

Assessing the Benefits of Storage Applied to Energy Communities

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Abstract

Community energy systems are an emerging concept which aims to re-organize the local energy system through efficient integration of Distributed Energy Resources (DERs) and engagement of local communities. A better understanding of the possible benefits of deployed DERs such as community energy storage systems is therefore required, along with an active energy management system within the control framework of community smart-grids, in order to integrate and optimize the operation of flexible resources within the energy communities.

An efficient model of a community energy management system is proposed in this thesis for communities equipped with grid-connected PV and Battery Energy Storage System (BESS). An algorithm is developed which controls the power flow between the electricity end-users, the communal BESS and the power grid, based on historical and instantaneous PV generation and load consumption data attained from three real communities in the UK. Increased accessibility to smart-meters and market availability of Time-of-Use electricity tariff schemes, which amplifies off-peak/peak cost difference, are exploited to achieve energy cost minimization for energy end-users in the communities through energy-shifting and increment of PV self-consumption.

The methods of choosing a battery size which balances the trade-off between increasing battery capacity and reducing system cost is demonstrated and their impact on the annual household electricity cost is assessed. Similarly the effects on energy loss and cost saving by choosing converter ratings which

are lower than the maximum power of the system is demonstrated and using a method of power-bins, the rating is determined for each community.

Assessment has been done on communities in the UK to develop an algorithm for a Community Power Flow Battery Management System (CPF BMS), and to better understand the benefits that battery energy storage, in particular centrally controlled systems, can bring to an energy community. The operation of loads clustered as a community as opposed to individual users has been assessed and the results show that community operation achieves higher energy cost savings. It also allowed for larger optimum battery and converter sizes, which in turn allows higher self-consumption of local PV generation, better energy-shifting from off-peak hours to high-tariff band periods through battery storage, and finally lower energy bills.

This project contributes to the increasing number of technologies and business models focusing on the decarbonisation of the energy sector through cost reduction incentives to the electricity end-users, and empowering the community to have a greater control of their energy usage and resources.

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“For indeed, with hardship [will be] ease”, Quran 94:5

“Allah does not charge a soul except [with that within] its capacity”,

Quran 2:286

LIST OF ABBREVIATIONS

ANM	Active Network Management
AVC	Active Voltage Control
AVR	Advanced Voltage Regulator
BESS	Battery Energy Storage System
BPSO	Binary Particle Swarm Optimization
CCC	Committee of Climate Change
CPF	Community Power Flow
CPF-BMS	Community Power Flow Battery Management System
CPP	Critical Peak Pricing
CS	Control Strategy
DC	Direct Current
DER	Distributed Energy Resources
DER-CAM	Distributed Energy Resources-Consumer Adoption Model
DECC	Department of Energy and Climate Change
DLR	Dynamic Line Rating
DNO	Distribution Network Operator
DoD	Depth of Discharge
DSM	Demand Side Management
DW	Dish Washer
ESCo	Energy Services Company
ESS	Energy Storage Systems
EV	Electric Vehicle
FACT	Flexible AC Transmission System

FIT	Feed-in-Tariff
FLC	Fuzzy Logic Control
FR	Frequency Regulation
GHG	Greenhouse Gas
HRES	Hybrid Renewable Energy System
μ CHP	Micro Combined Heat and Power
MPC	Model Predictive Control
NWP	Numerical Weather Prediction
OPF	Optimal Power Flow
PCC	Point of Common Coupling
PV	Photovoltaic
RES	Renewable Energy Sources
RG	Renewable Generation
RMSE	Root Mean Square Error
RTP	Real Time Pricing
SOC	State of Charge
SOH	State of Health
STOR	Short Term Operating Reserve
TFM	Total Final Consumption
ToU	Time of Use
TNUoS	Transmission Network Use of System
V2G	Vehicle-to-Grid
WM	Washing Machine

TABLE OF CONTENTS

1 INTRODUCTION.....	2
1.1 INTRODUCTION	2
1.2 PROJECT AIMS AND OBJECTIVES	7
1.2.1 Aim.....	7
1.2.2 Objectives	7
1.3 CONTRIBUTIONS TO KNOWLEDGE	10
1.4 THESIS CHAPTERS	11
2 BACKGROUND AND LITERATURE SURVEY.....	15
2.1 INTRODUCTION	15
2.2 COMMUNITY ENERGY	19
2.3 INTEGRATION OF DISTRIBUTED ENERGY RESOURCES (DERs) IN ENERGY COMMUNITIES.....	23
2.3.1 Community Energy Storage Systems	24
2.3.2 Community Renewable Energy Sources (RES)	28
2.4 CONTROL FRAMEWORKS FOR COMMUNITY ENERGY MANAGEMENT	30
2.5 CONCLUSION	39
3 CHALLENGES AND LEARNINGS FROM PROJECT EMPOWER.....	43
3.1 INTRODUCTION	43
3.2 WHAT WENT WELL	51
3.2.1 Results to illustrate good performance of DSM over a few days ..	51
3.3 WHAT WENT BADLY	61
3.4 LEARNINGS FROM THE PROJECT	71

3.5 CONCLUSION	77
4 DESIGN OF BATTERY MANAGEMENT ALGORITHM AND SIZING TOOL.....	80
4.1 INTRODUCTION	80
4.2 DESIGN METHODOLOGY: BATTERY MANAGEMENT ALGORITHM.....	82
4.2.1 Overview of Energy Management Schemes	82
4.2.2 Communities used for Load and PV Generation Data.....	86
4.2.3 Tariff Model.....	87
4.2.4 Battery Model	89
4.2.5 Grid Interface Model.....	89
4.2.6 Design of Energy Management Scheme	91
4.3 BATTERY SIZING METHODOLOGY	104
4.4 POWER CONVERTER SIZING METHODOLOGY	109
4.5 EFFECTS OF APPLICATION OF DESIGNED CPF BATTERY ALGORITHM ONTO THE COMMUNITY OF PROJECT EMPOWER	122
4.5.1 Results to illustrate superior performance of CPF based battery management system, over EmPower EmPower Battery Management System	123
4.6 CONCLUSION	137
5 EVALUATION OF CPF CONTROLLER ENERGY MANAGEMENT SYSTEM THROUGH ADDITIONAL COMMUNITIES	143
5.1 INTRODUCTION.....	143
5.2 COMMUNITIES USED FOR LOAD AND PV GENERATION DATA	146
5.3 BATTERY SIZING METHODOLOGY	148
5.4 POWER CONVERTER SIZING METHODOLOGY	155

5.5 EFFECTS OF APPLICATION OF DESIGNED CPF BATTERY ALGORITHM ONTO THE COMMUNITIES OF MILTON KEYNES AND CARBON LEGACY	167
5.5.1 <i>Energy Shifting Patterns through CPF BMS</i>	172
5.5.2 <i>Battery Control Strategy for Weekends</i>	174
5.5.3 <i>Baseline Comparison of CPF BMS</i>	176
5.6 COMMUNITY VS INDIVIDUAL RESULTS	180
5.7 CONCLUSION	182
6 IMPERFECT PREDICTION OF DISTRIBUTED ENERGY RESOURCES	187
6.1 INTRODUCTION.....	187
6.2 COMMUNITIES AND TYPES OF FORECASTS USED FOR INCORPORATION OF IMPERFECT PREDICTION ONTO CPF BMS	189
6.3 EFFECTS OF IMPERFECT PREDICTION ON THE RESULTS OF CPF BATTERY ALGORITHM ONTO THE COMMUNITIES OF MILTON KEYNES AND CARBON LEGACY	192
6.4 ALGORITHM USING PERSISTENCE FORECAST VS. NO FORECAST	197
6.5 RESULTS OF CPF BMS CONSIDERING 3-DAY-AHEAD AVERAGE EXPORT FOR PV GENERATION AND LOAD CONSUMPTION PREDICTION.....	207
6.6 CONCLUSION	212
7 CONCLUSION	216
7.1 INTRODUCTION.....	216
7.2 PROPOSED BATTERY MANAGEMENT SYSTEM AND CONTROL FRAMEWORK	217
7.3 SUMMARY OF SIMULATION RESULTS AND ANALYSIS FOR DEVELOPED MODELS.....	219

7.3.1 Results from the Corsham Community	Error! Bookmark not defined.
7.3.2 Results from Additional Communities with Complete Datasets	Error! Bookmark not defined.
7.4 LIMITATIONS AND RECOMMENDATIONS	222
7.5 FUTURE WORK	224
7.5.1 Areas of Improvement	224
7.5.2 Alternative Operational scenarios	227
8 REFERENCES	232
9 APPENDICES	242
APPENDIX A	243
APPENDIX B	247
APPENDIX C	248
APPENDIX C- CONTINUED	249

List of Figures

FIGURE 2.1: COMMUNITY ENERGY AS DEPICTED BY E.ON.....	20
FIGURE 3.1: OVERVIEW OF EMPOWER PROJECT COMMUNITY WITH INDIVIDUAL GENERATION, STORAGE AND CONTROLLABLE LOAD.....	48
FIGURE 3.2: FLOWCHART OF CONTROL COMMANDS	49
FIGURE 3.3: FLOWCHART OF CONTROL COMMANDS	50
FIGURE 3.4: ENERGY SHIFT OF DISH WASHER OPERATION CYCLES FOR CC9TN DURING A DAY IN AUTUMN.....	52
FIGURE 3.5: ENERGY SHIFT OF DISH WASHER OPERATION CYCLES FOR CC9TN IN AUTUMN: A) UNCONTROLLED DW LOAD B) CONTROLLED DW LOAD C) DW LOAD IN MONITORING MODE.....	53
FIGURE 3.6: COMMUNITY BATTERY CHARGING PROFILE FOR THE 1ST OF OCTOBER	56
FIGURE 3.7: COMMUNITY BATTERY CHARGING PROFILE OVER OCTOBER WEEK-3 IN RELATION TO PV GENERATION AND ELECTRICITY IMPORT TARIFF.....	58
FIGURE 3.8: COMMUNITY BATTERY DISCHARGE PROFILE OVER OCTOBER WEEK-3 IN RELATION TO ELECTRICITY TARIFF.....	58
FIGURE 3.9: COMMUNITY BATTERY DISCHARGE PROFILE OVER OCTOBER WEEK-1 IN RELATION TO PV GENERATION AND ELECTRICITY IMPORT TARIFF.....	59
FIGURE 3.10: CC9TN BATTERY CHARGING AND DISCHARGING PROFILE	60
FIGURE 3.11: ENERGY SHIFT OF DISH WASHER OPERATION CYCLES FOR CC9TN DURING SUMMER: A) UNCONTROLLED DW LOAD B) CONTROLLED DW LOAD C) DW LOAD IN MONITORING MODE.....	62
FIGURE 3.12: WASHING MACHINE (WM) LOAD OVER ONE WEEK FOR CC9TN PROPERTY	63
FIGURE 3.13: SUGGESTED AND ACTUAL DELAYS OF CONTROLLABLE APPLIANCES IN EACH HOUSEHOLD	65
FIGURE 3.14: BATTERY CHARGING PROFILE IN RELATION TO PV GENERATION, GRID EXPORT AND TARIFFS, OVER WEEK-1 IN OCTOBER.....	67
FIGURE 3.15: BATTERY DISCHARGE PROFILE OVER 13TH TO 19TH AUGUST.....	68
FIGURE 3.16: BATTERY CHARGE PROFILE OVER 13TH - 19TH AUGUST.....	69
FIGURE 3.17: EXCESS EXPORT RESULTING FROM BATTERY OPERATION	69
FIGURE 3.18: CHARGING PATTERN OFFSET DURING A WEEK IN DECEMBER.....	70
FIGURE 4.1: OVERVIEW OF DESIGNED ENERGY MANAGEMENT SCHEME	85
FIGURE 4.2: MULTI-LEVEL TIDE TARIFF RATES IN p/kWh OFFERED BY GREEN ENERGY UK.....	88
FIGURE 4.3: TOTAL LOSS CALCULATED FOR A 2 kW CONVERTER.....	92
FIGURE 4.4: EFFICIENCY OF THE 2 kW CONVERTER AT DIFFERENT PROCESSING POWER LEVELS.	92
FIGURE 4.5: FLOWCHART OF OVERALL SYSTEM SIMULATION SHOWING DETAILS OF THE CPF BMS	99
FIGURE 4.6: FLOWCHART OF BATTERY POWER FLOW DURING LOW TARIFF PERIOD...	99
FIGURE 4.7: FLOWCHART OF BATTERY POWER FLOW DURING PEAK TARIFF PERIOD	100
FIGURE 4.8: A) PLOT OF ANNUAL IMPORT ENERGY COST SAVING AGAINST BATTERY SIZES IN kWh, SHOWING THE KNEE-POINT B) CURVE SHOWING DISTANCE OF	

POINTS ON COST CURVE FROM STRAIGHT LINE IN ORDER TO IDENTIFY KNEE-POINT.....	103
FIGURE 4.9: PLOT OF PAYBACK PERIOD FOR DIFFERENT CONVERTER SIZES FOR CORSHAM COMMUNITY WHILE INSTALLED WITH THE OPTIMUM BATTERY CAPACITY OF 13 kWh.....	109
FIGURE 4.10: CHARGING ENERGY USED BY BATTERY AGAINST AVERAGE OPERATING POWER, OVERLAID WITH 3 kW CONVERTER EFFICIENCY CURVE FOR (A), AND 13 kW CONVERTER EFFICIENCY CURVE FOR (B), AND HOURS OF OPERATION AT EACH POWER BIN WITH AND WITHOUT 3 kW CONVERTER RATING (C) FOR A 13 kWh BATTERY.....	113
FIGURE 4.11: DISCHARGING ENERGY USED BY BATTERY AGAINST AVERAGE OPERATING POWER, OVERLAID WITH 3 kW CONVERTER EFFICIENCY CURVE FOR (A), AND 13 kW CONVERTER EFFICIENCY CURVE FOR (B), AND HOURS OF OPERATION AT EACH POWER BIN WITH AND WITHOUT 3 kW CONVERTER RATING (C), FOR A 13 kWh BATTERY.....	115
FIGURE 4.12: BATTERY CHARGING PROFILE IN RELATION TO NET POWER PROFILE, BATTERY SOC AND TIDE TARIFF LEVELS, OVER 1ST TO 7TH OCTOBER 2015	124
FIGURE 4.13: BATTERY CHARGING PROFILE IN RELATION TO NET POWER PROFILE AND BATTERY SOC, OVER 1ST TO 7TH OCTOBER 2015.	125
FIGURE 4.14: BATTERY CHARGING PROFILE IN RELATION TO NET POWER PROFILE, BATTERY SOC AND TIDE TARIFF LEVELS, OVER 13TH TO 19TH AUGUST 2015.....	127
FIGURE 4.15: BATTERY DISCHARGING PROFILE IN RELATION TO TIDE TARIFF LEVELS, OVER 13TH TO 19TH AUGUST 2015.	129
FIGURE 4.16: BATTERY CHARGE (A) AND DISCHARGE (B) PROFILE OVER FIRST WEEK OF DECEMBER FOR CORSHAM COMMUNITY.	130
FIGURE 4.17: ENERGY IMPORTED FROM THE GRID IN EACH TARIFF PERIOD OF TIDE USING CPF BMS (EGRID FINAL) ALONGSIDE THE BATTERY CHARGING AND DISCHARGING ENERGY IN EACH OF THESE PERIOD, CONTRASTED WITH THE IMPORT ENERGY IN THE SCENARIO WITHOUT A BATTERY (EGRID PREVIOUS), CONSIDERED FOR THE 8 PROPERTIES OF CORSHAM COMMUNITY FOR A) AUGUST B) OCTOBER AND C) DECEMBER.	132
FIGURE 4.18: OCT 1ST-3RD, 13 kWh BATT, 3 kW CONVERTER.	134
FIGURE 5.1: PLOT OF ANNUAL IMPORT ENERGY COST SAVING AGAINST BATTERY SIZES IN kWh, SHOWING THE KNEE-POINT OF CARBON LEGACY COMMUNITY AT 18 kWh (LEFT) AND MILTON KEYNES COMMUNITY AT 17 kWh (RIGHT)	146
FIGURE 5.2: CURVE SHOWING DISTANCE OF POINTS ON COST CURVE FROM STRAIGHT LINE IN ORDER TO IDENTIFY KNEE-POINT FOR CARBON LEGACY (LEFT) AND MILTON KEYNES (RIGHT) COMMUNITIES.....	146
FIGURE 5.3: PAYBACK PERIOD FOR DIFFERENT CONVERTER SIZES FOR MILTON KEYNES AND CARBON LEGACY COMMUNITIES WHILE INSTALLED WITH THE OPTIMUM BATTERY CAPACITY.	155
FIGURE 5.4: CHARGING AND DISCHARGING POWER DEMAND AT RESPECTIVE AVERAGE POWER BINS FOR MILTON KEYNES (TOP) AND CARBON LEGACY (BOTTOM) COMMUNITIES, EMPLOYING THE OPTIMUM BATTERY SIZES WITHOUT ANY CONVERTER LIMIT.	159
FIGURE 5.5: ANNUAL ENERGY IMPORTED FROM THE GRID IN EACH TARIFF PERIOD OF TIDE USING CPF BMS (EGRID FINAL) ALONGSIDE THE BATTERY CHARGING AND DISCHARGING ENERGY IN EACH OF THESE PERIOD, CONTRASTED WITH THE IMPORT ENERGY IN THE SCENARIO WITHOUT A BATTERY (EGRID PREVIOUS), FOR COMMUNITIES OF MILTON KEYNES (TOP) AND CARBON LEGACY (BOTTOM).	165

FIGURE 5.6: ENERGY FLOW FROM GRID AND TO AND FROM BATTERY FOR MILTON KEYNES COMMUNITY OVER FOUR DAYS IN THE MONTH OF JANUARY.	169
FIGURE 6.1: DIFFERENCE IN ENERGY BETWEEN PREDICTED PV EXPORT (USING AVERAGE OF 3-DAY AHEAD DAILY EXPORT ENERGIES) AND ACTUAL PV EXPORT OF EACH DAY FOR MILTON KEYNES (TOP) AND CARBON LEGACY (BOTTOM)	198
FIGURE 6.2: COUNT OF UNDER- AND OVER-FORECASTED DAILY SURPLUS PV ENERGY BASED ON DAY-AHEAD EXPORT PERSISTENCE FORECASTS COMPARED TO PERFECT FORECAST, FOR CARBON LEGACY COMMUNITY OVER ONE YEAR....	199
FIGURE 6.3: MILTON KEYNES COMMUNITY ENERGY FLOW IN DIFFERENT TARIFF BANDS FOR PERFECT PREDICTION (TOP, REPRODUCED FROM FIGURE 5.6), 3-DAY-AHEAD EXPORT PREDICTION (BOTTOM), BOTH OPERATING ON CPF BMS. ...	205
FIGURE 6.4: CARBON LEGACY COMMUNITY ENERGY FLOW IN DIFFERENT TARIFF BANDS FOR PERFECT PREDICTION (TOP, REPRODUCED FROM FIGURE 5.6), 3-DAY-AHEAD EXPORT PREDICTION (BOTTOM), BOTH OPERATING ON CPF BMS. ...	206

List of Tables

TABLE 2.1: THREE CATEGORIES OF ENERGY STORAGE	25
TABLE 2.2: TIME-SENSITIVE PRICING SCHEMES IN THE ENERGY MARKET	28
TABLE 3.1: EQUIPMENT LISTING OF PROPERTIES FOR RECORDING MEASUREMENTS	45
TABLE 3.2: DW LOAD SHIFT ACROSS DIFFERENT TARIFF REGIONS DURING A WEEK OF OCTOBER DUE TO CONTROL STRATEGY	54
TABLE 3.3: MONTHLY AND ANNUAL BATTERY ENERGY STORAGE IN KWH FOR THE COMMUNITY	61
TABLE 3.4: DW LOAD SHIFT ACROSS DIFFERENT TARIFF REGIONS DURING A WEEK OF JULY DUE TO CONTROL STRATEGY	64
TABLE 3.5: SUMMARY OF APPLIANCE SHIFT INFORMATION FROM DIFFERENT SOURCE FILES	66
TABLE 4.1: DESCRIPTION OF EACH COMPONENT WITHIN FIGURES 4.3 AND 4.4..	92
TABLE 4.2: SUMMARY OF THE ROLE OF BATTERY AND GRID IN DIFFERENT TIME PERIODS DEFINED BY TIDE TARIFF	94
TABLE 4.3: INPUTS AND ASSUMPTIONS FOR ENERGY MANAGEMENT ALGORITHM	101
TABLE 4.4: BATTERY COST CALCULATION BASED ON TESLA POWERWALL II.....	109
TABLE 4.5: PAYBACK PERIOD FOR DIFFERENT CONVERTER SIZES FOR CORSHAM COMMUNITY WHILE INSTALLED WITH THEIR RESPECTIVE OPTIMUM BATTERY CAPACITY OF 13 KWH.....	109
TABLE 4.6: COMPARISON OF CHARGING AND DISCHARGING CAPABILITY LOST DUE TO SMALLER CONVERTER CUT-OFF POWER LIMIT IN RELATION TO A CONVERTER WHICH ENCOMPASSES THE ENTIRE CHARGING AND DISCHARGING POWER RANGE (INCLUDES LOSSES DUE TO CONVERTER EFFICIENCY, FOR BOTH SMALL AND LARGE CONVERTER).....	111
TABLE 4.7: DIFFERENCES IN IMPORT PRICES BETWEEN TARIFF BANDS IN TIDE SCHEME.....	117
TABLE 4.8: ANALYSIS OF COST SAVING ACHIEVED BY USING REDUCED CONVERTER SIZE GIVEN BY 5% CUT-OFF LIMIT INSTEAD OF CONVERTER SIZE TO ACCOMMODATE MAXIMUM BATTERY POWER.....	117
TABLE 4.9: TOTAL EXPORT OVER 1 ST TO 7 TH OCTOBER, BEFORE AND AFTER EMPLOYING CPF BMS	122
TABLE 4.10: TOTAL EXPORT OVER 13 TH TO 19 TH AUGUST, BEFORE AND AFTER EMPLOYING ENERGY MANAGEMENT SCHEME DEVELOPED IN THIS WORK.	125
TABLE 4.11: TOTAL CHARGE AND DISCHARGE ENERGY TO AND FROM THE BATTERY OVER SUMMER, AUTUMN AND WINTER, IN THE CORSHAM COMMUNITY USING CPF BMS	130
TABLE 4.12: PV ENERGY EXPORTED TO GRID OVER THREE DIFFERENT MONTHS FOR THE CORSHAM COMMUNITY WITH AND WITHOUT THE DESIGNED BATTERY...	130
TABLE 4.13: IMPORT KWH AND COST (£) OVER AUG, OCT AND DEC FOR DIFFERENT BATTERY SCENARIOS	132
TABLE 5.1: IDENTIFICATION OF REPRESENTATIVE PEAK-PERIOD LOAD CONSUMPTION REPRESENTATIVE OF OPTIMUM BATTERY SIZE FOUND THROUGH KNEE-POINT DETECTION FOR COMMUNITY A) MILTON KEYNES AND B) CARBON LEGACY	149

TABLE 5.2: TABLE SHOWING CONSISTENCY OF YEARLY MEAN OF THE 5 HIGHEST LOAD CONSUMPTION E_h OF EACH MONTH WITH OPTIMUM BATTERY SIZE GIVEN BY KNEE-POINT CALCULATION	152
TABLE 5.3: BATTERY COST CALCULATION BASED ON TESLA POWERWALL II .	153
TABLE 5.4: PAYBACK PERIOD FOR DIFFERENT CONVERTER SIZES FOR MILTON KEYNES AND CARBON LEGACY COMMUNITIES WHILE INSTALLED WITH THEIR RESPECTIVE OPTIMUM BATTERY CAPACITIES	155
TABLE 5.5: COMPARISON OF CHARGING AND DISCHARGING CAPABILITY LOST DUE TO SMALLER CONVERTER CUT-OFF POWER LIMIT IN RELATION TO A CONVERTER WHICH ENCOMPASSES THE ENTIRE CHARGING AND DISCHARGING POWER RANGE (INCLUDES LOSSES DUE TO CONVERTER EFFICIENCY, FOR BOTH SMALL AND LARGE CONVERTER).....	156
TABLE 5.6: DIFFERENCES IN IMPORT PRICES BETWEEN TARIFF BANDS IN TIDE SCHEME.....	161
TABLE 5.7: ANALYSIS OF COST SAVING ACHIEVED BY USING REDUCED CONVERTER SIZE GIVEN BY LOWEST PAYBACK PERIOD INSTEAD OF CONVERTER SIZE TO ACCOMMODATE MAXIMUM BATTERY POWER.....	161
TABLE 5.8: ANALYSIS OF COST BENEFIT ACHIEVED BY USING REDUCED CONVERTER SIZE GIVEN BY LOWEST PAYBACK PERIOD INSTEAD OF CONVERTER SIZE TO ACCOMMODATE MAXIMUM BATTERY POWER.....	163
TABLE 5.9: SUMMARY OF IMPORT AND EXPORT kWh AND COST (£) OVER ONE YEAR FOR DIFFERENT BATTERY MANAGEMENT SCENARIOS FOR CARBON LEGACY AND MILTON KEYNES COMMUNITIES	167
TABLE 5.10: IMPORT COST AND TOTAL EXPORT OF THE COMMUNITIES OF MILTON KEYNES AND CARBON LEGACY OVER ONE COMPLETE YEAR USING THE THREE DIFFERENT ENERGY FLOW CONTROL STRATEGIES (CS) FOR THE WEEKENDS .	173
TABLE 5.11: STANDARD ELECTRICITY IMPORT FLAT-RATE TARIFF OFFERED BY DIFFERENT ENERGY SUPPLIERS ALONG WITH YEARLY STANDING CHARGES AND FEED-IN-TARIFF FOR EXPORT	175
TABLE 5.12: COMPARISON OF ANNUAL IMPORT, EXPORT AND NET ELECTRICITY COST AND ENERGY FOR COMMUNITIES WITHOUT BATTERY (STANDARD FLAT-RATE TARIFF) AND WITH CPF BMS (TIDE TARIFF)	175
TABLE 5.13: EFFECT OF CPF BMS ON COMMUNITY ANNUAL IMPORT IN kWh AND IN £ FOR A SCENARIO WITHOUT PV GENERATION. A STANDARD FLAT-RATE IMPORT PRICE IS USED FOR THE CASE ‘WITHOUT BATTERY’	176
TABLE 5.14: ENERGY AND COST SAVING COMPARISON FOR INDIVIDUAL PROPERTIES IN A COMMUNITY VERSUS SAVING ACHIEVED BY THE COMMUNITY AS A UNIFIED SYSTEM FOR MILTON KEYNES COMMUNITY (TOP) AND CARBON LEGACY COMMUNITY (BOTTOM).....	179
TABLE 6.1: TOTAL YEARLY IMPORT COST SAVING (£), ADDITIONAL IMPORT kWh, AND EXPORT kWh FOR FIVE DIFFERENT SCENARIOS OF EXCESS PV PREDICTION, CONTRASTED WITH THAT OF PERFECT PREDICTION SCENARIOS (TOP), FOR CARBON LEGACY (MIDDLE) AND MILTON KEYNES (BOTTOM) COMMUNITIES	191
TABLE 6.2: SUMMARY OF IMPORT AND EXPORT kWh AND COST SAVING (£) OVER ONE YEAR FOR DIFFERENT BATTERY CONTROL SCENARIOS FOR CARBON LEGACY AND MILTON KEYNES COMMUNITIES	196
TABLE 6.3: SUMMARY OF COST SAVING AND ENERGY FLOW FOR CARBON LEGACY (TOP) AND MILTON KEYNES (BOTTOM) COMMUNITIES RESULTED FROM FORECAST TECHNIQUES USING MOVING AVERAGE FILTERS.....	202
TABLE 6.4: SUMMARY OF IMPORT AND EXPORT kWh AND COST (£) OVER ONE YEAR FOR DIFFERENT BATTERY MANAGEMENT SCENARIOS FOR CARBON LEGACY AND	

MILTON KEYNES COMMUNITIES, WHERE THE IMPERFECT PREDICTION IS GIVEN BY 3-DAY-AHEAD-AVERAGE EXPORT FORECAST	207
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1 INTRODUCTION

1.1 Introduction

The wider energy sector across the world, and in particular the UK, is going through a radical transformation as it moves towards a smart, decentralised, low-carbon energy system. Community energy can have an important role to play in this energy transition by being a more active, affordable, and environmentally sensitive energy system, and in promoting energy efficiency measures.

