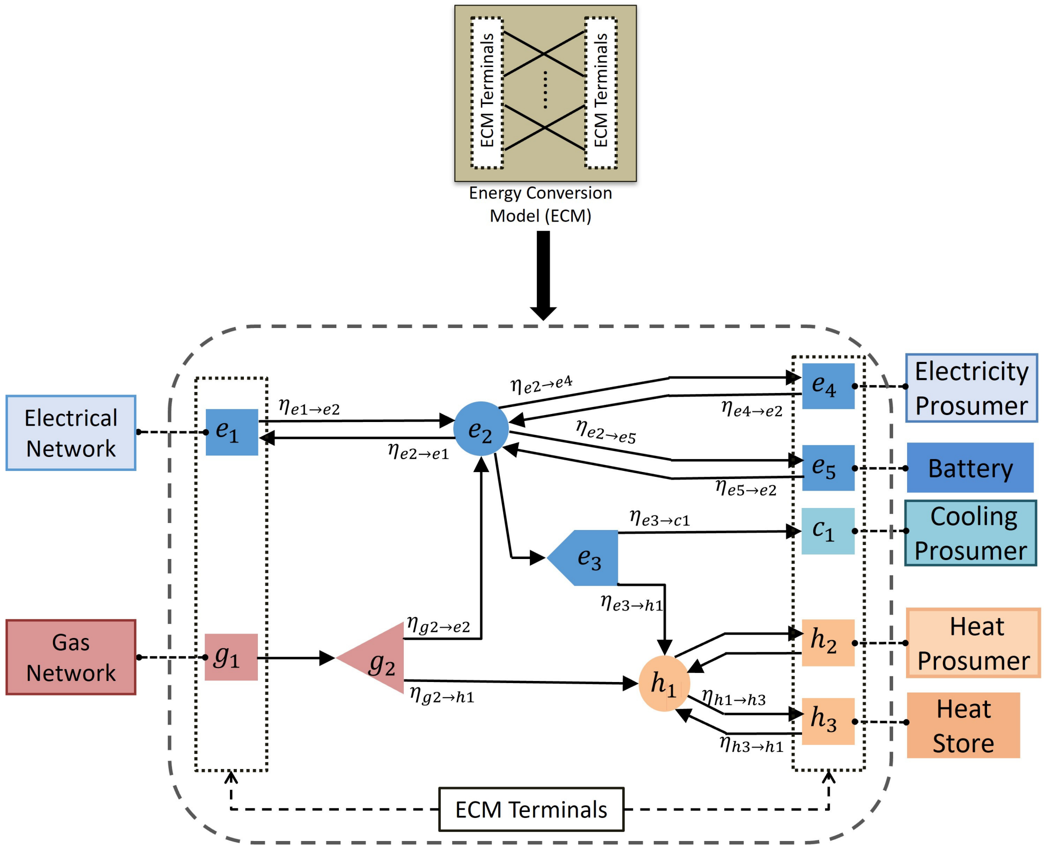

Figure 3.3: Example energy conversion model

Co-generation devices such as CHPs are modelled as transmitter nodes by requiring that each outgoing arc flow values are equal to the sum of incoming arc flows:

$$P_{(n_j \to n_k)}(k) = \sum_{i \in I_{\to n_j}} P_{(n_i \to n_j)}(k)\eta_{(n_i \to n_j)} \qquad \forall k \in I_{n_j \to} \tag{3.2}$$

Devices such as HP are modelled as switch nodes. They are similar to sum nodes with added mutual exclusivity constraints to ensure only one outgoing arc is enabled during different operating modes. Added binary decision variables $\delta_{(n_i \to n_j)}$ associated with outgoing arcs determine the active mode:

$$\begin{aligned} &P_{(n_i \to n_j)}(k) > 0 \iff \delta_{(n_i \to n_j)}(k) = 1 \qquad \forall k \in I_{n_j \to} \\ &\sum_{i \in I_{n_j \to}} \delta_{(n_j \to n_i)} \leq 1 \end{aligned} \tag{3.3}$$

Finally, terminal nodes represents interfaces to components outside the ECM. Examples of these components are energy network (electricity and gas), prosumers (set of fixed and/or flexible generators and/or consumers), fixed storage systems. Terminal nodes can be further sub-divided into three: input, output and input/out nodes. The terminal node type depends on whether power flows in or out of the ECM. Input nodes have a single outgoing arc and facilitate energy import to the ECM. Conversely, output node have a single incoming arc and facilitate energy export from the ECM. The input/output nodes have both a single incoming and single outgoing arc connected to the same adjacent node. Input/output nodes allow entities within MES connected to this node to both import and export energy. P_{n_j} is used to designate power entering or leaving the ECM at a terminal node n_j and the power balance for a terminal node is given by:

$$P_{n_j}(k) = P_{(n_i \to n_j)}(k)\eta_{(n_i \to n_j)} - P_{(n_j \to n_i)}(k) \tag{3.4}$$

The condition and mutual exclusive constraints given in (3.5) prevents simultaneous power flow between bi-directional power flow arcs. Also, condition given in (3.6) prevents feasible solutions where $P_{(n_i \to n_j)} = 0$ and $\delta_{(n_i \to n_j)} = 1$.

$$\begin{aligned} & P_{(n_i \to n_j)} > 0 \Longleftrightarrow \delta_{(n_j \to n_i)} = 1 \qquad && \forall j \in I_{n_i \to} \\ & \delta_{(n_i \to n_j)} + \delta_{(n_j \to n_i)} \leq 1 && \end{aligned} \tag{3.5}$$

$$P_{(n_i \to n_j)} - \delta_{(n_i \to n_j)}\overline{P}_{(n_i \to n_j)} \leq 0 \qquad \forall j \in I_{n_i \to} \tag{3.6}$$

With (3.1) - (3.4) and (3.5) and (3.6) applying to bi-directional power flow arcs, a system of equations for Figure 3.3 can be written down in a straightforward manner:

$$\textit{terminal node} \begin{cases} P_{e1} + P_{(e2 \to e1)}\eta_{(e2 \to e1)} = P_{(e1 \to e2)} & \text{(3.7a)} \\ P_{e4} + P_{(e2 \to e4)}\eta_{(e2 \to e4)} = P_{(e4 \to e2)} & \text{(3.7b)} \\ P_{e5} + P_{(e2 \to e5)}\eta_{(e2 \to e5)} = P_{(e5 \to e2)} & \text{(3.7c)} \\ P_{g1} = P_{(g1 \to g2)} & \text{(3.7d)} \\ P_{c1} = -P_{(e3 \to c1)}\eta_{(e3 \to c1)} & \text{(3.7e)} \\ P_{h2} = -P_{(h1 \to h2)}\eta_{(h1 \to h2)} & \text{(3.7f)} \\ P_{h3} = -P_{(h1 \to h3)}\eta_{(h1 \to h3)} & \text{(3.7g)} \end{cases}$$

$$
\textit{transmitter node}\begin{cases} P_{(g2\rightarrow e2)} = P_{(g1\rightarrow g2)}\eta_{(g1\rightarrow g2)} & (3.7\text{h}) \\ P_{(g2\rightarrow h1)} = P_{(g1\rightarrow g2)}\eta_{(g1\rightarrow g2)} & (3.7\text{i}) \end{cases}
$$

$$
\textit{switch node}\{ \quad P_{(e2\rightarrow e3)}\eta_{(e2\rightarrow e3)} = P_{(e3\rightarrow c1)} + P_{(e3\rightarrow h1)} \qquad (3.7\text{j})
$$

$$
\textit{sum node}\begin{cases} P_{(e1\rightarrow e2)}\eta_{(e1\rightarrow e2)} + P_{(e4\rightarrow e2)}\eta_{(e4\rightarrow e2)} + P_{(e5\rightarrow e2)}\eta_{(e5\rightarrow e2)} & (3.7\text{k}) \\ \quad + P_{(g2\rightarrow e2)}\eta_{g2\rightarrow e2)} = P_{(e2\rightarrow e1)} & \\ \quad + P_{(e2\rightarrow e3)} + P_{(e2\rightarrow e4)} + P_{(e2\rightarrow e5)} & \\ P_{(g2\rightarrow h1)}\eta_{(g2\rightarrow h1)} + P_{(e3\rightarrow h1)}\eta_{(e3\rightarrow h1)} + P_{(h3\rightarrow h1)}\eta_{(h3\rightarrow h1)} & (3.7\text{l}) \\ \quad = P_{(h1\rightarrow h2)} + P_{(h1\rightarrow h3)} + P_{(h1\rightarrow h4)} & \end{cases}
$$

3.1.2 Prosumer Model

Mathematical models to represent end-user's devices in MES, termed prosumers, were introduced in [33]. Prosumers are active energy users that own a set of fixed and/or flexible devices that can produce and/or consume energy. Example of electrical, cooling and heat prosumers shown in Figure 3.3 connected to terminal nodes e_4, c_1 and h_2 respectively. PM describes the energy consumption and/or generation patterns of these devices. Energy patterns of fixed devices can not be modified or modulated and must be met exactly. For flexible devices, their energy patterns can be modified and/or modulated based on specific device operations and user preferences. As a result, their flexibility can be exploited to achieve specific goals. In [8], four fundamental flexible characteristics were introduced that can be combined to describe a broad spectrum of flexible devices. These characteristics are:

- Shiftable (S): The commencement of the device is not fixed, however must run within the scheduled horizon but no interruptions are allowed.
- Adjustable (A): Baseline energy consumption profiles of such devices can be exceeded or curtailed.
- Pliable (P): Provided the total energy requirement of the device is meet, it's energy demand profile can be manipulated through the scheduling horizon.

- Interruptible (I): Once a device comes online at a fixed scheduled period, its energy demand can be paused between particular instant in the scheduling horizon.

Figure 3.1 shows the operation of the four individual flexible SAPI characteristics. These characteristics can be combined to model the operation of any flexible end-user device. The PM represents a set of components of a particular energy carrier n of energy demand and/or generation devices. The connection of the set of components to a terminal node $P_{n_j}(k)$ is represented by the equation given in (3.8). G_m represents the m^{th} generating component and L_w represents the w^{th} load component. N_{m,n_j} and N_{w,n_j} respectively represent the total number of generator and load components connected to n_j.

$$P_{n_j}(k) = \sum_{m=1}^{N_{m,n_j}} G_m(k) - \sum_{w=1}^{N_{w,n_j}} L_w(k) \tag{3.8}$$

As discussed in [8] and stated earlier, both the generator and load components can be divided into two types: fixed and flexible. The number of generating and load components can be separated as shown in (3.9) and (3.10)

$$\sum_{m=0}^{N_{m,n_j}} G_m(k) = \sum_{y=0}^{N_y} G_{y,flex,n_j}(k) + \sum_{z=0}^{N_z} G_{z,fix,n_j}(k) \tag{3.9}$$

$$\sum_{w=0}^{N_{w,n_j}} L_w(k) = \sum_{u=0}^{N_u} L_{u,flex,n_j}(k) + \sum_{v=0}^{N_v} L_{v,fix,n_j}(k) \tag{3.10}$$

The number of generating components equals the number of flexible plus fixed generating components i.e $N_{m,n_j} = N_y + N_z$. Similarly, for the number of load components $N_{w,n_j} = N_u + N_v$. It is important to note that prosumers must not always be a combination of generation and load components. They can be purely loads in which case there are no fixed or flexible generators (i.e. $N_{w,n_j} = 0$) connected to node n_j. An example is shown in Figure 3.3 with the cooling prosumer. This prosumer is a load as it is connected to the output terminal node c_1 which has only one incoming power flow arc. Similarly, generation and load components of a prosumer must not be a combination of both fixed and flexible device. As an example, if the generating components of a prosumer are made up of purely flexible devices, then $N_z = 0$ in (3.9).

To explain the remaining equations that describe the operation of prosumers, for simplicity, the remainder of this section will refer only to a load component. This is because flexible generator components can also be described using the same approach. The energy consumption profile of a particular flexible load n also called the baseline energy consumption profile can be split into N_n segments that once started, cannot be interrupted. Symbol n refers to a combination of the flexible S-A-P-I characteristics used to model the operation of the load. Energy consumption of the i^{th} segment of each demand during time period h, which is set equal to the sampling period k, is denoted as $l_{n,i}(h)$ and is given by:

$$l_{n,i}(h) = \tilde{l}_{n,i}(h) + \Delta l^{+}_{n,i}(h) - \Delta l^{-}_{n,i}(h) \qquad \forall n, i, h \tag{3.11}$$

$\tilde{l}_{n,i}$ is the energy consumption of the respective i^{th} baseline energy requirement. Variables $\Delta l^{+}_{n,i}$ and $\Delta l^{-}_{n,i}$ are adjustable flexibility slack variables that represent a degree of freedom to quantify the amount of energy increase or curtailment for each i^{th} segment from the baseline energy requirement during time period h. The cumulative sum over the scheduling horizon of the baseline energy consumption for the i^{th} segment of demand n must remain within the baseline lower and upper bounds of the segment's total energy requirement (3.12). If the P characteristic is not used to model demand n, it's baseline segment time profile is fixed and is not a degree of freedom. Hence, (3.12) collapses to the equality constraint (3.13).

$$\underline{E}_{n,i} \leq \sum_{h=0}^{N_H-1} \tilde{l}_{n,i}(h) \leq \overline{E}_{n,i} \qquad \forall n, i \tag{3.12}$$

$$\underline{E}_{n,i} = \overline{E}_{n,i} = E_{n,i} \qquad \forall n, i \tag{3.13}$$

The resulting energy consumption of each demand at a given h represented by L_n is related to the actual energy consumption of the respective segments:

$$L_n(h) = \sum_{i=1}^{N_n} l_{n,i}(h) \qquad \forall n \tag{3.14}$$

The connection of the energy consumption of L_n given in (3.14) within a prosumer that may contain other loads components is represented as:

$$\sum_{u=0}^{N_u} L_{u,flex,n_j} = L_0 + \cdots + \boldsymbol{L_n} + \cdots + L_{N_u} \tag{3.15}$$

To control the commencement and halting of individual demand segment, three binary decision variables are utilised. Segment processing binary variable, $\delta^p_{n,i}$, determines whether or not an energy segment i^{th} is processed during each h. If the load is modelled with a combination of only A, P or I attributes, the scheduled time for this load to come online, h_c, is set by the user i.e. $\delta^p_{n,1}(h_c) = 1$. However, if S attribute is used to model the load, $\delta^p_{n,1}(h_c)$ is determined by the controller. Segment complete binary variable, $\delta^c_{n,i}$, indicates whether or not a particular segment has been completed. Finally, segment waiting binary variable, $\delta^w_{n,i}$, indicates whether or not demand n is been halted between completed previous segment and yet-to-be processed current waiting segment. This binary variable applies only if the load is modelled with I attribute. If I is not used to model the load, $\delta^w_{n,i} = 0$. With I attribute, $\delta^w_{n,i}$ is determined by the controller, however limits on how long each segments halts is determined based on user preferences and is implemented by (3.16).

$$\underline{N}^w_{n,i} \leq \sum_{h=0}^{N_H-1} \delta^w_{n,i}(h) \leq \overline{N}^w_{n,i} \qquad \forall n, i \tag{3.16}$$

Hard limits on deviations, $\Delta l^+_{n,i}$ & $\Delta l^-_{n,i}$, are imposed by (3.17b)-(3.17c). The multiplication of $\delta^p_{n,i}$ by the lower and upper bounds of these deviations ensures that the corresponding continuous decision variable cannot be non-zero unless the particular segment i is currently been processed. Also, to prevent physically infeasible case where both deviations are greater than zero, the binary variables $\delta^+_{n,i}(h)$ and $\delta^-_{n,i}(h)$ are associated with each deviation and implemented as shown in (3.17a)-(3.17d).

$$\delta^+_{n,i}(h) + \delta^-_{n,i}(h) \leq 1 \qquad \forall n, i, h \tag{3.17a}$$

$$\epsilon \delta^p_{n,i}(h)\delta^-_{n,i}(h) \leq \Delta l^-_{n,i}(h) \leq \overline{\Delta l^-_{n,i}}(h)\delta^p_{n,i}(h)\delta^-_{n,i}(h) \qquad \forall n, i, h \tag{3.17b}$$

$$\epsilon \delta^p_{n,i}(h)\delta^+_{n,i}(h) \leq \Delta l^+_{n,i}(h) \leq \overline{\Delta l^+_{n,i}}(h)\delta^p_{n,i}(h)\delta^+_{n,i}(h) \qquad \forall n, i, h \tag{3.17c}$$

$$\underline{l}_{n,i}(h)\delta^p_{n,i}(h) \leq l_{n,i}(h) \leq \bar{l}_{n,i}(h)\delta^p_{n,i}(h) \qquad \forall n,i,h \tag{3.17d}$$

If the load is modelled with P attribute, the maximum and minimum amount of energy that can be scheduled for its demand segment is constrained by implementing (3.18). If P attribute is not used, (3.19) collapses to an equality constraint (3.18).

$$\underline{N}^p_{n,i} \leq \sum_{h=0}^{N_H-1} \delta^p_{n,i}(h) \leq \overline{N}^p_{n,i} \qquad \forall n,i \tag{3.18}$$

$$\underline{N}^p_{n,i} = \overline{N}^p_{n,i} = 1 \qquad \forall n,i \tag{3.19}$$

Equations controlling the correct succession of binary variables are provided by (3.20)-(3.24). Equations (3.20)-(3.22) ensure that once an energy segment has commenced, it must run to completion and (3.23) ensures correct sequencing of individual segments. To allow halting the next energy segment after it's predecessor has been completed, (3.24) is implemented.

$$\delta^p_{n,i}(h) + \delta^c_{n,i}(h) \leq 1 \qquad \forall n,i,h \tag{3.20}$$

$$\delta^p_{n,i}(h-1) - \delta^p_{n,i}(h) \leq \delta^c_{n,i}(h) \qquad \forall n,i \ \forall h \in \{1 : N_H - 1\} \tag{3.21}$$

$$\delta^c_{n,i}(h-1) \leq \delta^c_{n,i}(h) \qquad \forall n,i \ \forall h \in \{1 : N_H - 1\} \tag{3.22}$$

$$\delta^p_{n,i}(h) \leq \delta^c_{n,i-1}(h) \qquad \forall n,h \ \forall i \in \{2 : N_n\} \tag{3.23}$$

$$\delta^w_{n,i}(h) = \delta^c_{n,i-1}(h) - (\delta^p_{n,i}(h) + \delta^c_{n,i}(h)) \qquad \forall n,h \ \forall i \in \{2 : N_n\} \tag{3.24}$$

3.1.3 Storage Model

The COMMES framework considers storage devices but with the assumption that they are permanently present within the MES and connected to an ECM's terminal node n_j. Examples of fixed storage systems are the battery bank and hot water tank shown in Figure 3.3 connected to nodes e_5 and h_3 respectively. Fixed storage systems can be represented by a discrete-time state-space model (3.25)

$$E_{n_j}(k+1) = S_{n_j}E_{n_j}(k) + Q_{n_j}(k) \tag{3.25}$$

Input to the SM is the charging/discharging power Q_{n_j}. Output, $E_{n_j}(k)$ represents stored energy at time k and S_{n_j} is the standby efficiency of the storage system that aids modelling a decay in its SoC over time if $Q_{n_j} = 0$. Connection of the fixed storage system and a terminal node n_j is achieved by setting Q_{n_j} equal to the negated node power of the associated input/output terminal node as shown in (3.26), in order to maintain the sign convention.

$$Q_{n_j}(k) = -P_{n_j}(k) \tag{3.26}$$

Also, as fixed storage is connected to an input/output terminal node, (3.5) prohibits it from simultaneously charging and discharging.

3.2 Stochastic Programming

In many decision-making processes, there are several sources of uncertainty that affect the outcome of decisions. Deterministic programs are formulated assuming all parameters are known before a decision is made. However, real-world problems invariably include parameters that are unknown at the time decisions are made. These parameters often lie in some given set of possible values and can be described with certain probability distributions. Stochastic programming leverages this probability distribution to formulate problems that adequately considers these uncertain variables. Often in the formulation of these problems, decisions are made repeatedly, and the objective is to come up with a decision that will perform well on average [81].

3.2.1 Two-Stage Stochastic Programming

The most widely applied stochastic programming technique is the two-stage stochastic approach. The basic idea behind the two-stage stochastic approach is to make an optimal here-and-now decision such as determine power imports while considering possible real-time operations such as fixed energy demand and EV related uncertainties. Then correction actions are taken when these uncertainties are realised [82]. In the two-stage stochastic approach, decision variables are partitioned into two. The first-stage variables have to be decided before the actual realisation of the uncertain parameters becomes available. Once the random events have presented themselves, the values of the second-stage or recourse variables can be decided. These recourse variables are correction actions used to compensate for any infeasibility from the first-stage decisions. The objective is to choose the first-stage variables so that the sum of first-stage costs and the expected value of the random second-stage or recourse costs is minimised. A standard formulation of the two-stage stochastic program is:

$$\min_{\boldsymbol{x} \,\in\, \mathcal{X}} \left\{ J(\boldsymbol{x}) := \boldsymbol{c}^T \boldsymbol{x} + \mathbb{E}[Q(\boldsymbol{x}, \boldsymbol{w_s})] \right\} \tag{3.27}$$

$$\text{subject to}$$

$$\boldsymbol{A}\boldsymbol{x} = \boldsymbol{b}$$

where $Q(\boldsymbol{x}, \boldsymbol{w_s})$ is the optimal value of the second-stage problem

$$\min_{\boldsymbol{y}} \ \boldsymbol{q}^T \boldsymbol{y} \tag{3.28}$$

$$\text{subject to}$$

$$\boldsymbol{T}\boldsymbol{x} + \boldsymbol{W}\boldsymbol{y} \leq \boldsymbol{h}$$

where $\boldsymbol{A} \in \mathbb{R}^{r*n}$, $\boldsymbol{b} \in \mathbb{R}^r$, $\boldsymbol{x} \in \mathbb{R}^n$ is the first-stage decision vector, $\mathcal{X}$ is the first-stage constraints set, $\boldsymbol{y} \in \mathbb{R}^m$ is the second-stage decision vector, $\boldsymbol{w_s} = (\boldsymbol{q}, \boldsymbol{T}, \boldsymbol{W}, \boldsymbol{h})$ contains the data of the second-stage problem defined on a corresponding probability space.

In the first-stage, the cost $\boldsymbol{c}^T\boldsymbol{x}$ of the first-stage decision plus the expected value cost, $\mathbb{E}[Q(\boldsymbol{x}, \boldsymbol{w_s})]$, of the second-stage decision is optimised. The second-stage problem is simply an optimisation problem that describes the optimal behaviour when the uncertain data, $\boldsymbol{w_s}$, is realised. The solution to the second-stage problem is considered as a recourse or correction action where $\boldsymbol{W}\boldsymbol{y}$ compensates for any possible inconsistency of the system $\boldsymbol{T}\boldsymbol{x} \leq \boldsymbol{h}$ and $\boldsymbol{q}^T\boldsymbol{y}$ is the cost of the recourse action. The formulation of the two-stage problem assumes that the second-stage data can be modelled as a random vector $\boldsymbol{w_s}$ with a known probability distribution. This is justifiable where problems are solved repeatedly under random conditions which do not significantly change over the considered period. Problems in the real-world match this, and one may reliability estimate the required probability distribution and the optimisation on average could be justified by the Law of Large Numbers (LLN) [81].

3.2.2 Sample Average Approximation

There are two sources of difficulty in solving (3.27) especially if recourse variables contain integers [82]:

1. Exact evaluation of the expected recourse costs: For a discrete distribution, exact computation of the expectation would require solving integer recourse problem for all possible realisation of the uncertain parameters and maybe computationally prohibitive. For a continuous distribution of the uncertain parameters, the computational challenges are worse. Evaluating the expected recourse costs would require multi-dimensional integration of the value function, which is impossible.
2. Optimising the expected recourse costs: Even if the expected recourse cost function could be evaluated, the value function of integer programs are highly non-convex and discontinuous. Hence, the optimisation problem will be computationally difficult.

To address this difficulties, the expected cost function in (3.28) is replaced by a sample average approximation (SAA), making the corresponding optimisation problem easier to solve. The SAA is an approach to approximate stochastic problems. It allows the expected value function to be computed by taking into account samples $\boldsymbol{\xi}_1, \cdots, \boldsymbol{\xi}_N$ of N generated scenarios. Problem (3.28) can then be written as the deterministic equivalent:

$$Q(\boldsymbol{x}, \boldsymbol{w_s}) = N^{-1} \sum_{s=1}^{N} (\boldsymbol{q}_s^+ \boldsymbol{\xi}_s^+ + \boldsymbol{q}_s^- \boldsymbol{\xi}_s^-) \tag{3.29}$$

subject to

$$\boldsymbol{\xi}_s^+ \geq \boldsymbol{Hx} - \boldsymbol{w_s}$$

$$\boldsymbol{\xi}_s^- \geq -(\boldsymbol{Hx} - \boldsymbol{w_s})$$

$$\boldsymbol{\xi}_s^+, \boldsymbol{\xi}_s^- \geq 0$$

where $\boldsymbol{\xi}_s^+$ and $\boldsymbol{\xi}_s^-$ are recourse vectors used to compensate for infeasibility from the first-stage decisions. $\boldsymbol{q}_s^+$ and $\boldsymbol{q}_s^-$ are penalty coefficient row vectors. In compact form, the random constraints are $\boldsymbol{Hx} - \boldsymbol{w_s} = 0$. Problem (3.29) allows for the SAA to be used to address the difficultly in solving the two-stage stochastic program as the expected value function is computed by taking into account samples $\boldsymbol{\xi}_1, \cdots, \boldsymbol{\xi}_N$ of N generated scenarios. Problem (3.27) can then be rewritten to obtain a sample average approximation of the stochastic problem:

$$\min_{\boldsymbol{x} \in \mathcal{X}} \left\{ J(\boldsymbol{x}) := \boldsymbol{c}^T \boldsymbol{x} + N^{-1} \sum_{s=1}^{N} (\boldsymbol{q}_s^+ \boldsymbol{\xi}_s^+ + \boldsymbol{q}_s^- \boldsymbol{\xi}_s^-) \right\} \tag{3.30}$$

subject to

$$\boldsymbol{\xi}_s^+ \geq \boldsymbol{Hx} - \boldsymbol{w_s}$$

$$\boldsymbol{\xi}_s^- \geq -(\boldsymbol{Hx} - \boldsymbol{w_s})$$

$$\boldsymbol{Ax} = \boldsymbol{b}$$

$$\boldsymbol{\xi}_s^+, \boldsymbol{\xi}_s^- \geq 0$$

Problem (3.30) is said to have complete recourse if the feasible set of the second-stage problem stays non-empty [83] i.e. it is always possible to respond to all possible disturbance realisation.

3.2.3 Solution Validation

Based on the LLN, as the sample size for an experiment becomes larger, the results should be close to the expected value and will tend to become closer to the expected value as more experiments are performed. This method relies on repeated random sampling to obtain numerical results. The larger the number of repetitions, the better the approximation tends to be. The Monte Carlo method can be used to obtain the approximated problem (3.30). However, slightly different solutions will be obtained each time (3.30) is solved. With $\hat{\boldsymbol{x}}_{\boldsymbol{N}}$ and $\boldsymbol{x}^*$ denoting the optimal solution to the SAA (3.30) and true problem (3.27) respectively, it has been shown in [84] that $\hat{\boldsymbol{x}}_{\boldsymbol{N}}$ converges to $\boldsymbol{x}^*$ as the sample size N tends to infinity. To aid in handling the computational complexity in solving (3.30) and help choose an adequate N, confidence in $\hat{\boldsymbol{x}}_{\boldsymbol{N}}$ needs to be determined.