The depletion of oil and gas resources due to finite reserves alongside the expected growth of electrical energy demand has led to concerns over the security of energy supply for authorities around the world. A legally binding target from the 2008 Climate Change Act sets the target of greenhouse gas (GHG) emissions below 80% of the 1990 baseline [3]. Currently, UK stands at a reduced emission by 43% compared to 1990 baseline most of which is contributed by the power sector. However, an analysis by the Department of Energy and Climate Change projects that the UK's electricity demand between 2015 and 2035 will go up by nearly 20% [4]. The Committee of Climate Change (CCC), UK has put forward recommendations to the government, based on the learnings of the last decade, which includes supporting low-cost options such as onshore wind and PV installations, and increasing efficiency in buildings [5]. Besides gradual transformation of energy to renewable sources, a further

contribution towards increasing the security of supply and reducing the GHG emissions is the electrification of heat and transport which is expected to occur in the UK in the near future. This transformation would again result in a substantial increase in electricity demand.

Another mandatory target for European governments, driven by the Kyoto Protocol established in 1997, calls for 27% of the EU's overall Community energy consumption to be produced from renewable sources by 2030 [6]. The worldwide cumulative installed capacity of photovoltaic (PV) has already grown at an average rate of 49% per year throughout the last decade, with Stanford University providing a roadmap which envisions a total worldwide PV penetration of 47% by 2050 [7].

One of the most significant ways to minimize greenhouse gas emission footprint is the transformation of the current structure of the electrical power grid. The future electrical grid should progress towards a smarter, more efficient and sustainable form which is able to replace centralized fossil-fired generation with localized distributed renewable generation technologies leading to zero carbon emissions. The ability to control load demand will also allow optimizing the use of the distributed energy resources (DERs).

In order to efficiently manage the available resources and load demand, a shift from individual energy users to community energy strategy is taking place, whereby energy is generated, purchased, and managed, and the benefits of the outcome shared, collectively by a group of residential and/or commercial establishments. Although more than 5000 communities in the UK have taken part in community energy initiatives in the last 5 years, the sector is

still small compared to countries such as Denmark and Germany which have long since adopted sustainable approaches to combat the energy crisis [8].

The percentage increase in installed renewable generation, mainly based on wind and PV energy, is projected to be just over 200% by 2035 compared to the 2015 mark [4]. Even with the latest developments in forecasting techniques for intermittent renewable generation systems, errors for a day ahead forecast can reach up to 10% Root Mean Square Error (RMSE) [9]. Consequently, due to the high forecast inaccuracies and non-flexibility of these intermittent generations, cost-effective alternatives need to be deployed in order to integrate these emerging resources. Incorporation of a sufficient degree of active management of flexible Distributed Energy Resources (DERs) such as Energy Storage Systems, dispatchable loads (their operation period could be shifted in time leading to Demand Side Management) etc. at different levels in a smart grid control framework may balance the variations as well as derive maximum benefits from inflexible scenarios.

In recent years home Battery Energy Storage Solutions (BESS) in combination with solar PV energy production systems are becoming commercially available and more affordable. MOIXA offers a 2 kWh battery and a 2 kW peak PV systems as a package, with an all-inclusive price of £4995 [10]. The newest of the offered Battery ESS, the Tesla Powerwall with a 13.5 kWh capacity and 5 kW real power output is offered at £ 7,644 including labour, bits, sales fee and a 20% VAT along with 10 years warranty [11]. If the battery is installed with PV, the VAT further drops to 5% while it drops to 0% if the battery is installed as part of a new build house. The relatively larger

capacity offered makes it convenient for aggregated community energy storage. Similarly, the 6 kWh SolaX Battery with SolaX AC 3.7 kW battery inverter costs £6811 including installations, overhead, and sales cost including 20% VAT (D. Hill, Managing Director of Carbon Legacy Ltd., personal communication, November 27, 2017).

These Battery Energy Storage Systems (BESS) are presented as an ideal solution for households to minimise the cost of import energy through capturing and storing surplus locally generated renewable energy during the high generation periods and use it during periods of low or no renewable generation with high demand. Working together with communities and other partners can help understand how customers' energy bills may best be reduced by capturing energy from PV panels and delaying its use of the excess energy with a storage device such as battery. Battery storage employed in communities is also able to shift energy by charging from the grid during periods of low import tariff overnight and discharging this stored energy during high import-tariff periods of morning and evening peaks when household members are either leaving to or returning from work.

Energy Services Companies (ESCOs), aided by the advent of affordable smart meters, can be a driving force in energy shifting through BESS by providing time-of-Use (ToU) tariffs which incentivise battery charging during off-peak hours using cheap p/kWh electricity, and by including an expensive peak-period which encourages users to meet load demand from previously stored cheap electricity or surplus PV rather than from the grid. The BESS in

this case needs to be equipped with intelligent controls that respond to the ToU tariff signal to lower household bills and increase system efficiency.

For domestic customers, the local benefits offered by demand side services are currently limited to the Economy-7 tariffs introduced in the 1970s and the Economy-10, due to the undeveloped local supply market [12]. However, several smaller energy providers are now gearing up to offer ToU tariffs such as the multi-level Tide tariff from Green Energy UK [13].

Thus, the homeowners with installed BESS are able to minimise their reliance on its energy provider, can save more money on their energy bills, be less affected by price hikes and at the same time maximise the consumption of the self-consumption of their generated energy. The operation electricity consumers grouped together as communities rather than individuals helps to use larger storage devices and allow more substantial load and PV shift. It also allows increased opportunities for distributed and renewable energy usage during the time of generation and demand. The larger the number of properties within a community, the more defined and less variable the load and PV profiles are expected to be, and therefore the utilization of the BESS can be better controlled.

The analysis of data from households belonging to real existing energy communities across the UK containing dispatchable energy resources and control schemes to manage them need to be gathered and studied in order to derive learnings on battery management systems based on real-life scenarios. Whether the community BESS can provide benefit for the electricity end-users needs to be assessed including the benefits, if any, to operate as a community

rather than individual users of electricity. The emergence of newer higher capacity batteries such as Tesla can be studied for their impact and benefit, if any, on community energy. The importance of behavioural change from electricity users also needs to be addressed to derive maximum benefits from energy shifting through BESS.

1.2 Project Aims and Objectives

1.2.1 Aim

The overarching aim of the project is to better understand the benefits that battery energy storage can bring to an energy community, and in particular how a centrally controlled energy storage system can provide more benefit than batteries controlled at household level.

As part of this work, additional aims were to understand how a battery system could be sized to meet community energy needs, and how it should be controlled to exploit local generation and time-of-use tariffs.

To meet these aims, the following objectives have been set.

1.2.2 Objectives

A number of objectives are to be met during the project to fulfil the aims described above. Two real life challenges in terms of the Corsham community and the local company Carbon Legacy, which provides renewable energy solution to its customers, have presented themselves which have driven the motivation for the project. Analysis of the results from EmPower project

relating to Corsham community has called for the demonstration of an effective algorithm for control of power flow within energy storage units. Involvement of Carbon Legacy has resulted from a need for a better way to size storage devices for the clients of the company. Carbon legacy was also eager to provide customer data in order to derive ‘simple rule of thumb’ sizing approach for battery systems.

Based on these motivations, the objectives of this thesis are specified below, including the component targets to be achieved for meeting each objective.

OBJECTIVE 1: Undertake literature Review of existing challenges, policies and possibilities

- ✓ Literature survey of community energy and Demand Side Management (DSM), to find a gap in research and identify the scope of the thesis.
- ✓ Review of existing policies to support viability of community energy and storage systems

OBJECTIVE 2: Familiarize with real community load and PV data and their challenges

- ✓ Corsham EmPower trial data
- ✓ Learning from data analysis and challenges identified to be incorporated into new battery algorithm

OBJECTIVE 3: Design battery algorithm for community energy

- ✓ Develop a novel algorithm to effectively control the stochastic power flow of a community smart grid and reduce customers' energy bills by employing BESS.
- ✓ Base model on currently available tariff structure, i.e. Green Energy UK TIDE tariff scheme
- ✓ Establish increment of self-consumption
- ✓ Reduction of energy consumption at peak tariff rates
- ✓ Determine the operational limitations of the developed algorithm in terms of DER flexibility and storage capacity and adjust the algorithm based on limited economic size of battery and power converter
- ✓ Demonstrate the operation of this algorithm within multiple real-life communities
- ✓ Make assessment for both perfect and imperfect prediction of data on achieved energy shifting and savings.

OBJECTIVE 4: Methodology to size Battery

- ✓ Derive battery size which gives optimal cost saving over a year
- ✓ Consider load consumption of different days of the year or seasons to have an indicator for sizing battery.
- ✓ Taking into account efficiency losses for grid interfaces

OBJECTIVE 5: Evaluation of algorithm using additional communities

- ✓ Obtain load and PV data from additional real-life communities

- ✓ Effectiveness of battery management algorithm in enhancing self-consumption, reducing peak period energy consumption, and maximizing energy savings for end-users.
- ✓ Impact of working as an energy community, i.e. compare benefits of individual energy user vs. community usage

Having defined the objectives of the project, the following system deliverables are proposed for the project.

1. Working battery management algorithm
2. Battery sizing tool

1.3 Contributions to Knowledge

A novel algorithm for community battery storage systems is developed in this work based on currently available variable electricity tariff rates [13] and battery systems in the market, in order to capture available energy from dispatchable sources for peak time usage as well as charging the battery at off-peak times to meet demand during peak periods. The resulting energy management system is expected to maximize cost benefits for electricity end-users within energy communities. A methodology is also developed to optimize the sizing of battery for each community and the relative energy savings established by the battery algorithm for individual users vs. community usage is evaluated to show the merits of community energy. The following points list the contributions to knowledge achieved by this thesis.

1. Battery control algorithm

- Driven by a domestic variable tariff which penalises electricity consumption at peak evening time
 - Applicable to a virtual community
 - Using simple but reliable prediction of generation and load
2. Novel Battery Sizing strategy
 - Introduction of the knee-point approach
 - Based on optimum energy cost saving
 3. Novel power converter sizing strategy
 4. ‘Rule of Thumb’ for sizing battery systems
 - Carbon Legacy presented its need for a better way to size storage devices for the clients of the company
 - Analysis of the available data for this thesis suggests it is possible to derive a rule of thumb in sizing battery systems based on consumption patterns across different months during a year.
 5. Evaluation of Battery Management System (BMS) performance with data from real communities
 - Three different communities considered
 - Varying year/location etc.
 6. Comparison of individual vs. community operation
 - Benefits measured in terms of cost and energy

1.4 Thesis Chapters

Having presented the introduction and the aims of this thesis, a summary is now given about the organization of the rest of the thesis, the entirety of which

is spread over 7 chapters. The remainder of the thesis begins by providing the motivation of this project in terms of a literature survey in Chapter 2 and the challenges and learning from a real-life energy community at Corsham in the UK in chapter 3.

The literature survey in chapter 2 addresses the need for energy management systems in modern microgrids and discusses previous works and solutions provided to address the barriers for integration of renewable resources. The available community energy management frameworks and control techniques for implementation of storage systems in energy communities of such systems are also presented in chapter 2. It includes problems of electricity expenditures and available tariff schemes in the UK.

Since no real-life energy community assessment exists in the literature, chapter 3 analyses the data from the real-life community of Corsham in comprehensive details in an aim to develop a community energy management system and control framework based on real-life data rather than modelled data. This chapter also acts as a motivation for the project and focuses on the learnings from the Corsham trial data and presents the challenges which need to be met in upcoming designs of energy management and control systems.

Chapter 4 introduces a new proposed energy management framework consisting of a battery management algorithm based on Community Power Flow (CPF) Control. The battery management system (BMS) is designed to provide regulation to power flow to and from the battery with the grid and PV system, depending on a Time-of-Use (ToU) tariff structure, in order to achieve energy and cost benefits for the electricity user community. Modelling

techniques and data sources used in the simulation procedure are introduced in detail in this chapter. The battery sizing methodology is briefly described along with details of the converter sizing. Comparisons are made with the existing battery management system in the Corsham community and results of applying the proposed BMS to the community are presented.

In chapter 5, evaluation of the proposed new Community Power Flow Battery Management System (CPF-BMS) is carried out through real-life data from two additional communities. A more detailed analysis of battery sizing is presented. The different simulation scenarios, including results and economic analysis for the different proposed and existing strategies are presented.

Chapter 6 deals with the effect of prediction of data from Distributed Energy Resources (DERs) and user load consumption. Several forecast scenarios are introduced and their effect on successful energy shifting and cost savings is analysed, in comparison to scenarios with a perfect forecast. A suitable prediction technique for energy communities is suggested at the end of the chapter.

Chapter 7 draws the conclusion of this thesis providing a synopsis of the key results in each stage and summarising the main achievements of the project. It ends with pointing out some challenges for the community energy sector and recommendation for future work.

2 BACKGROUND AND LITERATURE SURVEY

2.1 Introduction

The 2018 IEA overview for global energy scenario has reported renewable sources such as solar PV, wind, solar thermal, geothermal, expanding at a fast pace. Among them, solar PV has seen a notable increment of 31.1% and wind has expanded by 14.2%. However, the renewables still account for less than 2% of global primary energy production together while fossil fuels accounted for 81% of production [14].

The energy use by most economic sectors has been fairly stable for several years. The total final consumption (TFC) of energy remains to be dominated by the industrial sector with 37%, followed by the transport sector whose consumption significantly increased from 23% of TFC in 1971 to 29% in 2016. With 22% of TFC, the residential sector ranked third in the list of largest global energy consumers in 2016 [14].

With the ever-increasing constraints on world resources, energy generation from renewable sources has enjoyed an increasing focus of research during the last decade. Measures to reduce fuel consumption not only preserves limited fuel resources, leads to reduced pollution of air and water, strengthens the social responsibility of the energy sector, but also draws attention to

economic benefits for users. Several studies have discussed the role of the economics of renewable energy, either accepting or rejecting the notion [15], [16], [17].

In the last decade more and more attention has been directed towards the integration of intermittent renewable energy sources onto the electrical power network in the form of dispatchable resources which are able to provide power to the network in a more efficient and predictable manner, rather than just having them as uncontrollable additional generation. Hybrid systems which operate renewable energy generation sources and storage devices in combination with fossil fuelled generators have gained importance to combat these issues [18], [19], [20], [21].

The intermittency of renewable energy sources, and their variability depending on the time of day or year, demands that multiple inter-dependent resources be employed as powering options. The mass integration of these electrical resources would affect the operation of the network and push them to their statutory limits. To tackle this, Distribution Network Operators (DNOs) would need to expand the capacity of their network with additional underground cables which can be expensive and time-consuming. A cost-effective solution for integrating the emerging resources is the incorporation of enough degree of active management of flexible DERs at different levels in a smart grid control framework. An effective control and distribution system therefore need to be in place which can ensure efficient management of energy. Different enabling technologies in an active management system include but are not limited to the following [22]:

- Demand side management (DSM)
- Energy Storage Systems (ESS)
- Dynamic Line Rating (DLR)
- Voltage and power control

According to Clark W. Gellings in [23], ‘Demand Side Management (DSM) is the planning and implementation of those electric utility activities designed to influence customer uses of electricity in ways that will produce desired changes in the utility’s load shape.’ DSM therefore aims to adjust electric usage of electricity customers, through a load shape change, in response to network congestion or emergencies, typically through pricing incentives [24]. The increased availability of smart meters capable of recording the time of day, the rate at which energy is consumed, and the quantity of energy consumed make the realisation of DSM a reality. However additional factors such as user awareness and flexibility, good communication between network elements, and ToU tariff structures with significant difference between peak and off-peak period rates are also required for the widespread acceptance of DSM. DSM can shave the load peaks and fill in the gaps in the daily pattern of electric power consumption. The ultimate success of the program relies on the ability to balance utility and customer needs. Integration of DG and emerging loads can be accommodated through DSM technology, although as noted in [25], successful implementation of DSM requires bidirectional control and communication between the DNO and its customers.

Energy Storage Systems (ESSs) can be a good solution to smooth power fluctuations, improve system reliability, load demand management, and energy

shifting etc. Electrical energy can be transformed and stored as different forms. Energy, for example, as mechanical energy, thermal, electrical, chemical, etc [26]. For deployment in active management systems, storage devices need to be able to convert of the stored energy back into electricity which could be supplied to the consumers, at a flexible operation time. ESS can act either as a load or as a generator which makes them valuable to power systems. They can provide increased advantages when connected to the grid through power electronic inverters. Several algorithms for optimal ESS placement and sizing are proposed in the literature [27], [28], [29], [30].

One of the earliest references in literature for storage systems in energy regulation of power systems occurs in the form of hydroelectric pumped storage station [31]. Storage options need to be considered depending on the storage scale and environment of application to determine the type of storage technology to be used. A mix of storage technologies can be employed to cater to different requirements and sources.

As mentioned by [32], Dynamic Line Rating (DLR) systems allow monitoring real weather conditions to calculate the actual ampacity of overhead electric transmission lines. Thus, it can increase the estimated current carrying capacity of the lines by considering dynamic line limits (e.g. ambient temperature, solar radiation, and wind speed) instead of static ones and thereby aid in the integration of DERs.

The voltage and power control functions within power systems ensure stable and optimum operation of the distribution network. Different technologies that can provide the necessary voltage and power control operation

through active management include four different categories namely, in-line voltage regulators, Optimal Power Flow (OPF) and generation curtailment, use of power electronic devices such as Flexible AC Transmission Systems (FACTS) within the distribution networks, and Advanced Voltage Regulators (AVR) adapted to basic active voltage control (AVC) relays.

The current trend towards renewable energy generation in the developed world that involves community members is a positive step away from current carbon-intensive energy practices. With over ninety percent of the UK energy market being controlled by just six companies, the ever-mounting costs and the threat of climate change, as well as resource scarcity is driving people to take control of their energies themselves. Local and community energy initiatives are emerging which focuses on the end-users and require re-organization of the energy systems for flexibility and optimal management of DERs such as PV Systems, storage devices, and modern electronic loads through community integration.

2.2 Community Energy

A report by the Department of Energy and Climate Change (DECC) defines ‘community energy’ as any project involving collective action to buy, manage, save or generate energy that was led or partially owned by a community group. Within the definition, ‘community group’ refers to any citizen group or third sector body who are responsible and/or accountable for the delivery of an energy project in the UK, or are intending to take responsibility for the delivery of an energy project in the UK in future [33].

Similarly, another study by Walker and Devine-Wright defines community energy to refer to those projects where communities (of place or interest) exhibit a high degree of ownership and control, as well as benefiting collectively from the outcomes such as energy saving or revenue-generation [34].

Figure 2.1 provides a visual representation of the definition of Community Energy provided by E.ON Energy suppliers in the UK. It illustrates how community energy uses low carbon solutions for renewable heat and power. It is produced locally and distributed via a heat network or private wire arrangement and has reduced transmission losses as it is produced close to where it's needed. Over the longer term, community energy is expected to lower the cost of energy as mentioned by the energy company.

There is no standardization for the definition of 'community energy', with varying degrees of community involvement. The term 'community energy' therefore covers a range of collective actions, from saving or reducing the use of energy, to purchasing, managing and generating it, which are led and

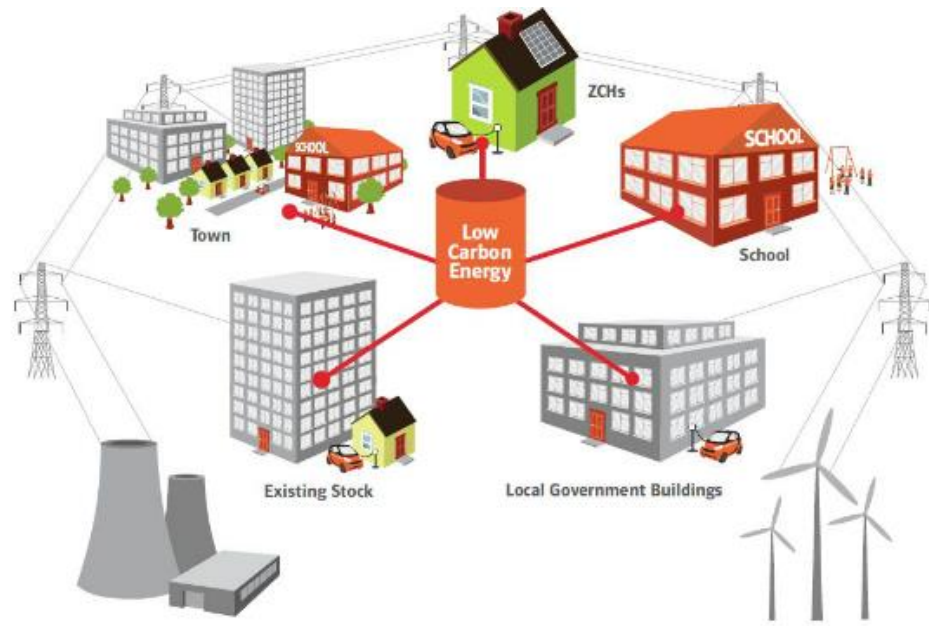


Figure 2.1: Community Energy as depicted by E.ON

developed by local engagement and control, for the benefit to local communities, who are usually in the same geographical area [35]. This definition provided by Community Energy Coalition will be primarily used throughout this thesis.

The first shared Renewable Energy or Community Energy emerged over a decade ago where the key focus of the program was attaining economic benefits for the members of the energy community [36]. Community energy projects can be developed by different types of organisations, including voluntary groups, social enterprises, co-operatives and charities. Commercial, government-supported initiatives, or individual efforts are not considered within the scope of community energy.

Community energy may include a range of diverse projects using different technologies and through various organisation types [34]. Sefyang et al discusses different community energy initiatives to reduce the carbon

footprint of a local area, community members owning and generating electricity from renewable sources as a group, community hall refurbishments introducing high levels of insulation and energy efficiency, programmes raising awareness among local groups in collective behaviour change for energy usage, and improving public receptivity to renewable energy installations etc. [37].

Due to the ability of community energy initiatives in engaging local populations in sustainable energy issues and being critical players in the transition to low carbon economy, it is important to develop strategies that are aimed to catalyse increased community energy activity, the most important among them being through economic incentives. In this work, the energy management framework developed therefore focuses on bringing techno-economic benefits to the energy end-users involved in the energy communities.

Community energy can give rise to several benefits including but not limited to the following:

- Improving Energy security for the community
- Keeping generated profits within the community
- Reducing greenhouse gas emissions
- Supporting the local by creating jobs
- Increasing public acceptance of renewable energy schemes

In [38], van der Schoor discusses how local community energy initiatives contribute to a decentralized sustainable energy production system. He investigates the activities, motives and ambitions of local community energy initiatives that determine their effectiveness and looks into the barriers encountered by energy communities. The study however focuses on the social

aspects of community energy rather than the technological, through case studies of early-stage projects and therefore lacks a quantitative analysis through a database with validated key characteristics and performance measures. The study concludes that community energy provides a useful grassroots approach for many citizens to engage in the transition to a sustainable energy future, although further development of organisation structures and viable visions for local energy governance is necessary to achieve lasting results. Similar discussion is presented in [39], highlighting the importance of a locally grounded energy transition implemented by, in and for local places and communities. The study concludes that place and local entrepreneurship affect the emergence of grassroots innovations of renewables, while energy policies and funding schemes should recognise local socio-geographic circumstances in order to support further diffusion of community-based energy transition.

2.3 Integration of Distributed Energy Resources (DERs) in Energy Communities

The ongoing growth of decentralized energy generation resources can be strengthened by small-scale, grid-connected community-energy storage solutions, as reported by a feasibility study by DNV-GL [40]. It argues that, given current costs for lithium-ion battery technology and grid expansion projects, community storage can be both economically and socially viable. The same report defines Community Storage as a technology that provides several services, including one or more system services to the regional grid operator. These services may include energy arbitrage, peaking power generation, energy

loss reduction, system upgrade deferral, GHG emission reduction and reactive power support. Due to regulations in most countries barring the network operator from owning these distributed storage solutions, an independent company owns the battery facility and sells its capacity as a service to the DNO and other stakeholders.

2.3.1 Community Energy Storage Systems

Community storage may be installed in a residential, commercial or industrial area ‘in front of the meter’ and should serve more than one user rather than just its owner or only an operating company. Usually community storage is located within defined boundaries which serves the community within that boundary. However, lack of standardised definition of community storage, besides other challenges, is one of the barriers that prevents the implementation of this technology.

Community storage can encompass a wide range of storage technologies, including batteries, thermal storage, as well as electric vehicles (EVs). In [41], an optimal sizing algorithm is presented for the pumped hydro storage in a stand-alone Wind-PV hybrid renewable energy system. Authors in [42] explored a large-scale battery application which provides ancillary services in an electricity market, while [43], presents the design and testing of a community energy storage system composed of used electric or plug-in hybrid electric vehicle (EV/PHEV) battery packs. In [44], energy storage is used to provide load-levelling through Demand Side Management (DSM) and PV-shifting under a Time of Use (ToU) tariff scheme.

Table 2.1: Three categories of Energy Storage Invalid source specified.

Common Name	Example Applications	Discharge Time Required
Power Quality	Transient Stability, Frequency Regulation	Seconds to Minutes
Bridging Power	Contingency Reserves, Ramping	Minutes to ~1 hour
Energy Management	Load-levelling, Firm Capacity, T&D Deferral	Hours

Technical, economic and environmental considerations need to be made in order to see their suitability of storage technology to a particular application. One pointer of selecting the ESS would be to look into the intermittency of the generators and the inter-dependence. The round-trip efficiency of storage devices is an important consideration since energy loss takes place during storing of energy and during using the stored energy. The round-trip energy efficiency is given by equation 2.1 [45].

Round Trip Efficiency

$$= \frac{\text{Energy Delivered to Loads during Discharge}}{\text{Energy Injected to Store Initial Charge Level}} \quad [2.1]$$

Stored energy capacity can be defined by the magnitude and duration of load [46]. Storage application can be generally divided into three categories based on the application and required storage time [47], as displayed in table 2.1. Firstly, storage systems with low charging and discharging time between few seconds to minutes can be used to improve the quality of power delivered by smoothing high-frequency mismatch between generated and average power. Secondly, to ensure power availability during blackouts and emergencies, or the ability to decouple synchronization between generation and consumption in grid connected storage systems, the energy supply should be able to last between

several minutes to hours. The third category corresponds to energy flexibility, or the ability to shift bulk energy over periods of several hours or more.

Within this thesis, the energy management aspect of the storage system will be investigated and battery storage technology is considered over other available storage technologies, keeping in mind the new larger capacity lithium-ion batteries which are commercially available now such as the Tesla Powerwall II. Both [30] and [28] discuss community energy storage in the form of Lithium-ion batteries due to its maturity for small-scale grid-connected applications and high efficiency. The former proposes an optimal strategy for allocation of multiple battery storages integrated with PV generation and presents the benefits accrued from and costs incurred by community storage deployment to a utility. The latter work conducts performance evaluation on community energy storage and calculates optimum cost benefits of the system for both lead-acid and lithium ion battery technologies.

2.3.1.1 Batteries

Batteries have been a dominant non-fuel energy storage which store electrical energy in the form of chemical energy. Batteries consist of cells which contain a positive and a negative electrode, immersed in an electrolyte which assists the transfer of electrons between the electrodes for flow of electricity in external circuit, during discharging. These electrochemical cells are connected in series and/or parallel to achieve the desired voltage and current for the battery. The battery capacity is given in amp-hours, referring to the amount of charge it can deliver before the battery voltage drops below a specified value. The state of charge (SOC) of the battery, given by Eq. (2.2), is a measure of

the full range of available energy that can be delivered by a battery . The SOC can be used to control the charging and discharging of the battery [48].

$$SOC = \frac{\text{Ah capacity remaining in the battery}}{\text{Rated Ah capacity}} \quad [2.2]$$

Batteries have the highest specific energy in Wh/Kg which makes them suitable candidates for long-term energy storage for energy-shifting and back-up power [49]. Other characteristics which define specific battery operation includes temperature dependence, State-of-Health (SoH), Depth-of-Discharge (DoD), Self-Discharge and Charge/discharge rate limit.

The growth in battery technology has remained relatively stagnant till the last decade, but with recent advancement, some of these technologies, in conjunction with high power density storage devices can offer solutions for the survival and efficient operation of renewable energy systems.

Batteries can be a good solution to smooth power fluctuations, improve system reliability, load demand management, and energy shifting etc. The community battery storage system can be considered as a shared customer asset which can give shared benefits such as back-up power or energy time-shift to the community members. When operated in conjunction with shared PV within the community, the shared battery storage is able to store surplus PV generation from the ‘prosumers’ (rather than exporting the excess energy to the grid at a lower rate than import tariff) and then dispatch this energy when it is needed which improves the energy efficiency and reduces electricity import tariff. Consumers may also benefit from lower-cost off-peak energy by using storage technologies in order to postpone some consumption operations to an overnight shift [50]. The aim is to help energy users reduce their bills and contribute to a

Table 2.2: Time-Sensitive Pricing schemes in the Energy Market

Tariff Structure	Description
Time-of-Use (ToU) Tariffs	Demand rates for peak and off-peak hours. In the UK, it corresponds to Economy7, Economy-10 and TIDE tariff schemes.
Critical Peak Price ⁷ (CPP)	Uses real-time prices for designated cases of extreme peak
Real Time Pricing (RTP)	Considers hourly or half-hourly prices which reflect wholesale electricity prices for the same day or day ahead.

more sustainable energy mix with lower greenhouse-gas (GHG) emissions [40], [51]. Three different price-based schemes which incentivise modification of the electricity profile in response to price variations are shown in table 2.2, along with a brief description of each [52]. The different tariff structures and regulation contribute to load-shifting in peak times and can give benefit for both non-dispatchable and dispatchable demand response strategies which incorporate storage systems. However most current electricity consumers in the UK are charged a near-constant retail price for electricity, which does not reflect the wholesale price at the time of consumption, despite substantial hourly variation in the wholesale market price. The ToU tariff is the only time-sensitive pricing scheme which is offered to retail consumers in the UK currently.

Distributed resources such as the PV also put an extra strain on the local electricity distribution infrastructure. Another use of community storage from the viewpoint of the utility is to handle the peaks in generation output which challenge the capacity of the network, and thereby help defer system upgrade.

2.3.2 Community Renewable Energy Sources (RES)

With rapidly depleting conventional energy resources in the world, it has become very important to gain a clear understanding of the new renewable

energy technologies in order to be able to deploy them in avoiding the coming crisis and designing them for maximum impact. Gaining understanding of the daily and annual production patterns of renewable energy technologies can help manage their impact on the overall energy management system.

Renewable energy technologies such as solar and wind power are location dependent. Photovoltaics (PV) is the fastest developing green technology of this time. With zero-emissions from this abundant energy source, it is a necessary step to try to integrate solar energy into contributing towards community power requirements.

2.3.2.1 Solar PV

The earth receives abundant free energy on its surface in the form of sun's rays. Besides geographical location and surface orientation, solar radiation also depends on the day of the year, and the time of the day. The highest radiation and PV output is experienced during the summer months, particularly of June and July, while the winter months such as December and January have the lowest PV output. During individual days, solar radiation gradually reaches peak intensity around midday, after sunrise, and then gradually reduces to zero after sunset. Cloud conditions, mounting orientation of panels, surface reflectivity, panel efficiency, and other forms of shading all have an impact on the resulting PV output.

Photovoltaic cells composed of semiconductors convert solar energy to Direct Current (DC) electrical power, thereby harnessing the energy from sun and providing a usable source of power. The cells consist of pn junction diodes, which can be arranged together in a module to generate a required power. The

modules can be mounted in horizontal frames, tilted frames at a certain fixed angle, or rotating frames which track the sun at variable angles, with the foremost being the least efficient and least expensive. Rooftop PV panels or PV arrays on community owned land is a reasonable resource integration into a microgrid community which would attempt to capture the available solar energy in the geographical location of the community.

What remains to be seen is the state-of-the-art energy management frameworks in general and in community smart grids employing DERs in order to learn from and improve on the design for integration of renewable and storage technologies in energy communities. A literature review of the available smart grid frameworks and active network management algorithms relevant to this thesis are presented in the next sub-section.

2.4 Control Frameworks for Community Energy Management

Several established works and ongoing research have been studied to learn about successful energy management strategies and their drawbacks which could be improved on. In general, energy management systems have been used on community and smart grids to meet the target of any of the five following optimization models [53].

- Minimization of electricity cost [54]
- Maximization of social welfare [55]
- Minimization of aggregated power consumption [56]
- Minimization of both electricity cost and aggregated power consumption [57]

- Both the maximization of social welfare and minimization of aggregated power consumption [58]

The literature provides many definitions of energy management. Based on the definitions given in [50], [59], [60], [61], [62], the energy management can be defined as a set of strategies and functions that can adjust and optimize the energy use among microgrid elements. These set of functions increase the energy efficiency, coordinate the energy resources and target to reach a set of predefined objectives. It is the process of observing, controlling and conserving electricity usage in a building, a neighbourhood, etc. Energy management should be able to optimize costs and to minimize the risk of loss of production excess. The predefined objectives for an energy management scheme may include minimizing operating costs as established in [63], maximizing the revenues according to electricity market price as shown in [64], through controlling the power flow within the distribution network.,

A wide variety of intelligent management techniques and algorithms can be applied to the flexible resources of the microgrid to achieve these objectives such as those used in [65], [66], [67], [68], [69]. In [65] an energy management scheme is designed by using local prediction and local scheduling algorithm is proposed in order to improve energy efficiency and extending the life of the storage devices in a grid-connected energy community. In [66] the design of the energy management system controls the storage system to correct the hourly deviations of a forecasted energy plan in a grid-connected microgrid through a predictive control technique. The authors in [45-49] used a predefined load trajectory of individual devices rather than instantaneous power flow data for

the optimisation algorithm in their management scheme. These stochastic methods prevent the algorithm from dynamically adjusting the regulation of power flow within the community and having the required control of DERs.

To tackle the drawback of relying on local prediction and scheduling, many studies have incorporated dynamic scheduling of load and renewable dispatchable generation through elaborate simulated models.

Several models have been presented in the literature to derive consumption models for power flow control and network performance analysis [70], [71], [72]. A stochastic dynamic programming method for electricity usage is proposed in [70] which assumes known transition probabilities of states such as price and outdoor temperature, for Demand Response optimization. The study in [71] presents a residential demand response algorithm using Q-learning is presented. The algorithm considers that both load demand and electricity price are stochastic and decides how long the demand request should be delayed to reduce the cost. However Q-learning is inefficient for problems with high dimensional state and action space, therefore this algorithm is only suitable for simple task and price model.

A fine-grained domestic load model is developed in [73] which provides averaged electrical load data with one-minute resolution per consumer on a low voltage distribution network in the context of a typical UK urban feeder from a primary transformer. The aim of the work is to help provide a risk assessment of over-voltage and over-heating in the network when used in association with a power flow analysis package. The profiles generated by this model however

have a limitation on the diversity, which in turn leads to poor results estimating the energy demand in the validation of the models.

A Demand Side Management (DSM) based simulation tool is used in [74] which optimizes operation of household appliances in order to control, regulate, and reduce energy consumption within the dwellings. The main aim of this study was to use Binary Particle Swarm Optimization (BPSO) algorithm to illustrate customer-driven DSM operation, and evaluate an estimate for home electricity consumption while minimizing the customer's cost. The operation of household appliances was simulated as a Hybrid Renewable Energy System (HRES) with the help of the tool.

A grid-connected smart microgrid for a residential community is designed in [75] with new hierarchical optimization. Q-learning based battery management is used to learn state transition probabilities from the stochastic environment in order to make optimal discharging decision for a battery management system which aims to reduce the energy consumption cost considering stochastic elements. The stochastic loads are represented as schedulable and fixed energy consumption tasks for a residential community with 10 houses and 4 micro CHP systems and the simulation is run for a week using Dynamic Demand Response modelling. External information of day-ahead broadcasted time-varying utility electricity price and hourly updated wind power forecast is required for the model.

In [76], the authors present a community power flow control (PFC) strategy which reduces peak grid demand, and increases self-consumption of renewable energy, by controlling Demand Side Management (DSM) based

direct load control and the battery storage, resulting in energy cost savings in smart communities with grid-connected photovoltaic (PV) systems. The Power Flow Control operates by setting a power target set-point based on the predicted average community power demand and compares the instantaneous community power to the power target to make the decision of charging or discharging the energy storage or of starting or delaying the dispatchable loads. However for the residential community model, the study relied on simulation of domestic demand created using the Centre for Renewable Energy Systems Technology (CREST) tool [77]. The CREST tool was used to generate 100 residential power profiles with a time resolution of one minute including the on/off switch signals for allowing DSM of individual appliances for each house. The energy prices are based on Real Time Pricing (RTP) which are made up of half-hourly electricity prices to reflect the price on the wholesale market. In the real UK energy market, the RTP however is not offered to electricity consumers as of yet and therefore a realistic scenario cannot be derived from this tariff scheme.

Similarly, [78] also discusses the community power flow concept in designing a hierarchical control structure for optimal dispatch of distributed energy resources within different levels of the distribution network and optimizing the operation of flexible resources at the community cell level. A bottom-up approach is taken to control the hierarchical structure which contains the cell community level, the cluster of community cells intermediate level and the distribution network clusters top level. The simulation results show effectiveness of the load and storage dispatch in meeting the objective function of maintaining community's power flow below a pre-specified threshold.

The electricity demand model is however again obtained through a bottom-up model created in MATLAB. The model generates demand profiles for every individual domestic load and the overall demand for a dwelling with a resolution of 1 minute. The active occupancy of residents is derived through a Markov Chain Technique which in turn influences the appliance usage prediction of the users. The Heat Demand data and the Micro Combined Heat and Power (μ CHP) data within the study are also derived through models based on other literature.

As such, there is a gap in knowledge for designing energy management systems derived from analysis of real load and generation data of the electricity prosumers and energy communities. This thesis, therefore, attempts to fill this gap in literature by deriving all presented analysis and design based only on real energy data of consumption and generation collected from different energy communities across the UK. The results derived from the Community Power Flow Battery Management System (CPF-BMS) reflects the techno-economic benefits that are obtained when the control framework is implemented on real communities. The methodologies presented for sizing the battery for communities are also based on analysing real historic data of several households and commercial properties which can give a more realistic estimation for future energy communities.

A similar study to this thesis is undertaken by [79], where the study quantifies the financial benefits for end-users and energy management authority by simulating different operating scenarios for power flow to and from the battery storage and the elements of a community smart grid. The study analyses

the electricity cost for the end-users to find the most financially suitable PV penetration along with the community energy storage capacity and overnight charging level were identified. The study uses real load data as CREST input for the consumption and generation profiles of the houses, but bases the assessment on only a single community consisting of 8 houses. Hence the validity of the results has not been justified by implementing the control framework in additional communities. The battery modelling used is specific to lead-acid technology, and therefore cannot be applied to the general battery storage profiles or the increasingly popular and market-available larger-capacity lithium-ion battery technologies such as the Tesla Powerwall. The tariff scheme used in this work is the Economy-7 [28], [80], [81], which has been previously used in other studies, however this tariff structure does not emphasize the difference in ToU rates of peak and off-peak hours and therefore neglects the potential of cost benefits through energy-shifting under such a scheme.

In [82], a model-based framework is presented to assess the value of community energy systems for the local communities using the distributed energy resources-consumer adoption model (DER-CAM), and open access smart meter data of electricity and gas consumption of real households in the Netherlands. The main objective of the model is to minimize annualized total energy costs for the community which consist of annual utility costs for electricity and gas of each household; annualized DER capital; operation and maintenance costs, and revenues from the annual electricity sales outside of the community. However, the study focuses on economic and environmental benefits from the community perspective rather than the development of the

management algorithm itself. ToU tariff based incentive is not incorporated in the research which can also greatly impact the electricity end-user cost savings and consumption behaviour. Instead, a mix of volumetric and fixed tariff charges for the electricity and gas supply services are considered in the study.

The study in [83] presents the design of a low complexity fuzzy logic controller in an energy management system for a residential grid-connected microgrid with storage capability where the main goal of the design is to minimize the grid power profile fluctuations while keeping the battery state of charge within secure limits. An agent-based simulation is undertaken in [84] to demonstrate that community-based operation of a large-size storage battery is useful for distributing loads on an electrical grid and as an electricity buffer for a crisis situation when electricity power companies dynamically change the price of electricity. This study is based on the electricity management model of a community in Japan that includes multiple homes with home solar photovoltaics and share a large-size storage battery. The paper confirms that sharing electricity between houses in a community has some effect to reduce the amount of electricity generated by an electric power company.

The control of community energy storage system composed of repurposed electric or hybrid electric vehicle (EV/PHEV) battery packs in conjunction with power electronic interfaces is used in [85] to perform grid support applications and provide grid ancillary services. Consumption data is obtained from occupied residential homes for simulation of the load and a lithium ion battery model is used for the generation and charging characteristics. The services to the grid that were achieved include delivering peak shaving,

providing potential regulation and spinning services, providing voltage support through reactive power and providing uninterrupted service.

The main objective of the studies above in [63-65] is smoothing the power profile of the community exchanged with the main grid and facilitating the grid operator control. This project instead attempts to contribute to the increasing number of technologies and business models focusing on the decarbonisation of the energy sector through cost reduction incentives to the electricity end-users. Allowing the role of the end-users to change from passive consumption to active ‘prosumers’ will drive the movement towards community-led sustainable energy practices and at the same time empower the communities to have a greater control of their energy usage and resources.

Most referred literature also focuses on the community as a whole, trading energy with the grid, rather than on internal sharing of energy amongst the community end-users in an attempt to maximize community benefits through strategic management of the flexible DERs. For example, the control strategy in [86] prioritize selling surplus electricity generated by the renewable energy as the premise of energy distribution and increasing the life of Li-ion batteries deployed by maintaining battery SOC above 50% through the fuzzy control. In [87], a new framework is developed based on a game-theory approach that enables a number of distributed storage units in a smart grid belonging to different customers to individually choose the amount of stored energy that they wish to sell to other customers such as demand from different nodes or substations on the grid. The study in [88] presents the application of a hybrid optimization algorithm for DER management in smart grid operation

where the seller decides the asking price based on the minimum fuel cost determined by a hybrid-immune-system-based particle swarm optimization, thereby allowing the profits for the seller and buyer to be maximized.

In contrast, the community energy management system addressed in this work focuses maximizing cost benefits for electricity end-users within energy communities by developing a novel algorithm for community battery storage systems based on currently available variable electricity tariff rates [13] and battery systems in the market. The algorithm captures available energy from PV generation for peak time usage as well as charges the battery at off-peak times to meet demand during peak periods.

2.5 Conclusion

The study undertaken in this thesis introduces the very first use of a market available multi-level ToU tariff scheme (TIDE Tariff) in designing the energy management system and analysing the resulting benefits through real community data. The majority of literature either focuses on Economy-7 tariff which does not provide a significant price differential between peak and off-peak consumption periods to help drive value creation for energy-shifting and battery systems in typical residential dwellings, or it focuses on Real Time Price (RTP) which does not currently exist as an available tariff plan in the electricity market. As such, there was a need for a new algorithm which focused on this new market-available tariff scheme to attain efficient energy-shifting (arbitrage) and PV self-consumption increment using real generation and consumption data in order to make the case for the feasibility of community energy and storage system under existing resources, practices and market scenarios. Further

benefits of the ToU may appear due to this price-based demand-response scheme as it will encourage users to manage their power usage and consume electricity in periods of lower demand when the price is cheaper, using the electricity smart meters.

The work also highlights and presents results of relative benefits of implementing energy management systems across a community as opposed to individual households, which has not been covered in many other literatures in a quantitative manner. Energy users grouped together as communities are more likely to be able to take advantage of ToU tariff, benefit from economies of scale for energy storage systems (ESS) and have higher self-consumption due to the varied of load profile across the community.

More robust and sophisticated energy management systems have been reported in the literature such as Fuzzy Logic Control (FLC), Model Predictive Control (MPC) etc. [86], [89], [90], [91]. Furthermore, more degrees of freedom can be incorporated in the energy communities, such as additional and varied storage elements (fuel cells, electric vehicles) and controllable loads (heat pumps, CHP, dispatchable loads for DSM etc.) [83]. However, these strategies are complex, include advanced forecasting for both generation and demand, and requires re-defining the system as soon as any single element is altered within the system. Forecasted load is highly stochastic at a low aggregation level, therefore its adaptation in community-level optimisation algorithm is expected to result in an ineffective optimisation.

A primary motivation behind the undertaking of this thesis was the EmPower community energy trial project at Corsham, UK, whose result

analysis discovered several limitations and drawbacks of current community energy management systems originally designed based on modelled simulation data. Details of the project and analysis are presented in the next chapter. The project was also fuelled by Carbon Legacy wanting a better way to size the battery capacity instalments for their customers since such tools are currently not available in the market.

Considering the gap in the literature, along with the need for demonstrating a robust algorithm as understood from the EmPower project, a significant time during this project was spent to analyse and learn from the real data available from existing community energy projects. These real consumption power data were used to develop a novel deterministic control algorithm that could incorporate renewable generators (i.e. solar) and communal energy storage systems (ESS) in existing conventional installations in a simple way through necessary power flow control functionality and data real-time coordinated dispatch of the available DERs, using historical yearly records and instantaneous power generation and load consumption. In addition to that, the majority of the reported literature do not account for the sizing of communal battery storage system. A methodology was therefore developed to obtain an optimum battery size for maximum economic benefits for a community using only historical yearly records of the community end-users, such that simple rules-of-thumb could be derived for the storage capacity estimation.

3 CHALLENGES AND LEARNINGS FROM PROJECT EMPOWER

3.1 Introduction

With the increasing penetration of distributed generation in communities and businesses, customer engagement with the energy market is ever more prevalent in the UK, along with continued growth in energy demand, particularly in the domestic sector [92]. The movement for decarbonisation in the energy sector remains strong under the risk of depletion of fossil fuel sources and increased evidence of climate change [93]. In order to efficiently manage the available resources and load demand, a shift from individual energy users to community energy strategy is taking place, whereby energy is generated, purchased, and managed, and the benefits of the outcome shared, collectively by a group of residential and/or commercial establishments.

Demand Side Management (DSM) is one of the many solutions presented in recent times to combat the issue of highly varying load magnitude and time patterns by influencing customer's use of electricity and allowing a desired change in the utility's load shape [94]. Utility grids receive the benefits of DSM as it strives to establish a balance between generation and demand, constraining consumption at peak demand times and reducing the need for

additional backup generators which otherwise remains underutilized for the majority of the day when the demand is below average. DSM also allows the optimization of planned generation resources within smart grids, such as PV or battery storage system. Both indirect and direct load control schemes are in place which attempts load shifts through incentive policies, tariff benefits, discounts etc. for the former and in case of the latter, through controller devices which alter load patterns through a pre-programmed schedule or real-time monitoring of the consumption and generation profiles. Direct load control can achieve higher potentials when it is supported by indirect load control methods [95].

Over a one year period from May 2015 to June 2016, the EmPower project looked into the energy management of a community of 11 properties in Corsham in the south of England, comprising of 9 residential houses with a varying number of occupants, a school and an office building. The energy management scheme has been provided by e2E, a satellite telecommunications company, whose aim was to utilise the network management techniques from the telecom industry in the management of local energy markets with access to distributed generation and storage [96]. The e2E energy management system aimed at providing distributed DSM solution for electricity networks in order to optimise energy generation and usage at the community level rather than individual property level. Each of the properties has their own metering, some are equipped with domestic Photovoltaic (PV) panels, and among them, four properties have been installed with small energy storage systems.

The community is grid-connected and can interact with the grid in both importing and exporting energy. However, the community can be considered as ‘virtual’, since not all the properties within the community are located in the same area geographically. This analysis therefore also opens doorways to possibilities for Energy Services Companies (ESCOs) on the financial viability study of managing users from different locations under a ‘virtual community’. Measurements are made for recording the energy generation through PV, and the export and import energy readings in kWh to and from the grid. To measure Import, Export, and PV, different properties were fitted with either CT clamps, Disc readers or S0 pulses, which have their own accuracies, and 16A Eltako wireless sensors to monitor the battery. Table 3.1 summarizes the information of installed meters in each property along with the employed battery.

Appliances within each household have been selected to establish DSM, by controlling the operation time of the appliance, ideally moving it from a peak-demand period to an off-peak period, when the user is able to

Table 3.1: Equipment listing of properties for recording measurements

Property	Import	Export	Load	PV	Battery
SF9AY	3Ph + CT	3Ph + CT	calculate	S0	2xFWZ61-16A
JW9QL	Disc	3Ph + CT	calculate	3Ph + CT	2xFWZ61-16A
CC9TN	3Ph + CT	3Ph + CT	calculate	S0	2xFWZ61-16A
JK9TZ	Disc				
V09TZ	3Ph + CT				
TW8ER	Disc	3Ph + CT	calculate	S0	2xFWZ61-16A
PH9EY	3Ph + CT	3Ph + CT	calculate	S0	
AW0BY	3Ph + CT				
AW7DP	3Ph + CT				
MB8PB	3Ph + CT				
TCS9DF	3Ph + CT			S0	

accommodate the load-shift. Direct load control has been employed in the Corsham trial, whereby the dispatchable appliances within the households are selected to be Washing Machines, Dish Washers and Tumble Dryers, whose operation times are flexible enough to shift although with some inconvenience to the user. Users were however given the authority to override load-shift control commands and being in charge of their appliance when necessary. There are three main categories with regard to remote control of appliances:

- Type 1: Once started, the appliance can be turned off and will retain settings when turned back on and cycle/run will continue without any user input.
- Type 2: Once started, the appliance can be turned off and will retain settings when turned back on but cycle/run will require user input (e.g. press 'start' button) to resume.
- Type 3: Once started, the appliance can be turned off but will not retain settings and will have to be reset by the user and the cycle/run will begin from the start again.