Let the optimal solution of the SAA (3.30) and true problem (3.27) be denoted as $J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})$ and $J(\boldsymbol{x}^*)$ respectively. Based on LLN, it is well known that

$$\mathbb{E}[J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})] \leq J(\boldsymbol{x}^*) \tag{3.31}$$

A lower bound to $J(\boldsymbol{x}^*)$ can be obtained by estimating $J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})$. $J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})$ is solved M times. Each time N independent samples of the uncertain parameters in (3.30) are generated. Optimal objective values $J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})^1, \cdots, J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})^M$ are obtained and the quantity

$$\bar{J}_N^M = M^{-1} \sum_{m=1}^{M} J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})^M \tag{3.32}$$

is an unbiased estimator of $\mathbb{E}[J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})]$, and therefore a statistical lower bound to $J(\boldsymbol{x}^*)$. Estimate of the variance of the above estimator can be computed as

$$S^2_{\bar{J}_N^M} = \frac{1}{M(M-1)} \sum_{m=1}^{M} \left[J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})^M - \bar{J}_N^M\right]^2 \tag{3.33}$$

Estimating an upper bound to $J(\boldsymbol{x}^*)$ helps give confidence to $\hat{\boldsymbol{x}}_{\boldsymbol{N}}$ as the smaller the difference between the upper and lower bounds proves that the problem is tightly bounded. However, $J(\boldsymbol{x}^*)$ is difficult to determine as it requires knowledge of the exact scenario size. Hence, an estimated scenario size N' is used to determine an approximate true solution $J(\boldsymbol{x}^*_{\boldsymbol{N'}})$ such that $N' >> N$. That is

$$J(\boldsymbol{x}^*_{\boldsymbol{N'}}) = \boldsymbol{c}^T \boldsymbol{x}^*_{\boldsymbol{N'}} + \frac{1}{N'} \sum_{n=1}^{N'} Q(\boldsymbol{x}^*_{\boldsymbol{N'}}, \boldsymbol{w}_{\boldsymbol{n}}) \tag{3.34}$$

Hence, $J(\boldsymbol{x}^*_{\boldsymbol{N'}})$ is an unbiased estimator of $J(\boldsymbol{x}^*)$. Consequently $\boldsymbol{x}^*_{\boldsymbol{N'}}$ is a feasible point of the true problem and $J(\boldsymbol{x}^*_{\boldsymbol{N'}})$ gives a statistical upper bound of the true optimal solution value. Estimate of the variance of $J(\boldsymbol{x}^*_{\boldsymbol{N'}})$ can be computed as

$$S^2_{J(\boldsymbol{x}^*_{\boldsymbol{N'}})} = \frac{1}{N'(N'-1)} \sum_{n=1}^{N'} \left[\boldsymbol{c}^T \boldsymbol{x}^*_{\boldsymbol{N'}} + Q(\boldsymbol{x}^*_{\boldsymbol{N'}}, \boldsymbol{w}_{\boldsymbol{n}}) - J(\boldsymbol{x}^*_{\boldsymbol{N'}})\right]^2 \tag{3.35}$$

The difference between the unbiased estimators of $\mathbb{E}[J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})]$ and $J(\boldsymbol{x}^*)$ is termed the optimality gap. The optimality gap can be estimated using (3.32)-(3.35)

$$\text{gap} = \bar{J}_N^M + S^2_{\bar{J}_N^M} - J(\boldsymbol{x}^*_{\boldsymbol{N'}}) + S^2_{J(\boldsymbol{x}^*_{\boldsymbol{N'}})} \tag{3.36}$$

However, it has been proven in [82] that as (3.29) is determined a predefined number of times M with increasing N and N', the optimality gap tends to zero and $S^2_{J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})}$ and $S^2_{J(\boldsymbol{x}^*_{\boldsymbol{N'}})}$ tend to be negligible each time (3.30) is solved. Hence, confidence is established for the optimal solution $\hat{\boldsymbol{x}}_{\boldsymbol{N}}$ to the SAA problem such that

$$\text{gap}(\hat{\boldsymbol{x}}_{\boldsymbol{N}}) \approx \bar{J}_N^M - J(\boldsymbol{x}^*_{\boldsymbol{N'}}) \tag{3.37}$$

3.3 Model Predictive Control

The COMMES framework, while applicable elsewhere, is primarily developed for MPC applications. MPC provides a systematic method of dealing with constraints on inputs and states of a system. MPC was initially developed in the chemical industry and is now arguably the most widely accepted modern control strategy. Its receding horizon implementation offers an explicit approach using a system's dynamic model to forecast future system behaviour and compute the control law. The control law is determined after solving a practical optimisation problem subject to a system's constraints, at each sample time using the system's current state provided through the feedback mechanism. Only the first input sequence in the control law is applied to the system before the optimisation problem is resolved at the next sample time. The general form of the optimisation problem implemented within the MPC formulation is represented as:

$$\min \; J(\boldsymbol{x}(k), \boldsymbol{u}(k)) \tag{3.38a}$$

$$\text{subject to}$$

$$g(\boldsymbol{x}(k), \boldsymbol{u}(k)) = 0 \qquad \forall k \tag{3.38b}$$

$$l(\boldsymbol{x}(k), \boldsymbol{u}(k)) \leq 0 \qquad \forall k \tag{3.38c}$$

where $\boldsymbol{x} \in \mathbb{R}^n$ represents the system's state at time k and $\boldsymbol{u} \in \mathbb{R}^m$ represents input to the system at time k. $J(\centerdot)$ is the optimisation problem, $g(\centerdot)$ are equality constraints and $l(\centerdot)$ are inequality constraints. It is worth highlighting that the MPC formulation to any system provided a dynamic model of the system can be obtained.

Figure 3.4 shows where MPC is typically placed in industrial applications. It is placed between the real-time optimisation (RTO) and regulatory layers. The RTO is responsible for defining economical optimal set-points repetitively with a frequency of typically hours/days based on up-to-date system planning and scheduling decisions made based on multiple operating processes in the layer above. The regulatory layer comprises primarily single-input single-output control loops like proportional-integral-derivative (PID) control that work to satisfy set-points computed by the MPC. Below the regulatory control layer, actuators and sensors that operate at a very high frequency implement control actions determined by the upper layer, then measure and feedback system's states. MPC exists within the advanced process control layer. It operates at a frequency higher than the RTO layer. It uses the set-point provided by this layer and a dynamic model of the system in an optimisation problem to predict the future evolution of a system over a finite-time horizon with respect to a performance index.

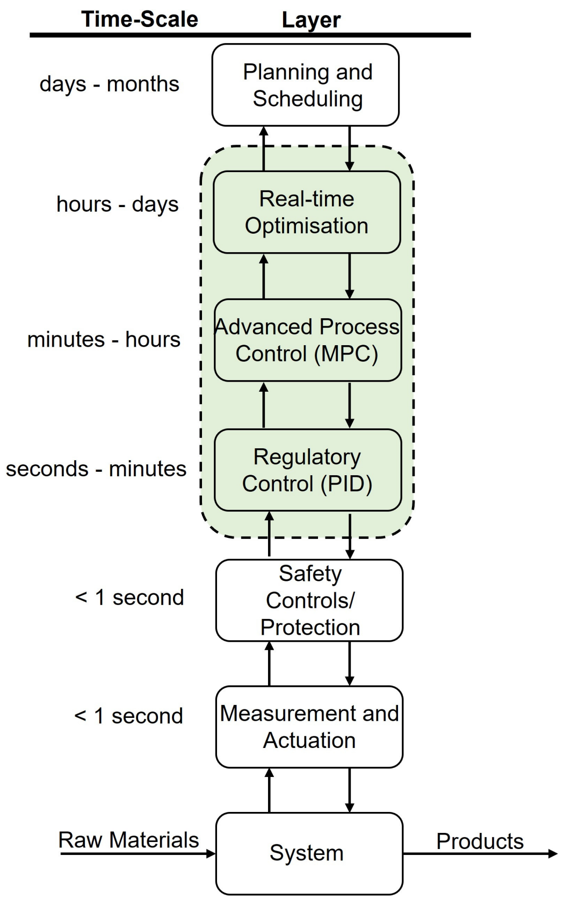

Figure 3.4: The traditional hierarchical paradigm employed in industrial process systems (adapted from [2])

3.3.1 Conventional Model Predictive Control

Conventional MPC plays the role of a regulator that steers the system to some fixed optimal set-point provided by the RTO layer in Figure 3.4. The objective function implemented within the conversational MPC is quadratic. It measures the predicted squared weighted error of the systems' states and inputs from their corresponding steady-state or target reference values. As such conventional MPC is also known as tracking MPC. The optimisation problem for conventional MPC is mathematically represented by:

$$\min J(\boldsymbol{x}(k), \boldsymbol{u}(k)) = \sum_{i=0}^{N_H-1} \Big(\parallel x(k+i|k) \parallel_Q^2 + \parallel u(k+i|k) \parallel_R^2 \Big) \tag{3.39a}$$

subject to

$$\boldsymbol{G}(k)x(k) = \boldsymbol{g}(k) \qquad \forall k \tag{3.39b}$$

$$\boldsymbol{L}(k)[\boldsymbol{x}(k)\ \boldsymbol{u}(k)]^T \leq \boldsymbol{l}(k) \qquad \forall k \tag{3.39c}$$

where $\parallel x \parallel = x^T Q x$ and $Q \in \mathbb{R}^{n*n}, R \in \mathbb{R}^{m*m}$ are positive definite matrices (Q may be positive semi-definite). The tuning parameters Q and R are chosen to assign priorities to particular state and input variables, respectively. If R is relatively large with respect to Q the controller response will be slower as the size of the control effort will be reduced, resulting in a sluggish regulator. Conversely, if Q is larger than R, state variables' deviation from the reference is given priority and minimised quickly but at the cost of a large control effort. Reference tracking is provided in (3.39a) by replacing $x(k)$ with $r(k) - y(k)$ where $r(k)$ is a vector of reference or set-point values corresponding to the vector of output variables $y(k)$. The system dynamics are contained in the equality constraint (3.39b), which can be described using the discrete-time state-space representation:

$$x(k+1) = \boldsymbol{A}x(k) + \boldsymbol{B}u(k) \tag{3.40a}$$

$$y(k) = \boldsymbol{C}x(k) + \boldsymbol{D}u(k) \tag{3.40b}$$

$$x(0) = x_0 \tag{3.40c}$$

Limits on the system's states and control inputs are imposed by the inequality constraints (3.39c). They represent limits on physical actuators, must always be represented, and are known as hard constraints. When safety considerations arise, it is common that strictly obeying them is not always feasible. Such constraints are known as soft constraints, and they can be relaxed accordingly to improve the controller's performance [2]. The function $J(\centerdot)$ is convex; hence a unique global minimum can be guaranteed. Also, the choice of $J(\centerdot)$ ensures that large deviations are penalised much more than small ones, which is desirable from a control perspective.

3.3.2 Economic Model Predictive Control

Based on the experience of implementing MPC in the chemical process industry, the development of economic MPC (EMPC) has been proposed to extract more significant economic benefits where achieving steady-state operation may not be the economically optimal operation [2, 85]. EMPC integrates the RTO and advanced process control layers shown in Figure 3.4. The cost function implemented within EMPC may be a direct or indirect reflection of the process/system economics [85]. However, a by-product of this modification is that the system is not required to operate at a specified steady-state or target reference. As EMPC aligns with process economics, it will be beneficial in real-time energy management and is used in Chapters 4, 5 and 6 of this thesis. A general linear form of the optimisation problem implemented within an EMPC formulation is represented as:

$$\min\ J(\boldsymbol{x}(k), \boldsymbol{u}(k), \boldsymbol{p}(k)) = \sum_{i=0}^{N_H-1} h(\boldsymbol{x}(k), \boldsymbol{u}(k), \boldsymbol{p}(k)) \tag{3.41a}$$

subject to

$$\boldsymbol{G}(k)x(k) = \boldsymbol{g}(k) \qquad \forall k \tag{3.41b}$$

$$\boldsymbol{L}(k)[\boldsymbol{x}(k)\ \boldsymbol{u}(k)]^T \leq \boldsymbol{l}(k) \qquad \forall k \tag{3.41c}$$

where $h(.)$ is the cost function, and $\boldsymbol{p}(k)$ reflects the economic part of the function (e.g. cost of purchasing and selling energy to the grid, and/or generator start-up and short-down cost). Note that quadratic terms may exist within $h(.)$. However, they are usually for safety concerns. As an example, to prolong the life-cycle of power conversion devices such as transformers or battery banks in energy management systems, penalties are imposed in the formulation of (3.41) on the rate of change of energy imports/exports and/or the rate of charging/discharging storage systems. Such penalty is included in the optimisation problem formulated in Chapter 6 as penalties a placed on the charge/discharge rate of EVs. Parameters of an economical cost function may vary with time resulting in the optimal state of a system changing each time the economic parameters of the cost function change. However, as the response of the controllers in the layers below the regulatory control in Figure 3.4 may be faster than the sampling interval of the EMPC, the EMPC problem would be simplified. This is because the optimal economic state of the system is reached at each sampling instant and is maintained throughout the current sampling period. Note that EMPC also allows for a non-linear system model as well as non-linear constraints. However, to aid comparison with the conventional MPC in section 3.3.1, the linear formulation of EMPC is provided by (3.41).

3.3.3 Stochastic Model Predictive Control

Mathematical models of a system can be separated into two parts: the actual process model and the disturbance model, and both parts are needed to formulate an MPC problem. The actual model represents a system's dynamics, and the disturbance model represents inputs into the system. Although no developed model fully represents a physical system, a reasonable model approximation of an actual model can be obtained using standard methods (e.g. step and impulse response). However, it is non-trivial for disturbance models as it is highly dependant on the nature of the system inputs, which are most often uncertain. Typically, uncertainties are unexpected behaviour resulting from model inaccuracies. Three main trends in MPC theory have evolved to address these uncertainties. These are *Certainty Equivalent* MPC (CEMPC), *D*eterministic MPC (DMPC), *R*obust MPC (RMPC) and *S*tochastic MPC (SMPC).

CEMPC uses a simplistic approach to handling uncertainty by assuming that forecasted future values of uncertain variables will be realised according to their predictions and then rejects unanticipated disturbances by relying on the receding horizon feedback mechanism. CEMPC is often used as a benchmark when analysing DMPC, RMPC and SMPC methodologies. It was used in the development of the original COMMES framework in [8,32,33]. Although MPC offers a certain degree of robustness to system uncertainties due to its receding horizon implementation, its formulation does not appropriately incorporate uncertainty hence renders the MPC inadequate for systematically dealing with uncertainties [80]. In real-world problems, realised uncertainty variables are often different from forecasted variables. DMPC uses the average of the forecasted uncertain variables in its formulation. However, sub-optimal solutions will be obtained if realised uncertain variables deviate significantly from the mean. In the presence of bounded uncertainties, RMPC guarantees stability, constraint satisfaction and convergences the system's state to a given steady-state condition, for all possible realisations of uncertainty [86]. However, uncertainties are often probabilistic in real-world scenarios, and SMPC has been developed to incorporate the probabilistic descriptions of uncertainties into a stochastic optimal control problem. SMPC allows for systematically seeking tradeoffs between fulfilling the control objectives and guaranteeing a probabilistic constraint satisfaction due to uncertainties [80].

SMPC deals with the cases when uncertainty is random, with a known probability distribution, rather than been assumed known or lie in a given bounded set. It is worth noting that a unique way to classify the numerous SMPC approaches explored in literature does not exist. However, an attempt to provide a clear distinction between SMPC approaches based on system dynamics is provided in [80]. Stochastic programming-based approaches are highly favoured in formulated and for solving SMPC problems. Specifically, the two-stage stochastic programming approach is discussed in Section 3.3. The optimisation problem for SMPC developed using the two-stage stochastic approach can generally be represented as:

$$\min \ J(\boldsymbol{x}(k), \boldsymbol{u}(k), \boldsymbol{w_s}(k)) = \mathbb{E}_k \Big[\sum_{i=0}^{N_H-1} h(\boldsymbol{x}(k), \boldsymbol{u}(k), \boldsymbol{w_s}(k)) \Big] \tag{3.42a}$$

subject to

$$\boldsymbol{G}(k)x(k) = \boldsymbol{g}(k) \qquad \forall k \tag{3.42b}$$

$$\boldsymbol{L}(k)[\boldsymbol{x}(k)\ \boldsymbol{u}(k)\ \boldsymbol{w_s}(k)]^T \leq \boldsymbol{l}(k) \qquad \forall k \tag{3.42c}$$

where the notation $\mathbb{E}_k(\cdot)$ indicate that the expectation is conditional on information available to the controller at time k, and is therefore dependent on the distribution of the model uncertainty $\boldsymbol{w_s}$. It is worth noting that CEMPC, DMPC, RMPC and SMPC can be formulated either as conversational or economic MPC. The SMPC implemented in Chapter 5 and 6 are economic. Penalties are placed on the cost of purchasing and selling energy to the grid and also on slack variables associated with $\boldsymbol{w_s}$ that aid power imbalance of the system. These slack variables are related to uncertainties of energy demands and charging station utilisation by EVs. In Chapter 6, an added penalty on the charge/discharge rate of EVs is included in the optimisation problem.

3.4 Software Tools and Extensions

The original COMMES framework was developed using both MATLAB and Python. Throughout this research, the decision was made to continue using MATLAB as the modelling framework is novel. MATLAB is well conversant within the research community, making further development and application of the COMMES framework relatively easy. MATLAB (an abbreviation of "MATrix LABoratory") is a proprietary multi-paradigm programming language and numeric computing environment developed by MathWorks. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages. MATLAB comes with an additional package, Simulink, which adds graphical multi-domain simulation and model-based design for dynamic and embedded systems. However, Simulink was not used throughout this research because it is not well suited to the modelling framework in [8] and the modifications proposed in this thesis.

As mentioned in Section 1.2, the COMMES framework was primarily developed to be implementable within predictive control schemes. However, optimisation problems formulated using the COMMES framework are mixed-integer programming problems. If the mixed-integer problem is linear, the function `intlinprog` can be called in MATLAB to solve the problem. If the mixed-integer problem is quadratic, MATLAB has no in-built functions to solve such problems. CPLEX for MATLAB Toolbox and Cplex class were added as extensions in MATLAB to resolve this. CPLEX is part of an optimisation software package, CPLEX Optimisation Studio, developed by IBM. These extensions allow MATLAB to solve not only mixed-integer quadratic problems but a variety of mathematical programming problems such as constrained mixed-integer least-squares problems and quadratically constrained mixed-integer least squares problems. This feature makes CPLEX well suited in this research as it can be used to solve any mixed-integer problem formulated with the COMMES framework.

3.5 Chapter Summary

This chapter discussed three topics that are utilised later in this thesis. In particular, the original COMMES framework was discussed in Section 3.1 highlighting its three components. However, the COMMES framework does not readily allow for the representation of mobile storage charge/discharge operations. In designing the stochastic EMS in Chapter 5 and 6, a stochastic programming approach is used to formulate the optimisation problems. The stochastic programming approach utilised is discussed in Section 3.2. As EMSs developed in Chapters 4, 5 and 6, are based on the MPC methodology, Section 3.3 discusses some formulations of MPC. The conventional MPC formulation for regulatory control is discussed first before the EMPC, which allows a system's economics to be reflected in the objective function is presented. As uncertainties exist when solving real-world problems, the SMPC is discussed in the concluding subsection. Finally, the main software tools and extensions used to conduct the research throughout this thesis is discussed in Section 3.4.

Chapter 4

Mobile Storage Modelling and Analysis

In this chapter, the model representation of mobile storage systems is presented and incorporated into the COMMES framework. In particular, the EV charge/discharge operation model presented matches the modular nature of the original COMMES framework by matching its generality. The model provides a systematic approach for modelling successive EV charge/discharge operations in MES without exact knowledge of the number or types of EVs in the network.

The remainder of this chapter is organised as follows: The EV charge/discharge operation model is formally introduced in Section 4.1. This is followed by the development of a general deterministic EMS in Section 4.2 to show how the EV charge/discharge operation model is incorporated into the COMMES framework. In Section 4.3, description of a case-study MES is presented. Simulation Analysis of the general deterministic EMS applied to the case-study MES are discussed in Section 4.4 together with comparative analysis of operational cost. Finally, a summary of the chapter is presented in Section 4.5.

4.1 Electric Vehicle Charge/Discharge Model

4.1.1 Accounting for Electric Vehicle Charge Level

As the modular nature of the original COMMES framework allows for the charge level of a fixed storage system to be represented using a discrete-time state space model, the same state-space model can be used to represent the charge level of an EV connected to a charging station. Figure 4.1 shows an EV connected to a charging station. Its SoC is accounted for using the

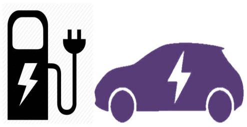

Figure 4.1: Illustration of a single EV utilising a charging station

discrete-time state-space model shown in (4.1) and the EV's connection to the charging station is achieved using (4.2). The power flowing through the charging station is represented as P. The charging/discharging power of the EV is represented as Q_{EV}. If the EV does not have bi-directional energy exchange capability, Q_{EV} represents the EV's charging power. The standby efficiency that models the decay of the EV's battery SoC over time is represented as S_{EV}.

$$E_{EV}(k+1) = S_{EV}E_{EV}(k) + Q_{EV}(k) \tag{4.1}$$

$$Q_{EV}(k) = -P(k) \tag{4.2}$$

In residential areas where an EV utilises a particular charging station most likely installed on the EV owner's premises, it is safe to assume that this EV will be the only one to utilise the charging station. Hence, it is sufficient to use (4.1) and (4.2) to account for the EV's SoC when designing an EMS. However, in commercial and public areas where a charging station will likely be utilised multiple times over a certain period and by different EVs, it is not optimal to use (4.1) and (4.2) when designing EMSs. In commercial and public areas, the ownership of a charging station is not assigned to a specific EV driver as it is expected that a charging station can be utilised multiple times, as illustrated in Figure 4.2. Also, it has been proven in [87] that although the ownership of charging stations are known in residential areas, EV owners can, on occasion, recharge their vehicles more than twice a day.

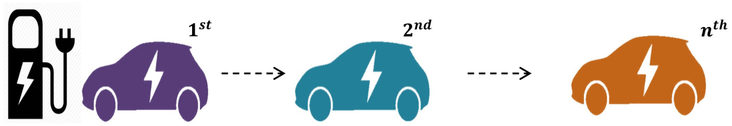

Figure 4.2: Illustration of multiple EVs utilising a charging station

To match the generality of the original COMMES framework, the representation of EVs' charge/discharge operation within energy networks should have a modular structure that suits application in residential, commercial and public areas.

4.1.2 Connecting Successive Electric Vehicle Charge Level Models

To facilitate the incorporation of the EV charge/discharge operation model into the COMMES framework, the SM is sub-categorised into two: fixed storage model and mobile storage model. The storage model considered in the original COMMES framework is the fixed storage model, and it is described in Section 3.1.3. Mobile storage devices most noticeably EVs are modelled using the mobile storage model. An illustration of the operation of fixed and mobile storage devices, when connected to an energy network, is shown in Figure 4.3. Compared to the fixed

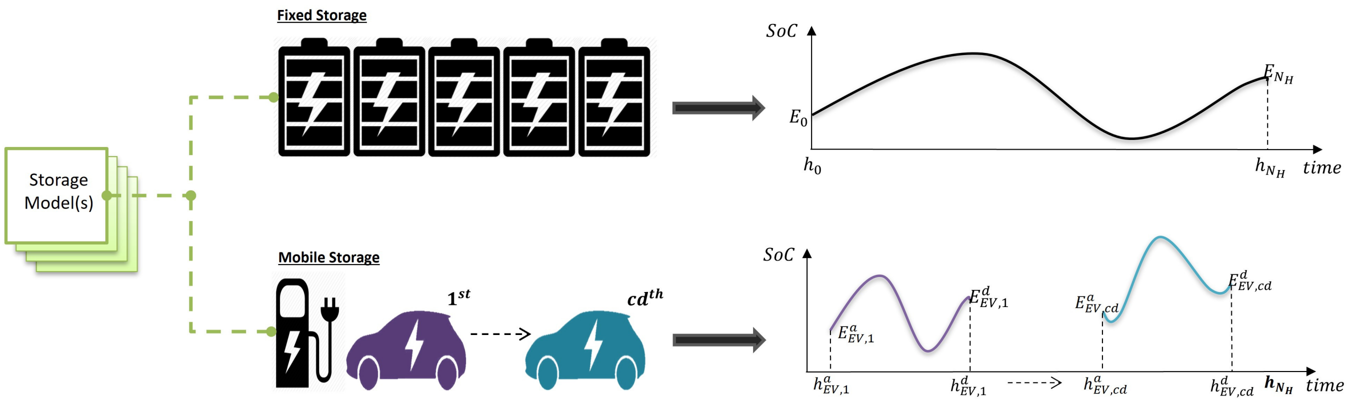

Figure 4.3: Illustration of the operation of fixed and mobile storage devices

storage model, added considerations are required to allow the dynamics of mobile storage devices to be represented within the COMMES framework. Some of these considerations are the arrival and departure time of EVs denoted as h^a_{EV} and h^d_{EV} respectively, and their respective energy level at both times denoted as E^a_{EV} and E^d_{EV}. Also required are the battery capacity of EVs denoted as Cap_{EV}, their respective battery efficiency S_{EV} and charge/discharge power limits $\pm Q_{EV}$. An illustration of EVs successively utilising a changing station is also shown in Figure

4.3. Modification to the COMMES framework to incorporate a representation of mobile storage devices was preliminarily introduced in [88]. However, the introduced EV charge/discharge event model is now redefined as the EV charge/discharge operation model to avoid confusion with event-based control schemes. An illustration of the modified overview of the COMMES framework that incorporates the mobile storage model is shown in Figure 4.4.

The mobile storage model developed matches the modular nature of the original COMMES framework by matching its generality. The mobile storage model provides a systematic approach for modelling successive EV charge/discharge operations in MES without exact knowledge of the number or type of EVs that will utilise the same charging station in the network. The EV charge/discharge model is based on the utilisation of charging stations within MES assuming some charging stations have bidirectional energy exchange capabilities. In Chapter 3, it was discussed that terminal nodes represent interface to components outside the ECM. Charging stations are examples of such interface hence they are represented as terminal nodes. Charging stations represent charging equipment drivers connect their EVs to when they arrive to recharge their batteries. To obtain an understanding of the charging/discharging pattern of EVs, it is assumed that historical information on different EVs that have utilised a charging station has been collected and categorised, and it contains: EV availabilities (arrival and departure times) (4.3a), SoC at arrival and departure (4.3b), charge/discharge power limits (4.3c), battery capacities (4.3d), battery efficiencies (4.3e), V2X capabilities (4.3f) and cd, the number of charging/discharging operations or number of utilisation of a charging station over a certain period. Superscripts a and d represents arrival and departure respectively.

$$T_{n_j} = \Big[h^a_{EV,1},\ h^d_{EV,1} \dots\ h^a_{EV,cd},\ h^d_{EV,cd}\Big] \in \mathbb{R}^{(2*cd)}_{\geq 0} \tag{4.3a}$$

$$SoC_{n_j} = \Big[E^a_{EV,1}, E^d_{EV,1} \dots E^a_{EV,cd}, E^d_{EV,cd}\Big] \in \mathbb{R}^{(2*cd)}_{\geq 0} \tag{4.3b}$$

$$Q_{n_j} = \Big[\pm Q_{EV,1} \cdots \pm Q_{EV,cd}\Big] \in \mathbb{R}^{cd}_{\geq 0} \tag{4.3c}$$

$$Cap_{n_j} = \Big[Cap_{EV,1} \dots\ Cap_{EV,cd}\Big] \in \mathbb{R}^{cd}_{\geq 0} \tag{4.3d}$$

$$S_{n_j} = \Big[S_{EV,1} \dots\ S_{EV,cd}\Big] \in \mathbb{R}^{cd}_{\geq 0} \tag{4.3e}$$

$$\delta^{V2X}_{n_j} = \Big[\delta_{EV,1} \dots\ \delta_{EV,cd}\Big] \in \mathbb{I}^{cd}_{\{0:1\}} \tag{4.3f}$$

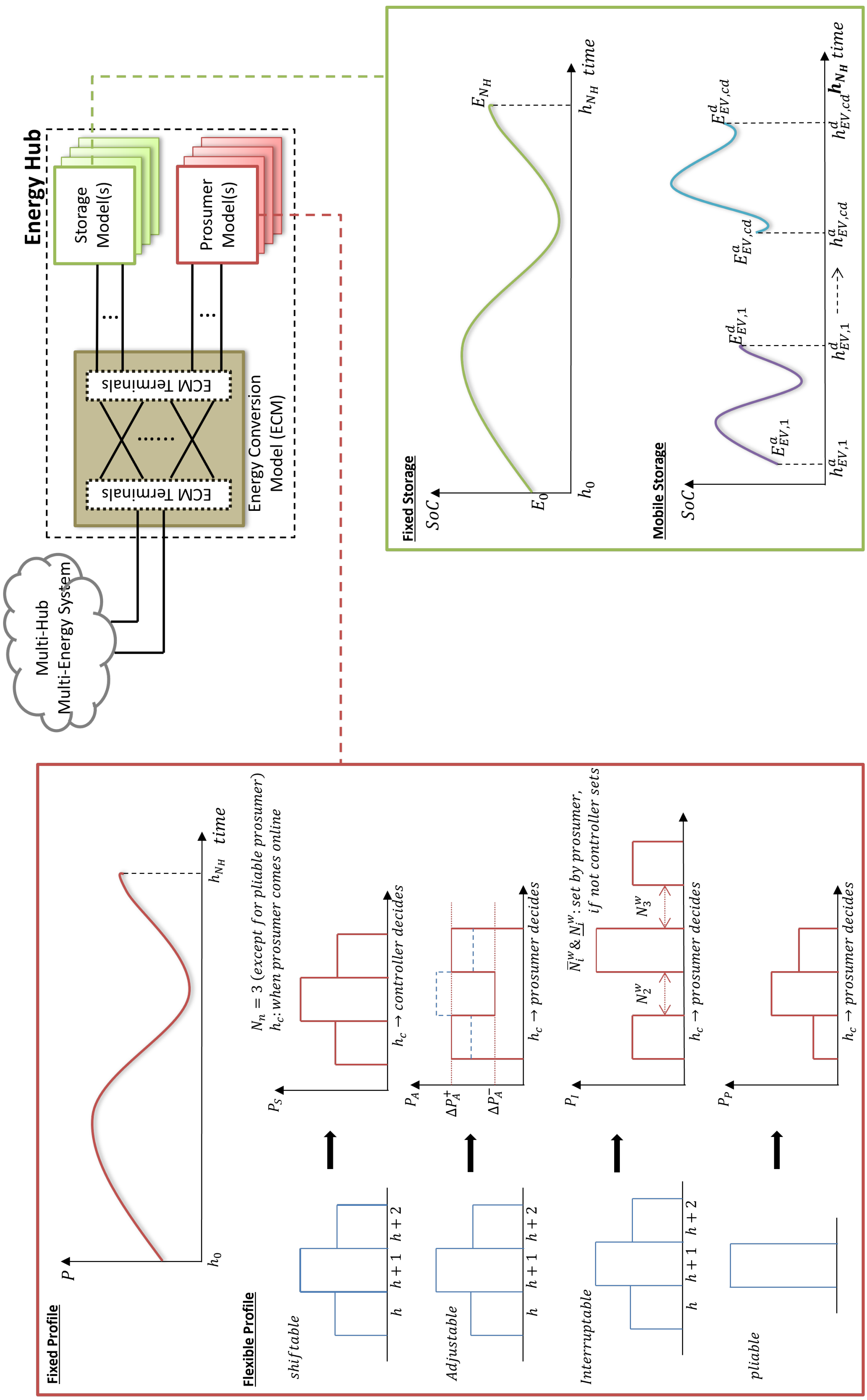

Figure 4.4: An illustrative overview of modifications to COMMES framework

The charging/discharging operation of an EV is defined as a bi-directional energy exchange to/from an EV while it is connected to a charging station. To account for the SoC of an EV connected to terminal node n_j during charging/discharging operation i, a discrete-time state-space model is utilised as shown in (4.4) and the connection to a charging station is given in (4.5). P_{n_j} represents the power flow through the charging station. $Q_{EV,i}(k)$ represents the charging/discharging power of an EV whose minimum value can be set to zero when a driver decides to opt-out of V2X once they connect to n_j. During the i^{th} charge/discharge operation, $S_{EV,i}$ represents standby efficiency of the EV's battery and $Q_{EV,i}$ represents the EV's charging/discharging power. $S_{EV,i}$ facilitates modelling a decay of the EV's battery SoC over time if $Q_{EV,i} = 0$. The minimum value of $Q_{EV,i}$ can be set to zero when a driver decides not to participate in V2X once they connect to the charging station. As (4.4) and (4.5) are required only during a charging/discharging operation, they are active only during the availabilities contained in T_{n_j}.

$$E_{EV,i}(k+1) = S_{EV,i}E_{EV,i}(k) + Q_{EV,i}(k) \qquad \forall i \in \{1 : cd\} \quad \forall k \in \{h^a_{EV,i} : h^d_{EV,i} - 1\} \tag{4.4}$$

$$Q_{EV,i}(k) = -P_{n_j}(k) \qquad \forall i \in \{1 : cd\} \quad \forall k \in \{h^a_{EV,i} : h^d_{EV,i} - 1\} \tag{4.5}$$

To prevent physically infeasible case where $P_{n_j}(k) \geq 0$ and $k \notin \left\{h^a_{EV,i} : h^d_{EV,i} - 1\right\}$, a binary variable δ_{n_j} is employed as shown in (4.6). The multiplication of this binary variable by the charging and discharging power limits of the charging station ensures that power $P_{n_j}(k) = 0$ when an EV is not connected (4.7).

$$\delta_{n_j}(k) = \begin{cases} 1, & \text{if } k \in \{h^a_{EV,i} : h^d_{EV,i} - 1\} \quad \forall i \in \{1 : cd\} \\ 0, & \text{if otherwise} \end{cases} \tag{4.6}$$

$$\underline{P_{n_j}}(k)\delta_{n_j}(k) \leq P_{n_j}(k) \leq \overline{P_{n_j}}(k)\delta_{n_j}(k) \qquad \forall i \in \{1 : cd\} \tag{4.7}$$

It is worth highlighting that a combination of PM, specifically pliable characteristics, and fixed storage model can be used to model EV charging/discharging operations, however, the resulting model would include redundant constraints. In addition, the resulting model would contradict the definition of PM as a representation of individual devices by giving the illusion of multiple utilisation of a charging station by different EVs.