Type 2 and 3 were treated as the same for the project. There are also two main appliance categories with regards to a manual delay of appliance cycles.

- Type A: Appliance can be set to delay the cycle/run by the user in advance
- Type B: Appliance cannot be set to delay the cycle/run by the user in advance

An ideal appliance for the trial will be from category 1 and A. However participants in the EmPower trial were asked not to delay any cycles to avoid problems with scheduling the appliance loads and therefore the delay functions remained unused. All appliances were therefore able to take part in the trial as long as they were within the range of signals. Detailed user surveys were carried out before the trial to get as much information as possible for the types of appliances in each house and their usage patterns, although sometimes the information provided was incorrect and appliances had to be changed from type 1 to type 2 in the middle of the trial.

The battery storage employed in the community is also able to shift energy by charging from the grid during periods of low import tariff overnight and from PV generation during low load hours of day-time, and discharging this stored energy during high import-tariff periods of morning and evening peaks when household members are either leaving to or returning from work. Thus the energy management system works to establish both the Load shift (DSM) and the PV shift to achieve electricity cost savings for each household if a half-hourly real-time electricity tariff is used, and to peak-shave grid imports in order to allow cheaper generation cost, lower losses and capacity requirement of distribution and transmission assets.

ESCOs, aided by the advent of affordable smart meters, can be a driving force here by providing time-of-Use (ToU) tariffs which incentivise battery charging and load operation during off-peak hours and when renewable generation is plentiful, by providing cheaper p/kWh during those hours. The business model entails buying energy in advance during periods of cheaper

electricity and consuming that energy later on in the day through successfully shifted load demand. Batteries or similar storage devices can be equipped with intelligent controls that respond to the ToU tariff signal to lower household bills and increase system efficiency.

For domestic customers, the local benefits offered by demand side services are currently limited to the Economy-7 tariffs introduced in the 1970s and the Economy-10, due to the undeveloped local supply market [97]. However, several smaller energy providers are now gearing up to offer ToU tariffs such as the multi-level Tide tariff from Green Energy UK [98]. The impacts on customer bills also rely on behavioural change of electricity users and a group or community operation for a substantial shift of load profile. Figure 3.1 shows the households within the control scheme of the community and their

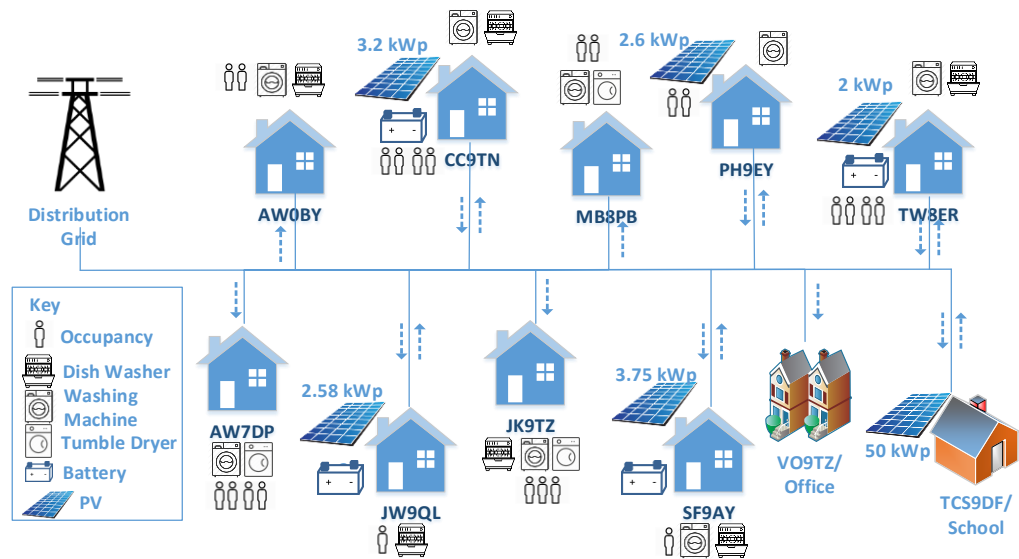


Figure 3.1: Overview of EmPower Project community with individual generation, storage and controllable load

dispatchable resources along with a number of occupants in each domestic property and the installed peak capacity in houses available with PV generation.

The interconnections of the resources are established through wireless sensors and controllers along with communication interface and wireless plug/socket for equipment control. The Raspberry-Pi with FHEM server, along with an EnOceanPi act as the Gateway Controller for the home automation solution. The EnOceanPi is employed as the control box to interface the control algorithm to the equipment for its ease of access, low cost, and simplistic solution. Figure 3.2 shows a flowchart of a typical command signal through these devices.

For Type-1 appliances, once the user presses the start button on their appliance, the EMPower controller automatically switches off power to the appliance within a couple of minutes and its central control system uses intelligent algorithms within FHEM server to determine the best time for the

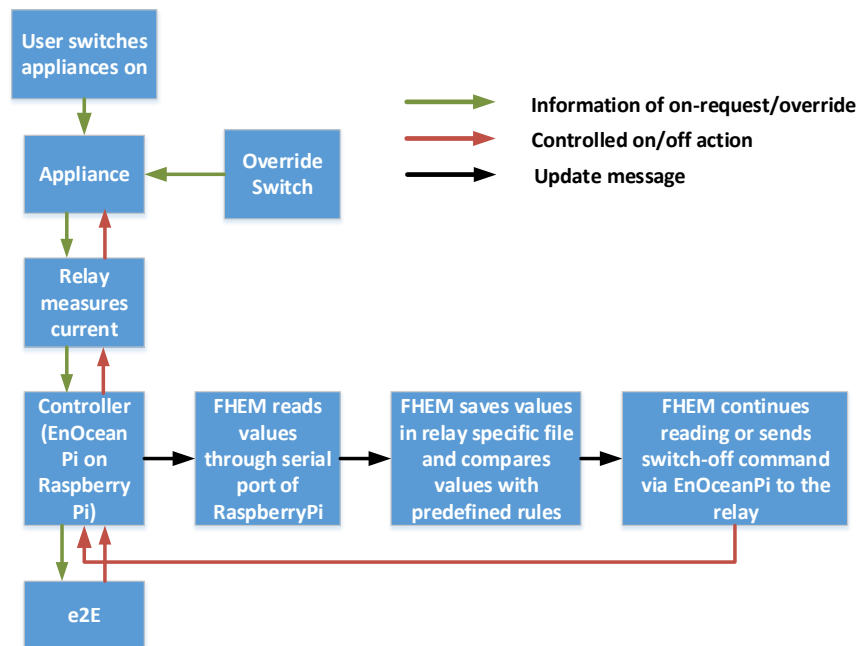


Figure 3.2: Flowchart of control commands

appliance to re-start. This happens within each half-hour period, and once a time has been selected a text message is automatically sent to the user to let them know what time their appliance would automatically restart.

For a type-2 appliance, the steps of operation are the same, except that the user has to manually press the start button of the appliance at the suggested time provided in the text message. Energy monitoring is carried out through easy-to-fit optical pulse counters, wired pulse readers, current clamps and wireless meters. For monitoring and control of the dispatchable loads, Eltako relay with current measurement is utilised. 2 kWh 0.5 kW Moixa Maslow batteries are installed on four properties which have PV generation within the community. The battery is mounted, installed and connected to grid supply and PV along with meters to monitor imports and exports with the grid. Figure 3.3 shows one of the installed units during the project. Communication within the



Figure 3.3: 2 kWh 0.5 kW Moixa Maslow batteries installed on one of the four properties of Corsham Trial.

system and with the occupants is maintained through smartphone text messages and switches.

The control algorithm applied prioritizes cost benefits through the operation of batteries in suitable tariff regions. It is achieved by causing the batteries to charge at a time of low import price and discharge at a time of high import price. It should also be noted that the algorithm design was such as to charge or discharge each cycle of the battery by 100% to be able to move on to its next alternative cycle. The controllable loads are aimed to be shifted to either late evening hours or early morning hours the next day when the import prices are low, unless the control is overridden by the user.

3.2 What went well

3.2.1 Results to illustrate good performance of DSM over a few days

For analysing the effectivity of DSM, the dispatchable load profile of property CC9TN is presented for an individual day and a week in October 2015. Figure 3.4 shows the operation of the dishwasher on the 1st of October 2015 under both uncontrolled (red power profile) and controlled scenario (blue power profile). The results are derived by analysing the text messages which were sent to the users to accordingly start their appliance at a later given time. A half-hourly Time-of-Use (ToU) Tariff from Elexon is used to derive the three different tariff levels used [99].

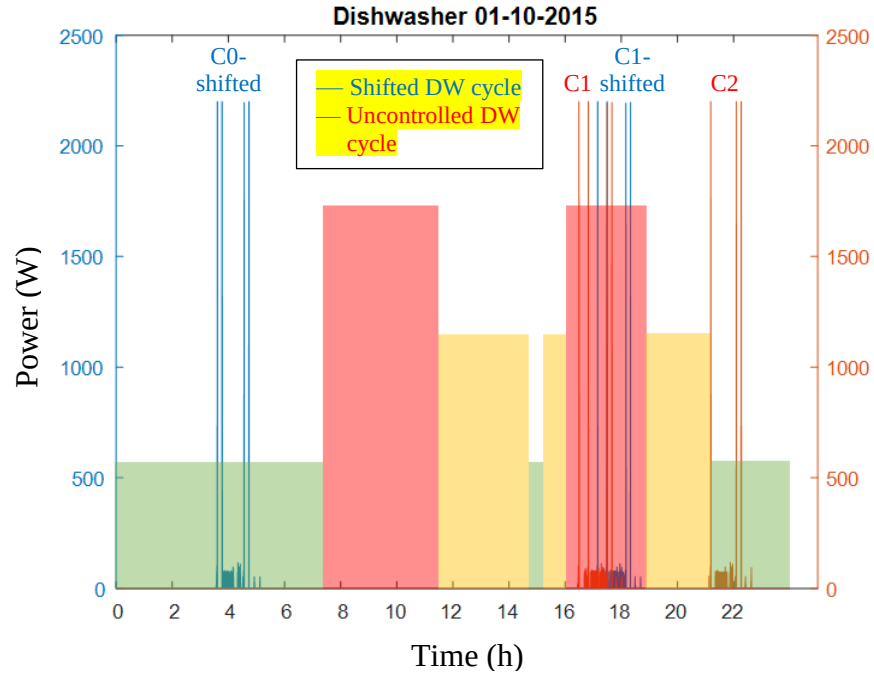


Figure 3.4: Energy shift of Dish Washer operation cycles for CC9TN during a day in autumn

In each of the figures, the green region represents cheap import tariff, yellow denotes moderately priced import and red represents an expensive import tariff period. The height of these bars representing tariff bands have no quantitative meaning. The cheap and expensive regions are determined according to the half-hourly tariff being 10% below or above the average tariff of the day respectively. It can be seen that on the 1st of October, the first power peaks (C0-shifted) show the operation of dishwasher in the early morning hours, having been shifted from a high tariff period the previous day. The next two washing cycles (C1 and C1-shifted) follow one another closely where the user had overridden the suggested delay approximately an hour after the actual request. The fourth cycle (C2) shows an operation under the uncontrolled scenario only, whose controlled power profile counterpart appears on the early morning hours the next day as a result of DSM load shift.

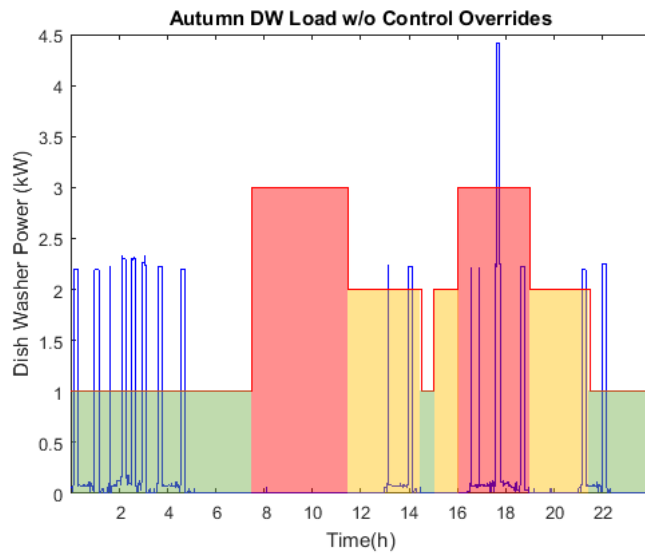
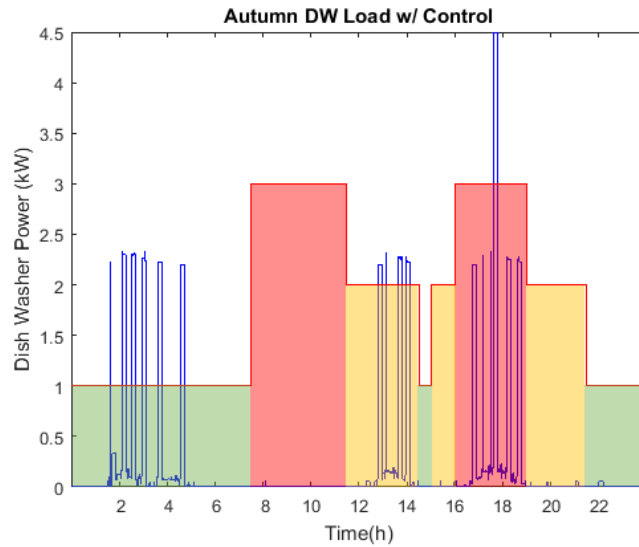
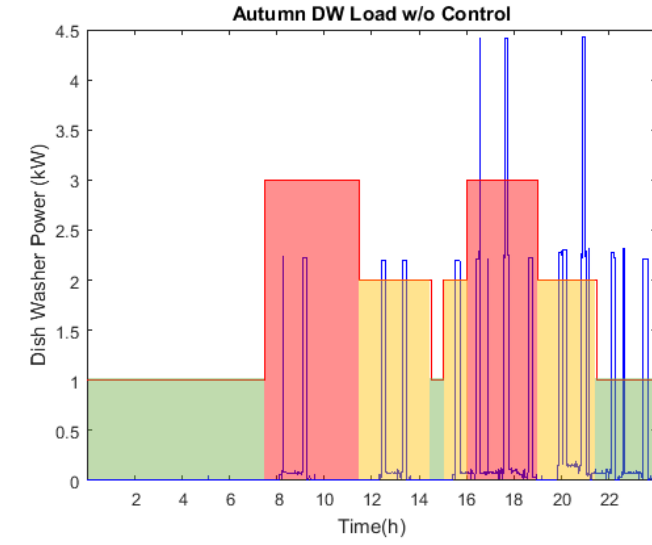


Figure 3.5: Energy shift of Dish Washer operation cycles for CC9TN in Autumn: a) Uncontrolled DW load b) Controlled DW load c) DW load in monitoring mode

Figure 3.5 shows the superimposed daily power consumption of a dishwasher (DW) in the property CC9TN over the week of 30th September to 5th October. Figure 3.5a shows the DW load profile over a week if no control strategy was imposed on it and the user was free to start the appliance whenever needed. Figure 3.5b shows the DW load profile after having applied the control algorithm to shift the operations from high electricity import tariff periods to low-tariff ones whenever permitted by the user, and Figure 3.5c. illustrates the potential shift of energy if the user had not overridden the control commands for delaying the appliance.

The figures show that a bulk of the DW load was successfully moved to off-peak hours by the Demand Side Management. Some evening peak loads are not shifted to cheaper periods even in the ideally controlled scenario as a result of having multiple usage requests on the same evening. It should therefore be noted that only one instance of load shift is possible during each peak period of the day, after accommodating for increased usage.

3.2.2 Some calculations to extrapolate benefits of energy shifting due to DSM (energy moved from peak to low-cost time, improvement in self-consumption)

Table 3.2 shows the total kWh imported by the DW load in each of the three different tariff regions of cheap, moderate and expensive electricity for the

Table 3.2: DW load shift across different tariff regions during a week of October due to control strategy

	Without Control (kWh)	With Control (kWh)	Monitoring (kWh)
Cheap	0.97	2.80	4.02
Moderate	3.04	1.38	0.93
Expensive	2.36	2.27	1.42

uncontrolled, controlled and monitoring (controlled without overrides) scenarios. It can be seen from the calculations that 1.8 kWh of energy use has been moved from expensive/moderate to cheap-tariff period over the six days after imposing the control strategy on the DW. This is approximately 109 kWh of energy or 31 cycles shifted to off-peak hours over a whole year for a single household. A further 73 kWh could have been moved over the year to cheap tariff region if the control was not overridden by the user.

This demand-shift for the dishwasher is carried out for one house only. If extrapolated to all other properties with a DW in the community, assuming that all the households have similar operating patterns for the DW, a collective 654 kWh can be shifted from peak demand periods to off-peak times over a year.

3.2.3 Results to illustrate good performance of battery over a few days

Figure 3.6 depicts the combined charging and discharging pattern of the three batteries in the community on the 1st of October. The battery is charging throughout the early morning hours in order to take advantage of the lower import prices and store the energy for later use. It is also charging during the

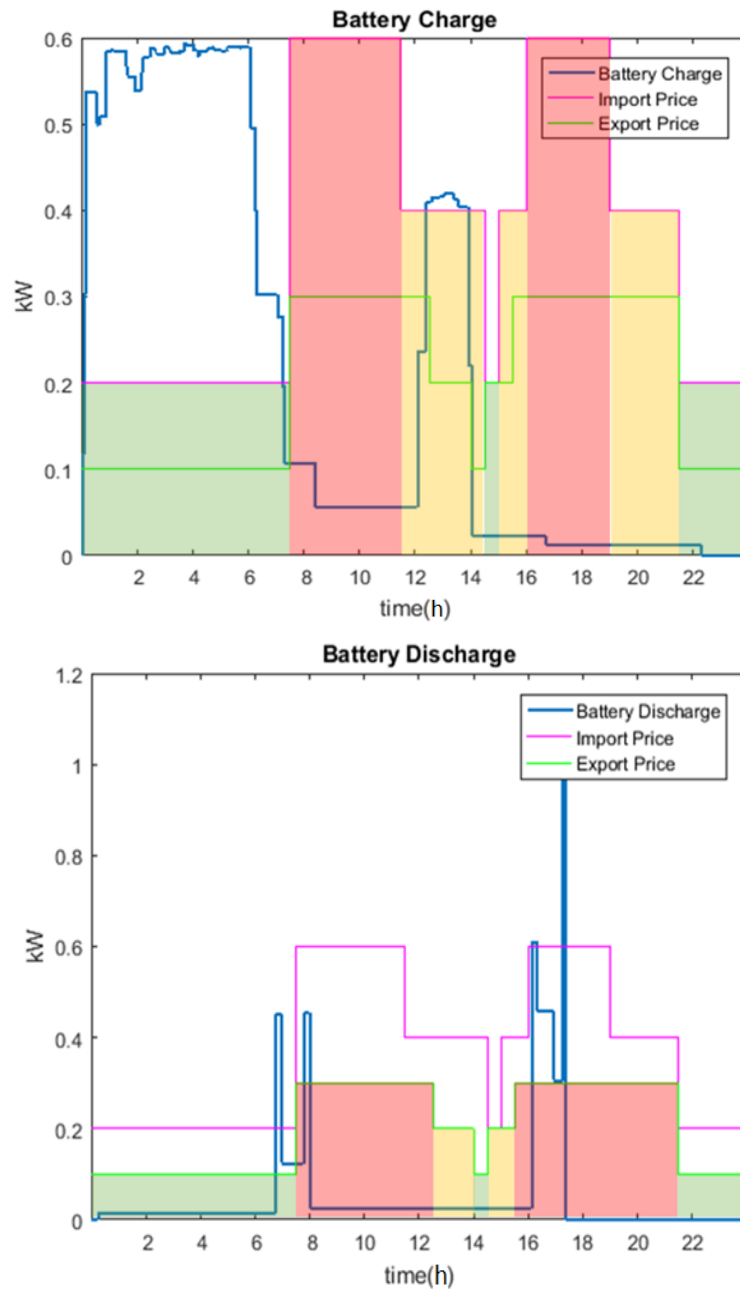


Figure 3.6: Community battery charging profile for the 1st of October

afternoon from excess PV generation. The discharge profile shows that the battery is releasing energy to the community during part of the morning and evening peak hours to reduce import of expensive electricity during times when there is no or weak PV for consumption.

Figure 3.7 shows the collective battery charge profile over the week of 15th to 21st October for all the batteries within the community. The profile shows that the batteries are following the same principle as the day above in charging from the grid overnight when the import tariff is low as well as during the peak PV generation hours (marked by red boxes for the first day). The total energy stored in the community battery during this period is 30.3 kWh, which can be released during peak demand hours, after accounting for battery and inverter losses, thereby reducing import of higher-priced electricity.

Figure 3.8 shows the battery discharge profile over the same week of October when the battery is discharging regularly during the morning peak hours, and during the evening peak on the last day of the week. The total energy discharged from the battery is 20.1 kWh. Hence an energy shift of 20.1 kWh has been achieved over the week, thereby reducing peak-tariff consumption from the grid by the same amount.

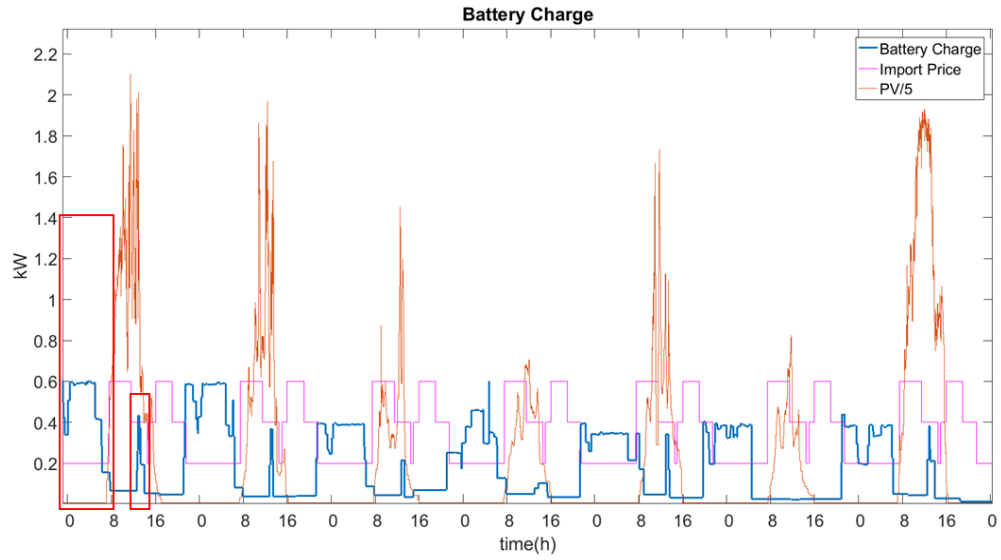


Figure 3.7: Community battery charging profile over October week-3 in relation to PV generation and electricity import tariff.

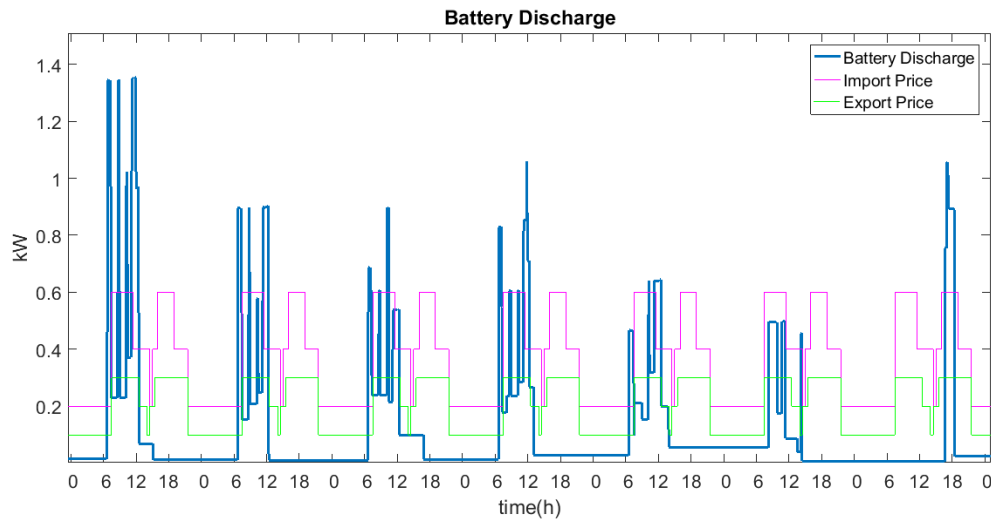


Figure 3.8: Community battery discharge profile over October week-3 in relation to electricity tariff.

Figure 3.9 shows battery discharge profile over 1st to 7th October 2015.

On most days, discharge is taking place during both the morning and evening peak hours when the import prices are expensive, and when there is no PV generation. It can also serve the purpose of supporting the grid in meeting peak demands, however, the discharge kW is relatively low for a real impact on the grid.

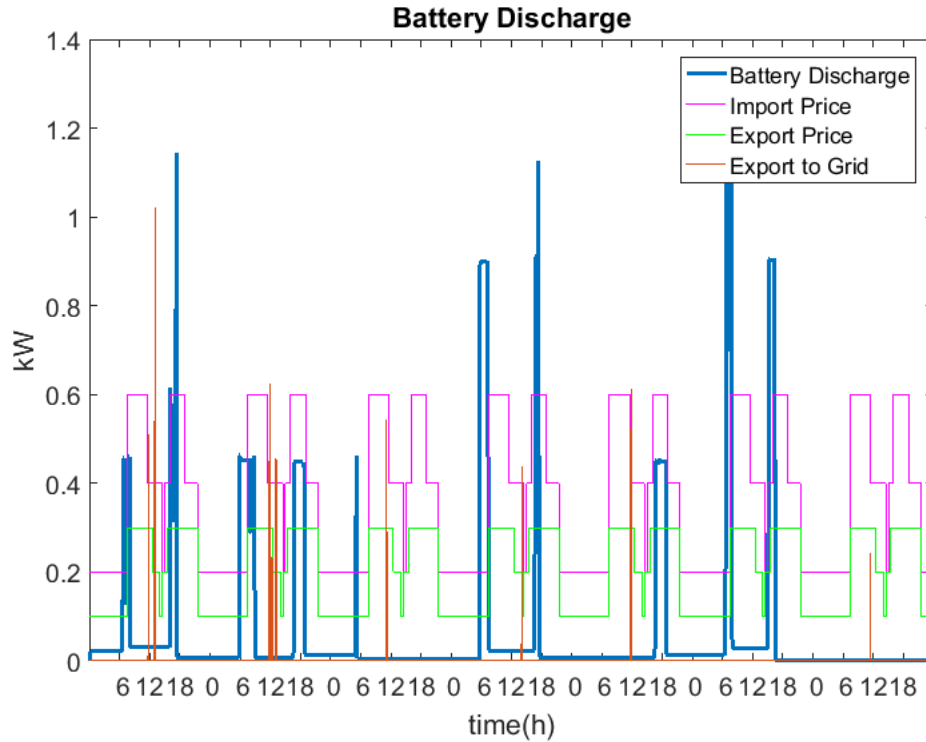


Figure 3.9: Community battery discharge profile over October week-1 in relation to PV generation and electricity import tariff

The export to the grid does not coincide with the battery discharge, hence all the energy taken from the battery is used to support consumption within the community. The figure shows that on a number of days, the battery discharge starts right before the morning peak tariff, which may have occurred since the control algorithm was using half-hourly ToU tariff as opposed to the average range depicted in the figures. The total energy discharged over the week is 10.2 kWh for the community.

3.2.4 Calculations to extrapolate benefits of energy shifting due to batteries

Figure 3.10 shows the successive energy meter readings for the battery charge and discharge profile over the first (June to September 2015) and second half (October 2015 to April 2016) of the year under observation. The smaller

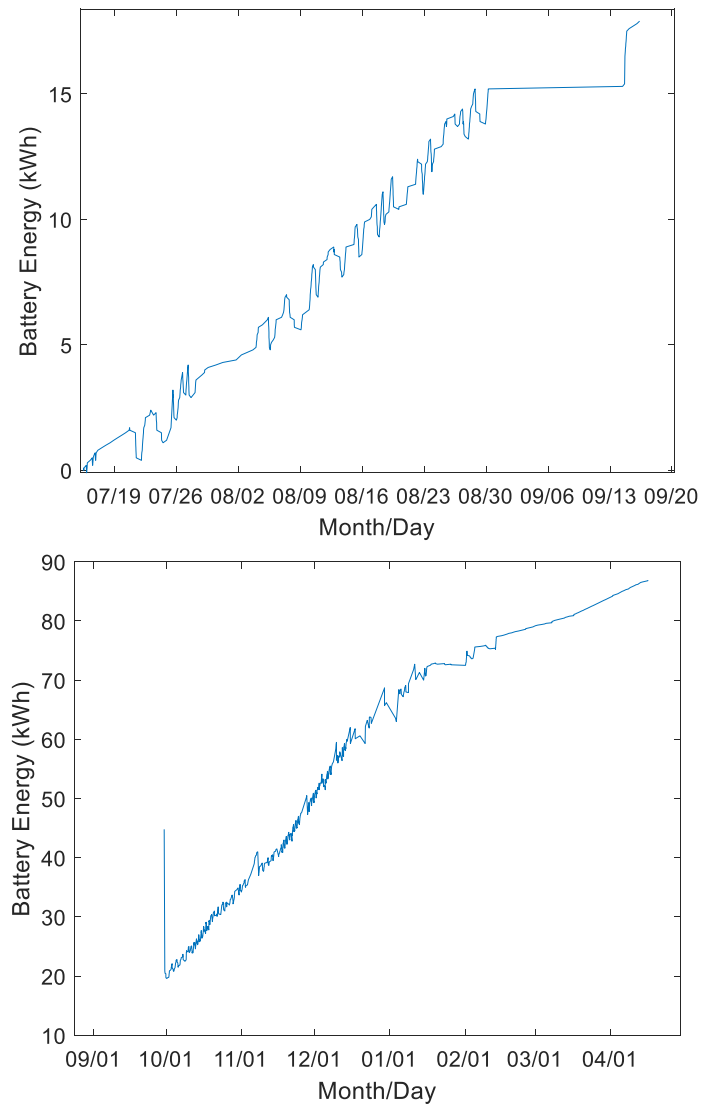


Figure 3.10: CC9TN battery charging and discharging profile

rising and falling energy slopes throughout the profile signify each charge-discharge cycle of the battery. The overall gradient in the profiles shows that there is a constant loss from the battery system calculated to an average of 14 W. Over a year the energy loss is therefore 491 kWh for the aggregate of four battery systems in the community. This loss is generally reflected in the extra import drawn from the grid by the deployed system.

Table 3.3 summarizes the charging and discharging energy to and from the batteries over the three different seasons analysed. Extrapolating these

Table 3.3: Monthly and annual battery energy storage in kWh for the community

	Energy Charged (kWh)	Energy Discharged (kWh)	Efficiency (%)
August	84.3	52.4	62
October	109.7	66.6	61
December	46.5	39.6	85
Yearly Extrapolation	1050.6	675.6	64

seasons into the remaining year, considering spring as an equivalent of autumn, the total energy consumption which can be supported by the battery amounts to 676 kWh for the community, therefore reducing this import from the grid at peak time, if the batteries charge and discharge in the correct times throughout the year.

3.3 What went badly

3.3.1 Results to illustrate bad performance of DSM over a few days
Figure 3.11 shows the power consumption of a dishwasher (DW) in the property CC9TN over the week of 21st July to 27th July. Contrary to the DW DSM seen during autumn above, the figures show that in summer the combination of control strategy and user intervention in effect has shifted more load to expensive tariff hours than operation scenario without control. This is due to the overriding of control delay commands at expensive hours by the user for the loads which were scheduled to have been shifted from moderate regions to cheap regions. It may be inferred that in times of high demand for dispatchable load operation, it is better to operate the system without control or integrate an option to offer nearest moderate/cheap period when override takes place at expensive time slot.

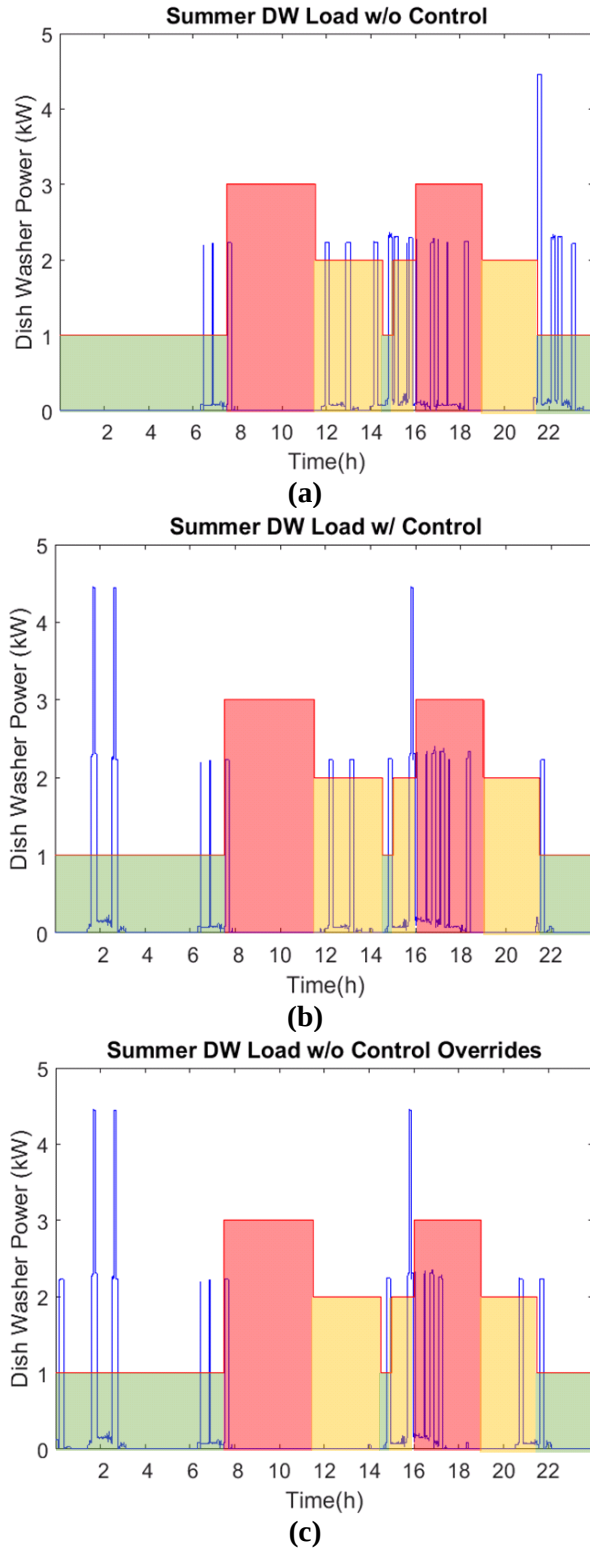


Figure 3.11: Energy shift of Dish Washer operation cycles for CC9TN during summer: a) Uncontrolled DW load b) Controlled DW load c) DW load in monitoring mode.

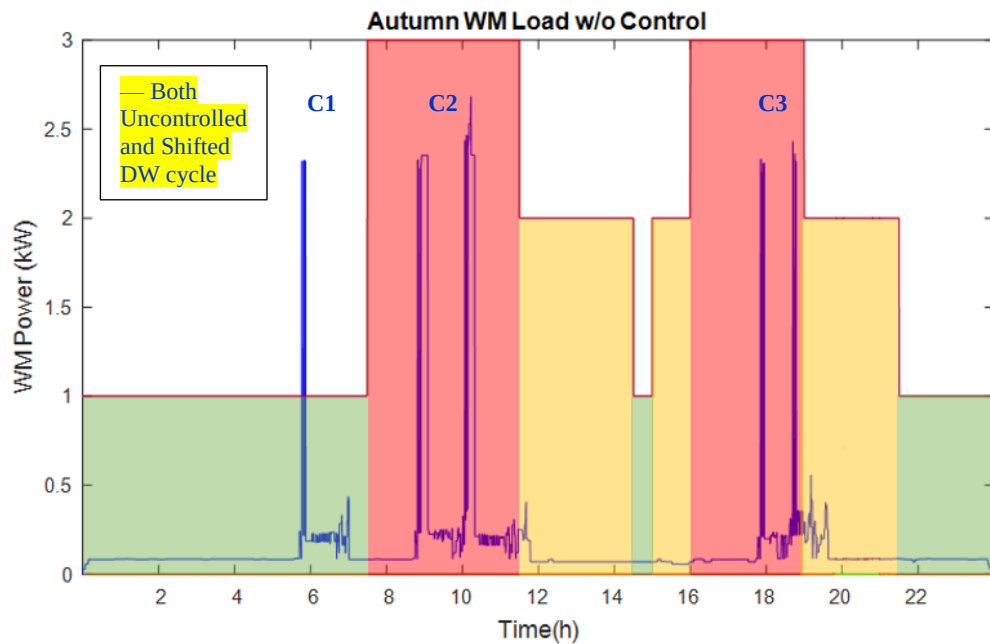
Table 3.4 shows the total kWh imported by the DW load in each of the

Table 3.4: DW load shift across different tariff regions during a week of July 2015 due to control strategy

	Without Control (kWh)	With Control (kWh)	Monitoring (kWh)
Cheap	2.70	2.79	3.83
Moderate	2.38	1.80	1.36
Expensive	1.59	2.12	1.51

three different tariff regions of cheap, moderate and expensive electricity for the uncontrolled, controlled and monitoring scenarios. It can be seen that 0.53 kWh of energy consumption has been shifted to peak-tariff due to the implementation of the control strategy whereas the increment of cheap-tariff operation is negligible. It can also be seen from the table that had there been no user overrides, the control strategy would have shifted the load to cheap-tariff instead of expensive hours.

Figure 3.12 shows the Washing Machine (WM) load of household CC9TN over a week in autumn for both the controlled and uncontrolled scenario. The frequency of WM usage is less throughout a week in comparison

**Figure 3.12: Washing Machine (WM) load over one week for CC9TN property**

to dishwashers. The load profile in both summer and autumn have shown a relatively negligible difference when control strategy is implemented, part due to user overrides and part because the system was in monitoring mode during the WM requests and therefore did not receive text messages or delay requests. It can therefore be seen that DSM in this instance has not been effective in shifting energy.

The control of tumble dryers are observed to be generally overridden, likely due to the fact that users do not want to keep their wet laundry waiting, and therefore no effective DSM has been achieved from Tumble dryer operations. The analysis was difficult since for most instances the only text file available was that of the control override, while the texts for appliance request and suggested time delay are missing for most cases.

Figure 3.13 shows an analysis of all the text messages sent to the users of dispatchable appliances in the community. The figures summarise the delays suggested by the control unit as opposed to the actual delays permitted by the user before overriding it. The results show that appliances were overridden approximately 50% of the times. It also shows that a number of times the actual delay was more than the suggested delay. This has resulted due to a number of problems in the analysis of the text messages received, such as machines not starting at suggested time, control overrides taking place after the suggested start time has elapsed, causing a higher count of actual delay than suggested one.

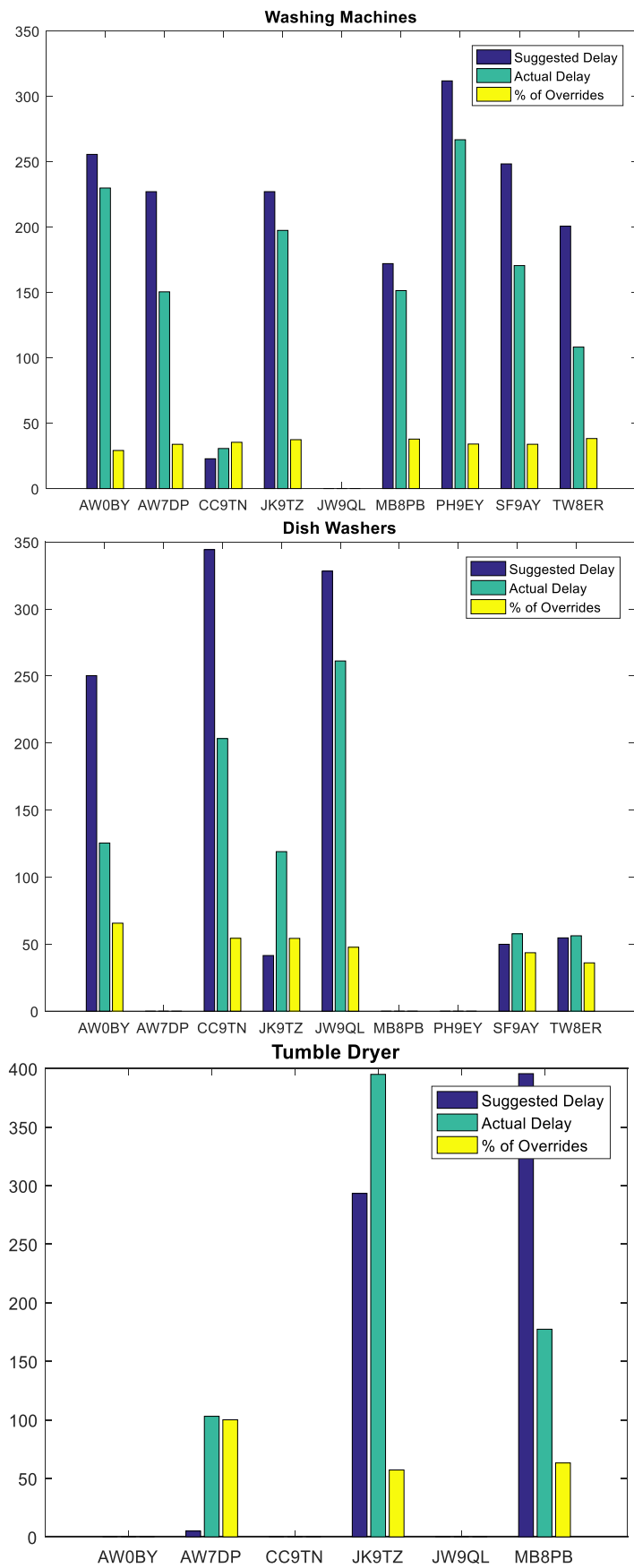


Figure 3.13: Suggested and actual delays of controllable appliances in each household.

Table 3.5: Summary of appliance shift information from different source files

	Find Request Time	Find delay suggested	Find if overridden	Find actual delay
Text Messages	√	√	√	√
Fhem files	√		√	√
Enocean files	√		√	√

Analysis of the text messages is also the only option to retrieve the information of delay suggested by the control strategy since it cannot be extracted from FHEM or EnOcean files, as summarised in Table 3.5. In many instances, these text messages are missing after a text of request acknowledgement. At other times control override takes place before the arrival of any text message with request acknowledgement or suggested time, which has also resulted in the problem stated above.

3.3.2 Results to illustrate bad performance of battery over a few days

Figure 3.14 depicts the battery charge profile of user CC9TN over a week in October 2015, in relation to PV generation, grid export, and import and export tariffs. In most days of the week, the battery has failed to capture excess PV during midday which has instead been exported to the grid. The red boxes highlight the instances when there is export to the grid which could have been used to charge the battery.

Since import prices are consistently higher than export prices, more savings could have been achieved had the energy been stored in the battery for use during peak demands rather than exporting it to the grid at the time of generation. The purple boxes show that the battery is charging at mid import price region, before the low tariff hours begin, which should have been avoided

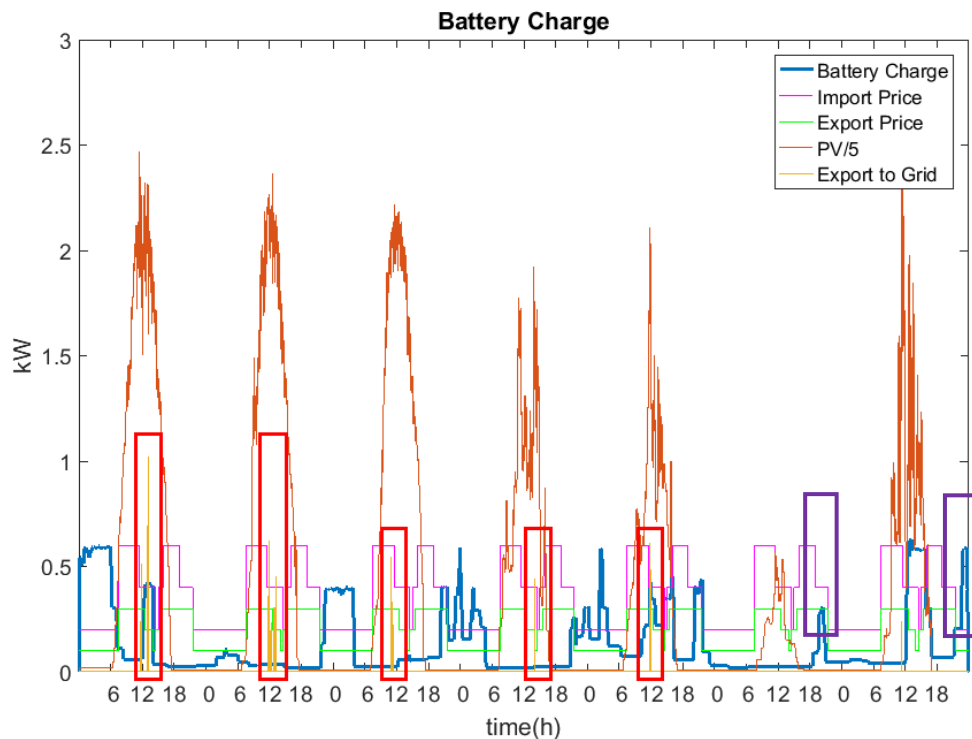


Figure 3.14: Battery charging profile of CC9TN in relation to PV generation, grid export and tariffs, over Week-1 in October.

as it not only adds to the cost but also to the round-trip losses to and from the battery system.

Total energy charged by the battery over the week is 21.8 kWh. Table 3.4 shows that the overall charge and discharge over the month of October is 109.7 kWh and 66.6 kWh respectively, which equates to a low efficiency of 61%.

Figure 3.15 shows the battery discharge profile of CC9TN for 13th to 19th August 2015. It can be seen that the battery is discharging at an odd time around midday when PV generation is the highest and is, therefore, contributing to grid export along with PV. The energy discharged from cycles marked with red boxes have been exported to the grid since there was no extra demand in the community to meet during the middays. It can also be noted on the second and

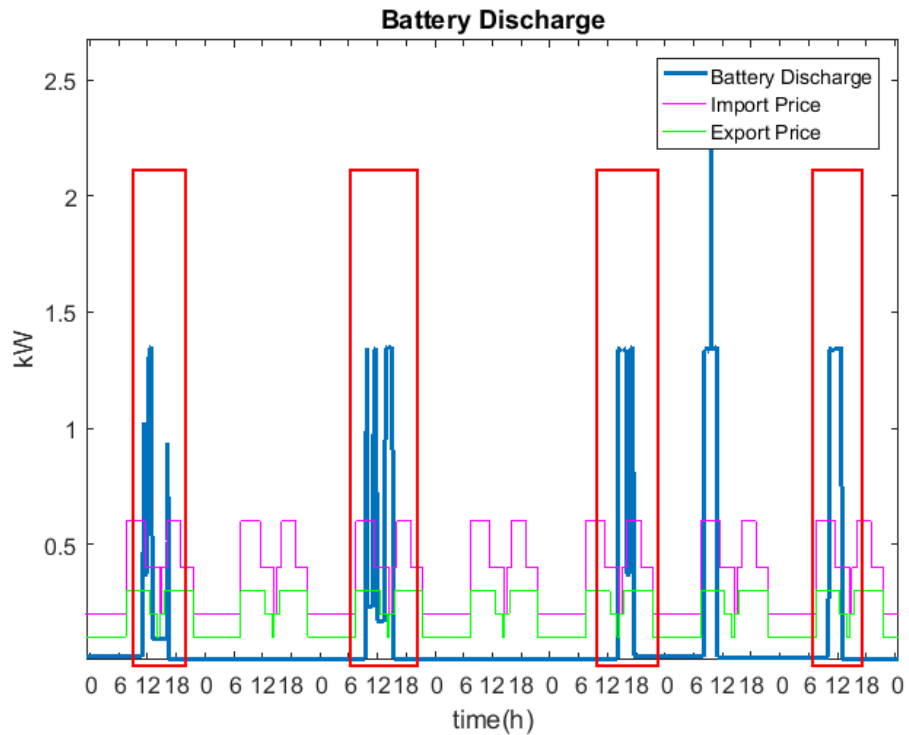


Figure 3.15: Battery Discharge profile of CC9TN over 13th to 19th August

fourth day in figure 3.15 that the battery has not discharged at all, whereas from figure 3.16 we can see that the battery did charge on the mornings of those particular days, so it should have had enough energy to meet some demand peaks. The discrepancy in the discharging cycle may have resulted due to the

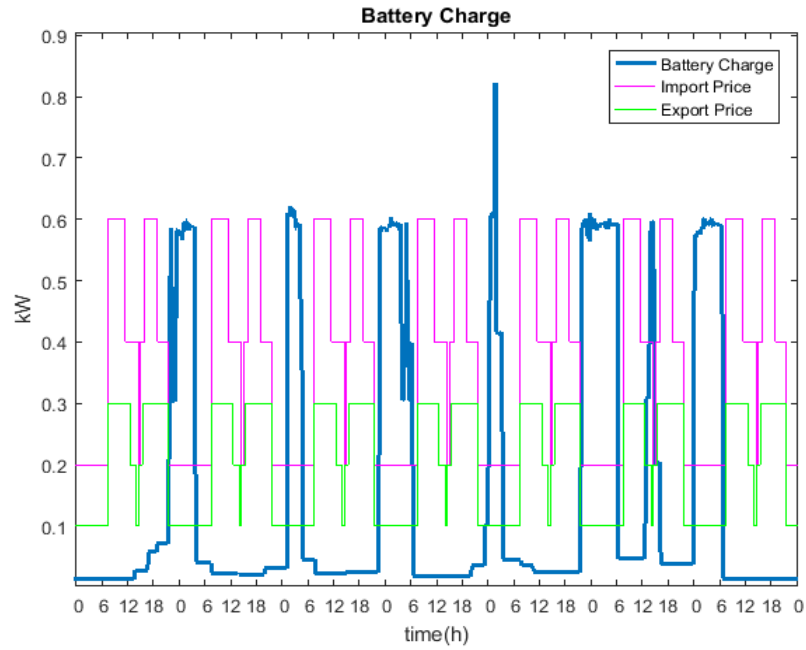


Figure 3.16: Battery charge profile of CC9TN over 13th - 19th August.

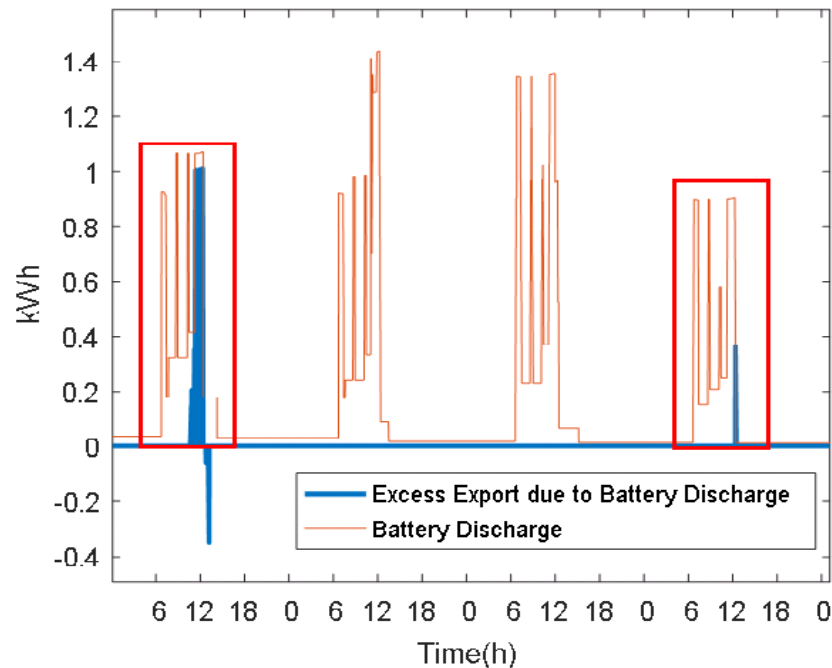


Figure 3.17: Excess export resulting from battery operation of CC9TN during October 13th to October 16th

operation of the battery strictly following high import price times and not taking into account the higher PV generation during the summer season. There might also be a delay in control signals reaching the battery which could have potentially kept the battery discharging even after the high import price band had ended.