4.2 Deterministic Energy Management Scheme

To exemplify the incorporation of the EV charge/discharge model to the COMMES framework, a deterministic EMS is designed to minimise the cost of purchasing and/or selling energy from/to the grid plus cost on the adjustable portion of flexible prosumers that may exist within a EH.

4.2.1 Problem Formulation

An index set is adopted to facilitate a clear distinction between different nodes and components within an EH. The index set Su, Tr Sw and T identify all sum, transmitter, switch and terminal nodes, respectively. Bi-directional arcs are identified as Bi. Prosumers are identified with the index set $GL = \{GL^n, GL^s\}$, with GL^n identifying flexible prosumers modelled using any combination of S, A, P, I. GL^s identifies fixed prosumers. The index set $Es = \{Es^n, Es^s\}$ identifies all energy storage components. Es^n and Es^s respectively identify fixed and mobile storage components.

The controller's objective is to minimise the cost of purchasing electricity and gas and maximise the profit of selling electricity plus cost on the adjustable portion of flexible prosumers. The control objective is given by (4.8). It must be met while considering the utilisation of any charging station by EVs and flexible prosumers that may exist in the MES. At time k, we look N_H steps into the future, with scheduling period h set equal to k, and minimise the cost $J(k)$ subject to the system's model and constraints.

$$\min_{P_{(n_i \to n_j)}, \delta_{PM}} J(k) = \sum_{k=0}^{N_H - 1} \Big[P_{cost}(k+h) + P_A(k+h) \Big] \tag{4.8}$$

subject to

$$\begin{array}{ll} \text{ECM equations} & (3.1)\forall Su, (3.2)\forall Tr, (3.3)\forall Sw, \\ & (3.4)\forall T, (3.5)\&(3.6)\forall Bi \\ \text{PM equations} & \begin{cases} (3.8) - (3.10) & \text{if } GL = GL^n \\ (3.8) - (3.24) & \text{if } GL^s \in GL \end{cases} \\ \text{SM equations} & (3.25)\&(3.26)\ \forall Es^n \\ & (4.4) - (4.7)\ \forall Es^s \end{array}$$

where

$$\begin{aligned} P_{cost}(k+h) = & \Big[\pi_e^{buy}(k+h) P_{(e_1 \to e_2)}(k+h) - \pi_e^{sell}(k+h) P_{(e_2 \to e_1)}(k+h) \eta_{e_2 \to e_1} \\ & + \pi_g^{buy}(k+h) P_{g_1}(k+h) \Big] \\ P_A(k+h) = & \sum_{A \in GL^n} \Big[\sum_{u=1}^{N_n} \Big[\lambda_A^+(k+h) \Delta l_{A,u}^+(k+h) + \lambda_A^-(k+h) \Delta l_{A,u}^-(k+h) \Big] \Big] \end{aligned}$$

P_{cost} is the economic cost with π_e^{buy} and π_e^{sell} representing the per-unit purchase price and received revenue for selling electricity respectively, while π_g^{buy} represents the cost of purchasing gas. P_A relates to the adjustable portion of the flexible prosumers that may exist in the MES. N_n is the length of each flexible prosumers' baseline requirement. $\Delta l_{A,u}^+$ and $\Delta l_{A,u}^-$ are slack variables for these prosumers. λ_A^+ and λ_A^- respectively represent a penalty and incentive for exceeding or not meeting the baseline requirement of each prosumer. In the objective function, $P_{(n_i \to n_j)}$ represents the bi-directional arcs connected to charging stations which are manipulated by the controller to determine power flow to and from connected EVs. The operation of flexible prosumers are manipulated using their respective related binary variables denoted as δ_{PM}. These binary variables are binary processing δ^p, completed δ^c and waiting δ^w variables discussed in Chapter 3. Due to the presence of binary variables, the optimisation problem is a MILP, which is solved at each k. Problem (4.8) is defined over a future control horizon, which without loss of generality is set equal to the scheduling horizon, N_H. Following standard receding horizon implementation, N_H remains constant throughout the simulation.

4.2.2 Receding Horizon Constraint Update

The charge/discharge operation model is presented as part of an optimisation problem to be solved repeatedly over the horizon N_H. Hence it is necessary to account for the presence and effect of controlled charging/discharging of EVs over a prediction horizon N_H. The notation $(k+h|k)$ is adopted to correspond to schedule h steps ahead that are predicted using information available at time k. If after solving the optimisation problem at k, the controller assigns energy to the EV when charging/discharging operation i is occurring, the EV's SoC will be different at the next sampling instant and needs to be updated accordingly:

$$\text{if } h^a_{EV,i} \leq k < h^d_{EV,i} \quad \rightarrow \quad E_{EV,i}(0|k) = E_{EV,i}(1|k-1) \qquad \forall i \in \{1 : cd\} \tag{4.9}$$

where $E_{EV,i}(k+1|k-1)$ denotes an EV's SoC during the second scheduling period ($h = 1$) after assigned $Q_{EV,i}(k|k-1)$ at $k-1$. Also, δ_{n_j} is updated accordingly:

$$\delta_{n_j}(h-1|k) = \delta_{n_j}(h|k-1) \qquad \forall h \in \{1 : N_H - 1\} \tag{4.10}$$

Finally, (4.3a) - (4.3f) become functions of time and at the end of the i^{th} charging/discharging operation, when $k = h^d_{EV,i}$, affiliated information is removed from these matrices. Note that the above equations also apply when an EV has not connected to a charging station because constraints used to estimate the charging/discharging operation in the controller must be updated. In addition, if before solving the optimisation problem again, a new EV is connected, these constraints are replaced with constraints relating to the newly connected EV.

4.2.3 Deterministic Predictive Control Implementation

Based on the optimisation problem (4.8), an algorithm is formulated for controlling the charge/discha power of connected EVs and to determine electricity and gas import/export to meet all energy demands. Without loss of generality, N_H is set to the scheduling horizon and problem (4.8) is solved repeatedly at every time instant k, with scheduling period h set equal to k. The control algorithm is implemented according to Algorithm 1. Following this algorithm, the controller can react preemptively to estimate of future known operations while taking the system constraints into account.

Algorithm 1 Deterministic EMS

For each charging station n_j, estimate cd. If $cd > 1$, ensure operations do not overlap.
Initialise $E_{EV}(0), S_{EV}$ if $\exists EV$
Initialise $E_{n_j}(0)$ if $\exists Es^n$
for $k = 1, \ldots N_H$ **do**
    if $k = h^a_{EV}$ **then**
        $h^a_{EV,i} \leftarrow h^a_{EV}$
        $h^d_{EV,i} \leftarrow h^d_{EV}$
        $E^a_{EV,i} \leftarrow E^a_{EV}$
        $E^d_{EV,i} \leftarrow E^d_{EV}$
        $\pm Q_{EV,i} \leftarrow \pm Q_{EV}$
        $Cap_{EV,i} \leftarrow Cap_{EV}$
        $S_{EV,i} \leftarrow S_{EV}$
        $\delta_{EV,i} \leftarrow \delta_{EV}$
    end if
    Solve (4.8). Denote solution as $[\boldsymbol{x}(k), \ldots, \boldsymbol{x}(k + N_H - 1)]$
    Apply $\boldsymbol{x}(k)$ to the system
    $E_{EV}(k+1) = E_{EV}(k) \rightarrow (4.9)$
    $\delta_{EV}(k+1) = \delta_{EV}(k) \rightarrow (4.10)$
    $E_{n_j}(k+1) = E_{n_j}(k) \; \forall Es^n$
    $G_{y,flex,n_j}(k+1), L_{u,flex,n_j}(k+1) \leftarrow$ constraints in [33], $\forall GL^n$
    if $k = h^d_{EV}$ **then**
        delete h^a_{EV}
        delete h^d_{EV}
        delete E^a_{EV}
        delete E^d_{EV}
        delete $\pm Q_{EV}$
        delete Cap_{EV}
        delete S_{EV}
        delete δ_{EV}
    end if
end for

The deterministic EMS begins by estimating the number of charge/discharge operations cd that will occur at each charging station. Estimate the information on successive EV that will utilise each charging station from historical information (4.3a)-(4.3f). For all fixed storage systems that exists, initialise their SoC, E_{n_j}. If EVs are connected to charging stations, initialise their SoC E_{EV}. Before starting the iteration, set $k = 1$. If any EV is connected to a charging station, obtain their characteristics $(E^a_{EV}, E^d_{EV}, \pm Q_{EV}, Cap_{EV}, S_{EV})$, availabilities (h^a_{EV}, h^d_{EV}) and owners charging preferences (δ_{EV}) and use them to replace the estimates (i.e. $h^a_{EV,i}, h^d_{EV,i}, E^a_{EV,i}, E^d_{EV,i}, \pm Q_{EV,i}, Cap_{EV,i}, S_{EV,i}, \delta_{EV,i}$) during the i^{th} charging/discharging operation that correspond the charging stations they are connected to. Solve the optimisation problem (4.8). Apply the solution $\boldsymbol{x}(k)$ to the MES. Update the SoC and the binary variable monitoring the presence of EVs connected to a charging station or estimates of connected EVs using constraints (4.9) and (4.10). Also, update the SoC E_{n_j} of all fixed storage systems. If any flexible prosumers exist with the MES, their constraints is updated according to [33]. As the iteration continues, when any EV departs (i.e. $k = h^d_{EV}$), remove corresponding constraints in the optimisation problem. The procedure is repeated over the horizon N_H where N_H is a predefined number that is usually a multiple of the chosen sampling rate h.

4.3 Multi-Energy System Description

The MES used to demonstrate the incorporation of the EV charge/discharge model in the COMMES framework discussed in Section 4.1 is shown in Figure 4.5. Electricity and gas are available for imports from the wider energy infrastructure. It is also possible to export electricity if EVs that utilise the three charging stations decide to participate in V2X. Imported gas can be converted to electricity and heat using the CHP device. The MES in Figure 4.5 is represented

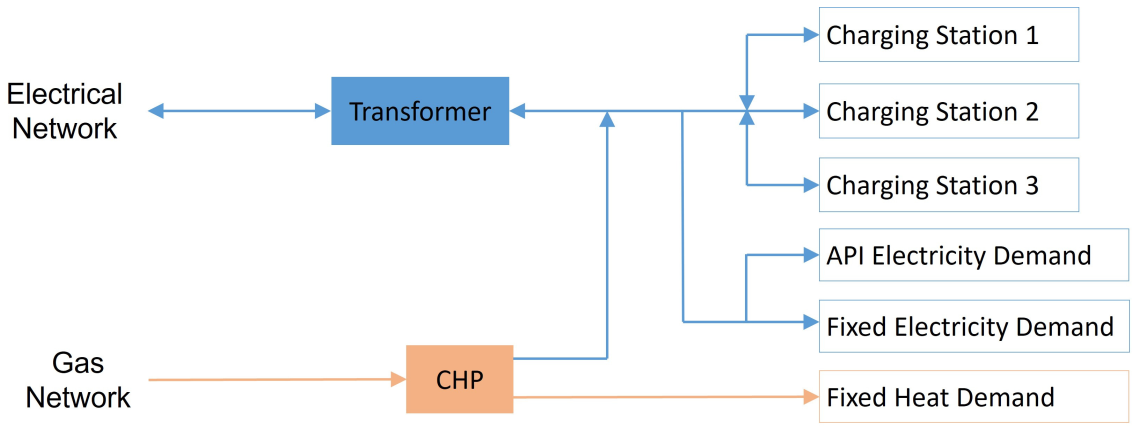

Figure 4.5: An multi-energy system schematic

using the EH graph shown in Figure 4.6. The EH graph is connected to the electricity and gas network via their respective terminal nodes. Within the ECM, the transformer in modelled using bi-directional arcs between node e_1 and e_2 and the CHP is modelled using transmitter node g_2. The prosumers are connected to terminal nodes e_3 and h_1. Nodes e_4, e_5, e_6 are dedicated terminal nodes that represent each of the three charging stations EVs connect to when they arrive to recharge their batteries. The set of equations that represent the ECM of Figure 4.6 are shown in (4.11a) - (4.11j). For simplicity, dependence of these equations on k is excluded.

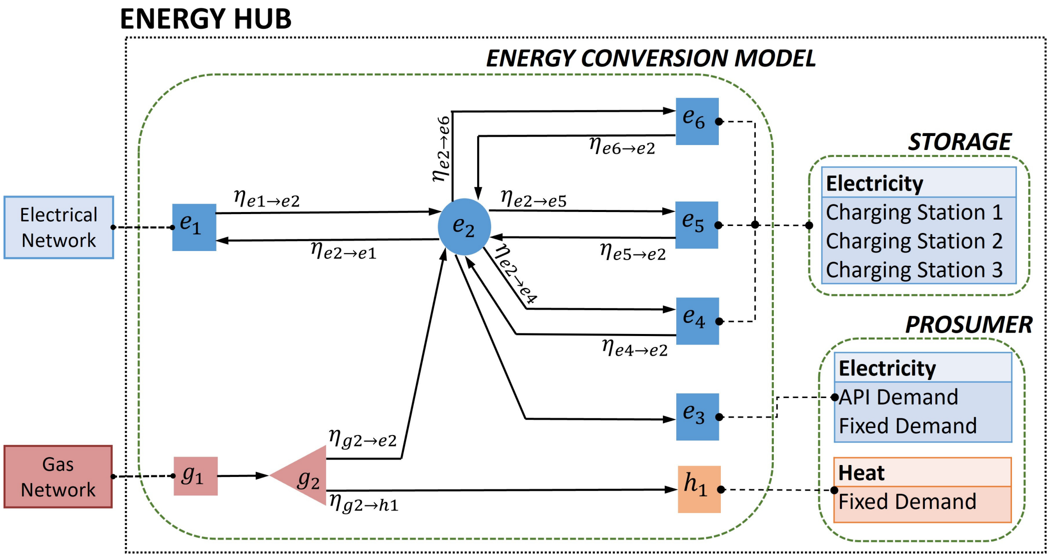

Figure 4.6: An energy hub model graph

$$P_{e1} + P_{(e2\to e1)}\eta_{(e2\to e1)} = P_{(e1\to e2)} \tag{4.11a}$$

$$P_{g1} = P_{(g1\to g2)} \tag{4.11b}$$

$$P_{e3} = -P_{(e2\to e3)}\eta_{(e2\to e3)} \tag{4.11c}$$

$$P_{e4} + P_{(e2\to e4)}\eta_{(e2\to e4)} = P_{(e4\to e2)} \tag{4.11d}$$

$$P_{e5} + P_{(e2\to e5)}\eta_{(e2\to e5)} = P_{(e5\to e2)} \tag{4.11e}$$

$$P_{e6} + P_{(e2\to e6)}\eta_{(e2\to e6)} = P_{(e6\to e2)} \tag{4.11f}$$

$$P_{h1} = -P_{(g2\to h1)}\eta_{(g2\to h1)} \tag{4.11g}$$

$$P_{(g1\to g2)}\eta_{(g1\to g2)} = -P_{(g2\to e2)} \tag{4.11h}$$

$$P_{(g1\to g2)}\eta_{(g1\to g2)} = -P_{(g2\to h1)} \tag{4.11i}$$

$$\begin{aligned} P_{(e1\to e2)}\eta_{(e1\to e2)} + P_{(e4\to e2)}\eta_{(e4\to e2)} + P_{(e5\to e2)}\eta_{(e5\to e2)} + P_{(e6\to e2)}\eta_{(e6\to e2)} + P_{(g2\to e2)}\eta_{(g2\to e2)} \\ = P_{(e2\to e1)} + P_{(e2\to e3)} + P_{(e2\to e4)} + P_{(e2\to e5)} + P_{(e2\to e6)} \end{aligned} \tag{4.11j}$$

Prosumers included in Figure 4.6 are Adjustable-Pliable-Interruptible (API) and fixed electrical demands both connected to node e_3, and fixed heat demand connected to node h_1. Equations that represents these prosumers connected to the ECM terminal nodes are shown in (4.12).

$$\begin{aligned} P_{e3}(k) &= -L_{API_{e3}}(k) - L_{fix_{e3}}(k) \\ P_{h1}(k) &= -L_{fix_{h1}}(k) \end{aligned} \tag{4.12}$$

$L_{API_{e3}}$ represents flexible API electrical demand whose operation can be exploited to achieve specific objectives. Equations that describe the operation of the API demand are (3.10)-(3.12), (3.14)-(3.17) and (3.19)-(3.24). Fixed demands $L_{fix_{e3}}$ and $L_{fix_{h1}}$ are uncontrollable, their consumption pattern unknown and must be met at each time instant k. Both $L_{API_{e3}}$ and $L_{fix_{e3}}$ are connected to the same terminal node to help reduce the computational burden when solving the optimisation problem as the number of equations are reduced. As the operation of flexible prosumers are controlled by manipulating individual devices directly this is a safe simplification.

4.4 Simulation Setup and Analysis

For the purpose of the MES shown in Figure 4.6, the sampling period is set to 15 minutes over a 24 hour control horizon i.e. $N_H = 96$. Table 4.1 shows ECM conversion efficiencies across each power flow arc. Other conversion efficiencies not shown are assumed as unity. Additional parameter values are shown in Table 4.2.

Table 4.1: Conversion efficiencies related to technologies

ECM arc factor	Device	Conversion	Value
$\eta_{e_1\to e_2}, \eta_{e_2\to e_1}$	Transformer	electricity	0.98
$\eta_{g_2\to e_2}$	CHP	gas to electricity	0.294
$\eta_{g_2\to h_1}$	CHP	gas to heat	0.485
$\eta_{e_2\to e_4}$	Charging Station 1	charging efficiency	0.9
$\eta_{e_4\to e_2}$		discharging efficiency	1/0.9
$\eta_{e_2\to e_5}$	Charging Station 2	charging efficiency	0.9
$\eta_{e_5\to e_2}$		discharging efficiency	1/0.9
$\eta_{e_2\to e_6}$	Charging Station 3	charging efficiency	0.9
$\eta_{e_6\to e_2}$		discharging efficiency	1/0.9

Regarding each charging station, some assumptions are made. All charging stations have CHAdeMO connectors which are V2X capable, and each has a fixed charging/discharging cable connected. Presently, EVs that have CHAdeMO sockets always have another charging socket

- either Type 1 or Type 2 for home AC charging [89]. It is estimated that over N_H, only one charging/discharging operation occurs at charging station 1, two at charging station 2 and three at charging station 3. In addition, EVs that connect during the first charging/discharging operation at all charging stations usually consent to charge via V2X. For clarification, the realised number of charge/discharge operations must not equal the estimated number (cd) for the modelling approach to be implementable as a key contribution of the model is the ability to adapt to unknown number of EVs that may utilise a charging station over a period.

Table 4.2: Additional simulation parameters

Parameter	Description	Value
$\overline{P_{e_4}}/\underline{P_{e_4}}$	charge/discharge limits of Charging Station 1	80kW
$\overline{P_{e_5}}/\underline{P_{e_5}}$	charge/discharge limits of Charging Station 2	80kW
$\overline{P_{e_6}}/\underline{P_{e_6}}$	charge/discharge limits of Charging Station 3	80kW

Furthermore, it is assumed that each charging station is equipped with an interactive display, and when an EV arrives and connects to a charging station, its arrival time, SoC, battery capacity and V2X capability are obtained. If an EV has bi-directional energy exchange capability, the driver can indicate their consent to participate in V2X when entering desired departure time and SoC via the display. Following this reasoning, if technology advances to an extent were all EVs and/or charging stations with Type 1, Type 2 or CCS sockets are made V2X capable, proposed methodology herein will still be applicable.

Regarding the API demand, it is assumed that its baseline energy consumption profile is divided into 4 segments, each with a baseline energy requirement of $40kW$. Limits on waiting periods between each segment ($\underline{N}^{w}_{API,u}$ and $\overline{N}^{w}_{API,u}$) are set to 5 and 15 respectively, $\forall u \in \{2:4\}$. The API demand is set to come online at 02:30am, processing limits ($\underline{N}^{p}_{API,u}$ and $\overline{N}^{p}_{API,u}$) are set to 1 and 2 respectively, the maximum deviations from the baseline energy requirement during each sampling period is $\pm 5kW$, and the penalty and incentive (λ^{+}_{A} and λ^{-}_{A}) for exceeding or not meeting the baseline requirement for each segment of the API demand are set to 5.

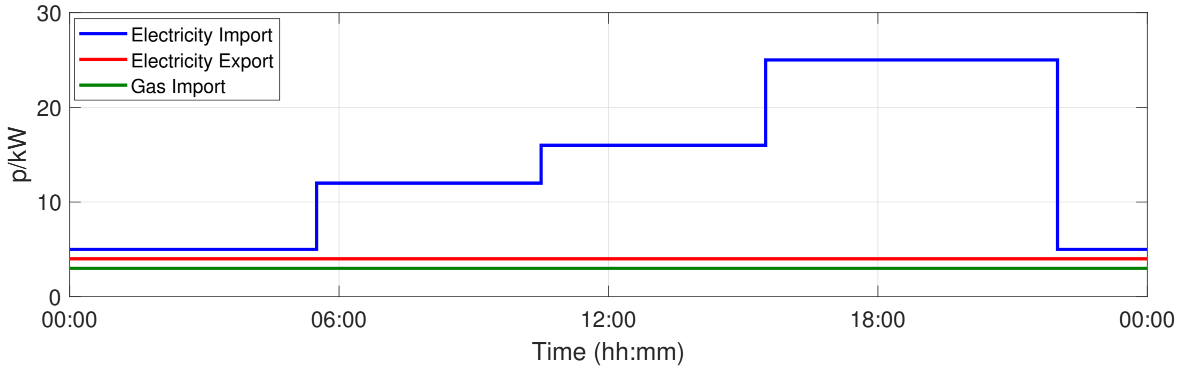

Figure 4.7: Import/export price of electricity and gas

The price tariffs for electricity and gas are shown in Figure 4.7. Fixed electricity and heat demands were collected from the University of Manchester (UoM) Estates department that operates a building management system that logs energy usage data collected from buildings relating to a particular energy vector. Information (4.3a)-(4.3f) needed to estimate EV charging/discharging operations at each charging station were obtained from discrete uniform distributions with intervals shown in Table 4.3. The MPC optimisation problem is solved with a commercial solver CPLEX at each k on a PC Intel Core i7-4700MQ CPU @ 2.40GHz with 32 GB RAM.

Table 4.3: Intervals to generate EV data from uniform distribution

	Charging Station		
	1	2	3
T_{n_j}	[2 10], [82 94]	[2 10], [24 40] [42 60], [62 94]	[2 10], [22 30] [32 40], [52 60] [62 70], [82 90]
SoC_{n_j}	[40 60], [80 100]	[40 60], [80 100] [40 60], [80 100]	[40 60], [80 100] [40 60], [80 100] [40 60], [80 100]
Q_{n_j}	[40 50]	[40 50], [40 50]	[40 50], [40 50] [40 50]
Cap_{n_j}	[90 100]	[90 100], [90 100]	[90 100], [90 100] [90 100]
S_{n_j}	[0.9 0.98]	[0.9 0.98], [0.9 0.98]	[0.9 0.98], [0.9 0.98] [0.9 0.98]

4.4.1 Index Sets

Index sets introduced in Section 4.2.1 are used to group nodes and components within Figure 4.6. It is to clearly differentiate the constraints used to model Figure 4.6 and classify the different node types. Table 4.4 lists the index set used to derive the optimisation constraints for Figure 4.6.

Table 4.4: EH index sets

$Bi :=$	$\{e_1 \leftrightarrow e_2, e_2 \leftrightarrow e_4, e_2 \leftrightarrow e_5, e_2 \leftrightarrow e_6\}$
$Su :=$	$\{e_2\}$
$Tr :=$	$\{g_2\}$
$Sw :=$	$\{-\}$
$T :=$	$\{g_1, e_1, e_3, e_4, e_5, e_6, h_1\}$
$GL^n :=$	$\{L_{API_{e_3}}\}$
$GL^s :=$	$\{L_{fix_{e_3}}, L_{fix_{h_1}}\}$
$Es^n :=$	$\{-\}$
$Es^s :=$	$\{E_{EV,i\rightarrow e_4}, E_{EV,i\rightarrow e_5}, E_{EV,i\rightarrow e_6}\}$

4.4.2 Discussion

The EV charge/discharge operation model is capable of representing any number of EVs that will utilise charging stations within a network provided there is adequate understanding of EV types and driving patterns. Table 4.3 contains information about EVs that have utilised the charging stations shown in Figure 4.6. Figure 4.8 shows the estimated and realised utilisation of all charging stations after implementing the MPC scheme in Section 4.2.3.

The estimated utilisation of all charging stations is represented as dotted lines in Figure 4.8. The solid blue lines are the realised utilisation of all charging stations after EVs arrive and connect to recharge their batteries. At charging station 1, it is assumed that the EV that typically utilises it stays connected over an extended period and chooses to participate in V2X such that it can be considered a fixed storage system. In Figure 4.8A, we see that the EV arrives earlier than estimated, sticks to its usual choice to participate in V2X and stays connected over an extended period. The EV initially discharges, together with the EVs connected at charging stations 2 and 3 during their respective first charging/discharging operations. The

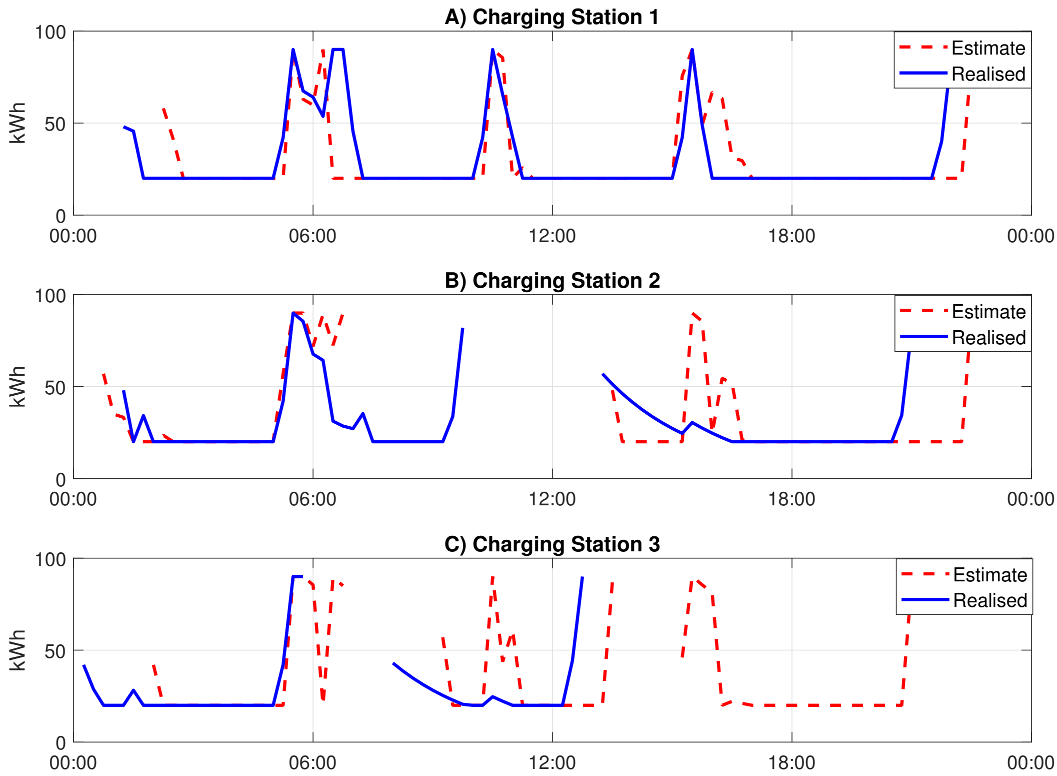

Figure 4.8: Estimated and realised utilisation of all charging stations

energy discharged from these EVs is used to meet fixed electricity demand. Around 06:00, the EVs connected to charging stations 1 and 2 charges to their maximum capacity before electricity import price increases. They then discharge to help meet the energy demand of the EV connected to charging station 3 before it departs and electricity demands shown in Figure 4.9B and Figure 4.9C.

It is estimated that two EVs will utilise charging station 2 over the horizon, and both will participate in V2X. In Figure 4.8B, it can be seen that the first EV arrives later than estimated, and the driver chooses to charge by V2X. The second EV arrives close to its estimated time, but the driver decides not to participate in V2X. This results in the gradual decline in SoC seen during the second charging/discharging operation in Figure 4.8B. This is due to the battery's efficiency, which is revealed to be 95%, resulting in a 5% reduction in stored energy over time as the EV remains ideal. A similar effect is also seen in Figure 4.8C during the second charging/discharging operation at charging station 3. It is estimated that three charging/discharging operations will occur at charging station 3 over the horizon. However, in Figure 4.8C, only two

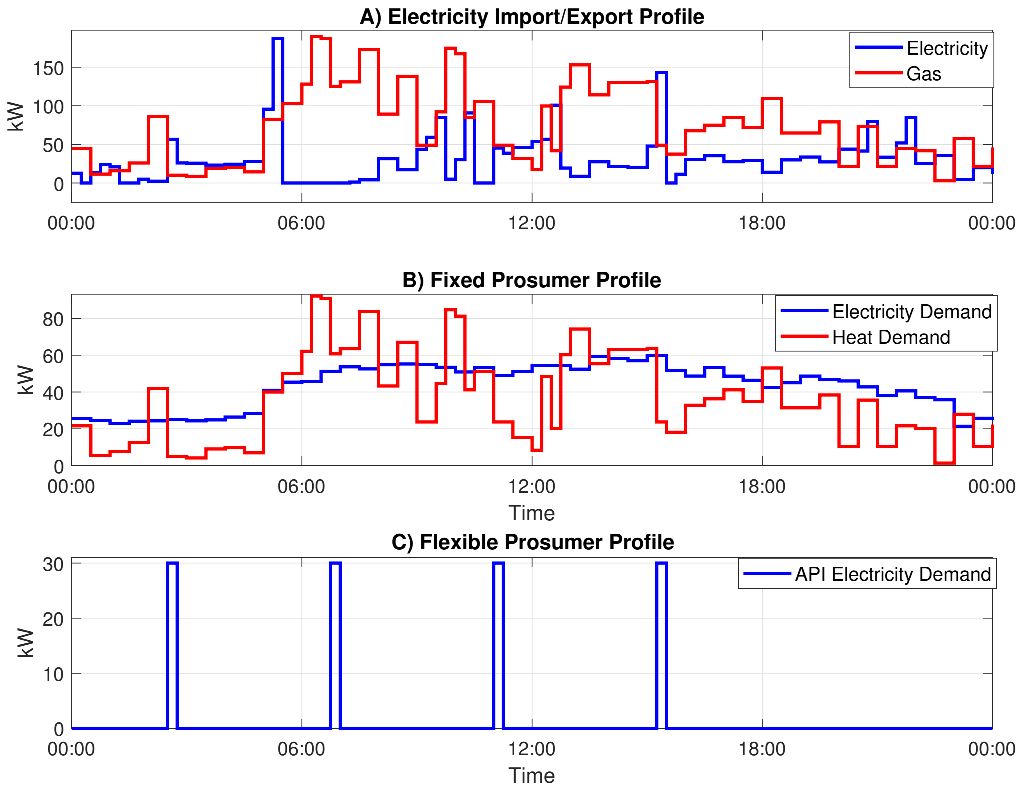

Figure 4.9: Electricity import/export profile and prosumer demand profiles

charging/discharging operations are realised. This validates a major contribution in this thesis that the proposed EV charge/discharge model is implementable even when the number of EVs in a network is not exactly known. The gaps between charging/discharging profiles in Figure 4.8B and Figure 4.8C are periods when charging stations 1 and 2 are not utilised.

The EV utilising charging station 1 does not retain enough charge to help satisfy energy demands due to its battery efficiency. Hence, sharp rises in its SoC are noticed in Figure 4.8A at approximately the same time electricity import price is about to increase (refer to Figure 4.7 for energy price profile). Shortly after each electricity import price increase, the EV discharges to help satisfy increasing electricity demands. This drastic change in SoC is also observed in Figure 4.8B during the first charging/discharging operation but not in Figure 4.8C. This is because the EV utilising charging station 3 during the first charging/discharging operation stays connect for a short period; hence could not be fully exploited to satisfy electricity demands. Most gas import shown in Figure 4.9A is used to satisfy heat demands shown in Figure 4.9B. Figure 4.9C shows the operation of the API electricity demand. It can be seen that the API demand comes online at the scheduled time and operates based on the specification outlined in Section 4.4. This verifies that the incorporation of the EV charge/discharge operation model to the COMMES framework does not affect the operation of prosumers.

4.4.3 Comparative Analysis

Using the MES in Figure 4.6, operational costs are compared by implementing some assumptions considered in research used in coordinating EV charging/discharging operations with the approach in this thesis. In particular, the four scenarios analysed represent the following cases:

1. All EVs participate in V2X. Only one charging/discharging operation occurs at all charging stations.
2. All EVs participate in V2X. Only one charging/discharging operation occurs at all charging stations. EV that utilises charging station 1 stays connected over a longer period.
3. Not all EVs participate in V2X. One, two and three charging/discharging operations are realised at charging stations 1, 2 and 3, respectively. EV that utilises charging station 1 stays connected over a longer period.
4. All EVs participate in V2X. One, two and three charging/discharging operation are realised at charging stations 1, 2 and 3 respectively. EV that utilises charging station 1 stays connected over a longer period.

The operational cost obtained from implementing the four scenarios is shown in Table 4.5. These costs are the summation of the cost obtained from the controller after solving the optimisation problem repeatedly over the horizon plus recourse cost when actual EV demand profiles are realised. The deterministic EMS implemented is the one outlined in Section 4.2.3.

Table 4.5: Operational cost of four scenarios

Scenario	1	2	3	4
Operational Cost (£)	625.46	597.21	583.21	568.93

Scenarios 1 and 2 are common assumptions typically made in research when coordinating EV charge/discharge operations. Scenarios 3 and 4 are some assumptions considered to prove the superiority of the proposed modelling approach.

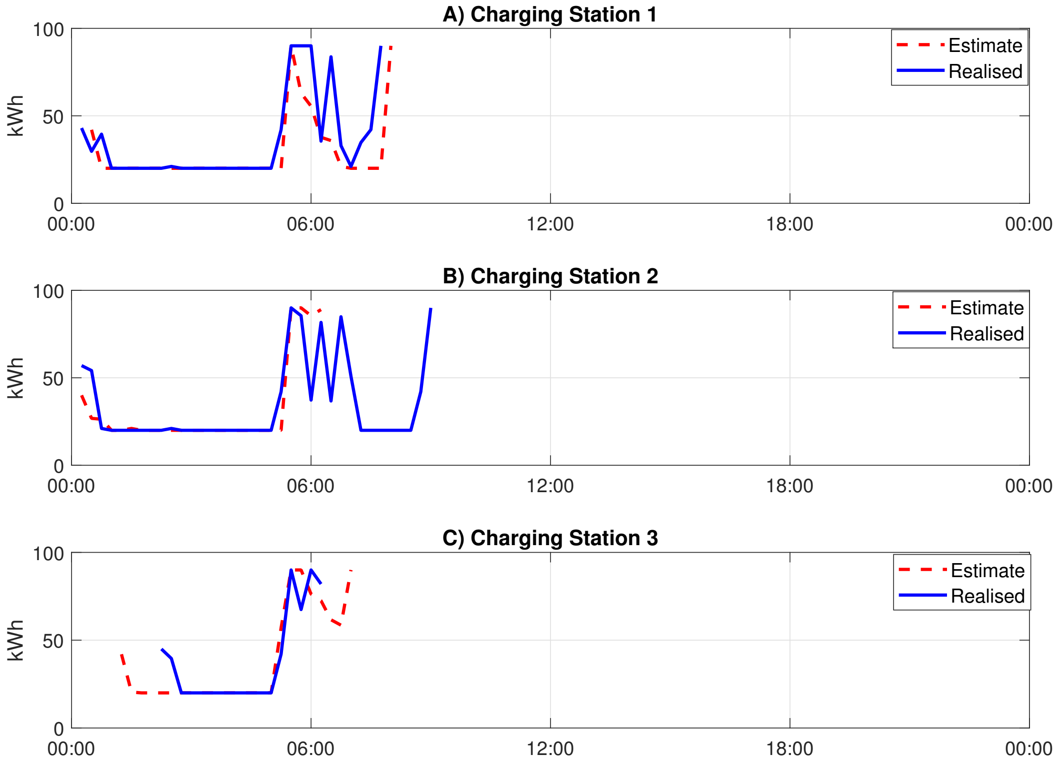

Figure 4.10: Scenario 1 - Estimated and realised utilisation of all charging stations

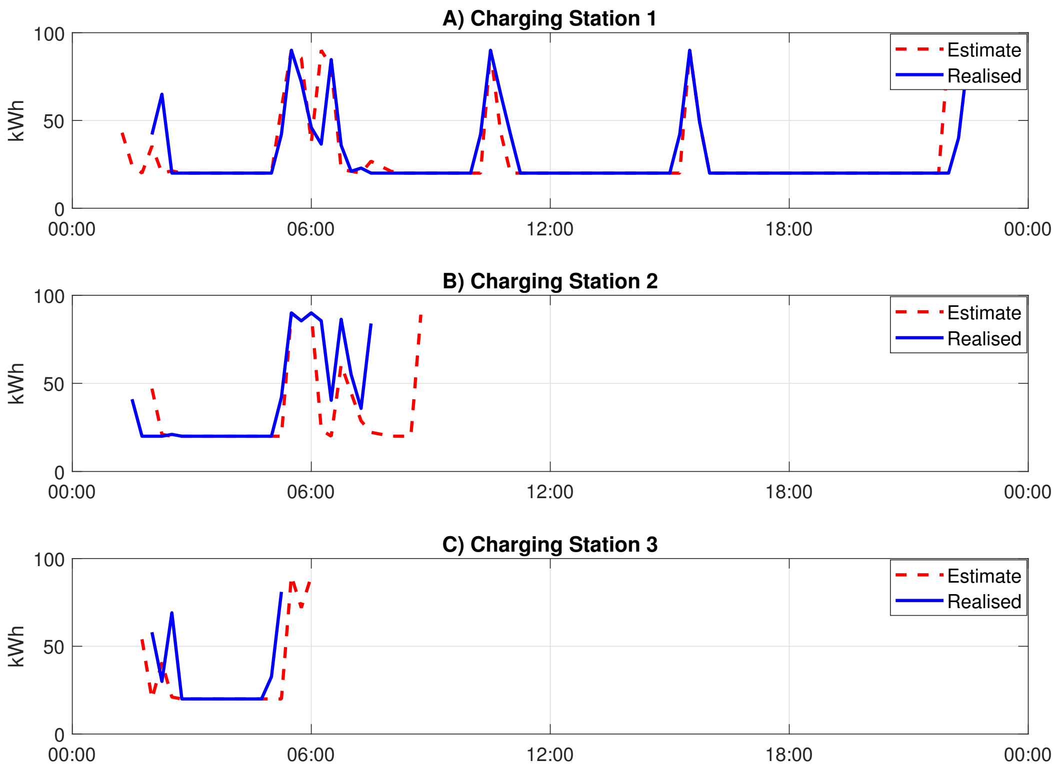

Figure 4.11: Scenario 2 - Estimated and realised utilisation of all charging stations

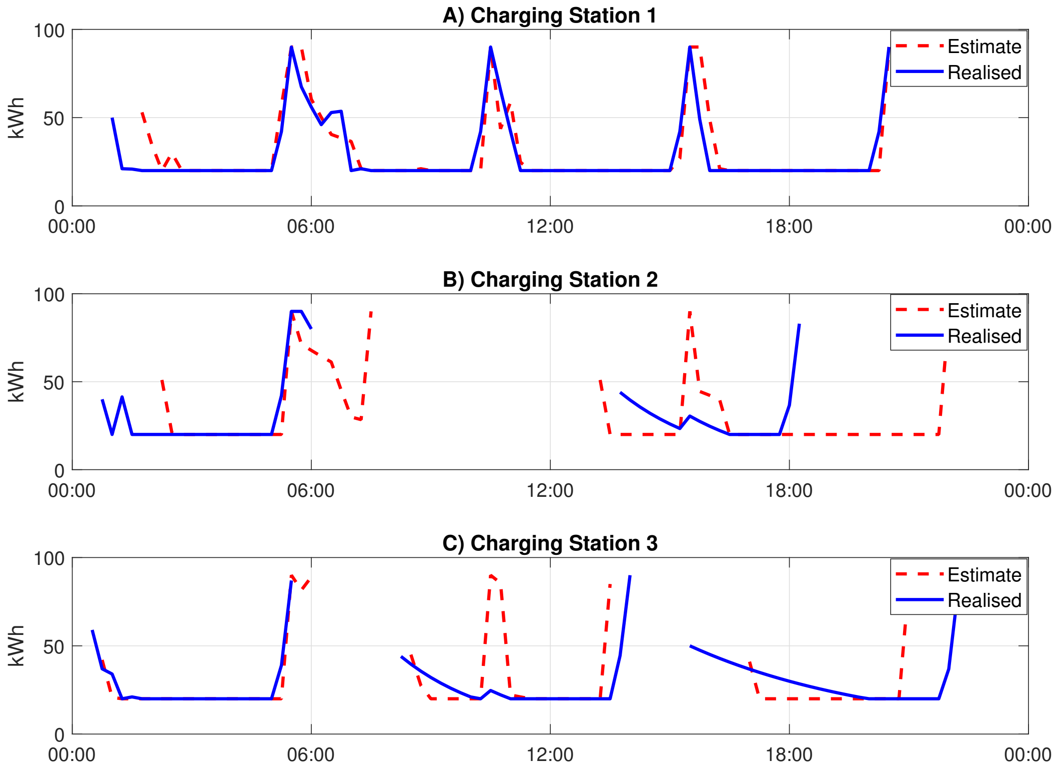

Figure 4.12: Scenario 3 - Estimated and realised utilisation of all charging stations

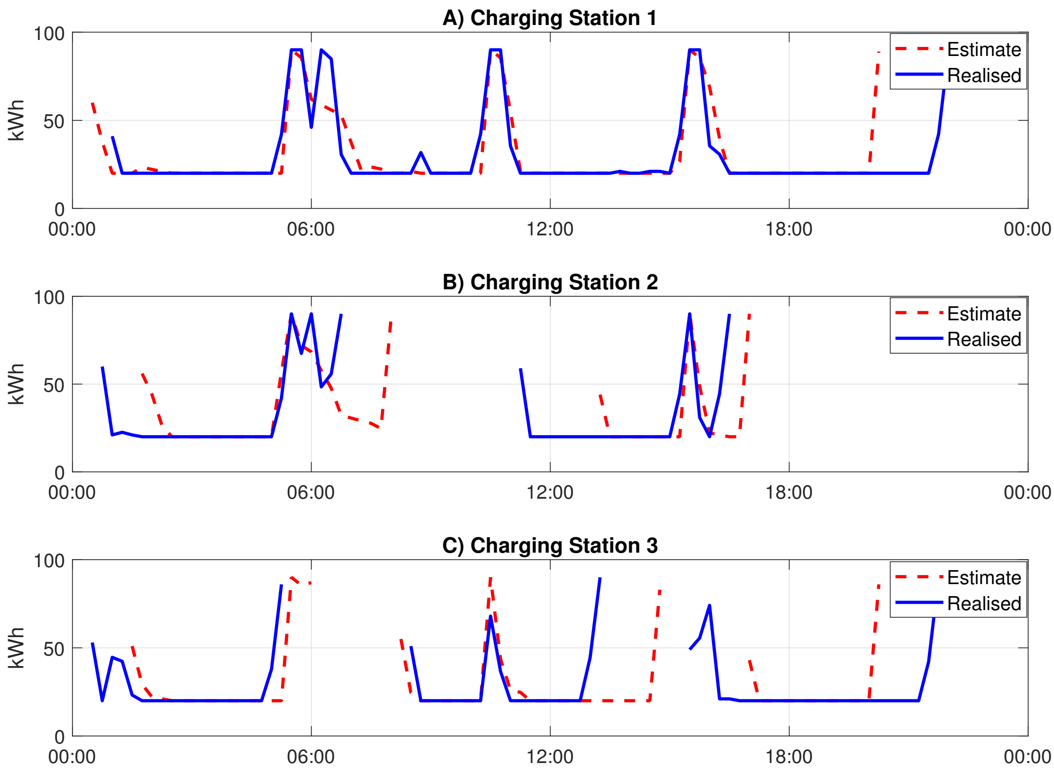

Figure 4.13: Scenario 4 - Estimated and realised utilisation of all charging stations

In scenario 1, all EVs have relatively short availabilities hence could not be significantly exploited to reduce operational cost. The resulting charge/discharge profiles of EVs connected to each charging station are shown in Figure 4.10. In scenario 2, the availability of the EV that utilises charging station 1 is set significantly longer than the EVs utilising charging stations 2 and 3. The resulting charge/discharge profiles of EVs in this scenario are shown in Figure 4.11. The availability of the EV that utilises charging station 1 is set to a similar duration as the EV utilising charging station 1 in Section 4.4. Hence the EV's storage capacity is used to help satisfy energy demands by charging when energy prices are cheap, reducing the operational cost compared to the cost obtained in scenario 1.

The setup of scenario 3 is similar to the setup in Section 4.4. However, all charging/discharging operations are realised. The resulting charge/discharge profiles of EVs in this scenario are shown in Figure 4.12. During the first charging/discharging operations at all charging stations, drivers consent to participate in V2X. Drivers during the second charging/discharging operations at charging station 2, and the second and third at charging station 3 choose not to participate in V2X when they connected their EVs to the charging stations. Although these drivers opted out of V2X, the operational cost for scenario 3 is less than that of scenarios 1 and 2. This is as a result of the storage capacity of the EV utilising charging station 1 been exploited by the controller, to help satisfy the EV demands from charging stations 2 and 3, and energy demands of the prosumers. From Table 4.5, it can be seen that the operational cost obtained in scenario 4 is the smallest as the controller has permission the utilise all EVs to aid satisfying energy demands. This is because all drivers gave consent to participate in V2X when they connected their EVs to each of the charging stations. Figure 4.13 shows the resulting charge/discharge profiles of EVs in scenario 4.

The results from scenarios 3 and 4 highlights the benefits of the EV modelling approach over scenarios 1 and 2 by showing that accommodating a diverse nature of EV characteristic as well as their individual availabilities and charging preferences significantly reduces operational costs. Specifically compared to scenario 1, the operational cost obtained in scenario 2 outperforms by approximately 4.52%. Operational cost obtained in scenario 3 and 4 but outperforms scenario 1 by 6.76% and 9.04% respectively.

4.5 Chapter Summary

In this chapter, details of the incorporation of the mobile storage model into the COMMES framework is presented. In particular, the EV charging/discharging operation model presented is able to account for the diverse nature of EV ownership even when the number of EVs that may utilise a charging station is not known exactly. An example system was analysed to demonstrate the modification to the COMMES framework.

Chapter 5

Stochastic Control Scheme Application

Consideration of uncertainty sources within the COMMES framework is described in detail in this chapter. In particular, a stochastic EMS is developed that effectively accounts for the modular nature of the COMMES framework, especially the ever-changing nature of the utilisation of charging stations by EVs and uncertainties they introduce into MES.

The remainder of the chapter is organised as follows: Discussion of how uncertainties are considered within the three components of the COMMES framework is presented in Section 5.1. This is followed by the development of a general stochastic EMS formulated using two-stage stochastic programming approach and incorporated into the MPC framework in Section 5.2. In Section 5.3, description of the case-study MES used to demonstrate how uncertainty sources are considered in the modified COMMES framework is presented. Simulation analysis of the general stochastic EMS applied to the MES described in Section 5.3 are discussed in Section 5.4 before a summary of the chapter is presented in Section 5.5.

5.1 Modifications of COMMES Framework

5.1.1 Uncertainty Sources

In single- or multi-energy systems, the operation of variable power generation and end-user devices are sources of uncertainty as they are difficult to predict. WT and PV are examples of variable power generation technologies as they have inherent uncertainty due to wind speed and solar radiation. Televisions, electric kettles, and microwaves are examples of end-user devices that introduce uncertainty in MES. The end-user determines how these devices operate, and the energy consumed by these devices must be met immediately. Within the COMMES framework, models of such devices are connected to the ECM via terminal nodes. Hence, P_{n_j} in (3.4) will not only depend on time instant k but also on the uncertainties introduced by these components. However, these uncertainties will not affect the arc power flows on the right-hand side of (3.4) because the arcs model part of physical devices within the ECM such as a transformer and HP.

In the COMMES framework, the operation of variable power generation and end-user devices are modelled using PM, specifically fixed prosumer components. This is because the energy they generate or consume must be considered instantly and needs to be forecasted. Hence, the values of G_{z,fix,n_j} in (3.9) and L_{v,fix,n_j} in (3.10) depends on the operation of devices they represent. The values of $G_{y,flex,n_j}$, and $L_{u,flex,n_j}$ depend on devices modelled based on their operation and user preferences; hence they have no inherent uncertainty. However, uncertainty could exist in user preferred operation time, but this is not considered in this thesis. EVs are also examples of end-user devices that introduce uncertainty in MES due to difficulty in accounting for individual EV characteristics, availabilities and charging preferences as they are unknown until an EV arrives and connects to a charging station. Hence, the charge/discharge operation of EV will be influenced by the uncertainty of these three factors

5.1.2 Mobile Storage Model

A modular approach to modelling the operation of mobile storage systems such as EVs makes accounting for EV related uncertainties difficult compared to other end-user devices that may exist within a MES. EVs can be disconnected and reconnected at a later point in time. Hence, their lack of fixed presence, uncertain time and location EVs disconnect and reconnect to the network and their energy levels are sources of uncertainty within MES. When viewed from the utilisation of charging stations, the type of EVs that will utilise a charging station, especially if the charging station is located in a public area, will also be a source of uncertainty within MES.

The aforementioned EV uncertainty sources are encapsulated in the historical information (4.3a) - (4.3f) as information on an EV charging/discharging its battery remains unknown until an EV actually arrives and connects to a charging station. However, to account for the nature of diverse EVs that may exist in residential, commercial and public areas, modifications are made to (4.3a) - (4.3f) such that information collected on successive EVs that have utilised a charging station are over longer periods, for example over days. The new matrices that represent such historical information on the utilisation of a charging station n_j are shown in (5.1a) - (5.1f), and W is the number of successive EV charge/discharge operations.

$$\boldsymbol{T_{n_j}} = \Big[[h^{a,1}_{EV,i} \cdots h^{a,W}_{EV,i}]^T \; [h^{d,1}_{EV,i} \cdots h^{d,W}_{EV,i}]^T \cdots [h^{a,1}_{EV,cd} \cdots h^{a,W}_{EV,cd}]^T \; [h^{d,1}_{EV,cd} \cdots h^{d,W}_{EV,cd}]^T\Big] \in \mathbb{R}^{W*(2*cd)}_{\geq 0} \tag{5.1a}$$

$$\boldsymbol{SoC_{n_j}} = \Big[[E^{a,1}_{EV,i} \cdots E^{a,W}_{EV,i}]^T \; [E^{d,1}_{EV,i} \cdots E^{d,W}_{EV,i}]^T \cdots [E^{a,1}_{EV,cd} \cdots E^{a,W}_{EV,cd}]^T [E^{d,1}_{EV,cd} \cdots E^{d,W}_{EV,cd}]^T\Big] \in \mathbb{R}^{W*(2*cd)}_{\geq 0} \tag{5.1b}$$

$$\boldsymbol{Q_{n_j}} = \Big[[\pm Q^1_{EV,i} \cdots \pm Q^W_{EV,i}]^T \cdots [\pm Q^1_{EV,cd} \cdots \pm Q^W_{EV,cd}]^T\Big] \in \mathbb{R}^{W*cd}_{\geq 0} \tag{5.1c}$$

$$\boldsymbol{Cap_{n_j}} = \Big[[Cap^1_{EV,i} \cdots Cap^W_{EV,i}]^T \cdots [Cap^1_{EV,cd} \cdots Cap^W_{EV,cd}]^T\Big] \in \mathbb{R}^{W*cd}_{\geq 0} \tag{5.1d}$$

$$\boldsymbol{S_{n_j}} = \Big[[S^1_{EV,i} \cdots S^W_{EV,i}]^T \cdots [S^1_{EV,cd} \cdots S^W_{EV,cd}]^T\Big] \in \mathbb{R}^{W*cd}_{\geq 0} \tag{5.1e}$$

$$\boldsymbol{\delta^{V2X}_{n_j}} = \Big[[\delta^1_{EV,i} \cdots \delta^W_{EV,i}]^T \cdots [\delta^1_{EV,cd} \cdots \delta^W_{EV,cd}]^T\Big] \in \mathbb{I}^{W*cd}_{\{0:1\}} \tag{5.1f}$$

The representation of historical information (5.1a) - (5.1f) allows understanding of EV drivers routine to be leverage through the way different charging stations are utilised over time. As such, forecasts of EV needs that matches reality is obtainable. Also, (5.1a) - (5.1f) facilitates the understanding of how charging stations in residential, commercial and public areas are utilised. For example, the characteristics, availabilities, and charging preferences of EV drivers using charging stations within residential areas will be easier to predict as residents will most likely own their individual EVs and have their own individual charging stations installed at home. Compared to the charging stations in public areas, EVs can come from anywhere to utilised them, and no charging station is own by particular EV drivers. Hence, making it more difficult to predict EV characteristics, availabilities and charging preferences.