Similar results can be seen in figure 3.17 for the 13th and 16th of October of the same year when there was excess export to the grid under the controlled scenario, due to a mid-day battery discharge.

There have also been weeks in December when an offset in charging pattern has been identified. The PV hour charging in figure 3.18 follows the early morning hour charging pattern, but they are shifted earlier under wrong tariff bands.

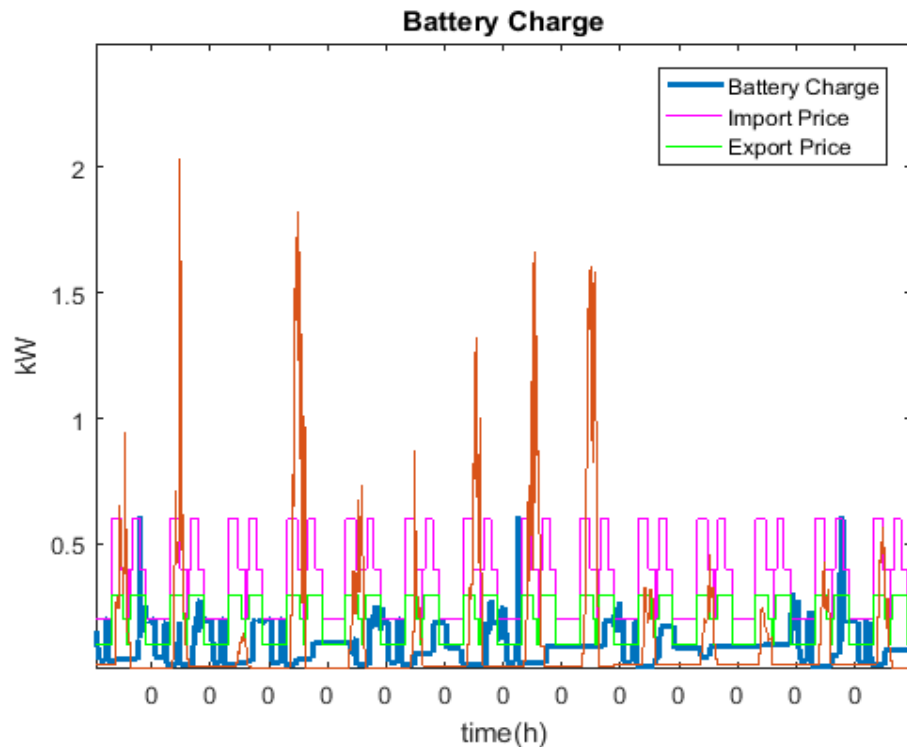


Figure 3.18: Charging pattern offset of CC9TN during a week in December

It therefore seems that problems relating to communication delay of battery responding to control signals, and adjustment of battery operation according to variations of PV generation over different seasons have not been properly taken into account, resulting in discrepancies of battery charging or discharging pattern in relation to tariff schedule.

3.4 Learnings from the Project

3.2.1 What did we do badly in the way of planning, management, data management

During deployment of the project, some issues which came up include access to meters to install current clamps or optical counters, access to local 240 V socket, LAN connection (wire) and Wi-Fi signal.

In terms of management of data, there have been issues about the resolution of the meters used for the various measurements. The dispatchable appliances have meters with resolutions as high as recording power every 20 seconds, while the import, export, and generation energy meters have a resolution of 0.1 kWh. This resulted in complications for the temporal comparison of the data.

It would also have been worth including a meter for consumption readings instead of deriving it from Import and Export meter readings, since these values reflect that of the community as a whole, with energy from PV generation and battery discharged being exchanged among the properties, as opposed to individual houses.

Wi-Fi signals were also an issue since there have been several days with missing data due to failed communication. Large power spikes have appeared across data whenever the system reconnected after a gap in communication leading to all the accumulated energy to appear across the meter at the same time. Figure 3.14 initially had similar peaks appearing in the PV data for CC9TN, which has been manually truncated to match the maximum PV rating of the property. Although the equipment was installed in 12 properties, due to communication failure of meters in certain properties e.g. the import meter of school, battery installation of JW9QL, data from these properties were not included in the decision-making process of the algorithm.

For a more comprehensive analysis, it is important to have good data management and backup priorities. It would have been useful to be able to access the data for the SOC of the battery, besides the charging and discharging energy readings. One of the factors hindering the effectivity of the battery may have resulted due to its need to fully charge/discharge according to the applied algorithm before it could start to discharge/charge again. Poor backup issues with data also led to the loss of text messages from the latter half of the project, preventing further analysis of DSM during that period.

A number of issues have been identified with the text messages used for the control of the dispatchable appliances which illustrate that better feedback method than text messages needs to be employed to maintain communication and operation of DSM. Following is a list of issues encountered.

1. Text messages arriving 30-40 minutes after the request was sent.

2. Text messages are time-stamped at the British Summer Time (BST) while the Raspberry Pi and e2E server continue to follow Greenwich Mean Time (GMT) all throughout the year, causing a mismatch of time during analysis.
3. Missing text messages containing suggested start time after request-text received.
4. Control override takes place before the arrival of any text message containing request acknowledgement or suggested time
5. Control is overridden after permission already given to start appliance.

A more effective way of recording the shift of appliances should be in place in order to make use of the collected results from the pilot project. A message containing suggested start time according to control algorithm could still be sent when an override is made simultaneously with a request, for the ease of analysis later.

3.2.2 What did we do well/badly with respect to interactions with volunteers and community members

A number of times the controllable appliances have been overridden at more expensive tariff times than the time of original request which has potentially increased electricity cost. The users could have been given an estimate of the peak tariff hours for restraining to override the machines at those times or allowing them to override from the start.

The users could be trained to spot when the communication devices had failed so they could restart them in order to re-establish the connection.

3.2.3 What could be improved with the basic technology?

The PV generation of the community in October amounts to 328.5 kWh, of which only 1.0 kWh has been exported to the grid. This shows that the community is utilising its PV generation and sharing it well within the different properties. A community-based solution for enhancing renewable energy-usage therefore seems effective for increasing self-consumption and reaping the benefits of PV energy.

There is a large discrepancy between the energy discharged by and the energy charged into the battery. To minimize losses due to converter efficiency, a possible approach could be to employ modular batteries by allowing each battery to run close to its peak capacity, and then bringing in more batteries one after the other when demand or generation increases.

3.2.4 How could the actual algorithm be improved?

The battery charge/discharge pattern in August over the whole month shows control based solely on tariffs. As a result, although the battery was discharging at high import tariff hours, it was being exported since there was already enough PV available to support load during that time. The battery has also not met much of the evening peaks despite having charged during earlier hours of the day. The algorithm must therefore be adjusted to take into account the available energy and net consumption to make decisions on the battery charging and discharging cycles.

As seen in Table 3.4 earlier, there is a discrepancy in the percentage of energy discharged from the battery over a week as it varies between 61 to 85%. In December, which shows the highest percentage of energy discharged with

respect to charging, the batteries had stopped charging or discharging by mid-month. The reason could have been a system trip which was left unattended as residents were away during the holiday season. Throughout the first half of the month, some discharging generally took place within PV generation hours. No exports had resulted from this activity since PV generation was low and load demand high, however, the battery energy could be maximized better by not discharging when PV is available. As a result, it can be analysed that the battery operation patterns need to be adjusted separately according to the season of the year, rather than being based solely on tariff periods.

Closer analysis of individual days has shown that batteries could have discharged more in peak periods with the available charge in the battery. The discrepancies may have risen due to the battery and power converter roundtrip efficiencies, and their varied dependence patterns on power consumption. The battery's ability to capture surplus available energy may have been limited due to the imposed control requiring the battery to fully charge/discharge in each cycle.

The battery control algorithm had aimed to export PV during periods of peak export prices, thereby battery charging from PV generation throughout the analysed months were a minimum. As a result, self-consumption of solar energy has not been significantly improved or impacted by battery operation. In some instances in autumn and summer, the battery has discharged during peak PV hours. Since export prices are consistently lower than import prices, the algorithm could achieve more monetary benefits by enhancing self-consumption instead of export, avoiding battery discharge at peak export tariff,

and discharging that energy during peak import periods to reduce the purchase of expensive electricity.

The battery analysis of August has shown the largest mismatch of battery discharge with demand, leading to unnecessary export to grid from the battery. Due to the presence of enough PV through an extended period of the day, the energy released from the battery during the peak tariff hours was in excess of net demand. The battery algorithm therefore needs to be adjusted for summer and winter to avoid such wastage of energy not only by reducing self-consumption but also due to roundtrip losses in battery and converter systems.

In terms of DSM, the appliances were always shifted to early morning hours, so self-consumption of PV was not generally utilised. Both of these factors need to be addressed in any future algorithm to make more effective use of PV self-consumption and tariff benefits.

3.2.5 What do we need to include to overcome predictable problems

No matter how good the technology is, there are inevitable problems such as communication failure, user overrides, equipment crashing etc. To counter such predictable problems, it may be beneficial to have both local and remote data logging in order to ensure maximum data is preserved from the setup. Wired connections are preferable to wireless communication due to their higher reliability. Indicators could be installed to alert users about crashing equipment which can be reported immediately. A guideline on peak hours can be presented to users so that overrides are not done at more expensive tariff times.

3.5 Conclusion

Analysis of data from EmPower project had been valuable in understanding the requirements of energy management systems to work with real-time data and actual communities, as opposed to simulated households, load profiles, and PV data. A number of technical issues were apparent throughout the duration of the trial and some algorithm level issues were suspected upon analysis of the gathered data, after the end of the trial period. Since the management algorithm was not accessible by the University partners, some issues remain to be certainly attributed to the algorithm.

The management system had primarily been designed to benefit the end user by reducing their energy cost and carbon footprint, however in many of the instances, conflicting behaviour from the storage system data has been observed which may have resulted from the algorithm also working towards the benefit of DNOs and energy suppliers to extend the life of distribution and transmission network assets. The project was also market-tested by partnering with an energy supplier to offer the target dwellings with community-focused and low-carbon electricity supply contract at competitive prices thereby allowing the concept to be validated and identifying practical challenges for offering such schemes on the energy market.

Behaviour of batteries in responding to real community data have been observed through the collected battery data and it seems that a more robust algorithm needs to be designed in order to make efficient use of the battery in effectively shifting energy for cost-effective operation and in reducing energy

consumption in the peak periods. Battery charge and discharge patterns also need to be adjusted more strategically to the tariff schedule being used by the community. A tariff scheme based on a few different levels of tariff throughout the day rather than half-hourly ToU tariff seems more reasonable given the fact that neither PV nor the household demand can yet be accurately predicted resulting in the introduction of more variability than is needed for saving overall community energy. A more reliable and efficient battery management algorithm will be developed in the following chapter, addressing the issues analysed in this chapter, in order to evaluate the learnings from the EmPower project.

4 DESIGN OF BATTERY MANAGEMENT ALGORITHM AND SIZING TOOL

4.1 Introduction

Following from the learnings of real-life data analysis of the Corsham community, the aim to develop an algorithm for community battery storage systems can be further defined and implemented. As defined earlier in this document and by the UK government [100], Community Energy refers to collective action to reduce, purchase, manage and generate electricity. Communities working together can save energy and bills in several ways, one of which is employing community energy storage which in turn can better accommodate collective or individual renewable energy generation sources.

This chapter will outline the design of a battery management algorithm based on currently available variable electricity tariff rates and battery systems in the market, in order to capture available energy from dispatchable sources for peak time usage as well as charging the battery at off-peak times to meet demand during peak periods.

A methodology is developed to optimize the sizing of battery for each community, based on historical consumption and generation data collected over a year for that community. The energy saving established by the battery algorithm for individual properties as well as relative energy savings as a community is to be evaluated to show merits of the battery algorithm on its own and further benefits for community energy.

Due to a gap in the literature, particular emphasis is given to sizing power converters for the energy storage systems, based on operational powers of the individual houses in the community. Analysing power bins of properties have helped in determining the best power level for each community to operate at, for optimal efficiency and losses, with the converter rating being expressed as a function of the battery capacity.

The remaining parts of this chapter are organised in the following way. Section 4.2 describes the design methodology of the battery management scheme, including details about the real communities whose data has been used to design and evaluate the battery management algorithm, along with introducing the tariff model, grid interface and battery model used in the system. Section 4.3 discusses the battery sizing methodology followed by techniques used for power converter sizing in section 4.4. The effects of the application of designed Community Power Flow (CPF) battery algorithm onto the community of Project EmPower and the results of energy shifting and energy cost savings achieved by the combined battery algorithm and sizing techniques have been presented in section 4.5. The chapter finally ends with section 4.6 summarising the original objectives and the key results obtained in this chapter.

4.2 Design Methodology: Battery Management Algorithm

In this section, the design methodology of an energy management scheme for residential smart grid is formulated, based on known information such as time-varying load demand, photovoltaic energy generation, and available electricity tariff rates, in order to control the action of an energy storage unit, such as a battery, for maximum cost benefits. A technical and economic evaluation is carried out, using simulations in one-minute resolution over a period of one year (when available), on real communities to demonstrate the impact of the proposed energy management. A sensitivity analysis is also performed in order to demonstrate the impact of imperfect forecasts of the time-varying load and PV data as opposed to perfect prediction [101].

4.2.1 Overview of Energy Management Schemes

According to different literature, energy management can be defined as a set of strategies and functions that can adjust and optimize the use of energy by coordinating the different energy resources within the household, community, micro-grid etc. [50]. The general aim of energy management systems is to enhance energy efficiency by reducing the loss of excess production and to optimize energy cost. This can be done through either or both of the following ways:

- PV Shifting
- Load Shifting
 - Direct Control
 - Indirect Control

PV shifting is achieved by utilising battery storage in a residence or community to store PV generated energy during low load hours of day-time, when most household occupants are away at work/studies, and discharging this stored energy during high import-tariff periods of morning and evening peaks when household members are either leaving for or returning from work. The battery can also be employed to charge from the grid during periods of low import tariff (e.g. overnight when property occupants are sleeping) when there is only a small load demand and support household demand peaks later on during the day.

Load shifting, in turn, can be achieved by either direct or indirect control schemes, whereby the former is governed by controlled devices which alter load patterns through a pre-programmed schedule or real-time monitoring of the consumption and generation profiles, and the latter is achieved through incentive policies, tariff benefits, discounts etc. Because, as seen in chapter 3, due to the unreliability of direct load shifting of appliances is heavily affected by user behaviour, the energy management scheme developed in this thesis focuses only on PV shifting and indirect load shifting through overnight charging of a battery storage system to achieve electricity cost savings for each household and/or community based on a Time-of-Use (ToU) electricity tariff. In other words, the work addresses grid-connected communities with solar generation and residential load where only the battery can be controlled. The primary control functions of the battery energy management can be stated as the following.

- The battery should support the entirety of load demand in the peak tariff period, through overnight charging and self-consumption of export, thereby removing demand from utility grid during that period.
- The battery should consume all the energy from PV generation which would otherwise have been exported to the grid in the absence of concurrent load demand, i.e. maximize self-consumption.
- The battery should prioritise charging through self-consumption over overnight charging.

These control strategies, in turn, achieve the benefits outlined below.

- Supporting the impact of renewables: by allowing the use of renewable energy at high-value times
- Increase in self-consumption: It is more economic and efficient to consume the solar energy at peak periods, than exporting the unused energy to the grid. The price paid for exported solar energy to the grid is always lower than the cost of buying energy from the grid.
- Load leveling: Storage is charged during off-peak periods, using low-cost energy, and discharged during high-load times when the energy value is higher. The benefits are improved load factor, deferred expansion of generation, and reduced purchase at peak times.
- Energy cost reduction for consumers: Since most of the energy needed to support loads at the high-tariff period is pre-purchased and stored in the battery during the low-tariff period, the consumer is expected to see a reduction in energy purchase cost.

- Enhancing transmission capacity: Storage units can add to available generation during peak periods, increasing total system capacity and, reducing peak loading of transmission lines, thereby effectively increasing transmission capacity.

Despite these strong technical merits for electricity storage, the initial purchase cost renders the setup of storage systems as too expensive for large-scale adoption. The costs of storage technologies, however, are dropping, and with newer ToU tariff schemes coming into the market, cost/benefit analyses have shown that it is economically justified in some cases [102]. Figure 4.1 depicts the different components of the Energy Management Scheme considered in this work. The following subsections give details of these components including the real communities used for the time-varying data for this work, the pioneering Time-of-Use (ToU) electricity tariff provided by the independent energy supplier Green Energy UK, which has been employed as

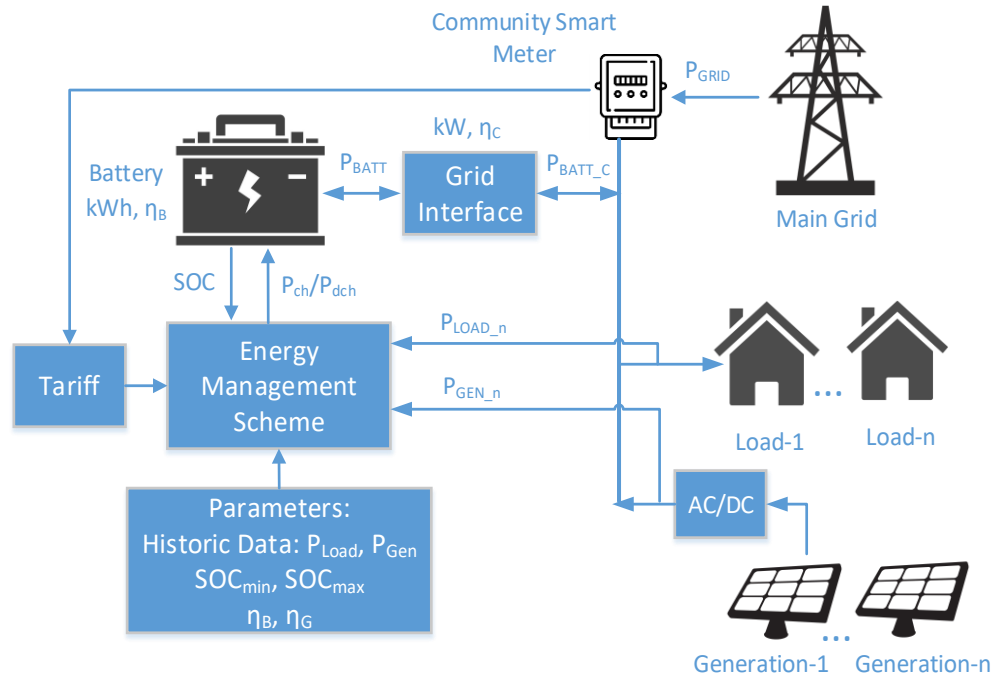


Figure 4.1: Overview of Designed Energy Management Scheme

the tariff model for this thesis, and the battery and grid interface models as well as a description of how the entire system is brought together and designed.

4.2.2 Communities used for Load and PV Generation Data

Consumption and PV Generation data for several properties in different communities are collected in order to form the inputs for the battery management algorithm design and evaluation. As detailed in Chapter 3, the EmPower project investigated the energy management of a community of 11 properties in Corsham in the south of England, comprising of 9 residential houses with a varying number of occupants, a school and an office building. However, only four residential properties from the total count were selected due to the consistency and low disruption of the data collected. For each of the four properties, it was possible to collect one week of unbroken consumption and PV generation data for 9 months of the year, while the battery behaviour for the remaining three months was extrapolated from the available data. Details of the Corsham trial can be found in Chapter 3.

Another project by the University of Loughborough which analysed electricity use at a one-minute resolution in 22 dwellings in Milton Keynes, UK, over the complete year of 2008 has contributed to the battery algorithm inputs of consumption and generation data [77]. For the measured data, each dwelling was fitted with a single high-resolution meter to monitor electricity use of the whole dwelling, whereby, the one-minute resolution allowed the switching of individual domestic appliances to be observed. The meters measured true active power and a survey form for each dwelling detailed its characteristics and the types of appliances and lighting installed.

Our collaboration with an energy consultant company also resulted in the acquiring of client data in the East Midlands, UK area, for hourly consumption and PV generation. The annual data of the four residential properties investigated spanned over October 2016 to September 2017 monitored by PowerRouter from Nedap [103]. This set of data was very reliable in terms of consistency of data and unbroken communication to a storage server at mypowerrouter.com.

For each of these three different datasets, analysis has been carried out for individual properties as well as the properties grouped together as a community. To be considered as a community, the individual consumption and generation data were aggregated to give the combined kWh for the community, and the battery was sized and managed accordingly. All input data are converted to minute-wise data to make the algorithm uniform over all scenarios investigated.

4.2.3 Tariff Model

The business model of ToU tariffs entails buying energy in advance during periods of cheaper electricity and consuming that energy later on in the day which successfully shifts demand from the grid. This is sometimes known as ‘arbitrage’. Batteries in the energy management scheme are equipped with intelligent controls that respond to the ToU tariff signal to provide potentially cheaper electricity bills for customers and reduced demand strain on the UK’s energy supplies [104]. The impacts on customer bills also rely on behavioural change of electricity users and a group or community operation for a substantial shift of load profile.

WEEKDAY				
13%	Low Tide		00:00 – 07:00	6.41p
24%	Tide Weekday		07:00 – 16:00	14.02p
19%	High Tide		16:00 – 20:00	29.99p
16%	Tide Weeknight		20:00 – 00:00	14.02p

WEEKEND				
5%	Low Tide		00:00 – 07:00	6.41p
24%	Tide Weekend		07:00 – 00:00	14.02p

Figure 4.2: Multi-level TIDE tariff rates in p/kWh offered by Green Energy UK [98]

Figure 4.2 shows the three-level TIDE tariff rates in p/kWh currently offered to customers by Green Energy UK. Facilitated by smart meters which provide an accurate real-time measurement of energy usage, the TIDE scheme offers prices varying between periods of high and low demand, with four hours of peak evening tariff which is roughly five times the off-peak tariff spread across seven overnight hours, and an intermediary tariff at all other times [98]. It should be noted that if charging at low tariff rates forms an important part of the control behaviour, a large difference between low and high tariff is required to provide the value for using the battery. It should be noted that during the weekend, only low and mid tariff bands are applicable which would require the battery management system to behave differently on weekends as opposed to weekdays to take advantage of the different tariff schemes.

Currently, TIDE is an online-only tariff and the only ToU tariff available in England. Hence the Green Energy UK TIDE tariff forms the basis of the intelligent battery control designed in this project. Several other smaller energy companies, aided by the advent of affordable smart meters, are now preparing

to offer time-of-Use (ToU) tariffs which incentivise battery charging and load operation during off-peak hours and when renewable generation is plentiful, by providing cheaper p/kWh during those hours [105].

4.2.4 Battery Model

The battery in this work is modelled as a generic energy source and sink, with a finite capacity in Wh and a constant efficiency. Depending on the amount of energy drawn into or out of the battery (i.e. charging and discharging), the State-of-Charge (SOC) of the battery is determined. SOC is a measure of how full the battery is, in other words, it is the battery's available capacity expressed as a percentage of its rated capacity. An upper and lower limit of SOC determines the maximum charging point and the minimum discharging point which in turn determines the full range of available energy that can be delivered by the battery [106]. For this work, the maximum and minimum SOC for the battery is chosen to be 90% and 10% respectively [107].

A fixed round-trip efficiency of 90% is considered for putting energy in or out of the battery [108]. As a result the energy going into and out of the battery will be multiplied by a factor of 0.9, which should be taken into account while determining how much energy is needed to be charged to or discharge from the battery, and understand the additional energy required by the community to operate the battery (i.e. supply its losses).

4.2.5 Grid Interface Model

For a seamless and safe operation of the battery, an interface is essential to bridge the gap between the AC grid and the DC battery. A bidirectional power

converter therefore needs to be employed which can convert the battery's DC into the grid's AC and vice versa. With the introduction of the converter comes losses associated with the conversion process. These losses can significantly vary with converter loading i.e. efficiency can reduce significantly at low loads. Therefore, the overall performance of a grid is linked to the converters' efficiency curves. The converter loss variation with load will therefore be presented as accurate as possible in order to give an accurate representation in the energy management algorithm later, which are representative of the real converter loading. This is done by using equations which represent converter loss in terms of converter loading.

From a study by P. Kulsangcharoen [109], losses for a 2 kW converter were assessed against its loading for a system with an 8 kHz switching frequency. The energy storage converter consists of a two-stage topology including an AC-DC stage to interface the AC grid with a constant DC voltage followed by a DC-DC stage that interfaces the constant DC-link voltage to the variable battery DC voltage. The total power loss, P_{TLoss} , is measured for both charging and discharging modes, using a N4L PPA2530 power analyser at the input, processing power (P_p) levels of 0.5kW, 1kW, 1.5kW and 2kW and at switching frequencies f_{sw} , between 5kHz to 10kHz. The total loss consists of filter components within the converter system which includes inductors, capacitors, and resistances along with power device conduction and switching losses. The results taken from [109] are presented in figure 4.3 and polynomial curve fitting is used to derive equations for the converter power loss and

converter efficiency as a function of processed power, shown in figure 4.4. These equations are given in 4.1, 4.2, 4.3 and 4.4.

$$P_{TLoss}(charging) = 1.63P_p^2 - 5.109P_p + 7.753 \quad [4.1]$$

$$P_{TLoss}(discharging) = 1.1P_p^2 - 3.65P_p + 6.815 \quad [4.2]$$

$$\eta(charging) = -1 \times 10^{-6}P_p^2 + 0.0036P_p + 93.185 \quad [4.3]$$

$$\eta(discharging) = -2 \times 10^{-6}P_p^2 - 0.0051P_p + 92.248 \quad [4.4]$$

The processing powers of these plots are scaled by appropriate factors when assuming efficiencies for converter systems other than 2 kW rated power. The equation for converter efficiency is then included in the battery management algorithm to get the converter efficiency at each value of input power, and thereby calculate the converter output power as a function of converter efficiency and input power. Table 4.1 gives the description of the components within figures 4.3 and 4.4, showing how the converter efficiency ‘ η ’ is derived from the total power loss (P_{TLoss} as a percentage of converter processing power) which is originally taken from [109].