In Section (4.1), equations (4.4) - (4.7) that accounts for the successive charge/discharge operation of EVs have to be modified to account the uncertainty encapsulated in information (5.1a) - (5.1f). Equations (4.4) that accounts for an EV's SoC and (4.5) that represents an EV's connection to a charging station are rewritten as:

$$E_{EV,i}(k+1) = S_{EV,i}E_{EV,i}(k) + Q_{EV,i}(k) \tag{5.2}$$

$$Q_{EV,i}(k) = -P_{n_j}(k) \tag{5.3}$$

$$\forall i \in \{1 : cd\} \qquad \forall k \in \left\{[h^{a,1}_{EV,i} \cdots h^{a,W}_{EV,i}]^T : [h^{d,1}_{EV,i} \cdots h^{d,W}_{EV,i}]^T - 1\right\}$$

Equations (4.6) and (4.7) employing the binary variable δ_{n_j} to monitor the presence of an EV connected to a charging station are modified to prevent infeasible cases where $P_{n_j}(k) \geq 0$ and $k \notin \left\{[h^{a,1}_{EV,i} \cdots h^{a,W}_{EV,i}]^T : [h^{d,1}_{EV,i} \cdots h^{d,W}_{EV,i}]^T - 1\right\}$.

$$\delta_{n_j}(k) = \begin{cases} 1, & \text{if } k \in \left\{[h^{a,1}_{EV,i} \cdots h^{a,W}_{EV,i}]^T : [h^{d,1}_{EV,i} \cdots h^{d,W}_{EV,i}]^T - 1\right\} \\ 0, & \text{if otherwise} \end{cases} \tag{5.4}$$

$$\underline{P_{n_j}}(k)\delta_{n_j}(k) \leq P_{n_j}(k) \leq \overline{P_{n_j}}(k)\delta_{n_j}(k) \tag{5.5}$$

$$\forall k \in \{1 : N_H - 1\} \qquad \forall i \in \{1 : cd\}$$

5.2 Stochastic Energy Management Scheme

Similarly to Chapter 4, an EMS is developed to minimise the cost of purchasing and/or selling energy from/to the grid plus cost on the adjustable portion of flexible prosumers that may exist within an MES. However, the EMS developed in this chapter varies slightly. In particular, it addresses uncertain from generation and demand sources by accounting for them using the two-stage stochastic programming technique when formulating the optimisation problem solved within the EMS.

5.2.1 Two-Stage Stochastic Problem Formulation

Following the split decisions made by the implementation of the two-stage stochastic approach discussed in Section 3.2.1, a stochastic optimisation problem can be formulated for an MES. The objective of the problem is to make an optimal here and now (first-stage) decision on the amount of energy to purchase from or sell to the grid plus cost on the adjustable portion of flexible prosumers that may exist within the MES while considering possible real-time realisations of generation and/or demand uncertainties. Then correction (second-stage) decisions are made when actual generation and/or demand are realised. The following subsections describe how a deterministic equivalent problem is formulated with a similar structure as problem (3.30). This is done by spiting the problem formulation into first- and second-stage functions before combining them to present a sample average approximated problem.

Index sets are again adopted to group different nodes and components that exist within an EH and facilitate the consideration of nodes affected by uncertain sources. The index set Su, Tr and Sw identify all sum, transmitter, and switch nodes, respectively. $T = \{T^n, T^s\}$ is the index set identifying terminal nodes, with T^n identifying those not connected to uncertainty sources and T^s identifying those connected to uncertainty sources. Bi-directional arcs are identified as Bi. Prosumers are identified with the index set $GL = \{GL^n, GL^s\}$, with GL^n identifying flexible prosumers modelled using any combination of S, A, P, I. GL^s identifies fixed prosumers. The index set $Es = \{Es^n, Es^s\}$ identifies all energy storage components. Es^n and Es^s respectively identify fixed and mobile storage components.

First-Stage Function

As the first- and second-stage functions are part of an optimisation problem to be solved within an MPC scheme, the objectives of both functions should consider a prediction horizon N_H. Hence, the aim in the first-stage is to look N_H steps into the future, with scheduling period

h and decide at time k the amount of electricity and gas to import/export while considering the costs on the adjustable portion of the flexible prosumers:

$$P_{first}(k+h) = \sum_{k=0}^{N_H-1} \left[P_{cost}(k+h) + P_A(k+h)\right] \tag{5.6}$$

subject to

$$\begin{aligned}
&\text{ECM equations} && (3.1)\forall Su, (3.2)\forall Tr, (3.3)\forall Sw, \\
& && (3.4)\forall T = T^n, (3.5)\&(3.6)\forall Bi \\
&\text{PM equations} && (3.8) - (3.24) \text{ if } GL = GL^n \\
&\text{SM equations} && (3.25)\&(3.26) \text{ if } Es^n \in Es
\end{aligned}$$

where

$$\begin{aligned}
P_{cost}(k+h) = &\Big[\pi_e^{buy}(k+h)P_{(e_1\to e_2)}(k+h) - \pi_e^{sell}(k+h)P_{(e_2\to e_1)}(k+h)\eta_{e_2\to e_1} \\
&+\pi_g^{buy}(k+h)P_{g_1}(k+h)\Big] \\
P_A(k+h) = &\sum_{A\in GL^n}\left[\sum_{u=1}^{N_n}\left[\lambda_A^{+}(k+h)\Delta l_{A,u}^{+}(k+h) + \lambda_A^{-}(k+h)\Delta l_{A,u}^{-}(k+h)\right]\right]
\end{aligned}$$

P_{cost} is the economic cost with π_e^{buy} and π_e^{sell} representing the per-unit purchase price and received revenue for selling electricity respectively. π_g^{buy} represents the cost of purchasing gas. P_A relates to the portion of flexible prosumers modelled using adjustable characteristics. λ_A^{+} and λ_A^{-} respectively represent penalty and incentive for exceeding or not meeting the baseline requirement of these prosumers. $\Delta l_{A,u}^{+}$ and $\Delta l_{A,u}^{-}$ are slack variables for these prosumers. N_n is the length of each flexible prosumers' baseline requirement.

Second-Stage Function

Correction decisions are needed when realised generation and/or demand uncertainties can not be satisfied by actual energy import/export. This power imbalance is represented through recourse variables in the stochastic problem. For example, in the case of energy surplus at time k, recourse variables represent the amount of energy to be exported to keep the power balance in the EH. Random or second-stage constraints are those influenced by uncertainty sources and can be written in the compact form $\boldsymbol{Hx}(k) - \boldsymbol{Gw_s}(k) = 0$ described in Section 3.2.2. Second-stage constraints are relaxed to consider $s = 1 \cdots N$ generated scenarios. As it has already been established that terminal nodes may connect components that introduce uncertainty within an EH, the vector of uncertain variables ($\boldsymbol{w_s}$) is defined to reflect generated scenarios and is presented together with the recourse variables ($\boldsymbol{\xi}_s^+, \boldsymbol{\xi}_s^-$) as:

$$\boldsymbol{w_s} = \boldsymbol{P}_{n_j}^s \qquad \boldsymbol{\xi}_s^+ = \boldsymbol{P}_{n_j}^{+,s} \qquad \boldsymbol{\xi}_s^- = \boldsymbol{P}_{n_j}^{-,s} \qquad\qquad \forall n_j = \{T | T = T^s\}$$

Hence, power balance for terminal nodes that connect components with uncertain sources is written as:

$$\begin{aligned} P_{n_j}^{+,s}(k) &\geq P_{n_j}^s(k) + P_{(n_i \to n_j)}(k)\eta_{(n_i \to n_j)} - P_{(n_j \to n_i)}(k) && \forall s \\ P_{n_j}^{-,s}(k) &\geq -(P_{n_j}^s(k) + P_{(n_i \to n_j)}(k)\eta_{(n_i \to n_j)} - P_{(n_j \to n_i)}(k)) && \forall s \\ &\forall n_j = \{T | T = T^s\} \end{aligned} \tag{5.7}$$

Energy generated/consumed by fixed prosumers that may exist within an EH (i.e. if $GL^s \in GL$) needs to be forecasted, hence (3.8)-(3.10) are rewritten to consider every generated scenario s:

$$P_{n_j}^s(k) = \sum_{m=0}^{N_{m,n_j}} G_m^s(k) - \sum_{w=0}^{N_{w,n_j}} L_w^s(k) \qquad \forall s \tag{5.8}$$

$$\sum_{m=0}^{N_{m,n_j}} G_m^s(k) = \sum_{y=0}^{N_y} G_{y,flex,n_j}(k) + \sum_{z=0}^{N_z} G_{z,fix,n_j}^s(k) \qquad \forall s \tag{5.9}$$

$$\sum_{w=0}^{N_{w,n_j}} L_w^s(k) = \sum_{u=0}^{N_u} L_{u,flex,n_j}(k) + \sum_{v=0}^{N_v} L_{v,fix,n_j}^s(k) \qquad \forall s \tag{5.10}$$

$$\forall n_j = \{T | T = T^s\}$$

The utilisation of charging stations that may exists within an EH (i.e if $Es^s \in Es$), needs to be forecasted as they depend on EV characteristics, availabilities and charging preferences. Hence, (4.4) and (4.5) accounting for EVs' energy level during series of charging/discharging operations and their connection to changing stations are also rewritten to consider every generated scenario

s per charging station.

$$E^s_{EV,i}(k+1) = S^s_{EV,i} E^s_{EV,i}(k) + Q^s_{EV,i}(k) \qquad \forall i, s \tag{5.11}$$

$$Q^s_{EV,i}(k) = -P^s_{n_j}(k) \qquad \forall i, s \tag{5.12}$$

$$\forall n_j = \{T | T = T^s\} \qquad \forall k \in \{h^{a,s}_{EV,i} : h^{d,s}_{EV,i} - 1\} \qquad \forall i \in \{1 : cd\}$$

Also, constraints (4.6) and (4.7) involving the binary variables monitoring the connection of an EV to a charging station are rewritten as:

$$\delta^s_{n_j}(k) = \begin{cases} 1 & \text{if } k \in \{h^{a,s}_{EV,i} : h^{d,s}_{EV,i} - 1\} \qquad \forall s, i \in \{1 : cd\} \\ 0 & \text{if otherwise} \end{cases} \tag{5.13}$$

$$\underline{P^s_{n_j}}(k)\delta^s_{n_j}(k) \leq P^s_{n_j}(k) \leq \overline{P^s_{n_j}}(k)\delta^s_{n_j}(k) \qquad \forall s \tag{5.14}$$

$$\forall n_j = \{T | T = T^s\} \qquad \forall k \in \{1 : N_H - 1\}$$

The second-stage function can then be written as shown in (5.15) with an aim to look N_H steps into the future, with scheduling period h and decide at time k on correction decisions to be made due to power imbalances when energy generation and demand are realised. Vectors $\boldsymbol{q}^+_s$ and $\boldsymbol{q}^-_s$ are penalty costs related to power surplus and shortage respectively, and corresponding probability related to each recourse variable pair is accounted for with $\frac{1}{N}$.

$$\begin{aligned} P_{second}(k+h) = \sum_{k=0}^{N_H-1} \sum_{s=1}^{N} \frac{1}{N} \Bigg[\sum_{\forall n_j = T^s} \Big[& \boldsymbol{q}^+_s \boldsymbol{P}^{+,s}_{n_j}(k+h) \\ & + \boldsymbol{q}^-_s \boldsymbol{P}^{-,s}_{n_j}(k+h) \Big] \Bigg] \end{aligned} \tag{5.15}$$

subject to

ECM equations	$(3.5)\&(3.6)\forall Bi, (5.7)\forall T = T^s$
PM equations	$(5.8) - (5.10), (3.11) - (3.24)$ if $GL^s \in GL$
SM equations	$(5.11) - (5.14)$ if $Es^s \in Es$

Sample Average Approximated Problem

In a similar form to (3.30), the deterministic equivalent problem is written by combining the first- (5.6) and second- (5.15) stage functions:

$$\min_{\boldsymbol{x}} \Big\{ J(\boldsymbol{x}) := P_{first}(k+h) + P_{second}(k+h) \Big\} \tag{5.16}$$

subject to

$$\begin{array}{ll}
\text{ECM equations} & (3.1)\forall Su, (3.2)\forall Tr, (3.3)\forall Sw, \\
& (3.4)\forall T = T^n, (3.5)\&(3.6)\forall Bi \\
& (5.7)\forall T = T^s \\
\text{PM equations} & \begin{cases} (5.8)-(5.10), (3.11)-(3.24) & \text{if } GL^s \in GL \\ (3.8)-(3.24) & \text{if } GL = GL^n \end{cases} \\
\text{SM equations} & (3.25)\&(3.26) \text{ if } Es^n \in Es \\
& (5.11)-(5.14) \text{ if } Es^s \in Es
\end{array}$$

The solution vector $\boldsymbol{x} = [\boldsymbol{P}_{\boldsymbol{SM}}^T, \boldsymbol{P}_{\boldsymbol{PM}}^T, \boldsymbol{\delta}_{\boldsymbol{PM}}^T]^T$ provides a schedule for all manipulated variables. $\boldsymbol{P}_{\boldsymbol{SM}}$ contains the charge/discharge rate of all connected storage systems. $\boldsymbol{P}_{\boldsymbol{PM}}$ contains energy schedule of all flexible prosumers and the binary variables that manipulate their operation are contained in $\boldsymbol{\delta}_{\boldsymbol{PM}}$. Due to the presence of binary variables, (5.16) is a MILP.

5.2.2 Evaluating Candidate Solutions

To implement the stochastic EMS later in this chapter, the number of scenarios N has to be chosen such that there is confidence in the solution to problem (5.16). Adopting the notation in Section 3.2.3, let $\hat{\boldsymbol{x}}_{\boldsymbol{N}}$ and $J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})$ be the optimal solution and optimal value of the SAA problem (5.16). Confidence in $\hat{\boldsymbol{x}}_{\boldsymbol{N}}$ can be established as explained in Section 3.2.3 and an adequate N can determined. A summary of Section 3.2.3 used to determine the optimality gap is presented in Algorithm 2. Adjustments are made to the parameters M, N and N' to trade-off computational effort with a desired confidence level.

Algorithm 2 Optimality Gap Estimation

for $m = 1, \dots M$ **do**
  Start timer $t(m)$
  Generate N scenarios
  Solve (5.16)
  $\hat{J}^m \longleftarrow J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})$
  $\hat{\boldsymbol{x}}^m_{\boldsymbol{N}} \longleftarrow \hat{\boldsymbol{x}}_{\boldsymbol{N}}$
  Generate N' scenarios ($N' >> N$)
  Solve (5.16) with $\hat{\boldsymbol{x}}_{\boldsymbol{N}}$
  $J^{*m} \longleftarrow J(\boldsymbol{x}^*_{\boldsymbol{N'}})$
  $\boldsymbol{x}^{*m}_{\boldsymbol{N'}} \longleftarrow \boldsymbol{x}^*_{\boldsymbol{N'}}$
  $S^2_{\hat{J}^m} \longleftarrow S^2_{J(\hat{\boldsymbol{x}}_{\boldsymbol{N}})}$
  End timer $t(m)$
end for
Determine $\bar{J}^M_N$ = mean of $\hat{J}^m$
Determine $S^2_{\bar{J}^M_N}$
for each $\boldsymbol{x}^{*m}_{\boldsymbol{N'}}$, $m = 1, \dots M$ **do**
  $\text{gap}^m = \bar{J}^M_N - J^{*m}$
  $\text{Var}^m = S^2_{\bar{J}^M_N} + S^2_{\hat{J}'(\hat{x}(m))}$
end for
Determine $\underline{t}$ = mean of $t(m)$

5.2.3 Receding Horizon Constraint Update

As problem (5.16) is to be solved repeatedly over N_H, it is necessary to account for the presence and effect of controlled charging/discharging of EVs as they are part of the optimisation problem. Receding horizon constraints that account for the effect of control actions on the operation of other components in the EH are in [33]. The notation $(k + h|k)$ is adopted to correspond to schedules h steps ahead that are predicted using information available at time k. If after solving the optimisation problem at k, the SoC of EVs in every N scenario representing charging/discharging operation i will be different at the next sampling instant and needs to be updated accordingly:

$$\text{if } h^{a,s}_{EV,i} \leq k < h^{d,s}_{EV,i} \qquad E^s_{EV,i}(0|k) = E^s_{EV,i}(1|k-1) \tag{5.17}$$

$$\forall s, i \in \{1 : cd\}$$

where $E^s_{EV,i}(k+1|k-1)$ denotes the SoC of EVs considered in all scenarios during the second scheduling period ($h = 1$) after assigned $Q^s_{EV,i}(k|k-1)$ at $k-1$. Also, δ^s_{EV} is updated accordingly:

$$\delta^s_{EV}(h-1|k) = \delta^s_{EV}(h|k-1) \qquad \forall s, h \in \{1 : N_H - 1\} \tag{5.18}$$

Finally, (5.1a)-(5.1f) become functions of time and at the end of the i^{th} charging/discharging operation, when $k = h^{d,s}_{EV,i}$, affiliated information are removed from these matrices.

When an EV connects to a charging station, that is a charge/discharge operation is realised, the inter-temporal relationship and dependence between the connected EV and scenarios of future EV charge/discharge operations needs to be accounted for. In the optimisation problem, this is achieved by setting the negated N charging/discharging powers over the period when the current EV is connected to the charging station equal to the EV input/output power, Q_{EV}. (5.19) is implemented to enforce this constraint. Also, the dynamic equation accounting for each N scenarios during the i^{th} charge/discharge operation based on information sampled from (5.1a)-(5.1f) are each replaced with a dynamic equation representing the EV currently connected to the charging station (5.20).

$$Q_{EV}(k) = -P^s_{n_j}(k) \qquad \forall n_j = \{T|T = T^s\} \tag{5.19}$$

$$E_{EV}(k+1) = S_{EV}E_{EV}(k) + Q_{EV}(k) \tag{5.20}$$

$$\forall k \in \{h^a_{EV} : h^d_{EV} - 1\}$$

5.2.4 Stochastic Predictive Control Implementation

In MPC, a projected view of a system into the future is used to minimise an objective function subject to a system's model and constraints. In the stochastic formulation, added considerations of uncertainties in a system are included. These uncertainties are described using probability distributions, and forecasts of what they might be are incorporated in the control scheme. Problem (5.16) is designed to consider uncertainty sources within an EH over a future horizon N_H. Without loss of generality, N_H is set to the scheduling horizon and the problem (5.16) is solved repeatedly at every time instant k, with scheduling period h set equal to k. The stochastic control scheme is implemented according to Algorithm 3.

Algorithm 3 Stochastic EMS

Determine cd and generate N scenarios.
Initialise $E_{EV}(0), S_{EV}$ if $\exists EV$
Initialise $E_{n_j}(0)$ if $\exists Es^n$
for $k = 1, \ldots N_H$ **do**
    if $k = h^a_{EV}$ **then**
        for $s = 1, \ldots N$ **do**
            $h^{a,s}_{EV,i} \leftarrow h^a_{EV}$
            $h^{d,s}_{EV,i} \leftarrow h^d_{EV}$
            $E^{a,s}_{EV,i} \leftarrow E^a_{EV}$
            $E^{d,s}_{EV,i} \leftarrow E^d_{EV}$
            $\pm Q^s_{EV,i} \leftarrow \pm Q_{EV}$
            $Cap^s_{EV,i} \leftarrow Cap_{EV}$
            $S^s_{EV,i} \leftarrow S_{EV}$
            $\delta^s_{EV,i} \leftarrow \delta_{EV}$
        end for
    end if
    Solve (5.16). Denote solution as $[\boldsymbol{x}(k), \ldots, \boldsymbol{x}(k + N_H - 1)]$
    Apply $\boldsymbol{x}(k)$ to the system
    $E_{EV}(k+1) = E_{EV}(k)$ if $\exists EV \rightarrow$ (4.9)
    $\delta_{EV}(k+1) = \delta_{EV}(k)$ if $\exists EV \rightarrow$ (4.10)
    if $h^{a,s}_{EV,i} \leq k < h^{d,s}_{EV,i}$ **then**
        $E^s_{EV,i}(k+1) = E^s_{EV,i}(k)\ \forall Es^n \rightarrow$ (5.17)
        $\delta^s_{EV}(k+1) = \delta^s_{EV}(k)\ \forall Es^n \rightarrow$ (5.18)
    end if
    $E_{n_j}(k+1) = E_{n_j}(k)\ \forall Es^n$
    $G_{y,flex,n_j}(k+1), L_{u,flex,n_j}(k+1) \leftarrow$ constraints in [33], $\forall GL^n$
    if $k = h^d_{EV}$ **then**
        delete h^a_{EV}
        delete h^d_{EV}
        delete E^a_{EV}
        delete E^d_{EV}
        delete $\pm Q_{EV}$
        delete Cap_{EV}
        delete S_{EV}
        delete δ_{EV}
    end if
end for

Before the stochastic EMS begins, determine N using Algorithm 2. Estimate the number of charge/discharge operations cd that will occur at each charging station and generate N scenario estimate of information on successive EV that will utilise each charging station from historical information (5.1a)-(5.1f). For all fixed storage systems that exists, initialise their SoC, E_{n_j}. If EVs are actually connected to any charging station, initialise their SoC E_{EV}. Before starting the iteration, set $k = 1$. For EVs connected to a charging station, obtain their characteristics ($E^a_{EV}, E^d_{EV}, \pm Q_{EV}, Cap_{EV}, S_{EV}$), availabilities ($h^a_{EV}, h^d_{EV}$) and owners charging preferences (δ_{EV}) and use them to replace each scenario estimate s (i.e. $h^{a,s}_{EV,i}, h^{d,s}_{EV,i}, E^{a,s}_{EV,i}, E^{d,s}_{EV,i}, \pm Q^s_{EV,i}, Cap^s_{EV,i}, S^s_{EV,i}, \delta^s_{EV,i}$) during the i^{th} charging/discharging operation that correspond the charging stations they are connected to. Solve the optimisation problem (5.16). Apply the solution $\boldsymbol{x}(k)$ to the MES. Update the SoC and the binary variable monitoring the presence of EVs connected to a charging station using constraints (4.9) and (4.10). For charging stations that are not currently been utilised, estimated scenarios of EVs are updated using constraints (5.17) and (5.18). Also, update the SoC E_{n_j} of all fixed storage systems and any flexible prosumers that exist with the MES. The prosumer constraints are updated according to [33]. As the iteration continues, when any EV departs (i.e. $k = h^d_{EV}$), remove corresponding constraints in the optimisation problem. The procedure is repeated over the horizon N_H where N_H is a predefined number that is usually a multiple of the chosen sampling rate h.

5.3 Multi-Energy System Description

The MES used to demonstrate the how uncertainty sources are considered in the modified COMMES framework discussed is shown in Figure 5.1. Electricity and gas are available for imports from the wider energy infrastructure. It is also possible to export electricity if EVs that utilise the two charging stations decide to participate in V2X. The different energy conversion technologies utilised to transform imported energy carriers are transformer and CHP. Also, heat energy can be stored by means of the hot water tank shown.

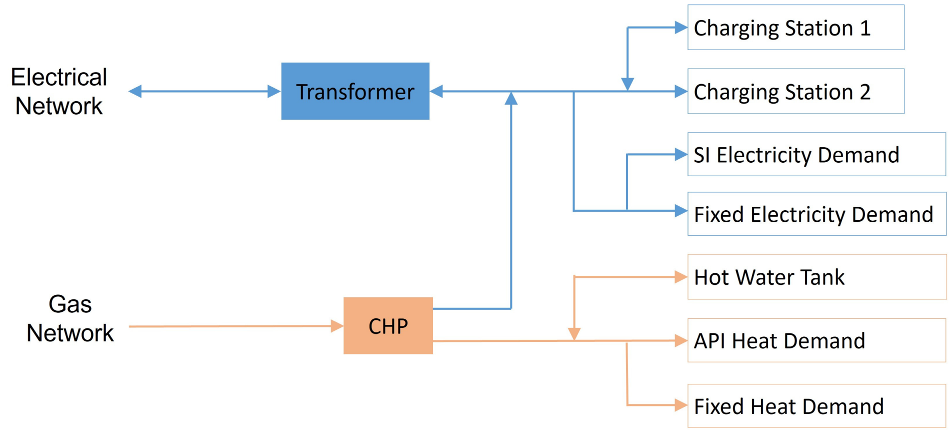

Figure 5.1: An multi-energy system schematic

5.3.1 Case Study Mathematical Model

The ECM within the EH shown in Figure 5.2 is made up of 7 terminal, 2 sum and 1 transmitter nodes. The electricity and gas networks are connected to terminal nodes e_1 and g_1 respectively. The transformer in modelled using bi-directional arcs between node e_1 and e_2 and the CHP is modelled using transmitter node g_2. The prosumers are connected to terminal nodes e_3 and h_2. Nodes e_4 and e_5 are dedicated terminal nodes that represent the two charging stations EVs connect to when they arrive to recharge their batteries. The set of equations describing the interconnections of nodes and arcs of the ECM that corresponds to the system shown in Figure 5.2 are shown in (5.21a) - (5.21k). For simplicity, dependence of these equations on k are excluded.

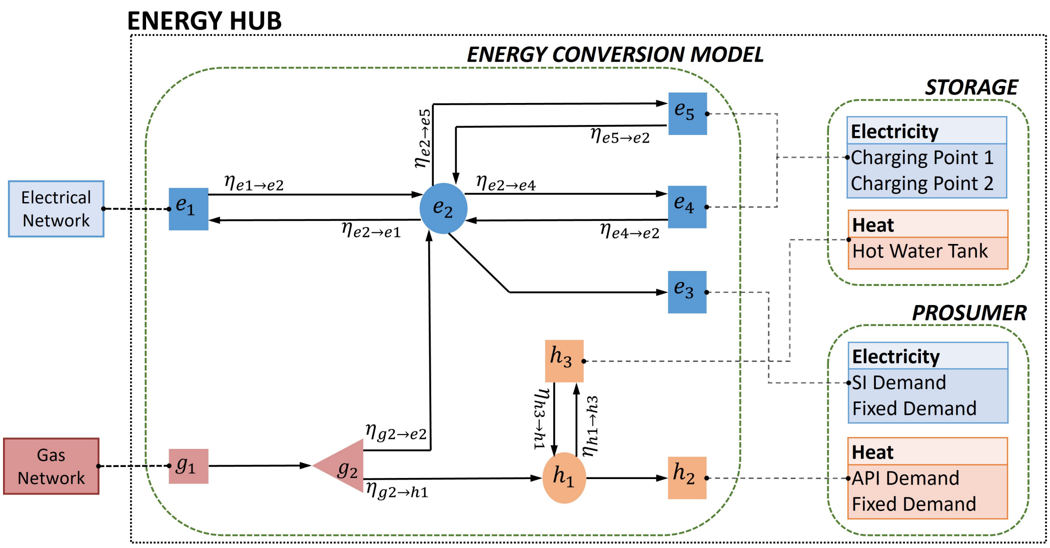

Figure 5.2: Case study multi-energy system

$$P_{e3} = -P_{(e2\to e3)}\eta_{(e2\to e3)} \tag{5.21a}$$

$$P_{e4} + P_{(e2\to e4)}\eta_{(e2\to e4)} = P_{(e4\to e2)} \tag{5.21b}$$

$$P_{e5} + P_{(e2\to e5)}\eta_{(e2\to e5)} = P_{(e5\to e2)} \tag{5.21c}$$

$$P_{h2} = -P_{(h1\to h2)}\eta_{(h1\to h2)} \tag{5.21d}$$

$$P_{e1} + P_{(e2\to e1)}\eta_{(e2\to e1)} = P_{(e1\to e2)} \tag{5.21e}$$

$$P_{g1} = P_{(g1\to g2)} \tag{5.21f}$$

$$P_{h3} + P_{(h1\to h3)}\eta_{(h1\to h3)} = P_{(h3\to h1)} \tag{5.21g}$$

$$P_{(g1\to g2)}\eta_{(g1\to g2)} = -P_{(g2\to e2)} \tag{5.21h}$$

$$P_{(g1\to g2)}\eta_{(g1\to g2)} = -P_{(g2\to h1)} \tag{5.21i}$$

$$\begin{aligned} P_{(e1\to e2)}\eta_{(e1\to e2)} + P_{(e4\to e2)}\eta_{(e4\to e2)} + P_{(e5\to e2)}\eta_{(e5\to e2)} + P_{(g2\to e2)}\eta_{(g2\to e2)} \\ = P_{(e2\to e1)} + P_{(e2\to e3)} + P_{(e2\to e4)} + P_{(e2\to e5)} \end{aligned} \tag{5.21j}$$

$$P_{(g2\to h1)}\eta_{(g2\to h1)} + P_{(h3\to h1)}\eta_{(h3\to h1)} = P_{(h1\to h2)} + P_{(h1\to h3)} \tag{5.21k}$$

Prosumers in Figure 5.2 are SI ($L_{SI_{e_3}}$) and fixed ($L_{fix_{e_3}}$) electrical demands both connected to node e_3, and API ($L_{API_{h_2}}$) and fixed ($L_{fix_{h_2}}$) heat demands both connected to node h_2. Equations connecting these prosumers to the ECM terminal nodes are shown in (5.22). Equations that describe the operation of the SI electrical and API heat demands are (3.11) - (3.24).

$$\begin{aligned} P_{e_3}(k) &= -L_{SI_{e_3}}(k) - L_{fix_{e_3}}(k) \\ P_{h_2}(k) &= -L_{API_{h_2}}(k) - L_{fix_{h_2}}(k) \end{aligned} \tag{5.22}$$

The heat storage shown in Figure 5.2 is represented by a discrete-time state-space model:

$$E_{h_3}(k+1) = S_{h_3}E_{h_3}(k) + Q_{h_3}(k) \tag{5.23}$$

Input is the charging/discharging power, Q_{h_3}. Output, $E_{h_3}(k)$ represent stored energy at time k. The heat storage is connected within the MES via terminal node h_3. This connection is achieved by setting Q_{h_3} equal to the negated node power of the associated terminal node (5.24), to maintain the sign convention.

$$Q_{h_3}(k) = -P_{h_3}(k) \tag{5.24}$$

Also, as no storage system is 100% efficient, S_{h_3} represents the standby efficiency of the heat storage and causes a decay in its SoC over time if $Q_{h_3} = 0$.

5.3.2 Data on Fixed Energy Demands and Utilisation of Charging Stations

To validate the stochastic MPC scheme in Section 5.2.4 requires realistic data on fixed demands and utilisation of charging stations. Fixed electricity and heat demand data were collected from a month's worth of data collected from the UoM Estates department that operates a building management system that logs energy usage data related to a particular energy vector for every building on campus.. Regarding data on charging station utilisation, non exist to the best of the author's knowledge, that fully represents the information needed for the EV modelling approach presented in this thesis. Specifically, most data excludes the number of times an EV is charged or the number of utilisation of a charging station over a period. In addition, most EV data collected are from individual EV utilisation.

Data collected from the My Electric Avenue (MEA) [87] project was from the utilisation of individual EVs and it includes the number of times an EV is charged over a period. The MEA was a project carried out to understand the challenges and opportunities that come with the wide-spread adoption of EVs. The project was led by EA Technology in collaboration with the UK DNO Scottish and Southern Energy Network. EVs used for the project were Nissan LEAFs with SoC ranging from 0 (0%) to 12 (100%) units, with 1 unit = 2kWh. The charging metric collected during the project were: the number of times an EV is charged per day (charging event), start charging time, initial/final SoC, and percentage of EVs charging on the same day. These charging metrics are represented in [53] using Gaussian mixture models (GMM) which enables the representation of clusters within data set through a convex combination of several normal distributions through their means and variances.

Data from the MEA is used to implement the optimality gap and determine the number of scenarios N in Section 5.2.2 and validate the proposed stochastic MPC scheme in Section 5.2.4. However, modifications are made to outlined steps given in [53] to recreate the EV profiles so that information (5.1a) - (5.1f) can be generated to suit the EV charge/discharge model presented in this thesis. For instance, the data excludes departure time or stop charge time. However, as the initial and final SoC depends on the number of charging events and start charging time, the stop charge time can be estimated. In [87], V2X is not considered hence the charging operation of EVs are defined as charging events. As estimate stop charge time can be obtained, EV charge/discharge profiles can be generated to suit the definition of a charging/discharging operation in Section 4.1. In addition, the EV charge/discharge profiles are recreated in this thesis such that they represent diverse EV characteristics. This is done so that EV profiles can be generated to suit the utilisation of charging stations by different types of EVs to draw parallels to the utilisation of public charging stations as well as privately owned charging stations as in the MEA project.

5.3.3 Scenario Generation from Gaussian Mixture Models

It is assumed that an EV's charge/discharge operation begins once it arrives and connects to a charging station. From [53], initial and final SoC are redefined as arrival and departure SoC respectively. Also, start and stop charging times are redefined as arrival and departure times respectively. Values of an EV's battery capacity, battery efficiency and charge/discharge power limits, for this study, are generated artificially. Following [53], the selection of initial and final SoC depends on considering the GMM of a given arrival time. Steps listed below are followed to generate N scenarios to represent information (5.1a) - (5.1f). For each charging station:

1. Generate N scenarios containing artificial data on battery capacities and standby loss factor, and charge/discharge power limits for N EVs.
2. Randomly select N arrival times.
3. Randomly select N initial SoC, considering the GMM that corresponds to each arrival times.
4. Randomly select N final SoC. To consider time dependency, the GMM for the corresponding arrival times should be used. To consider battery degradation, ensure SoC lies within a safe range. In this paper, 20% and 90% of battery capacity are used as upper and lower limits.
5. Multiply each N initial and final SoC by 8.33% and their corresponding battery capacity obtained in step 1. This is done to get the SoC of each EV that corresponds to $24kWh$ capacity used in [53].
6. Estimate each departure time using corresponding arrival time, initial and final SoC, and

maximum charging limit. However, margin of error is added to each departure time to ensure that the duration of each charge/discharge operation is of significant length.

7. If two charge/discharge operations occur over the planned horizon, follow steps 1 to 7 and ensure that the charge/discharge operations do not overlap by generating arrival and departure time scenarios greater than those of the previous operation.

5.4 Simulation Setup and Analysis

For the purpose of the case study, the sampling period is set to 15 minutes over a 24h control horizon, i.e. $N_H = 96$. The technologies shown in Figure 5.2 were chosen to exemplify modifications to the COMMES framework. Table 5.1 shows conversion efficiencies of some power flow arcs of the ECM. Other conversion efficiencies not shown are assumed as unity. Additional parameter values are shown in Table 5.2. It is assumed that the baseline energy consumption of

Table 5.1: Conversion efficiencies related to technologies

ECM arc factor	Device	Conversion	Value
$\eta_{e_1\to e_2}, \eta_{e_2\to e_1}$	Transformer	electricity	0.98
$\eta_{g_2\to e_2}$	CHP	gas to electricity	0.294
$\eta_{g_2\to h_1}$	CHP	gas to heat	0.485
$\eta_{e_2\to e_4}$	Charging Station 1	charging efficiency	0.9
$\eta_{e_4\to e_2}$		discharging efficiency	1/0.9
$\eta_{e_2\to e_5}$	Charging Station 2	charging efficiency	0.9
$\eta_{e_5\to e_2}$		discharging efficiency	1/0.9
$\eta_{h_1\to h_3}$	Heat Storage	charging efficiency	0.8
$\eta_{h_3\to h_1}$		discharging efficiency	1/0.8

both flexible demands in Figure 5.2 over a sampling period is $40kW$. The SI electricity demand has 2 segments and the API heat demand has 4 segments. For simplicity, both demands have equal limits on waiting periods ($\underline{N}^w_{n_j,u}$ and $\overline{N}^w_{n_j,u}$) between each segment are set equal to 5 and 15 respectively, $\forall u \in \{2 : 4\}$ and $\forall n_j \in \{SI, API\}$. The API heat demand is set to come online at 02:30am with processing limits ($\underline{N}^p_{API,u}$ and $\overline{N}^p_{API,u}$) set to 1 and 2 respectively, and maximum deviations from the baseline energy requirement during each sampling period is set to $\pm 5kW$.

The following assumptions are made about each charging station. All have CHAdeMO connectors with bidirectional capabilities and a fixed charge/discharge cable connected to each of

Table 5.2: Additional simulation parameters

Parameter	Description	Value
$\overline{E_{h_3}}/\underline{E_{h_3}}$	max/min heat storage capacity	180/40kWh
$\overline{Q_{h_3}}/\underline{Q_{h_3}}$	max heat storage charge/discharge	40kW
S_{h_3}	heat storage standby loss factor	0.95
$P_{e_2\to e_4}, P_{e_4\to e_2}$	charge/discharge limits of Charging Station 1	100kW
$P_{e_2\to e_5}, P_{e_5\to e_2}$	charge/discharge limits of Charging Station 2	100kW

them. Presently, EVs that have CHAdeMO sockets always have another charging socket - either Type 1 or Type 2 for home AC charging [89]. For simplicity, it is assumed that charging station 1 is always utilised by a particular EV that stays connected over a long period and usually consent to charge via V2X. For charging station 2, it is assumed that two charging/discharging operations usually occur over a 24h period but EVs involved in both operations are usually different each day and occasionally participate in V2X. Furthermore, all charging stations are assumed to be equipped with an interactive display, and when an EV arrives and connects to a charging station, its arrival time, SoC, battery capacity and V2X capability are obtained. If an EV is V2X capable, a driver can indicate their consent to participate in V2X when entering desired departure time and SoC via the display. Following this reasoning, if technology advances to the extent that all EVs and/or Type 1, Type 2 or CCS charging stations are made V2X capable, the proposed methodology herein would still apply. Also, drivers can not interrupt the charge/discharge process after they enter their desired SoC at the departure, their departure time, and specified whether to participate in V2X or not. This way, the controller is free to decide the charging/discharging power while an EV is connected to a charging station.

It is worth highlighting that once the N scenarios are generated for each charging station following the steps outlined in Section 5.3.2, it will be in the form of a scenario fan. Each branch of the scenario fan will contain information to recreate two consecutive EV charge/discharge operations at most.

5.4.1 Index Sets, Variable Types and Forecasts

Index sets introduced in Section 5.2.1 are used to group nodes and components within Figure 5.2. This is to clearly differentiate constraints affected by uncertainty sources and those not affected by uncertainty sources. Table 5.3 lists the index set used to derive the optimisation constraints for Figure 5.2.

Table 5.3: EH index sets

$Bi :=$	$\{e_1 \leftrightarrow e_2, e_2 \leftrightarrow e_4, e_2 \leftrightarrow e_5, h_1 \leftrightarrow h_3\}$
$Su :=$	$\{e_2, h_1\}$
$Tr :=$	$\{g_2\}$
$Sw :=$	$\{-\}$
$T^n :=$	$\{e_1, g_1\}$
$T^s :=$	$\{e_3, e_4, e_5, h_2\}$
$GL^n :=$	$\{L_{SI_{e_3}}, L_{API_{h_2}}\}$
$GL^s :=$	$\{L_{fix_{e_3}}, L_{fix_{h_2}}\}$
$Es^n :=$	$\{E_{h_3}\}$
$Es^s :=$	$\{E_{EV,i\to e_4}, E_{EV,i\to e_5}\}$

Implementing Algorithm 3 for the MES shown in Figure 5.2 requires decisions to be made on energy imports/exports, charge/discharge operation of storage systems and the operation of flexible demands considering uncertain fixed demands and utilisation of charging stations. However, a clear distinction between decision and uncertain variables in the optimisation problem and forecasts obtained from scenario generation has to be made. Table 5.4 shows the decision and uncertain variables. Forecasts required in the formulation of the optimisation problem for Figure 5.2 are also shown. Adopting the compact form $\boldsymbol{Hx}(k) - \boldsymbol{Gw_s}(k) = 0$ described in

Table 5.4: Decision and uncertain variables, and forecasts

$\boldsymbol{x}(k) :=$	$\{P_{(e_1\to e_2)}(k), P_{(e_2\to e_1)}(k), P_{g_1}(k), Q_{EV,i\to e_4}(k), Q_{EV,i\to e_5}(k), Q_{h_3}(k), \Delta l^+_{n,i}(k), \Delta l^-_{n,i}(k), \delta^+_{n,i}(k), \delta^-_{n,i}(k), \delta^p_{n,i}(k), \delta^w_{n,i}(k), \delta^c_{n,i}(k)\}$
Forecasts	$\{cd, L_{fix_{e_3}}, L_{fix_{h_2}}, Cap_{EV,i}, S_{EV,i}, \pm Q_{EV,i}, E^a_{EV,i}, E^d_{EV,i}, h^a_{EV,i}, h^d_{EV,i}\}$
$\boldsymbol{w}_s(k) :=$	$\{P^s_{e_3}(k), P^s_{e_4}(k), P^s_{e_5}(k), P^s_{h_2}(k)\}$
$\boldsymbol{\xi}^+_s(k) :=$	$\{P^{+,s}_{e_3}(k), P^{+,s}_{e_4}(k), P^{+,s}_{e_5}(k), P^{+,s}_{h_2}(k)\}$
$\boldsymbol{\xi}^-_s(k) :=$	$\{P^{-,s}_{e_3}(k), P^{-,s}_{e_4}(k), P^{-,s}_{e_5}(k), P^{-,s}_{h_2}(k)\}$

Section 3.2.2 to represent the second-stage constraints, denote the vector collecting all decisions to be made on energy imports/exports, charge/discharge operation of storage systems and the operation of flexible demands at each k as $\boldsymbol{x}(k)$. $P_{(e_1\to e_2)}$ and $P_{(e_2\to e_1)}$ represent electricity import and export respectively. P_{g1} represents gas import. $Q_{EV,i\leftarrow e_4}$ and $Q_{EV,i\leftarrow e_5}$ represent the charging/discharging powers of EVs that will utilise charging stations e_4 and e_5 respec-

tively over time. Q_{h_3} is the charging/discharging power of the connected heat storage system. Flexible prosumer variables $\Delta l^{+}_{n,i}(k), \Delta l^{-}_{n,i}(k), \delta^{+}_{n,i}(k), \delta^{-}_{n,i}(k), \delta^{p}_{n,i}(k), \delta^{w}_{n,i}(k)$ and $\delta^{c}_{n,i}(k)$ are controlled to determine the operation of the API heat demand, $L_{API_{h_2}}$. Only $\delta^{w}_{n,i}(k)$ and $\delta^{c}_{n,i}(k)$ are controlled to determine the operation of the SI electrical demand, $L_{SI_{e_3}}$.

Within the prosumers shown in Figure 5.2, fixed demands $L_{fix_{e_3}}$ and $L_{fix_{h_2}}$ have to be forecasted. For EVs that will utilise charging stations 1 and 2 (i.e. e_4 and e_5 respectively), the number of EVs that will utilise each charging station over a period, cd, together with their respective battery capacities $Cap_{EV,i}$, efficiencies $S_{EV,i}$ and charge/discharge power limits $\pm Q_{EV,i}$ needs to be forecasted. Also, each EV's arrival and departure time ($h^{a}_{EV,i}$ & $h^{d}_{EV,i}$) and their respective energy levels at both times ($E^{a}_{EV,i}$ & $E^{d}_{EV,i}$) has to be forecasted. These, forecasts are used to predict the type of EV that will utilise each charging station hence, they directly influence an EV SoC during the charge/discharge process. The data required to forecast the utilisation of charging stations are gotten from historical information (5.1a) - (5.1f).

As the forecasts of fixed demands and charging station utilisations are disturbances introduced into the MES via connected terminal nodes as established in Section 5.1, the uncertain variables are the input/output power at terminal nodes connected to prosumers and EVs. Denote the vector collecting all uncertain variables as $\boldsymbol{w}(k)$ and their corresponding recourse variables that represent power imbalances in the optimisation problem are denoted as $\boldsymbol{\xi}^{+}_{s}(k)$ and $\boldsymbol{\xi}^{-}_{s}(k)$.

5.4.2 Validation of Proposed Energy Management Scheme

Artificial time-of-use tariff for all energy demands is used and assumed fixed. The price tariff is shown in Fig. 5.3. Information on EVs are generated as outlined in Section 5.3.3. Fixed electricity and heat demands are sampled from a month's worth of data collected by the UoM estate department for a particular building. The stochastic EMS is solved according to Algorithm 3 with a commercial CPLEX solver at each sampling period on a PC Intel Core i7-4700MQ CPU @ 2.40GHz with 32 GB RAM.

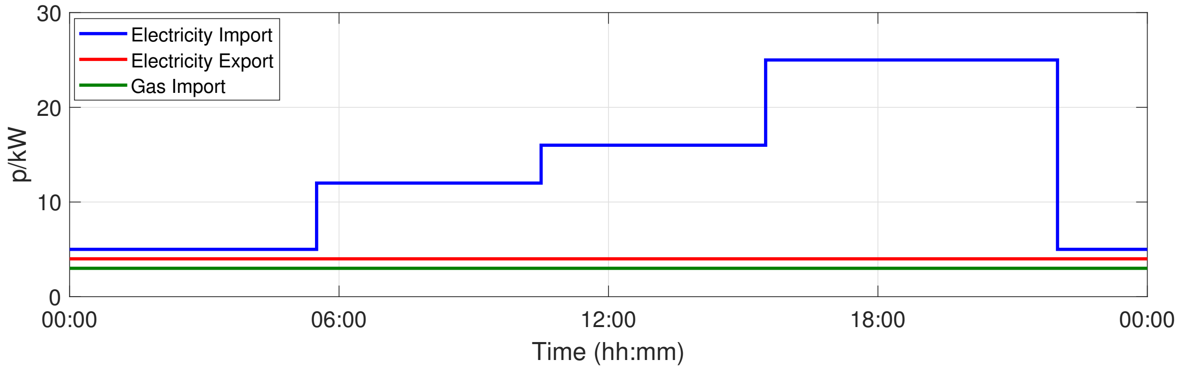

Figure 5.3: Import/export price of electricity and gas

In solving a SAA problem, the objective value and the solution of the approximated problem should converge to the optimal objective value and the solution of the true problem as the scenario size N is increased. Verifying this requires many scenarios, which is a disadvantage as it directly increases the computational burden required to solve the problem. Literature has examined the SAA approach to determine bounds that infer how the approximated problem correlates to the original problem, which in turn relates to the choice of an adequate number of scenarios needed to be implemented in Algorithm 3. Steps on how to determine these bounds are outlined in Section 3.2.3, and a summary is presented in Algorithm 2. Adjustments to the parameters M, N, and N' to trade-off computational effort with the desired confidence level.

Table 5.5: Optimality gaps estimation

N/N'	Min Optimality Gap ($*10^3$)	Variance ($*10^4$)	Optimality Gap (%)	Computational Time (secs) Mean	Computational Time (secs) Variance
5/60	1.675	16.155	14.561	19.863	897.309
10/60	0.698	6.752	5.692	29.894	930.968
20/60	0.216	4.464	1.733	32.753	1014.700
30/60	0.194	2.924	1.548	40.154	1273.900

Results shown in Table 5.5 were obtained by setting $M = 20$, $N' = 60$ and $N = \{5, 10, 20, 30\}$. Each time Algorithm 2 is implemented with the different N, 20 optimality gaps are obtained, the minimum is chosen and are shown in Table 5.5 along with their corresponding variance. The percentage optimality gap shown was calculated using the formula $\left(\frac{\bar{J}_N^M - min(J^{*m})}{\bar{J}_N^M}\right) * 100\%$. It can safely be concluded that solutions to the approximated problem (5.16) converges to the optimal solution because the decrease in optimality gap with increasing N verifies that the problem is tightly bounded. Also, it can be concluded that $N = 20$ is an adequate scenario number to run Algorithm 3. The mean computational time is calculated using times consumed when solving problem (5.16) for both N and N' within the loop while running Algorithm 2.

5.4.3 Discussions

It is prudent to examine the difference in outcomes between the stochastic EMS and a deterministic one, especially as the COMMES framework is relatively novel. In the deterministic case, the mean of 20 generated scenarios is used as an estimate of the uncertain parameters before solving problem (5.16). The optimisation problem consists of 8638 decision variables, of which 4032 are binaries. In the stochastic case, the optimisation problem consists of 36570 decision variables, of which 7680 are binaries. However, these numbers will be slightly different each time the stochastic EMS is implemented because the availability scenarios for EVs determine the length of the matrices that account for EVs' energy level. Hence, it significantly impacts the dimensions of the optimisation problem. When all charge/discharge operations has occurred at a charging station, the number of variables in the optimisation problem reduce by $N-1+\sum_{s=1}^{N}(N_H^s+\sum_{i=1}^{cd}(h_{EV,i}^{a,s}-h_{EV,i}^{d,s}+1))$. The part $N-1$ reduces the number of repetitions of P_{n_j} of the corresponding terminal node to 1. In the deterministic case, $N=1$. N_H^s accounts for the number of repetitions of the binary variable δ_{n_j} that monitors the presence of EVs over a series of charging/discharging operations per scenario, and the duration $h_{EV,i}^{a,s}-h_{EV,i}^{d,s}+1$ is the period over which an EVis connected to a charging station per scenario.

Comparisons of operational cost and computational time are shown in Table 5.6. The results shown were obtained by running Algorithm 3 ten times and taking the mean and corresponding standard deviation of operational cost and computational time. For each implementation of Algorithm 3, the operational cost was computed by summing the estimated costs obtained from the controller's decision on the amount of energy to import/export at each instant k over the horizon plus extra energy imported/exported when uncertainties are realised. The lower operation cost obtained from the implementing the stochastic EMS demonstrates its outperformance compared to the deterministic one. However, the outperformance in operational cost is at the expense of higher computational time and larger deviations from the mean. The penalties $\boldsymbol{q}_s^+$ and $\boldsymbol{q}_s^+$ imposed on recourse variables for simplicity, were both set to 400 and used to obtain results shown in Table 5.5 and 5.6. The realised utilisation of the two charging stations shown in Figure 5.2 together with 3 random scenarios picked from the 20 EV charging/discharging profiles to show the estimated utilisation of the charging stations are shown in Figure 5.4 and Figure 5.5. The dotted lines are the estimated utilisations, and the solid blue lines are the realised utilisations of the charging stations.

Table 5.6: Comparisons of cost and computational time

	Operational Cost (£)		Computational Time (secs)	
	Mean	Standard Deviation	Mean	Standard Deviation
Deterministic	132.7	0.44	2.11	1.72
Stochastic	127.5	0.15	13.87	11.83

Figure 5.4 shows the estimate and realised utilisation of charging station 1. In Figure 5.4B, it is observed that the EV at charging station 1 arrives with an almost empty SoC and chooses its usual option to participate in V2X. The controller decides to utilise the storage capacity the EV provides by initially discharging the EV. Then the controller charges and discharges the EV three more times around the periods when electricity price increases (refer to Fig. 5.3) to help meet prosumer demands shown in Figure 5.7B and 5.7C. Estimate and realised utilisations of charging station 2 are shown in Figure 5.5. It can be observed that the EV utilising charging station 2 during the first realised charge/discharge operation arrives with relatively high SoC. However, the driver decides not to participate in V2X once the vehicle is plugged into the charging station. As a result, a gradual decline in the EV's SoC is observed in Figure 5.5B because its battery is not 100% efficient hence can not maintain a constant energy level while ideal. The controller exploits the fact that electricity prices will increase at 05:30 to charge the EV to its maximum capacity, then allows the EV to discharge until the desired SoC at departure is reached. The next EV that utilises charging station 2 decided to participate in V2X once its vehicle is connected to the charging station. The sharp decline in EV's SoC observed in Figure 5.5B is the EV discharging to help satisfy energy demands within the EH as a result of the driver's decision to participate in V2X. In Figure 5.7B, it can be observed that electricity demands between 17:30 and 21:00, the same period when the second EV utilises charging station 2, is not significantly large compared to earlier hours. As electricity prices are significantly higher than gas prices over this period, more gas is imported to help satisfy the driver's specified SoC before the EV departs.

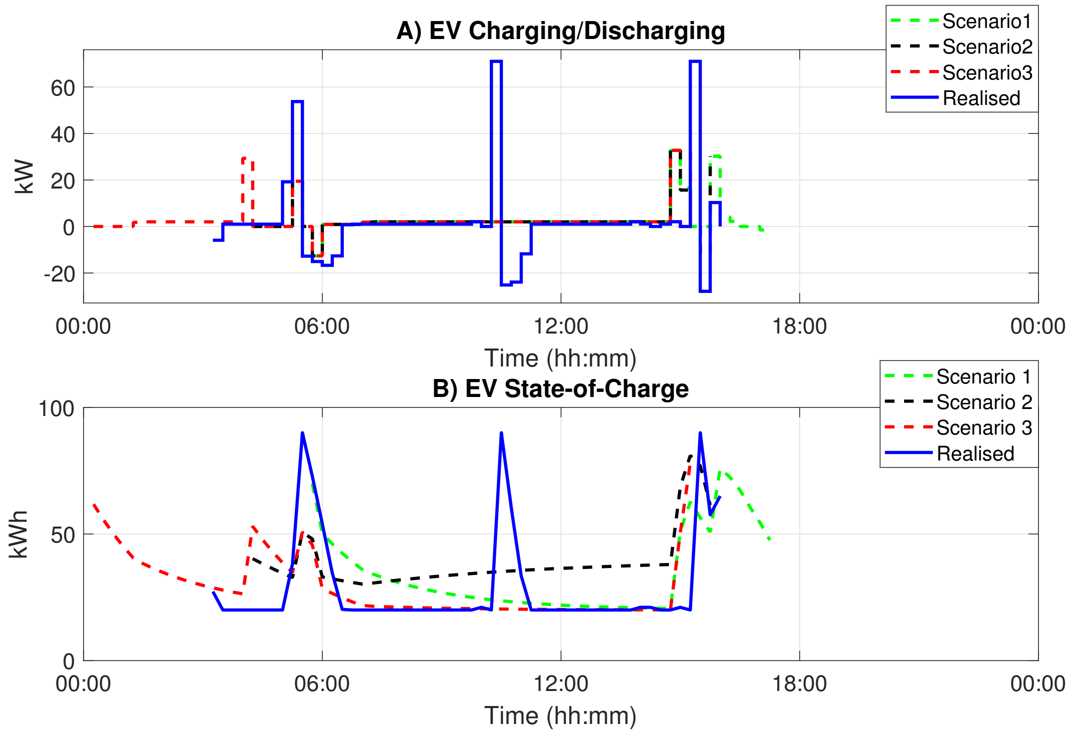

Figure 5.4: Estimated and realised utilisation of charging station 1

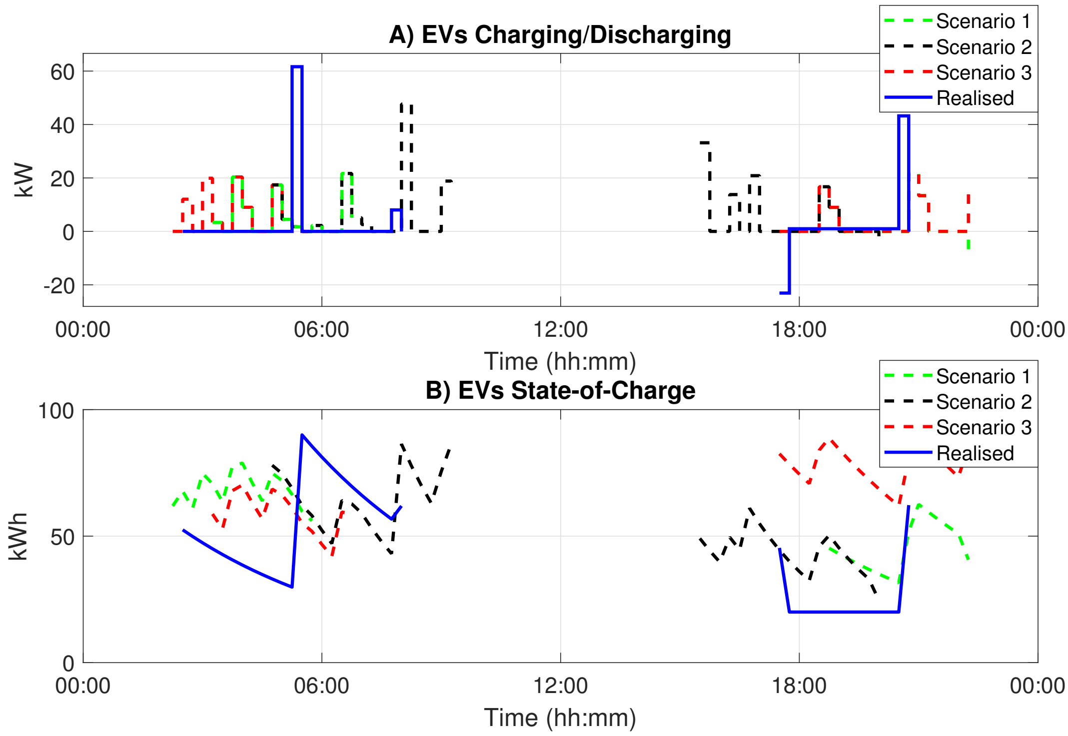

Figure 5.5: Estimated and realised utilisation of charging station 2

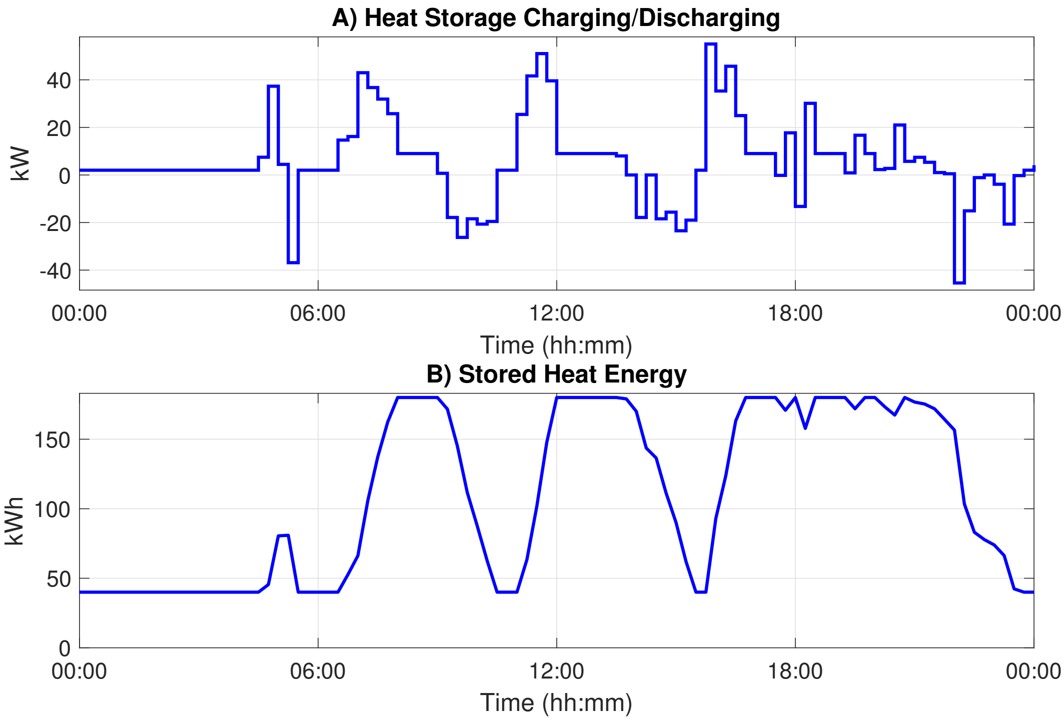

Figure 5.6: Operation of heat storage system

Figure 5.6 shows the operation of heat storage over time. As electricity prices are high between the hours of 05:30 and 21:00, mostly gas is imported between these hours to meet both electricity and heat demands as shown in Figure 5.7A, with excess gas used to charge heat storage as shown in Figure 5.6. The utilisation of heat storage is most noticeable during the period when the second EV is utilising charging station 2, which coincides with the period when the difference between electricity and gas prices is significantly large. A small portion of gas imports during this period is utilised to help meet the energy demand of the second EV before it departs, and excess gas is used to charge heat storage, causing a considerable increase in its SoC as observed in Figure 5.6 before the controller discharges it to help meet energy demands. Figure 5.7C shows the flexible prosumer operations. Figure 5.7C shows that the API demand comes online at the set time of 02:30 am and runs considering the constraints outlined in Section 5.4. The maximum deviation from the baseline requirement for the API demand is set to $\pm 5kW$ per segment. However, observe that in Figure 5.7C some segments of the API demand consume $30kW$. This is because the maximum processing limits due to the pliable portion of the API demand is set to 2. Hence, some segments are processed twice, each with a reduction of $5kW$ due to the adjustable portion of the API demand. The SI demand