Not much work has been done in this area for appropriately sizing converters for households and communities. A methodology is therefore also developed for finding the best possible converter size for a given load/loads, based on their power consumption history.

4.2.6 Design of Energy Management Scheme

The battery energy management scheme developed in this work is based on a Community Power Flow Control (CPF) control scheme [110] and relies primarily on the different Time-of-Day periods of fixed tariff levels offered by

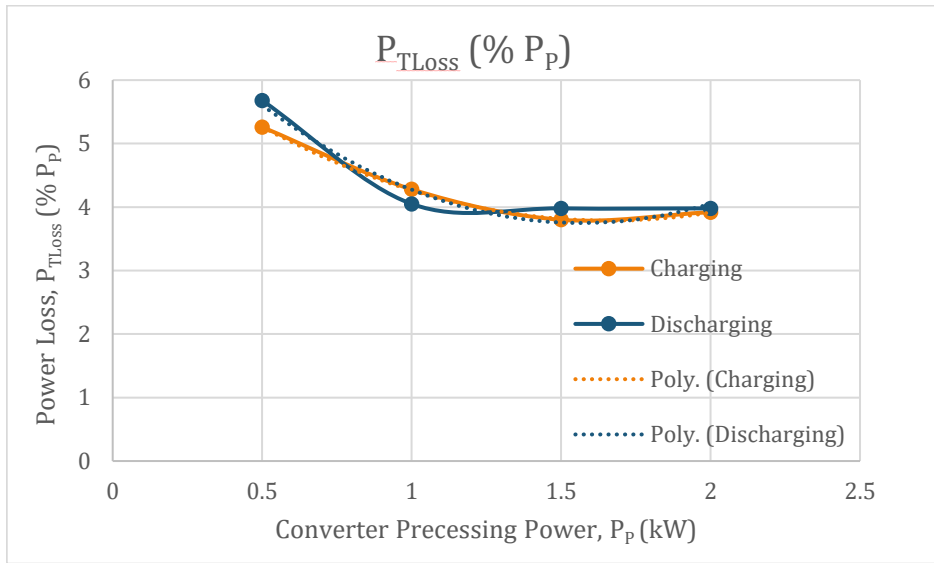


Figure 4.3: Total Loss calculated for a 2 kW converter

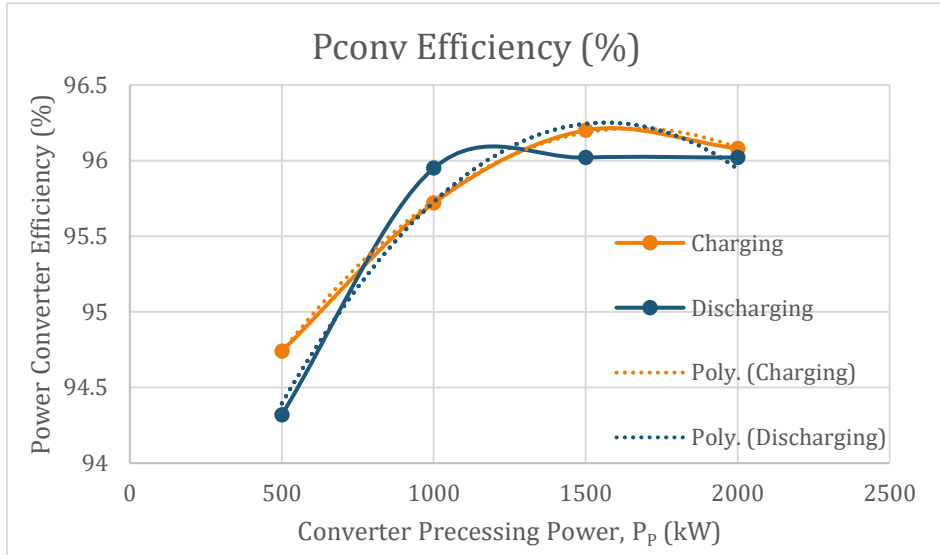


Figure 4.4: Efficiency of the 2 kW converter at different processing power levels.

Table 4.1: Description of each component within figures 4.3 and 4.4.

Converter rated power	2 kW
Total power loss as a percentage of converter processing power, P_{TLoss} (% P_P)	Taken from figure 10 at [109]
Converter processing power, P_P (kW)	Power input to converter
Converter Efficiency, η (%)	$100 - P_{TLoss}$ in % P_P
P_{TLoss} (kW)	$\frac{P_{TLoss} \text{ in } \% P_P}{100} \times P_P$

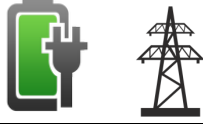
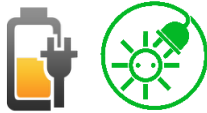
Green Energy UK TIDE scheme. The management scheme also requires historical load and generation data of properties in the community and

parameters defining the efficiency of the battery and power converter, along with the current State of charge (SOC) of the battery and its upper and lower limits. **In this work, the historical data is considered to be available in advance for the whole year, which achieves ‘perfect prediction’ of excess available PV of the day and accordingly sets the SOC of the battery at different periods.** Inputs to the EMS are also instantaneous load demand from individual properties or community, along with instantaneous PV generation. The net demand of the consumers is found by subtracting PV generation from load demand. When net demand is negative, there is excess PV generation which should either be stored in the battery for use during peak demand periods or exported to the grid if the battery is full. If the net demand is positive, the unmet load is supported either through battery discharge (during peak tariff period) or by the grid if the battery has reached its minimum SOC.

As seen from figure 4.2 earlier, a weekday can be divided into four distinct segments based on the variable tariff levels, and the energy management algorithm for each period is described below, with Table 4.2 summarising the role of battery and the grid at each interval. The supporting power flow equations denote the battery charging ($P_{\text{Batt, ch}}$), battery discharging ($P_{\text{Batt, dch}}$) and grid power (P_{grid}) during interval where ‘t’ is instantaneous time, d is the day in the year, P_{Net} is the net load P_{Load} is the power demand and P_{PV} is the generated PV power.

- 00:00-07:00 hrs

Table 4.2: Summary of the role of battery and grid in different time periods defined by TIDE Tariff.

Time-of-Day	Battery	Grid
00:00 – 07:00 hrs (Low Tariff)	Charge from grid to maximum SOC less excess PV energy available for the day. 	Charge Battery Meet load demand 
07:00 – 16:00 hrs (Mid Tariff-1)	Charge from excess PV 	Meet load demand 
16:00 – 20:00 hrs (Peak Tariff)	Discharge to minimum SOC Charge from excess PV 	Meet load demand only if battery SOC reaches minimum limit. 
20:00 – 00:00 hrs (Mid Tariff-2)	Discharge any remaining capacity. Charge from excess PV 	Meet load demand only if battery SOC reaches minimum limit. 

- The grid must meet net load demand at this interval since import tariff is the lowest at this time. Net demand and grid power are given by equation (4.5) and (4.6).

$$P_{Net,t} = P_{Load,t} - P_{PV,t} \quad [4.5]$$

$$P_{grid,t} = P_{Net,t} + P_{batt,ch,t} \quad [4.6]$$

- The grid must charge battery to maximum capacity less the predicted PV energy export for the day after 7 am, as given by

(4.7). This will ensure that the battery has enough capacity remaining to accommodate the free “export” PV energy available during the day. Accurate PV forecasting will play a major role here to determine how much of the battery capacity is to be left empty for PV charging throughout the day. In the absence of a perfect prediction of available PV during the day, the generation profile of the previous day is used to estimate the capacity that should be left empty in the battery and accordingly chose a maximum SOC for overnight charging.

$$P_{batt_{ch},t} = \frac{((SOC_{max}-SOC_t) \times BatteryCapacity) - (E_{export,d})}{7\text{ hours}-t} \quad [4.7]$$

- No battery discharge should take place during this interval since grid import prices are low, and because the battery should primarily hold charge to meet peak hour load.

$$P_{batt_{dch},t} = 0 \quad [4.8]$$

- 07:00-16:00 hrs

- The grid should supply the net positive energy consumption of the community defined by (4.9).

$$P_{grid,t} = P_{Net,t} \text{ iff } P_{Net} > 0 \quad [4.9]$$

- Battery should charge up using any unused PV energy, i.e. the PV exports defined by (4.10).

$$P_{batt_{ch},t} = P_{Net} \text{ iff } P_{Net} < 0 \text{ \& Battery SOC } \leq 90\% \quad [4.10]$$

- No battery discharge should take place during this interval, as shown by (4.11), since the battery should primarily hold charge to meet peak hour load.

$$P_{batt_{dch},t} = 0 \quad [4.11]$$

- 16:00-20:00 hrs

- Battery should be discharged to the minimum allowed SOC to meet any load demand, defined by (4.12).

$$P_{batt_{dch},t} = P_{Net} \text{ iff } P_{Net} > 0 \text{ \& Battery SOC} > 10\% \quad [4.12]$$

- The grid supplies load demand if and only if the battery has reached minimum SOC, or power exceeds maximum battery system power, given by (4.13).

$$P_{grid,t} = P_{Net,t} \text{ iff } P_{Net} > 0 \text{ \& Battery SOC} < 10\% \quad [4.13]$$

- Battery should charge up any using any PV exports, given by (4.14).

$$P_{batt_{ch},t} = P_{Net} \text{ iff } P_{Net} < 0 \text{ \& Battery SOC} \leq 90\% \quad [4.14]$$

- 20:00-00:00 hrs

- Any remaining battery energy should be discharged to meet load.

$$P_{batt_{dch},t} = P_{Net} \text{ iff } P_{Net} > 0 \text{ \& Battery SOC} > 10\% \quad [4.15]$$

- Charge battery if there is surplus PV

$$P_{batt_{ch},t} = P_{Net} \text{ iff } P_{Net} < 0 \text{ \& Battery SOC} \leq 90\% \quad [4.16]$$

- Grid supplies load consumption if and only if battery SOC falls lower than 10%.

$$P_{grid,t} = P_{Net,t} \text{ iff } P_{Net} > 0 \text{ \& Battery SOC} < 10\% \quad [4.17]$$

The energy management algorithm for the battery system during weekends comprises of only two tariff bands with an off peak-period from midnight, until 7 am in the morning, and a moderate tariff band applied for the remainder of the day from 7 am till midnight. No high tariff band is applied throughout the day. During the off-peak period from midnight till 7 am, the control methodology applied is the same as that applied overnight during the weekdays. The battery charges to maximum SOC from the grid, leaving enough capacity to be ‘topped-up’ by PV generation of the day. It does not discharge during this period.

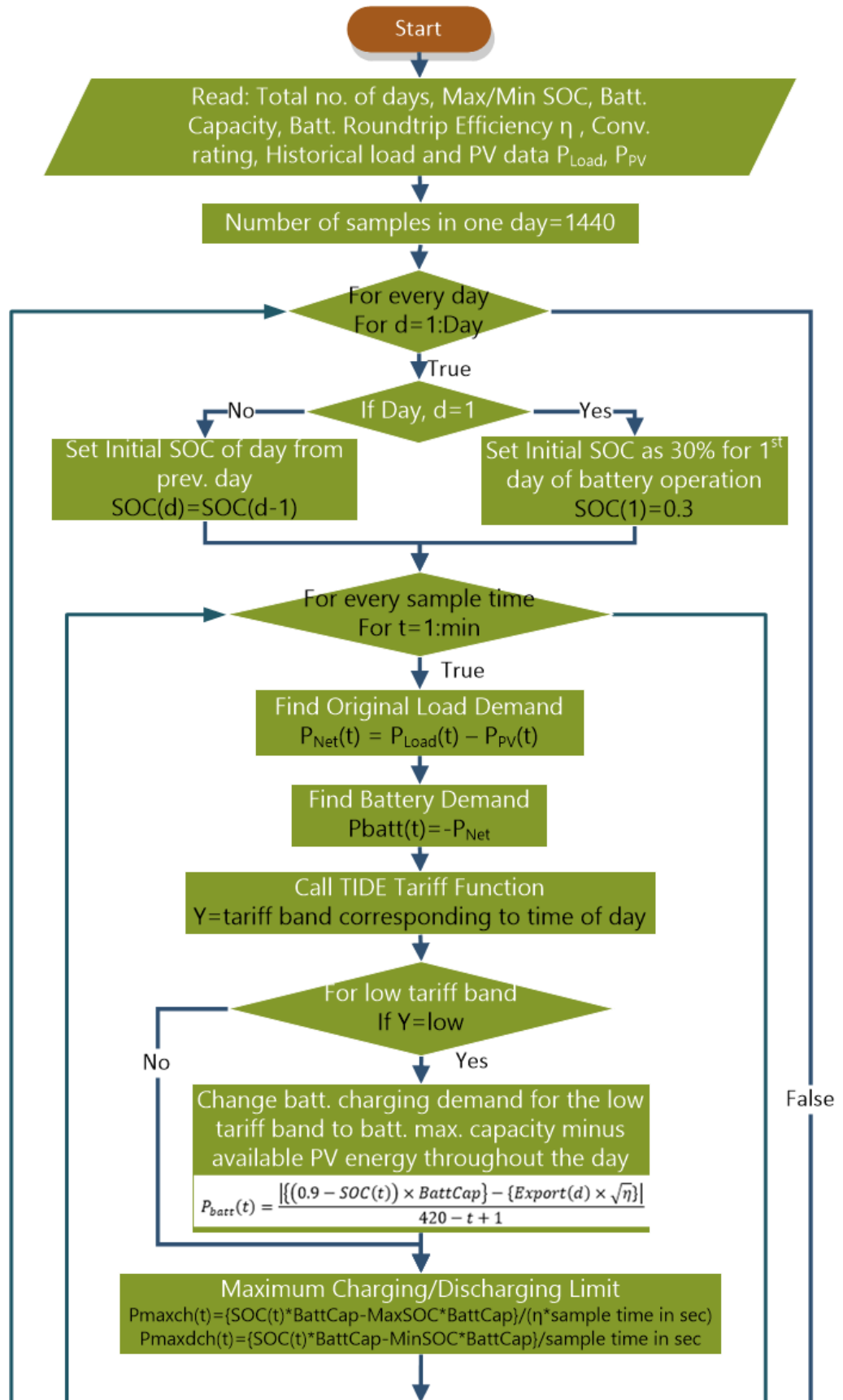
For the rest of the day of the weekend from 7 am to midnight, the control strategy applied is the same as that applied during the 20:00-00:00 hrs of the weekdays corresponding to ‘Mid Tariff-2’. All available battery energy is discharged to meet load. The battery is charged only if there is surplus PV. The grid supplies load consumption only when battery SOC falls lower than its minimum 10%. Since there is no ‘peak tariff’ during the weekend, it is not required to hold the battery capacity to the maximum until the start of the peak-period, as is done in the control algorithm corresponding to ‘Mid Tariff-1’. The battery can therefore be discharged to support load as soon as the low-tariff band is over. This will ensure maximization of load-support through battery from the cheapest electricity of off-peak times, as well as allow more available capacity for self-consumption of PV during the day.

The justification for choosing the control algorithms for the two tariff bands of weekends to correspond to ‘Low Tariff’ and ‘Mid Tariff-2’ is further justified in chapter 5 showing that the highest import cost saving and self-

consumption is achieved by using the mentioned control strategies for each band.

The Energy Management Scheme is controlled by the CPF algorithm which takes as input certain variables and assumptions to give the desired and varying results in each time period of the TIDE Tariff. Figure 4.5 presents the flowchart showing the structure of the overall system simulation including the details of the CPF BMS. The flowchart illustrates how the various elements and models are interconnected with data input and power flow control algorithm, and indicates where system losses are calculated. Figure 4.6 and 4.7 further expands on the ‘Battery Power Flow Algorithm’ within the flowchart showing the power flow in and out of the battery during charging and discharging for the low tariff and peak tariff operations respectively. Table 4.3 summarizes the inputs required for the algorithm to operate and the assumptions made for the system.

The simulation model is developed in MATLAB and works by considering a time-step of one-minute resolution. In each time-step ‘ t ’, it attains the $P_{Load,t}$, $P_{PV,t}$ from input datasets and the current battery SOC_t is passed from the previous time-step which was found using (4.18). The algorithm then calculates $P_{Net,t}$ using (4.5) and decides whether to charge or discharge the battery based on the calculated $P_{Net,t}$, the time of the day and TIDE tariff band corresponding to ‘ t ’, the current battery SOC_t and resulting battery SOC_{t+1} , and the SOC limits. The battery does not charge if the current or resulting SOC is or goes above 90% and it does not discharge if the resulting SOC from this time-step is smaller than or equal to 10%. At the end of the charge/discharge process,



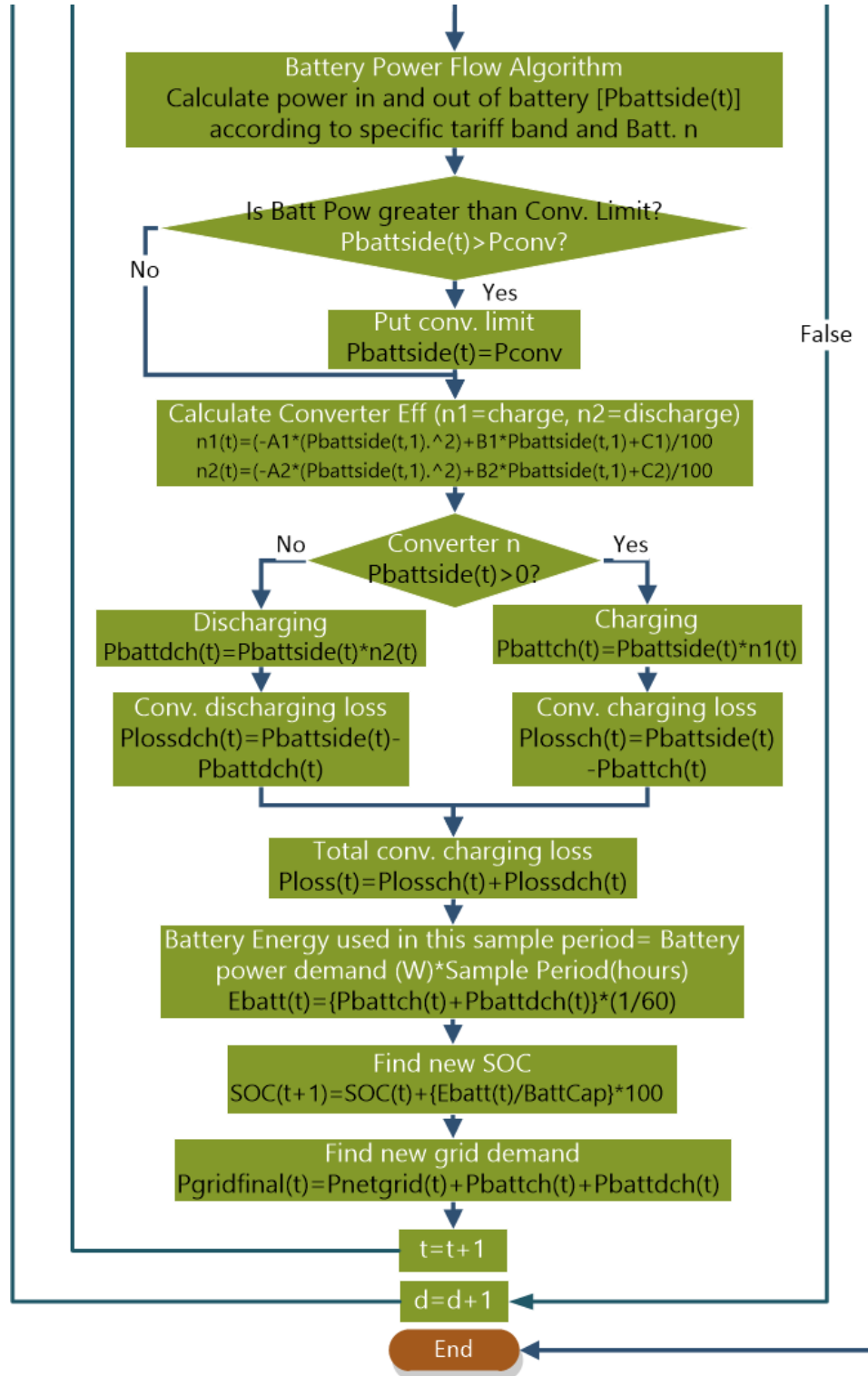


Fig 4.5: Flowchart of overall system simulation including details of the CPF BMS (flowchart continued from previous page).

battery control algorithm is used to determine system behaviour.

$$SOC_{t+1} = SOC_t + \left(\frac{\text{Charging or Discharging Energy}}{\text{Battery Capacity}} \times 100 \right) \quad [4.18]$$

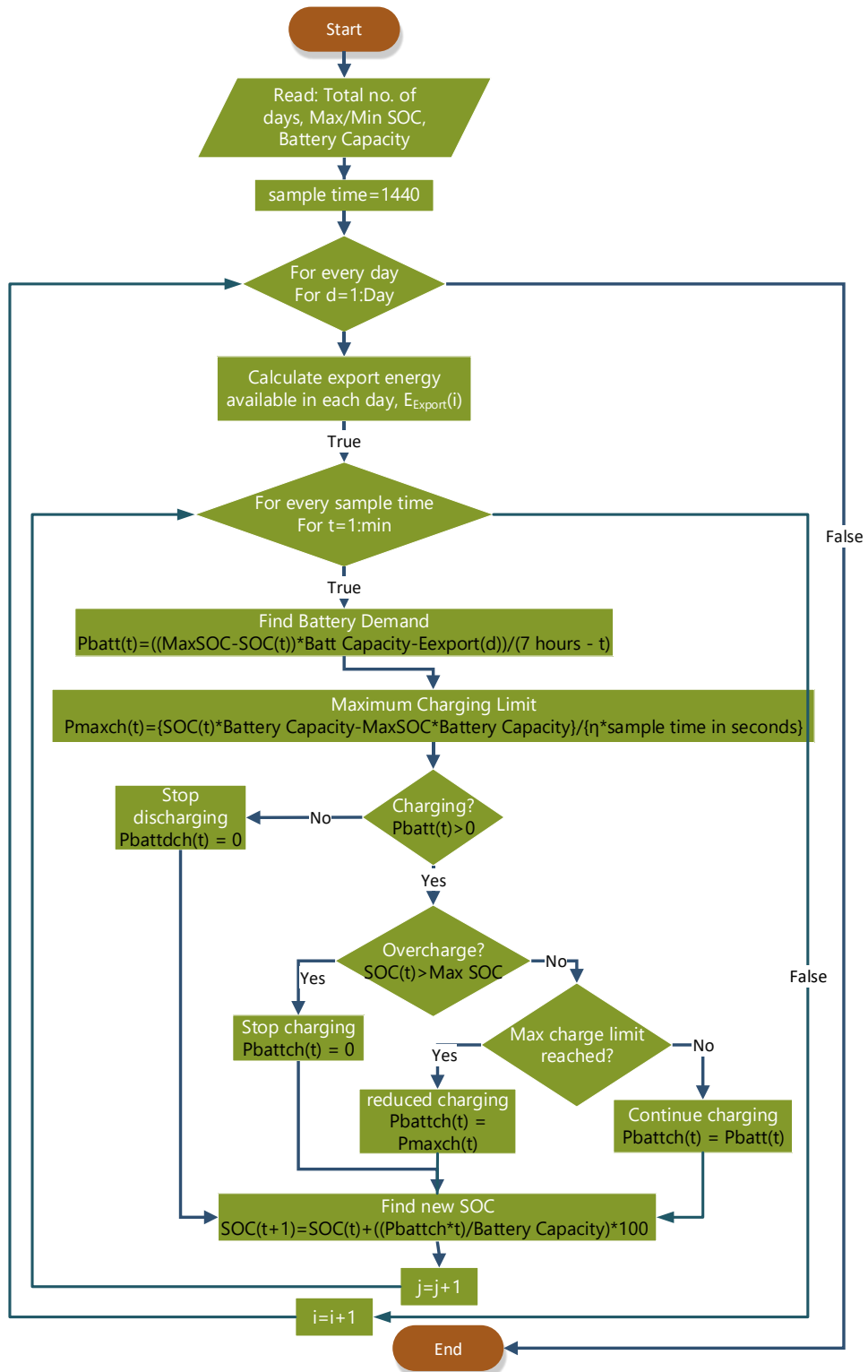


Fig 4.6: Flowchart of battery power flow during low tariff period

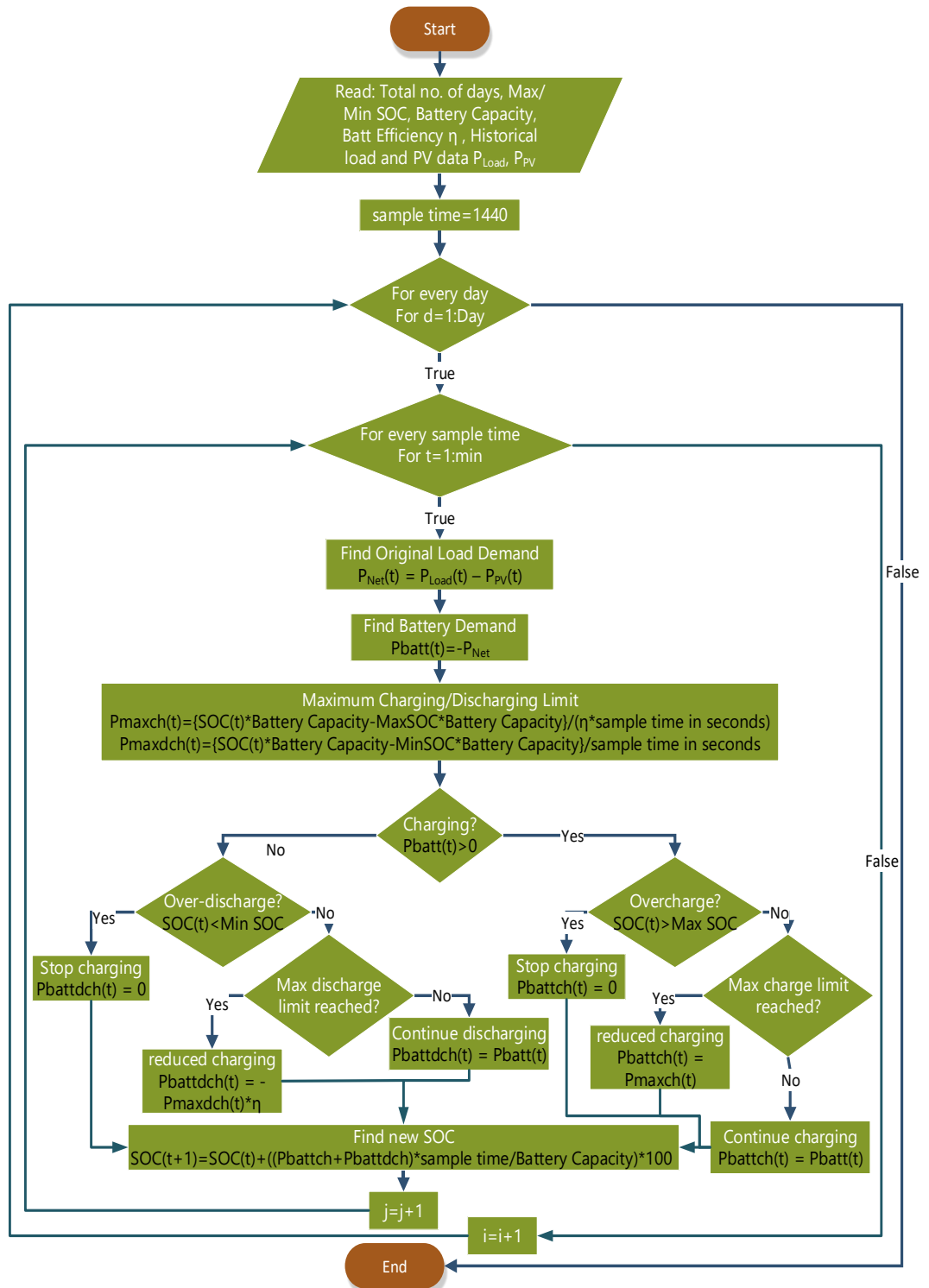


Fig 4.7: Flowchart of battery power flow during peak tariff period

It should be noted that a 30% initial SOC is considered for the first minute of each simulation considering that lithium-ion cells can be damaged if they are kept completely drained at the beginning of the battery life and neither

Table 4.3: Inputs and Assumptions for Energy Management Algorithm

Inputs	Assumptions
1. Load Profile in W per unit time, $P_{Load,t}$ 2. PV Generation Profile in W per unit time, $P_{PV,t}$ 3. Battery Capacity in Wh 4. Instantaneous battery SOC_t 5. Converter Rating in W 6. Battery Efficiency 7. Equation for variable Converter efficiency 8. TIDE Tariff Model 9. Number of days for which to run the algorithm	1. Battery efficiency is fixed at 90% 2. Battery degradation is not considered. 3. Converter efficiency collected from experimental literature work, given in equation 4.1 to 4.4 4. Perfect prediction of Generation and Consumption considered for sizing the battery and converter, and setting battery SOC at end of off-peak period. 5. Initial SOC of battery for the year is considered as 30%

must the SOC exceed 30% of rated capacity for standalone lithium-ion batteries during transportation, according to UN 3480 packaging instruction 965 (PI965). [111] [112].