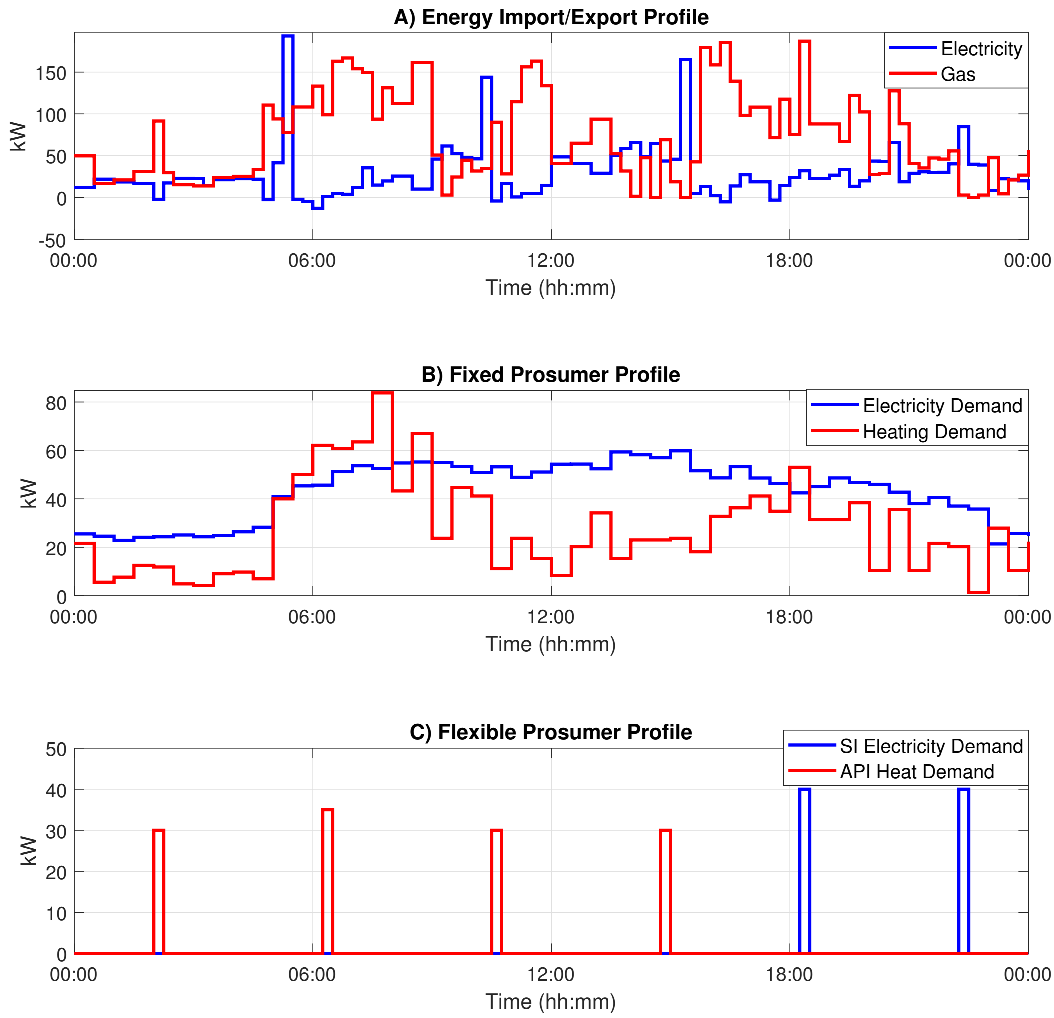

Figure 5.7: Energy import/export and prosumer profile

is not required to come online at a specific time. The controller decides to run it towards the end of the day when fixed energy demands are low and the storage capacity of the second EV utilising charging station 2 is available. The operation of both flexible prosumers verifies that the incorporation of the EV charge/discharge model together with modification to the COMMES framework to account for uncertainty sources does not affect their operation.

5.4.4 Computational Challenges

Unsurprisingly, the computational time obtained from implementing the deterministic EMS is shorter compared to implementing the stochastic EMS. Table 5.5 shows the resulting computation time after implementing both EMS. The shorter computational time is a result of the deterministic approach requiring far less memory when solving (5.16) as the average of the generated scenario is used to construct the optimisation problem. Although the proposed stochastic EMS requires more computational time, it is much less than the 15 minutes (900 seconds) sampling period used. However, for a given MES, the computational burden would be further compounded by increasing the number of charging stations and the number of utilisation of charging stations over time. For example, consider different charging stations located within residential, commercial and public charging areas. Different computational challenges will result from implementing a stochastic EMS in each region due to how these charging stations are utilised.

The MES analysed in this chapter is comparably small-scale. The utilisation of the charging stations is similar to what is expected in a residential or private commercial area. For large-scale cases such as public parking lots or large commercial buildings, the dimension of the optimisation problem solved within the stochastic EMS will be large. This is due to the large scenario numbers required to estimate the accurate operation of prosumers and charging stations. Hence, there will be a significant increase in the computational burden. In addition, advances in the modelling approach will also increase the computational burden. A detailed model of individual technologies within MES will hinder the online implementation of a stochastic EMS. It would be advantageous to investigate other possible control schemes such as those based on distributed control to lessen the computational burden.

5.5 Chapter Summary

This chapter has presented how uncertainties are considered in the modified COMMES framework. A stochastic EMS is developed. The optimisation problem solved within the stochastic EMS is defined using a two-stage stochastic programming approach and the SAA approach is used to formulate a deterministic approximation of the stochastic problem. The stochastic EMS is then implemented using the MPC framework. A case study MES is used to implement the stochastic EMS. The stochastic EMS is scaleable however computational burden will mostly like increase if a similar stochastic EMS is implemented on a MES of large scale with more diverse EVs utilising the charging stations within.

To validate the stochastic EMS, data collected from the MEA is used. To the best of the authors' knowledge, only data from the MEA includes multiple utilisation of charging stations. Fixed demand data was obtained from the BMS operated by UoM. Statistical tests are performed on the approximated problem to help determine optimality gaps that give validity to solutions of the optimisation problem. This fact helped the decision of the number of scenarios to consider when implementing the stochastic EMS. In addition, the statistical tests give confidence to the solution obtained from the controller's decision on the amount of energy to import/export to satisfy energy demands within the EH as well as the operation of the storage systems and flexible prosumers.

Chapter 6

Computational Considerations in Different Application Areas

The dimension of matrices representing mobile storage devices within the optimisation problem constantly each time when the problem is solved within an MPC framework. This is due to accounting for EVs' characteristics, availabilities, and charging preferences that will utilise charging stations within the network. This significantly impacts the computational time in solving the optimisation problem. Since the area where charging stations are located influenced the development of the mobile storage model in this thesis, their utilisation in residential, commercial and public areas is investigated in this chapter. In particular, the benefits and limitations of implementing a stochastic EMS with EV charge/discharge smoothing application in a residential, commercial and public case study is investigated.

The remainder of this chapter is organised as follows: Discussion on expected utilisation of charging stations in residential, commercial and public areas is presented in Section 6.1. In Section 6.2, the general case study to be used to demonstrate the utilisation of charging stations in the different areas is presented. The stochastic problem solved within the stochastic EMS is formulated with added penalties on smoothing EVs' charge/discharge rate in Section 6.3 to simulate the scenario that EVs are used for peak demand management. Section 6.4 outlines the simulation setup. Discussion on the benefits and limitations of the stochastic EMS based on a number of factors is presented in Section 6.5. Section 6.6 presents the chapter summary.

6.1 Coordinating Electric Vehicle Charge/Discharge Operations

In previous chapters, three factors mentioned multiple times in relation to the utilisation of charging stations are:

1. **EV characteristics**
2. **EV availabilities**
3. **EV owner's charging preferences**

These factors are vital in designing EMS for coordinating EVs' charge/discharge operations. They vary significantly when EVs utilising charging stations in residential, commercial, and public areas. **EV characteristics** refer to its technical specification, i.e. an EV's battery capacities, charge/discharge power limits, bidirectional energy exchange capabilities. **EV availabilities** refer to the duration between an EV's arrival and departure times. This thesis assumes that when an EV arrives, the driver connects their vehicle to a charging station and disconnects the vehicle from the charging station when the driver wants to depart. An **EV owner's charging preferences** encapsulates the driver's choice to charge via V2X if their EV has bidirectional energy exchange capability and the driver's desired SoC at departure. It is quite challenging to use these factors to model an EV's charge/discharge operations based on individual EV usage, primarily because EVs can utilise any charging station located anywhere to recharge their batteries. However, developing the model based on the utilisation of charging stations allows the aforementioned three factors to be efficiently utilised to model EVs' charge/discharge operations. An assumption made in this thesis that allows for the chosen EV modelling approach is that EV drivers have daily schedules, which includes the charging stations they use to recharge their batteries. This assumption makes it easier to estimate which charging stations are utilised and collect data on EVs that have utilised them. In addition, the premise allows for leveraging EV drivers schedules for categorising EV charge/discharge operation patterns based on charging stations located in residential, commercial and public areas. Hence, making it easy to predict EV characteristics, availabilities and charging preferences, and design coordination schemes for EVs that will utilise charging stations in residential, commercial and public areas.

6.1.1 Assumptions for Residential Area Application

It is safe to assume that EV owners will likely have their individual allocated charging stations installed on their owners' premises in residential areas. Hence, it will be easy to estimate the characteristics of EVs that will utilise each charging stations in the area as they are likely to be owned by residents. Such a scenario is shown in Figure 6.1 as the same colour is used to illustrate the same EV utilising their individually allocated charging station. Based on charging station utilisation or EV driving schedule, EV availabilities can also be easily estimated based on drivers daily schedules. In addition, EV owners' charging preferences will often be consistent, making it easy to predict.

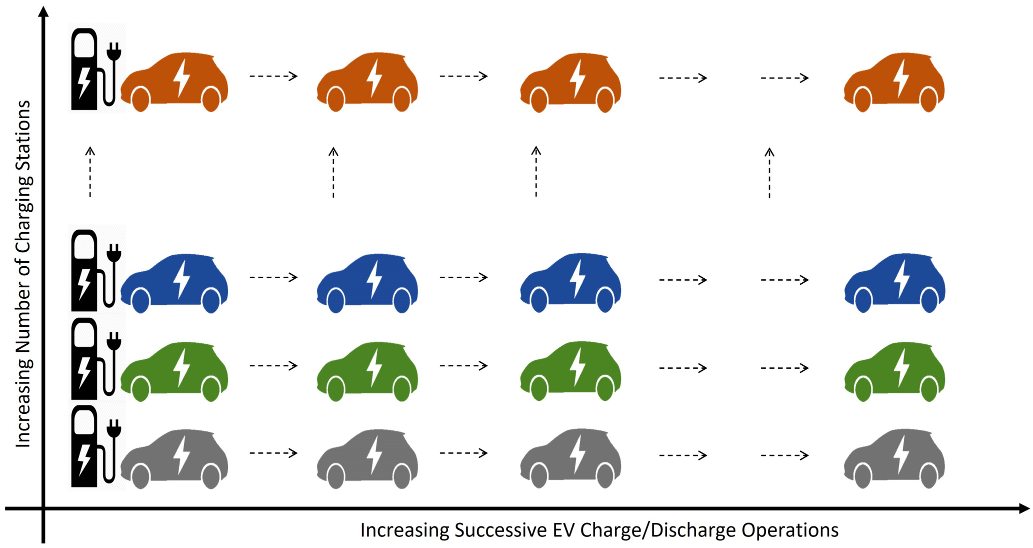

Figure 6.1: Utilisation of charging station in residential areas

The MEA trial done in UK [87] revealed that most EV owners recharge their batteries twice a day, but on occasion, some recharge their batteries up to five times a day. Regarding EV owners charging preferences, it was revealed in [41] that they are more consistent as most EV drivers will likely recharge overnight. This makes predicting EV characteristics, availabilities and charging preferences in residential areas easy hence it is safe to assume few scenarios are required to implement a stochastic EMS to coordinate their charge/discharge operations.

6.1.2 Assumptions for Commercial Area Application

It is safe to assume that frequent visitors to a commercial area will utilise the charging stations available. This makes estimating EV characteristics easy. However, charging stations are not allocated to specific EV drivers, so estimating EV characteristics will not be as easy as residential areas. This is illustrated by the set of different coloured EVs utilising different charging station shown in Figure 6.2. EV drivers not being allocated to specific charging stations in commercial areas will also make estimating their availabilities and owners charging preferences difficult, although these factors might be consistent with individual EV drivers that frequently utilise charging stations in the area.

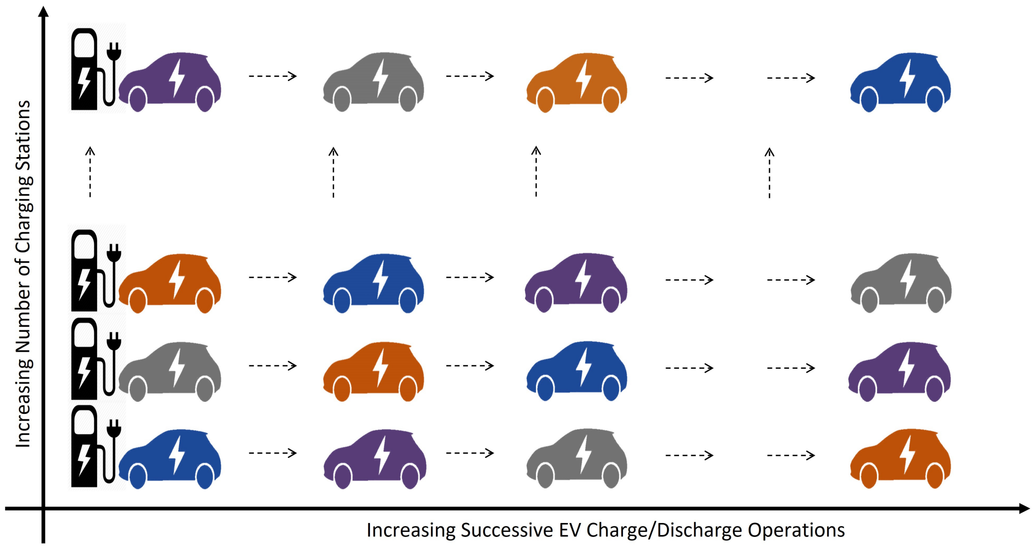

Figure 6.2: Utilisation of charging station in commercial areas

Charging stations in commercial areas can also be utilised by EV fleets as well as by individual EVs. Hence, it will be expected that charging stations are utilised more times than in residential areas, especially if they are used for work-related trips. An illustration of how EVs utilise charging stations in a commercial area is shown in Figure 6.2. EV characteristics will be quite consistent; however, as EVs are not allocated to specific charging stations, it is difficult to estimate their availabilities and charging preferences. Hence, compared to residential areas, more scenarios will be required when implementing a stochastic EMS to coordinate EV charge/discharge operations in commercial areas.

6.1.3 Assumptions for Public Area Application

Charging stations in public areas can be utilised by EVs from anywhere and at any time. It is represented by the different colours used in Figure 6.3 as it is quite impossible to establish a consistent pattern of how charging stations are utilised. However, it can safely be assumed that the EVs that will utilise the charging stations are frequent visitors to the area. Furthermore, charging stations are not allocated to specific EV drivers and charging stations can be utilised multiple times over certain periods. This makes estimating EVs' characteristics, availabilities, and charging preferences difficult due to the diverse nature of EVs utilising charging stations in public areas.

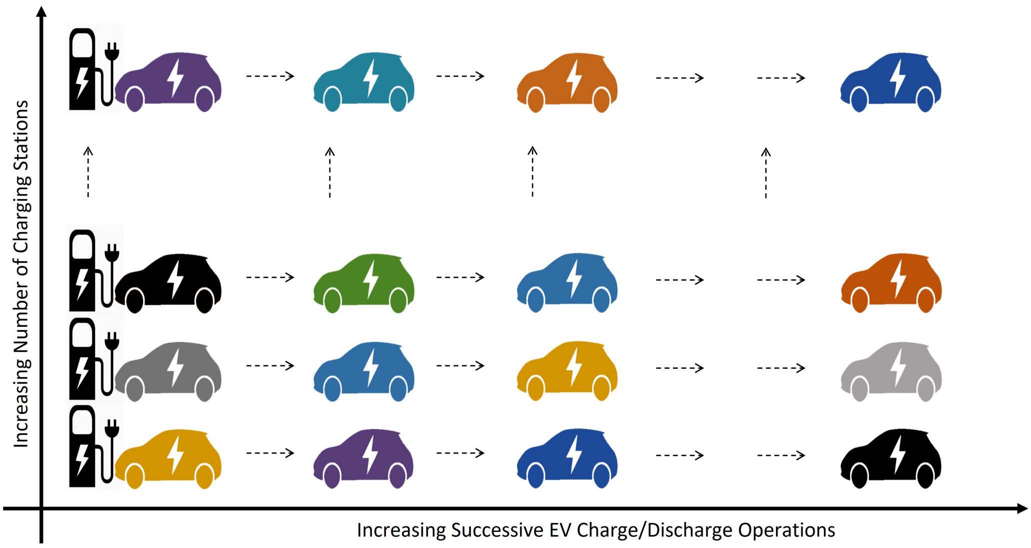

Figure 6.3: Utilisation of charging station in public areas

The expectation of diverse EVs utilising charging stations in public areas will result in large scenarios required to implement a stochastic EMS to coordinate all EVs' charge/discharge operations adequately. Following the LLN, a significant amount of scenarios has to be considered so that the resulting charge/discharge operation of EVs is close to what is expected. The LLN also applies when the stochastic EMS is implemented in residential and commercial areas. However, more scenarios will be required to implement the EMS in public areas due to the diversity of EV characteristics, availabilities, and charging preferences. An illustration of how public charging stations are utilised by different EVs is shown in Figure 6.3.

6.2 Multi-Energy System Description

A general MES is used to analyse the performance of a stochastic EMS implemented in a residential, commercial and public area. As the mobile storage model has the most impact on the dimension of the optimisation problem, to simplify the analyses of the stochastic EMS later in this chapter, the MES used is an electrical only system with a transformer and a number of charging stations. The MES examined in this chapter is shown in Figure 6.4.

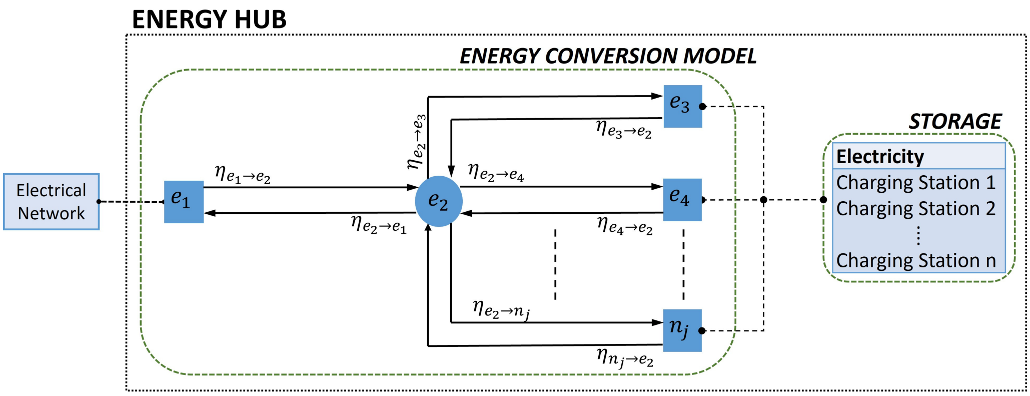

Figure 6.4: Case study multi-energy system

6.2.1 Data on Utilisation of Charging Stations

To adequately analyse the performance of the stochastic EMS implemented to coordinate charging stations in residential, commercial and public areas, the number of scenarios generated related to EV characteristics, availabilities and owners charging preferences is varied based on the assumptions explained in the previous section. For each scenario number considered, the number of charging stations together with the number of successive charge/discharge operations and prediction horizon length is varied to analyse the stochastic EMS's performance adequately.

At the time of writing, no charging station utilisation data exists, to the best of the author's knowledge, that contains information on different EVs that have utilised charging stations in residential, commercial or public areas that match the requirement of the mobile storage model proposed in this thesis. Hence, for simplicity, information on the utilisation of the charging stations shown in Figure 6.4 are sampled from assumed uniform distributions. Table 6.1 and Table 6.2 contains information about EVs used to run the simulation with $N_H = 96$ (24 hours) and $N_H = 48$ (12 hours) respectively. Column T_{n_j} contains interval of arrival and departure time. The intervals in the SoC_{n_j} column are percentage intervals and arrival and departure SoC of EVs. The intervals in the Q_{n_j} and Cap_{n_j} columns respectively contains intervals on EV charge/discharge power limits in kW and battery capabilities in kWh. Intervals containing EV batteries standby loss factor are in column S_{n_j}.

6.3 Two-Stage Stochastic Problem Formulation

The optimisation problem is designed with the additional service of smoothing EVs' charge/discharge rate to avoid large deviation in charge/discharge powers that could damage the EVs. The stochastic EMS is implemented according to Algorithm 3 later in this chapter. However, the optimisation problem solved within the EMS is different and is formulated in this section using the two-stage stochastic programming technique explained in Section 3.2.1. The index set as in Section 4.2.1 and 5.2.1 are adopted to group different nodes and components that exist within Figure 6.4 and facilitate consideration of nodes affected by uncertain sources.

First-Stage Function

The objective in the first-stage is to look N_H steps into the future, with scheduling period h and decide at time k the amount of electricity to import/export:

$$P_{first}(k+h) = \sum_{k=0}^{N_H-1} P_{cost}(k+h) \tag{6.1}$$

subject to

ECM equations $\quad (3.1)\forall Su, (3.4)\forall T = T^n, (3.5)\&(3.6)\forall Bi$

where

$$P_{cost}(k+h) = \left[\pi_e^{buy}(k+h)P_{(e_1\rightarrow e_2)}(k+h) - \pi_e^{sell}(k+h)P_{(e_2\rightarrow e_1)}(k+h)\eta_{e_2\rightarrow e_1}\right]$$

P_{cost} is the economic cost with π_e^{buy} and π_e^{sell} representing the per-unit purchase price and received revenue for selling electricity respectively. $P_{(e_1\rightarrow e_2)}$ and $P_{(e_2\rightarrow e_1)}$ represent electricity

Table 6.1: Intervals to generate EV data from uniform distribution with prediction horizon $N_H = 96$ (24 hours)

cd	T_{n_j}	SoC_{n_j}	Q_{n_j}	Cap_{n_j}	S_{n_j}
2	[2 10], [24 40] [42 60], [62 94]	[40 60], [80 100] [40 60], [80 100]	[22 50], [22 50]	[75 100], [75 100]	[0.9 0.99], [0.9 0.99]
3	[2 10], [24 30] [35 40], [55 60] [65 70], [85 90]	[40 60], [80 100] [40 60], [80 100] [40 60], [80 100]	[22 50], [22 50] [40 50]	[75 100], [75 100] [75 100]	[0.9 0.99], [0.9 0.99] [0.9 0.99]
4	[2 5], [10 13] [17 20], [25 30] [32 35], [40 45] [47 50], [55 60]	[40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100]	[22 50], [22 50] [22 50], [22 50]	[75 100], [75 100] [75 100], [75 100]	[0.9 0.99], [0.9 0.99] [0.9 0.99], [0.9 0.99]
5	[2 5], [10 13] [17 20], [25 30] [32 35], [40 45] [47 50], [55 60] [62 65], [70 75]	[40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100]	[22 50], [22 50] [22 50], [22 50] [22 50]	[75 100], [75 100] [75 100], [75 100] [75 100]	[0.9 0.99], [0.9 0.99] [0.9 0.99], [0.9 0.99] [0.9 0.99]
6	[2 5], [10 13] [17 20], [25 30] [32 35], [40 45] [47 50], [55 60] [62 65], [70 75] [77 80], [85 90]	[40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100]	[22 50], [22 50] [22 50], [22 50] [22 50], [22 50]	[75 100], [75 100] [75 100], [75 100] [75 100], [75 100]	[0.9 0.99], [0.9 0.99] [0.9 0.99], [0.9 0.99] [0.9 0.99], [0.9 0.99]

Table 6.2: Intervals to generate EV data from uniform distribution with prediction horizon $N_H = 48$ (12 hours)

cd	T_{n_j}	SoC_{n_j}	Q_{n_j}	Cap_{n_j}	S_{n_j}
2	[2 10], [15 25] [30 35], [40 47]	[40 60], [80 100] [40 60], [80 100]	[22 50], [22 50]	[75 100], [75 100]	[0.9 0.99], [0.9 0.99]
3	[2 5], [10 15] [17 20], [25 30] [32 35], [40 45]	[40 60], [80 100] [40 60], [80 100] [40 60], [80 100]	[22 50], [22 50] [40 50]	[75 100], [75 100] [75 100]	[0.9 0.99], [0.9 0.99] [0.9 0.99]
4	[2 5], [7 10] [12 15], [17 20] [22 25], [27 30] [32 35], [37 40]	[40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100]	[22 50], [22 50] [22 50], [22 50]	[75 100], [75 100] [75 100], [75 100]	[0.9 0.99], [0.9 0.99] [0.9 0.99], [0.9 0.99]
5	[2 4], [6 9] [11 14], [16 19] [21 24], [26 29] [31 34], [36 39] [41 44], [46 48]	[40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100]	[22 50], [22 50] [22 50], [22 50] [22 50]	[75 100], [75 100] [75 100], [75 100] [75 100]	[0.9 0.99], [0.9 0.99] [0.9 0.99], [0.9 0.99] [0.9 0.99]
6	[2 4], [6 8] [10 12], [14 16] [18 20], [22 24] [26 28], [30 32] [34 36], [38 40] [42 44], [46 48]	[40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100] [40 60], [80 100]	[22 50], [22 50] [22 50], [22 50] [22 50], [22 50]	[75 100], [75 100] [75 100], [75 100] [75 100], [75 100]	[0.9 0.99], [0.9 0.99] [0.9 0.99], [0.9 0.99] [0.9 0.99], [0.9 0.99]

import and export respectively.

Second-Stage Function

Correction decisions are needed when an EV connects to a charging station and actual energy import/export can not satisfy its demand. Random or second-stage constraints are those influenced by uncertainty sources and can be written in the compact form $\boldsymbol{Hx}(k) - \boldsymbol{Gw_s}(k) = 0$ described in Section 3.3.2. The vector of uncertain variables ($\boldsymbol{w_s}$) and the corresponding recourse variables ($\boldsymbol{\xi}_s^+, \boldsymbol{\xi}_s^-$) used in Section 5.2.1 is adopted to define the second-stage constraints. The second-stage function can then be written as shown in (6.2). The aim of (6.2) is to look N_H steps into the future, with scheduling period h and decide at time k on correction decisions to be made due to power imbalances when a charging station utilisation is realised considering penalties on the change in charge/discharge powers of EVs.

$$
\begin{aligned}
P_{second}(k+h) = \sum_{k=0}^{N_H-1} \Bigg[\sum_{s=1}^{N} \Bigg[\sum_{\forall n_j = T^s} \frac{1}{N} \Big[\boldsymbol{q}_s^+ \boldsymbol{P}_{n_j}^{+,s}(k+h) + \boldsymbol{q}_s^- \boldsymbol{P}_{n_j}^{-,s}(k+h) \Big] \\
+ \sum_{\forall Es^s} \Big[\boldsymbol{P}_{n_j}^s(k+h+1) - \boldsymbol{P}_{n_j}^s(k+h) \Big]^2 \boldsymbol{\lambda}^s(k+h) \Bigg] \Bigg]
\end{aligned}
\tag{6.2}
$$

subject to

ECM equations	$(3.5)\&(3.6)\forall Bi, (5.7)\forall T = T^s$
SM equations	$(5.11) - (5.14)\forall Es^s$

Vectors $\boldsymbol{q}_s^+$ and $\boldsymbol{q}_s^-$ are penalty costs related to power surplus and shortage respectively, and corresponding probability related to each recourse variable pair is accounted for with N^{-1}. The means to prioritise EV charge/discharge smoothing action is provided using the tuning parameter $\boldsymbol{\lambda}^s$. Specifically, increasing the value of $\boldsymbol{\lambda}^s$ places greater emphasis on smoothing an EV's charge/discharge rate rather than ensuring the economic optimum is reached.

Sample Average Approximated Problem

As in Section 5.2.1, the deterministic equivalent can be written in a similar form to (3.30) by combining the first- (6.1) and second- (6.2) stage functions:

$$\min_{\boldsymbol{x}} \Big\{ J(\boldsymbol{x}) := P_{first}(k+h) + P_{second}(k+h) \Big\} \tag{6.3}$$

$$\text{subject to}$$

$$\begin{array}{ll} \text{ECM equations} & (3.1)\forall Su, (3.5)\&(3.6)\forall Bi \\ & (3.4)\forall T = T^n, (5.7)\forall T = T^s \\ \text{SM equations} & (5.11) - (5.14)\forall Es^s \end{array}$$

The solution vector $\boldsymbol{x} = \boldsymbol{P_{SM}}$ provides a schedule for manipulating the charge/discharge rate of all connected EVs. Due to the presence of binary variables and the quadratic term in the objective function, (6.3) is a mixed-integer quadratic programming problem (MIQP).

6.4 Simulation Setup

As with the case study presented in Chapter 5, the sampling period is set to half an hour, i.e. 15 minutes. The simulation is set up initially with two charging stations and then with three. Table 6.3 shows the conversion efficiencies of some power flow arcs of the ECM, and additional parameter values are shown in Table 6.4. Simulations are run with N_H set to 48 and 96 (i.e

Table 6.3: Conversion efficiencies related to technologies

ECM arc factor	Device	Conversion	Value
$\eta_{e_1 \to e_2}, \eta_{e_2 \to e_1}$	Transformer	electricity	0.98
$\eta_{e_2 \to e_3}$	Charging Station 1	charging efficiency	0.9
$\eta_{e_3 \to e_2}$		discharging efficiency	1/0.9
$\eta_{e_2 \to e_4}$	Charging Station 2	charging efficiency	0.9
$\eta_{e_4 \to e_2}$		discharging efficiency	1/0.9
$\eta_{e_2 \to e_5}$	Charging Station 3	charging efficiency	0.9
$\eta_{e_5 \to e_2}$		discharging efficiency	1/0.9

12 and 24 hours respectively), and also with increasing *cd*. Without loss of generality, N_H is set to the scheduling horizon, and the problem (6.3) is solved repeatedly at every time instant

k, with scheduling period h set equal to k. The stochastic control scheme is implemented according to Algorithm 3. However, problem (6.3) is solved instead of problem (5.16). The

Table 6.4: Additional simulation parameters

Parameter	Description	Value
$P_{e_2 \to e_3}, P_{e_3 \to e_2}$	charge/discharge limits of Charging Station 1	50kW
$P_{e_2 \to e_4}, P_{e_4 \to e_2}$	charge/discharge limits of Charging Station 2	50kW
$P_{e_2 \to e_5}, P_{e_5 \to e_2}$	charge/discharge limits of Charging Station 3	50kW

same assumptions made about each charging station in Section 5.4 applies to the charging stations shown in Figure 6.4. The price tariffs for electricity are shown in Figure 6.5. The stochastic EMS is solved according to Algorithm 3 with a commercial CPLEX solver at each sampling period on a PC Intel Core i7-4700MQ CPU @ 2.40GHz with 32 GB RAM.

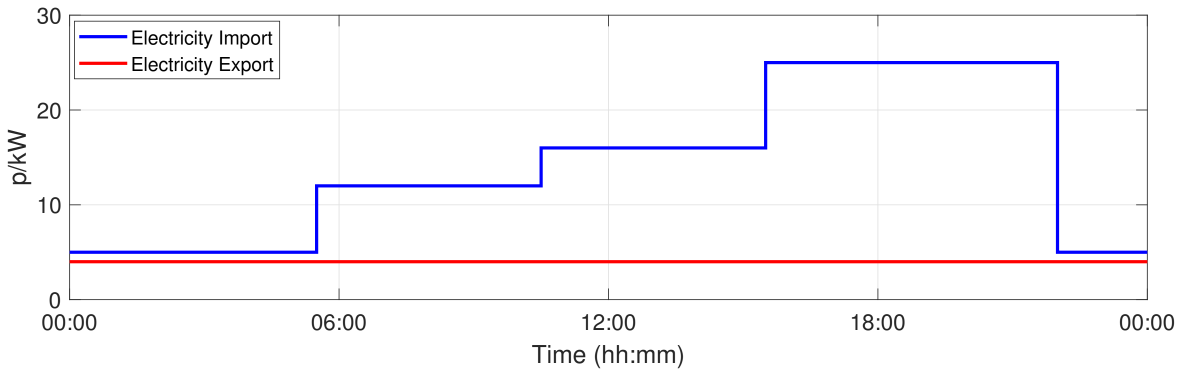

Figure 6.5: Import/export price of electricity

The mobile storage model was developed leveraging EV drivers' schedules to model the utilisation of charging stations. With the assumptions outlined in section 6.1 that the ease of predicting uncertainties in EV characteristics, availabilities and owners charge preferences decreases when going from residential to commercial to public areas, the stochastic EMS is analysed with assigned scenario numbers to specific areas. The scenario assignment used is shown in Table 6.5. As in Chapter 5, scenarios generated from Table 6.1 and Table 6.2 are in the form of a scenario fan with the length of the fan containing information on successive EV charge/discharge operations.

Table 6.5: Assignment of scenario size to residential, commercial and public areas

Areas	Residential	Commercial	Public
N	5	10	20

6.4.1 Index Set, Variables Types and Forecasts

Table 6.6 lists the index set used to derive the optimisation constraints for Figure 6.4. Implementing Algorithm 3 for the MES shown in Figure 6.4 requires decisions to be made on electricity imports/exports and the charge/discharge operation of EV considering uncertain utilisation of charging stations and smoothing EV charge/discharge rate. However, a clear distinction has to be made between decision and uncertain variables in the optimisation problem and forecasts obtained from scenario generation, especially as demand smoothing has been considered in formulating the optimisation problem. Table 6.7 shows the decision and uncertain variables. Forecasts required in the formulation of the optimisation problem for Figure 6.4 are also shown.

Table 6.6: EH index sets

$Bi :=$	$\{e_1 \leftrightarrow e_2, e_2 \leftrightarrow e_3, e_2 \leftrightarrow e_4, e_2 \leftrightarrow e_5\}$
$Su :=$	$\{e_2\}$
$Tr :=$	$\{-\}$
$Sw :=$	$\{-\}$
$T^n :=$	$\{e_1\}$
$T^s :=$	$\{e_3, e_4, e_5\}$
$GL^n :=$	$\{-\}$
$GL^s :=$	$\{-\}$
$Es^n :=$	$\{-\}$
$Es^s :=$	$\{E_{EV,i\rightarrow e_3}, E_{EV,i\rightarrow e_4}, E_{EV,i\rightarrow e_5}\}$

The charging/discharging powers of EVs that will utilise charging stations e_3, e_4 and e_5 over time are represented as $Q_{EV,i\leftarrow e_3}$, $Q_{EV,i\leftarrow e_4}$ and $Q_{EV,i\leftarrow e_5}$ respectively. For EVs that will utilise charging stations 1, 2 and 3 (i.e. e_3, e_4 and e_5 respectively), the number of EVs that will utilise each charging station over a period, cd, together with their respective battery capacities $Cap_{EV,i}$, efficiencies $S_{EV,i}$ and charge/discharge power limits $\pm Q_{EV,i}$ needs to be forecasted. Also, each EV's arrival and departure time ($h^a_{EV,i}$ & $h^d_{EV,i}$) and their respective energy levels at both times ($E^a_{EV,i}$ & $E^d_{EV,i}$) has to be forecasted. These, forecasts are used to predict the type of EV that will utilise each charging station hence, they directly influence an EV SoC during the charge/discharge process. The data required to forecast the utilisation of charging stations are gotten from historical information (5.1a) - (5.1f) which are sampled from Table 6.1 and Table 6.2. As the forecasts of charging station utilisations are disturbances introduced into the MES via connected terminal nodes as established in Section 5.1, the uncertain variables are the input/output power at terminal nodes connected to EVs. Denote the vector collecting all uncertain variables as $\boldsymbol{w}(k)$ and their corresponding recourse variables that represent power imbalances in the optimisation problem are denoted as $\boldsymbol{\xi}^+_s(k)$ and $\boldsymbol{\xi}^-_s(k)$.

Table 6.7: Decision and uncertain variables, and forecasts

$\boldsymbol{x}(k) :=$	$\{P_{(e_1\to e_2)}(k), P_{(e_2\to e_1)}(k), Q_{EV,i\to e_3}(k), Q_{EV,i\to e_4}(k), Q_{EV,i\to e_5}(k)$
Forecasts	$\{cd, Cap_{EV,i}, S_{EV,i}, \pm Q_{EV,i}, E^a_{EV,i}, E^d_{EV,i}, h^a_{EV,i}, h^d_{EV,i}\}$
$\boldsymbol{w}_s(k) :=$	$\{P^s_{e_3}(k), P^s_{e_4}(k), P^s_{e_5}(k), P^s_{h_2}(k)\}$
$\boldsymbol{\xi}^+_s(k) :=$	$\{P^{+,s}_{e_3}(k), P^{+,s}_{e_4}(k), P^{+,s}_{e_5}(k), P^{+,s}_{h_2}(k)\}$
$\boldsymbol{\xi}^-_s(k) :=$	$\{P^{-,s}_{e_3}(k), P^{-,s}_{e_4}(k), P^{-,s}_{e_5}(k), P^{-,s}_{h_2}(k)\}$

6.5 Benefits and Limitations of Real-World Implementation

The simulation is set up such that the stochastic EMS can be analysed in real-world situations. Specifically, the performance benefits in terms of computational time and the limits to which the number of charging stations in residential, commercial and public areas can be increased when implementing a stochastic EMS is investigated. As the mobile storage model developed in this thesis is based on the assumption that EVs utilising charging stations are frequent visitors or live in the area where the charging stations are located, implementation of a stochastic EMS will require different scenario sizes. It is highlighted in Section 6.1 that fewer scenarios will be required to implement a stochastic EMS in residential areas compared to a commercial area, and fewer to implement the stochastic EMS in a commercial area compared to a public area. In addition to varying scenario size, the performance of the stochastic EMS is analysed considering varying number of charging stations that may exist in an MES. Analysis of operational cost is excluded as it has been proven in Chapter 5 that increasing scenario size reduces the operational cost when implementing stochastic EMS. Table 6.8 and Table 6.9 shows the computational time mean (σ) and standard deviation (μ) with N_H set to 24 and 12 hours respectively. Results where obtained simulating the system with two charging stations and then with three charging stations.

6.5.1 Impact of Incorporating Multiple Charging/Discharging Operations

In Section 6.1.1, the assumption is that EVs utilising charging stations in residential areas are likely to be residents of the area. Hence, EV characteristics considered when implementing a stochastic EMS will be those owned by the residents. The availabilities of their EVs will be easily estimated as EVs will likely be available and connected to the network around specific times during the day. This makes it safe to assume that most EVs will charge on average twice a day. In the MEA trial in [87], it was proven that some EV owners even charge more than two times, especially during the weekend. It is equally safe to assume that each EV owner's charging preferences will be consistent and easy to predict. With these assumptions, it is assumed that 5 scenarios is adequate enough to account for EV related uncertainties in residential areas. The computational time mean and standard deviation over a 24 hour horizon for the stochastic EMS implemented with 5 scenarios are shown in Table 6.8. It can be observed that, for both simulations using two and three charging stations, the mean computational time does not increase significantly as more charge/discharge operations are incorporated into the stochastic EMS.

A noticeable increase in computational time is observed in Table 6.8 as more charge/discharge operations are incorporated into the EMS with N set to 10 to estimate the utilisation of charging stations in a commercial area. Further analyses revealed an average increase of 8.85% in mean computational time as more charge/discharge operations are considered in all three areas. Specifically, when the stochastic EMS was implemented considering two and then three charging stations, an average increase in mean computational time of 9.41% is obtained for simulations run with 5 scenarios, 8.65% for simulations run with 10 scenarios and 8.51% for simulations run with 20 scenarios. It is worth highlighting that EMS exploiting the flexibility provided by EVs in residential and commercial areas will likely incorporate this flexibility within DSM or IDSM strategies. Hence, the percentage increase in computational time will be different as more DERs are incorporated in the EMS. However, because the mobile storage

Table 6.8: Computational time with $N_H = 96$ (24 hours)

#charging stations	2						3					
N	5		10		20		5		10		20	
seconds	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
$cd = 2$	2.3717	1.6224	7.2147	4.7234	23.0908	21.1445	5.4664	3.5128	15.4260	12.5214	59.6202	37.9917
$cd = 3$	2.9321	1.5995	7.9979	5.3621	31.6876	22.9812	5.9023	3.1352	15.9156	13.3412	66.2651	38.2143
$cd = 4$	3.1942	1.6322	8.2464	5.5503	32.2440	23.4361	6.3934	3.2364	18.0471	14.4596	73.9371	38.5501
$cd = 5$	3.2702	2.0966	8.9120	5.5369	35.0237	24.1022	6.7803	3.1520	19.7939	14.9572	77.4679	39.1052
$cd = 6$	3.7450	1.4661	10.0634	5.7340	40.8628	24.8756	7.0134	3.3257	21.3701	14.5106	81.0202	39.3142

Table 6.9: Computational time with $N_H = 48$ (12 hours)

#charging stations	2						3					
N	5		10		20		5		10		20	
seconds	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
$cd = 2$	0.3591	0.2906	1.1566	0.8110	3.9518	2.7957	0.4788	0.3298	1.7051	1.6246	3.1772	5.4798
$cd = 3$	0.4233	0.3527	1.1285	0.7547	4.1317	2.7956	0.4358	0.3496	1.7765	1.5013	4.3274	5.5679
$cd = 4$	0.4372	0.2906	1.3276	0.7125	4.2892	2.7082	0.5066	0.3551	1.8216	1.2586	5.2761	5.5012
$cd = 5$	0.4590	0.2498	1.2069	0.8267	5.0386	2.2067	0.5380	0.3612	1.8169	1.7053	5.3116	5.4932
$cd = 6$	0.4728	0.4187	1.4297	0.8382	5.1914	2.6266	0.5434	0.3841	1.8574	1.7918	5.5164	5.5682

model has the most impact on the optimisation problem's dimensions, requiring more memory, it will significantly impact computational time. With charging stations located in public areas, expect a lot more successive charge/discharge operations, especially when EVs are fully adopted and charging stations are utilised how fuelling stations are utilised today. Hence, the computational time will also increase significantly as the number of charging stations and successive charge/discharge operations increase.

6.5.2 Impact of Incorporating Multiple Charging Stations

Unsurprisingly, incorporating more charging stations significantly increases the mean computational time along with the corresponding standard deviation, as shown in Table 6.8. The increase is especially noticeable in the columns with 20 scenarios used to represent the stochastic EMS implementation in public areas. Further analyses of results obtained with other scenarios revealed an average increase in mean computational time of 110.37% when comparing stochastic EMS implementation with two and then three charging stations. Specifically, comparing the mean computational time obtained using the two systems with N set to 5 resulted in a mean computational time of 105.31%. With N set to 10 and 20, the average mean computational time are 113.22% and 112.56%, respectively. The result suggests that when analysing case studies with a certain number of charge/discharge operations per charging station in residential, commercial or public areas, expect a significant increase in computational time. Specifically when more charging stations are aggregated compared to just increasing the utilisation of each charging station. However, as the computational time is smaller when the EMS is implemented in a residential area, more charging stations can be aggregated compared to when it is implemented in commercial or public areas.

6.5.3 Impact of Varying Prediction Horizon Length

Most EV owners in residential areas will likely charge their EVs twice a day, mainly in the evening and morning, after and before work which is approximately a 12 hour difference. EV owners will probably connect their vehicles to the energy network in commercial areas between the typical 9 hour work period. Most EV owners will likely utilise charging stations between 8 am to 6 pm when most people go about their daily activities in public areas. This implies there are certain periods when the frequency at which charging stations are utilised is high and certain periods when the frequency is low. To consider such situations, the stochastic EMS is implemented over a 12-hour horizon. EV related uncertainties are sampled from the distribution shown in Table 6.2. The distribution in the table is similar to that of Table 6.5. However, the number of charging/discharging operations are estimated to occur over a 12-hour period.

Implementing the stochastic EMS over a shorter prediction horizon resulted in smaller mean computational times shown in Table 6.9 as compared to results shown in Table 6.8. The mean computational time across the three different areas as more charge/discharge operations are considered increases at an average rate of 7.17%. This is smaller than the percentage increase when the EMS is implemented over a 24 hours prediction horizon. It should also be noted that the increase in mean computational time in Table 6.9 as N is increased is not as significant as what is shown in Table 6.8. In addition, increasing the number of charging stations results in a 23.91% average increase in computational time, much less than the 110.37% average increase when the stochastic EMS is implemented over a 24-hour horizon. This shows that it will be computationally beneficial to shorten the period horizon, especially for a stochastic EMS implemented in public areas where a large number of charging stations have to be aggregated. In addition, as a lot more successive charge/discharge operations occur in public areas than residential or commercial areas, shortening the prediction horizon allows consideration for more scenarios related to EV uncertainties without significantly increasing computational time. However, it is worth highlighting that although results reveal much more charging stations and/or successive charge/discharge operations can be considered in a stochastic EMS over a shorter prediction horizon; the sampling interval limits it. Ideally, the mean computational time should be less than the sampling interval to ensure that the optimisation problem can be solved before each time interval elapses.

6.6 Chapter Summary

The mobile storage model significantly impacts the dimension of the optimisation problem solved within the stochastic EMS and hence the computational time. This chapter has focused on analysing the computational burden associated with implementing a stochastic EMS in residential, commercial and public areas assigning different scenarios sizes to represent each area. The decision on the number of scenarios assigned to represent each area is based on assumptions made about the ease of predicting uncertainties in EV characteristics, availabilities and owners charging preferences. A stochastic EMS is implemented on a general electrical only system with a varying number of charging stations. The optimisation problem solved within the stochastic EMS is formulated with the additional service of smoothing EVs' charge/discharge power profile to avoid large deviation in charge/discharge powers that could damage the EVs, especially if the EVs are used to provide ancillary services to network operators. The number of charging stations, successive charge/discharge operations and prediction horizon are varied to investigate their impact of the performance of a stochastic EMS when implemented in either a residential, commercial or public area. It can be concluded that reducing the prediction horizon has more impact on reducing the computational time. It allows much more charge/discharge operations and/or charging stations to be considered when implementing the stochastic EMS. However, this will be limited by the sampling interval considered as ideally the mean computational time has to be less than the sampling interval ensuring the controller has time to solve the optimisation problem.

Chapter 7

Conclusion and Future Work

This chapter presents the concluding summary and highlights key contributions in this thesis. In addition, remarks on promising areas for future work are presented.

The remainder of the chapter is organised as follows: Conclusion of the thesis is provided with highlights of key contributions in Section 7.1. Some limitations of using the modelling framework are discussed in Section 7.2 before suggested future research parts are provided in Section 7.2.

7.1 Conclusion

This thesis has presented a generalised mobile storage model that allows mobile storage devices, most notably EVs, to be represented within single- and multi-energy systems. The model enables successive EVs charging/discharging operations to be represented based on the utilisation of charging stations instead of directly modelling a fixed number of EVs, which is the approach employed in most literature. The model structure facilitates the representation of individual EV characteristics and availabilities and allows their owners to set desired charging preferences before a charge/discharge operation begins.

The novel part of the mobile storage model is the ability to incorporate successive EV charge/discharge operations without knowing the exact number of EVs that will utilise a charging station. It gives the model a modular structure and allows it to be incorporated into the novel COMMES framework in [8]. In particular, as EVs with different characteristics, availabilities and owners charging preferences can utilise a charging station, the mobile storage model facilitates the analysis of how charging stations are utilised in residential, commercial and public areas. This is because charging station utilisations vary among these areas. As an example, it will be expected that EVs utilising charging stations in residential areas will be owned by residents compared to public areas where EVs are not allocated to specific charging stations.

As with the original COMMES framework, the mobile storage model is well suited to predictive control applications. In Chapter 4, a mechanism is provided for updating current and estimate of future EV charging/discharging operations to address inter-temporal constraints between successive EV charging/discharging operations. In addition, a general deterministic EMS is designed to exemplify the incorporation of the mobile storage model to the COMMES framework, and the operational cost comparison is carried out with some assumptions used in literature and compared to the approach used to develop the mobile storage model in this thesis.

As the COMMES framework does not readily consider uncertain energy sources, in accordance with the third objective in Section 1.3, parts influenced by uncertain generation and demand sources are identified. Modifications are made to the mobile storage model because the approach of leveraging drivers schedules to model the utilisation of charging stations revealed that EV characteristics, availabilities and owners charging preferences are uncertain and remain unknown until an EV actually arrives and connects to a charging station. To exemplify this modification, a general stochastic EMS is designed in Chapter 5 and implemented for an MES. At the time of writing, only data collected from MEA trials in [87] fits some requirements needed for the mobile storage model proposed in this thesis. In accordance with the fourth point in Section 1.3, modifications are made to the steps outlined within [53] to recreate the EV charging profile to be able to generate the information required for the mobile storage model. The optimisation problem solved in the stochastic EMS is formulated using the two-stage stochastic programming approach. The SAA approach is adopted within the stochastic EMS to categorise uncertain MES dynamics using a finite set of random realisations. This method of stochastic problem formulation is chosen because numerous proven analyses in literature allow assessing the trust-wordiness of solutions to the problem formulated with the two-stage stochastic approach and helps with choosing an adequate scenario number for implementing a stochastic scheme for an energy system. The results discussed highlight that increasing the scenario size in the stochastic EMS outperforms the deterministic implementation, which uses a single scenario.

As it has been established that EVs, unlike other DERs, are not permanently connected to a single- or multi-energy system, and also the way charging stations are utilised in residential, commercial and public areas vary. This is primarily due to the ease of predicting uncertainties related to EV characteristics, availabilities and owners charging preferences. Chapter 6 focuses on analysing the performance of a stochastic EMS in terms of computational time by varying the number of charging stations, multiple charge/discharge operation and prediction horizon. The assumption that the ease of predicting EV related uncertainties decreases going from residential to commercial to public areas allows assigning a number of generated scenarios to each area. The same algorithm followed to implement the stochastic EMS in Chapter 5 is used. However, the optimisation problem solved within is different. It includes a demand smoothing application to avoid significant deviation in EVs' charge/discharge powers, which can occur when EVs are utilised to provide ancillary services to power systems operators. Stochastic EMS allows consideration of a broad range of uncertainties, but it comes at the cost of increased computational burden as discussed in Chapter 5. Discussions in Chapter 6 focus not only on the computational burden accompanying the implementation of a stochastic EMS in residential, commercial or public areas, but also on the limits to which the number of charging stations, number of successive charging/discharging operations and the prediction horizon length can be increased.

So far, the model that began with the development of a generalised modelling framework for MES in [8] with a holistic view that addresses the shortfalls of other modelling and aggregation methods employed in literature has evolved to incorporate a general representation of mobile storage devices. In addition, the modelling framework has been adapted to consider uncertainties in energy generation and demand together with EV related uncertainties. The framework is still primarily for predictive control design with modifications making it well suited for both deterministic and stochastic control applications. Additionally, the framework now includes consideration for mobile storage devices, most noticeably EVs, and with the increased interest in EV adoption worldwide and the ancillary services they can provide to network operators, it is hoped that the framework will be of interest to the wider STEM community.

7.2 Critiques and Limitations

The original COMMES framework and the modifications proposed in this thesis allows the modelling of multi-energy networks, including EV, which are pretty difficult to incorporate in energy networks due to the difficulty addressing their characteristics, availabilities, owner's charging preferences. However, a centralised control scheme will be impractical to implement in reality, especially if large scenario sizes are required to solve the optimisation problem repeatedly within a predictive control framework, as the computational burden will be significantly high.

In addition, as the proposed EV charge/discharge model is based on the characteristics, availabilities, and owner's charging preferences of EVs, understanding how they are used in different locations and by various individuals can be quite challenging to obtain. This complexity may impact the trustworthiness of solutions from solving optimisation problems formulated using the modified COMMES framework in this thesis, especially if the framework is used to analyse EV utilisation in pubic areas such as the scenario analysed in Chapter 6.

7.3 Future Work

The development this thesis has highlighted some promising directions for future work. These include (but are not limited to) the following:

1. **Data on Utilisation of Charging Stations**

   To incorporate prosumers into EMS required an understanding of their consumption and/or generation patterns. This is usually done by obtaining energy demand and/or generation data on each individual prosumer component. Depending on the case study, for fixed prosumers, energy demand data is easily obtainable. Data that affects RES generation can be obtained from their corresponding energy sources, such as wind speed. For flexible prosumers, an understanding of individually controllable devices such as petrol generators, washing machines, and dryers can be obtained from user preferences, and the amount of energy each device consumes or generates. To incorporate fixed storage systems only requires an understanding of its characteristics. However, incorporating mobile storage systems, most noticeably EVs, in EMS requires knowledge of EV characteristics and their availabilities and owners charging preferences. Literature incorporating EVs in EMS has estimated EVs from data on individual EV drivers utilisation or assumed probability distributions used to represent drivers' schedules. The problem with this approach is that EVs' resulting estimated charge/discharge operations are unrealistic and do not account for the number of times and/or possible different charging stations an EV will utilise. This fact inspired the development of the generalised mobile storage model in this thesis. To validate the proposed EMS in Chapter 5, data from the MEA is used. Although the MEA trial was carried-out on specific residential EV drivers, vital information such as the number of times an EV is charged over certain periods was collected. However, EVs could have also utilised charging stations in commercial or public areas, and information on how these charging stations are utilised has to be considered. Hence, it is proposed that a study similar to the MEA trial could be carried out to collected information on the characteristics, availabilities and owners charging preferences of EV that utilised charing stations in residential, commercial and public areas so that a broad understand of EV demands can be obtained especially as EV become more widely adopted.

2. **Detailed Model Development of Individual DER Technologies**

The modified MES model in this thesis has enhanced the benefits of the original COMMES framework by providing a generalised approach to representing successive EV charge/discharge operations and adopting the entire modelling framework to consider uncertainties from generation and demand sources still relatively simple. The model primarily consists of power and conversion efficiencies. It also includes binary variables used to manipulate the operation of prosumers and mobile storage devices. Developing a detailed model of individual DERs within an MES will facilitate the model application in safety controls and protection. This is required when dealing with issues regarding current, frequency and voltage protection. In addition, further model development of individual DERs will facilitate analyses of thermal management schemes. This is because there is increasing adoption of DERs comprising a significant amount of power electronics that generate excess heat, thus requiring thermal management to improve reliability and prevent premature failure.

3. **Distributed Optimisation Application**

   A centralised optimisation framework has been utilised in numerous power system operations. However, there are some challenges in emerging energy systems that limit the performance of centralised control schemes. One is the growing multi-energy coordination scheme to improve energy reliability and economic efficiency, which has influenced the adoption of the MES concept. Also, it will be impractical to implement a centralised optimisation framework because of technical difficulties regarding solving complex models. Another challenge is regarding communication among assets in large-scale MES. The communication infrastructure for interacting with different assets in the MES will be complex and can lead to disruptive events in real-time such as software application failures. Distributed optimisation is an alternative that is gaining significant interest in power systems to address these challenges. Using a distributed optimisation framework, large-scale MES problems can be divided into smaller sub-problems for individual controllers to solve. Then, solutions can be effectively coordinated to obtain a final optimal solution. In addition, distributed optimisation framework limits communication complexity as information exchange only occurs between adjacent assets. Considering the variety of case studies that can be modelled using the modelling framework in this thesis, especially as it has been adapted to consider generation and demand sources, simulations could be run to implement control schemes based on distributed optimisation.

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