The simulation models output the community energy usage with and without the battery employment, particularly the grid import energy for the low, mid and high tariff consumption including the import cost in each of tariff. The energy used for charging or discharging the battery during different tariff regions can also be calculated including the losses incurred due to a non-ideal battery and converter efficiency during the charge/discharge process. The exported energy over the total duration for which the algorithm runs is also

displayed. The effect of both the battery and converter efficiencies are considered within the algorithm, whereby energy into the battery is divided by converter efficiency η while charging and the energy coming out of battery is multiplied by η to account for discharging losses of the converter. The battery size and converter efficiencies are discussed further in the next sections.

4.3 Battery Sizing Methodology

The battery sizing methodology is based on the results of using the above-described battery energy management algorithm in specific simulation studies. The simulation using the energy management algorithm determines the amount of energy imported by households/communities in each tariff band and calculates the total import energy cost based on TIDE tariff for different battery sizes over a period of one year using (4.19).

$$\begin{aligned}
 \text{Total Cost Saving}_k &= [(T1 \times L1) + (T2 \times L2) + (T3 \times L3)]_{\text{without battery}} \\
 &\quad - [(T1 \times L1) + (T2 \times L2) + (T3 \times L3)]_{\text{with battery } k}
 \end{aligned}
 \tag{4.19}$$

Where T1, T2, and T3 are the Low, Medium and High TIDE tariffs respectively and L1, L2 and L3 are the load consumption during the low, medium and high tariff bands over a one year period, respectively. It is assumed that there is no specific revenue from export (i.e. it is negligible). The annual import cost saving is plotted for different battery sizes, assuming infinite

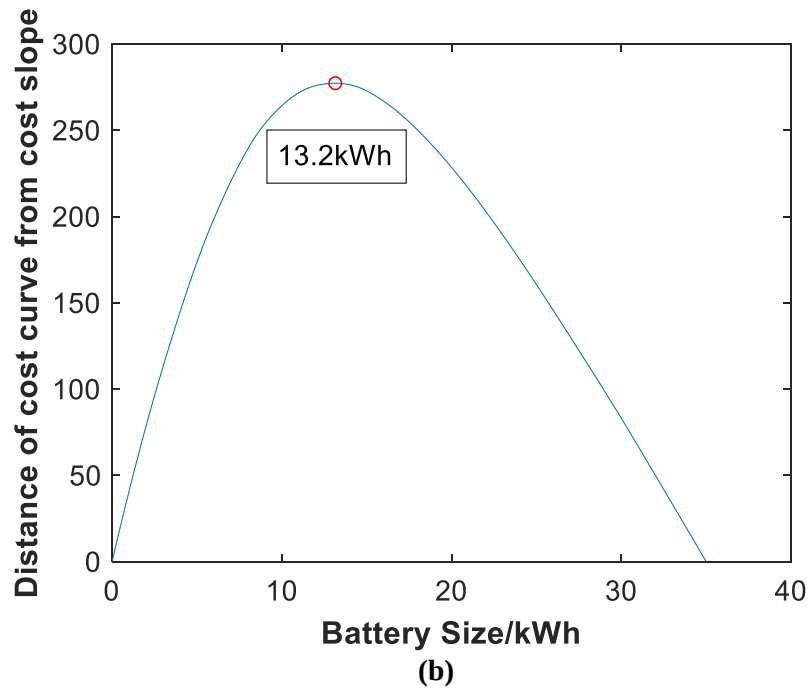
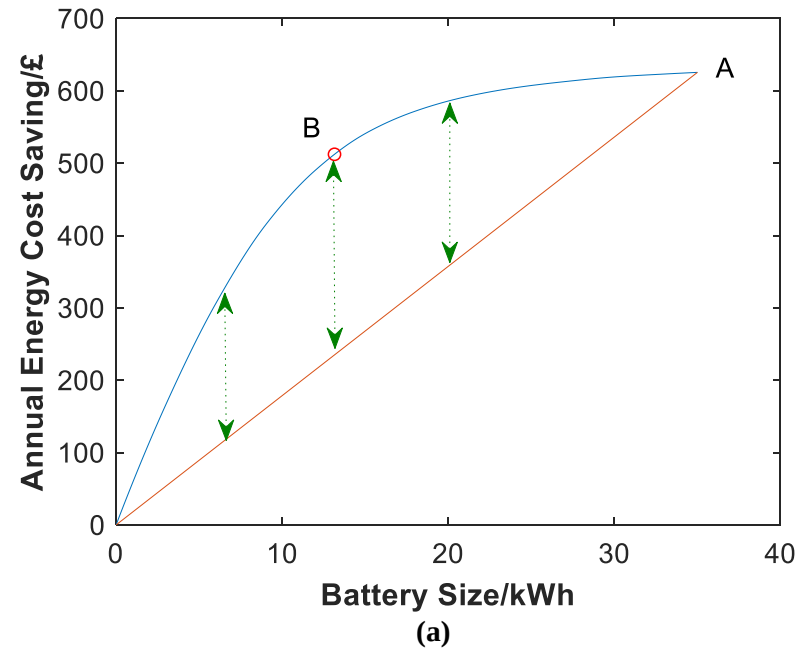


Figure 4.8: a) Plot of annual import energy cost saving against battery sizes in kWh, showing the knee-point b) Curve showing distance of points on cost curve from straight line in order to identify Knee-point

converter rating, to derive the optimum battery size for import energy cost saving. Figure 4.8a shows the annual import cost saving versus battery size curve for the Corsham community.

A typical plot of annual community import energy cost savings against battery size is a curve which eventually plateaus at point 'A'. This point defines the battery size beyond which any further increase in battery size will not result in further import cost reduction. Since the primary objective of the battery algorithm is to remove all grid import from the high tariff band, the battery size at point 'A' corresponds to meeting all the peak period demand for all the days of the year, even the maximum peak period demand. This is likely to be a day in winter with higher load demand due to increased lighting, heating etc. and limited PV generation. However this battery would incur the largest capital cost and will be oversized for most other months of the year, especially summer when PV generation is plentiful, and the load demand is relatively lower due to long daylight hours. An optimum point on the curve is therefore to be located which gives a solution to the bi-criteria problem of the two conflicting objectives of 1) increasing community import cost savings through battery discharge and 2) reducing the size/cost of the battery. Reducing the cost of battery, in turn, relates directly to reducing the battery size.

In this work, the optimum point in the curve is identified as the point after which an unfavourably large sacrifice in one objective is incurred in order to gain a small amount of additional benefit in the other objective, namely a knee-point [113]. Different multi-objective research has suggested ways to derive the knee-point [113] [114]. In [115], a general approach to knee-detection is proposed for discrete data sets, which is applicable to a wide range of systems and mathematically defines the knee-point as the maximum point of the curvature of a continuous function where the standard closed form curvature

$K_f(x)$ is defined by the following equation in terms of its first and second derivative given by (4.20).

$$K_f(x) = \frac{\ddot{x}}{(1+\dot{x}^2)^{1.5}} \quad [4.20]$$

The knee point of the cost saving against battery size curve is the point after which a large increase in battery size is required to obtain a small increase in import cost saving. In this work, the optimum point is chosen to be denoted by the ‘knee’ at point B and not the maximum derivative point since the maximum derivative point indicates the highest rate of cost-saving increase, which does not necessarily indicate the optimum battery cost. The cost-savings continue to increase significantly beyond the maximum derivative point until the knee point, which occurs when the curve becomes more flat, indicating a decrease in curvature. It should also be noted that this analysis is done using infinite converter rating, therefore in reality, for smaller battery sizes, the cost-saving curve will have a more gradual slope than that which is shown in figure 4.8a since the actual power converter limits will be more constraining for smaller battery sizes than larger ones, and fixed costs would become significant at this range causing diminishing cost benefits. There would also be a reduction in the recovered energy, and therefore cost savings, in figure 4.8a if the converter were to be sized according to the battery capacity.

In figure 4.8, the knee is denoted by the red circle point B which has the furthest vertical distance from the straight line joining the extreme points of the cost curve (denote this straight line as the “cost slope”) and shows the point of maximum curvature in the data set which in turn can indicate the best trade-off relation between the battery size and import cost savings. This point also

denotes the battery size which would give the highest additional benefits per kWh compared to the battery size which has the maximum annual cost saving at point 'A', and beyond which no further benefit to cost reduction is added with increasing battery size. The cost slope indicates the cost of battery, the vertical distance from the cost slope to the cost-saving curve indicates the difference between revenue and the cost of the battery. Since we want to maximize profit, which is the difference between revenue and cost, we seek to achieve the point which gives the biggest vertical distance.

For the EmPower dataset, one week of load and PV data gathered for each of the 9 months. The remaining days of the year are extrapolated, i.e. the missing months of May are reflected by April, June is reflected by July and May is reflected as an average of April and June. Drawing the annual import cost curve from this dataset and calculating the maximum vertical distance from the curve to the cost slope, with the help of a MATLAB script, gives a knee point at 13.2 kWh as the optimum battery size, as shown in figure 4.8a. Figure 4.8b shows how the distance between the points in the cost curve to the **cost slope** vary along the battery sizes, and that the maximum distance occurs at battery size 13.2 kWh. Since batteries come in fixed sizes in the market, this number is rounded to the nearest integer for simplicity. The Empower community will therefore operate with a 13 kWh battery centrally for all its properties for the most optimum energy and cost saving.

Once the optimum battery size has been identified using the knee-point over a known data set of one complete year, a general rule of thumb is to be formulated which can identify the days in the year most representative, in terms

of load, of the optimum battery size. In other words, looking at the load demand in kWh at certain days of the year, an estimation can be made about the optimum battery size, without having to calculate the import costs and knee points. This analysis will be described in chapter 5 while evaluating additional communities whose complete annual data has been available for analysis in the work.

4.4 Power Converter Sizing Methodology

An important parameter for the battery management system is an appropriately sized power converter to interface the battery with the grid side, as described earlier in section 4.2.5. In this section, the methodology for sizing a power converter for households and communities will be described through the EmPower Community data and results for the best converter size for this community will be presented.

In this work, the method to obtain the most appropriate power converter relies on analysing the payback period of the installed battery and converter system through its resulting energy cost savings. The CPF battery algorithm is run with different power limits and the associated efficiency of the power converters which are functions of the power going in and/or out of the converter. The efficiency curves for power converters result in increasingly poor efficiency as load power decreases from the rated power, as seen from section 4.2.5 and figure 4.4. As a result, a large converter will give high losses if the system operates in power levels considerably lower than the rated power of the converter. The minimum rating of the converter, on the other hand, can be determined by the amount of charging required in the early morning off-peak

period since the algorithm is designed to maximize battery charging during this period. In the absence of PV energy throughout the day, and considering battery SOC limits, 80% of the battery capacity would need to be charged throughout the 7 overnight hours. This gives equation (4.21) to determine the power converter minimum rating.

$$\text{Minimum } P_{conv} = \frac{\text{Usable Battery Capacity}}{7 \text{ hours}} \quad [4.21]$$

For the EmPower community, energy savings achieved by the battery-converter system over one year (comprising the complete months of August, October and December and one complete week replicated to 4 weeks for every month except April, May and June, which are replicated as March, average of March and July, and July respectively) are plotted for a range of power converter sizes until the maximum power instance of the system.

The payback period of the system, where the converter size is the only variable, is calculated based on the energy cost savings and the battery and converter capital costs. The cost of the battery is considered based on the price of the 13.5 kWh Tesla Powerwall II battery, the different components of which are presented in Table 4.4. A linear relationship is considered for the price per unit of battery kWh which was then used to derive the cost for the optimum battery size for the EmPower community. These values are also presented in Table 4.4. The unit cost of power converters is assumed to be £157/kW, based on an average drawn from available converters from Fronius and SMA in the market. The details of this calculation can be found in Appendix B. The calculation of payback period in years for each converter size is given by equation 4.22, where the battery size is fixed for each community or dwelling,

$$\textit{Payback Period} = \frac{(\text{Battery Size} \times \text{£}566.19) + (\text{Converter Size} \times \text{£}157)}{\text{Annual Saving on Energy (£)}} \quad [4.22]$$

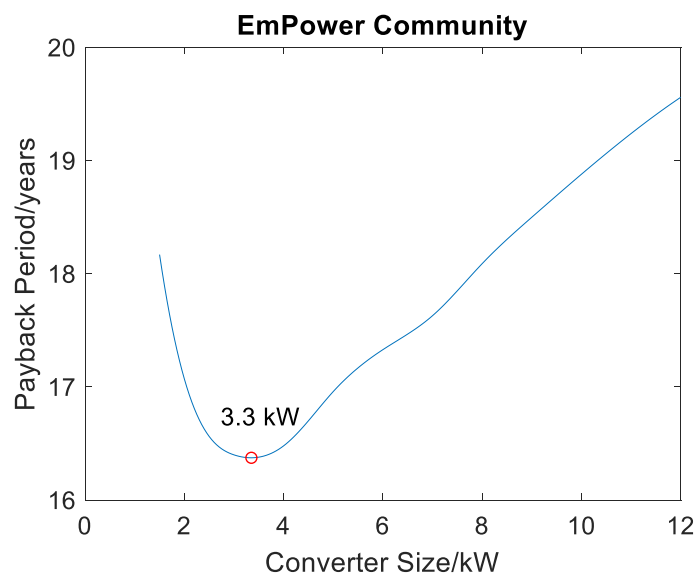
The results of equation 4.22 are presented in table 4.5 and figure 4.8 in order to derive the minimum payback period for the capital cost of the converter

Table 4.4: Battery cost calculation based on Tesla Powerwall II

Type	Battery Size	Cost (£)	
Tesla Powerwall II	13.5 kWh	Component	Cost
		Battery kit	4773
		Labour	160
		Bits	75
		Sales fee	300
		OHP	1061.6
		Vat @ 20%	1273.92
		Total	£7,643.52
Unit	£566.19		
EmPower	13 kWh	£7,360.43	

Table 4.5: Payback period for different converter sizes for Corsham community while installed with their respective optimum battery capacity of 13 kWh

EmPower Converter Size kW	Annual Saving £ on Energy	Battery +Converter cost Payback Period
1.5	418.00	18.17
2	449.7	17.07
3	477.50	16.40
4	484.80	16.48
5	480.30	16.96
6	479.00	17.33
7	479.80	17.63
8	476.40	18.09
9	474.30	18.50
10	473.1	18.88
12	472.5	19.56

**Figure 4.9: Plot of payback period for different converter sizes for Corsham community while installed with the optimum battery capacity of 13 kWh.**

and the battery system through energy savings achieved by the CPF BMS algorithm. It can be seen that the converter size with the lowest payback period for the EmPower community is 3.3 kW. In reality, power converters come in fixed sizes and therefore in this analysis, the minimum payback converter value will be floored to nearest integer kW rating at 3 kW. This value is also higher than the minimum converter power rating suggested by [4.21] for a 13 kWh battery, and therefore will be able to fill the entirety of the usable capacity of the battery during the 7 hours of early morning charging.

A 3 kW rated power converter will be used in the remainder of the chapter to derive energy saving calculations and comparisons. However, it should be noted from the table in 4.5 that the payback period for the power ratings of 3/4/5 kW has no significant difference amongst each other resulting in very less increment in payback period despite increased converter rating and capital cost. This suggests that it can be beneficial for communities to invest in the converters with higher power rating, which would allow future expansions of both PV and additional participants, without drastically increasing the payback period, as well as have the flexibility to incorporate different tariff scenarios which may become available in the future. It should also be noted that for better and more accurate results, at least one complete annual data set of community load and PV generation should be available, unlike the broken EmPower data set. The total and percentage capability lost over the year for both charging and discharging for the EmPower community, if the lowest payback period converter rating is used instead of a converter limit which accommodates the whole range of charging and discharging power, is derived

Table 4.6: Comparison of charging and discharging capability lost due to smaller converter cut-off power limit in relation to a converter which encompasses the entire charging and discharging power range (Includes losses due to converter efficiency, for both small and large converter).

	EmPower Community	
Battery Size	13 kWh (10.4 kWh usable)	
Power Limit	13k	3k
Charging energy lost (kWh)	197.0	160.7
Charging energy lost (%)	6.2	5.1
Discharging Energy lost (kWh)	221.4	490.7
Discharging Energy lost (%)	6.6	14.7

for the different battery capacities and shown in Table 4.6. The reduced power converter limit for the EmPower community is 3 kW while the converter limit which accommodates the whole range of charging and discharging power for EmPower community is 13 kW.

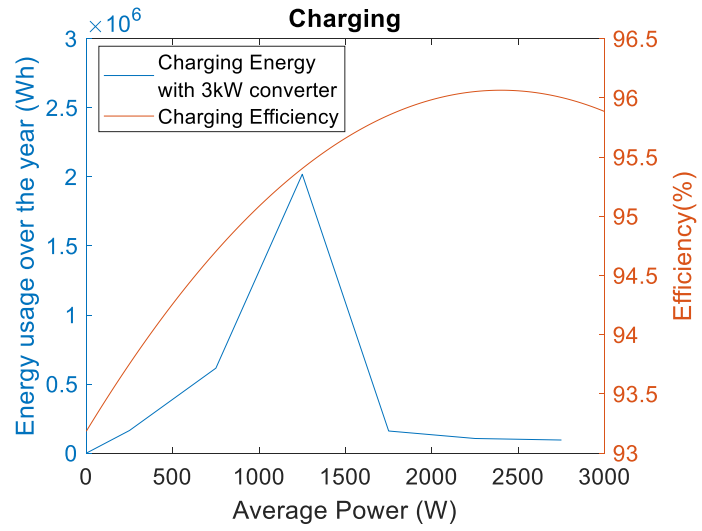
The presented converter losses incorporate lost capability due to truncated power exchange as a result of the converter maximum limit as well as the efficiency losses which vary according to the converter rating and their input power. Note that a larger power converter operates at a lower efficiency when operating well below rated power. It should also be re-emphasized that the battery efficiency is considered to be constant at 90% round-trip for all the systems as mentioned previously. This is due to the rapidly developing and changing battery technologies which have not stabilised enough to include specific details within their models. Any change in loss incurred for the considered scenarios are therefore affected only by converter sizing and their efficiency variation alone.

For the community of Corsham, the discharging losses are higher for the smaller 3 kW converter which incorporates both the power capability lost due to maximum the cut-off limit as well as converter efficiency. The larger 13 kW

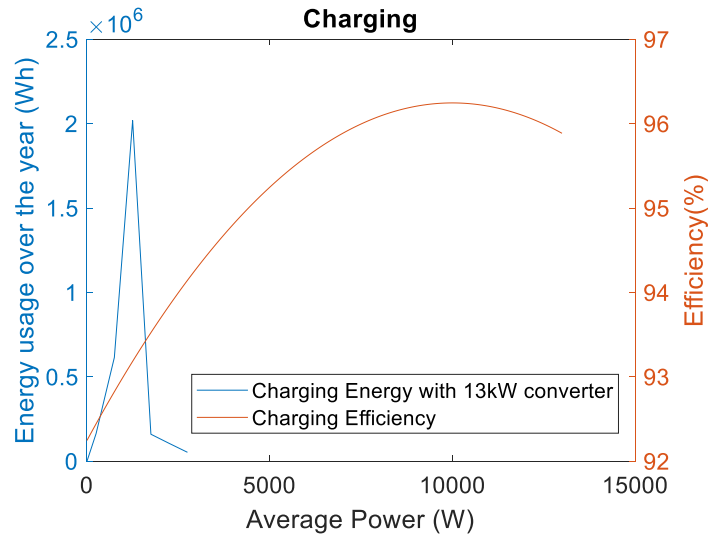
converter losses only incorporate the efficiency losses as its large value does not have any limiting effect on the power flow. It can be seen that the total increment of losses resulting from an imposed converter limit of 3 kW, including the converter efficiency losses are below 10% for discharging scenarios with a loss increment of 8.1% for discharging with the 13 kWh (10.4 kWh usable) battery going from 13 kW to 3 kW due to the unmet peak power. The loss increment therefore seems to be reasonable to justify the converter size chosen by the lowest payback converter rating.

On the other hand, the percentage energy lost from total charging instances are in fact higher for the 13 kW converter than the 3 kW converter, although the larger converter allows more peak charging. This is due to the load having higher power demand than the grid and PV charging, as well as the fact that charging at power levels significantly lower than the rated power results in poor efficiency for the converter. Figure 4.10 gives a clear understanding of what is happening.

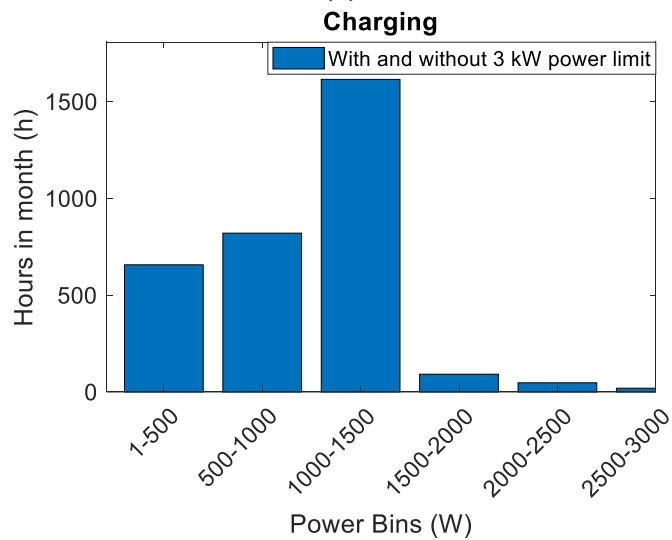
Figure 4.10a and 4.10b depicts battery charging energy demand at different power bins (denoted by the average power of each bin) over a year. From both the figures, it can be seen that the charging power demand for the Corsham community peaks at about 1.3 kW and the maximum charging power is around 2.5 kW. This ties in well with a 3 kW converter such that at 1.3 kW, the efficiency of the converter is still considerably close to its peak efficiency. As seen from 4.10a. On the other hand, looking at the 13 kW converter efficiency in figure 4.10b, it is evident that the efficiency of the converter given by the red trace is much lower when most of the power exchange is taking place



(a)



(b)



(c)

Figure 4.10: Charging energy used by battery against average operating power, overlaid with 3 kW converter efficiency curve for (a), and 13 kW converter efficiency curve for (b), and hours of operation at each power bin with and without 3 kW converter rating (c) for a 13 kWh battery.

for the battery charging. Due to this low efficiency, the charging energy lost is higher for a 13 kW converter compared to 3 kW converter. It should also be noted that the peak charging power over the year for the Corsham community is 3 kW. As a result, no peak charging power is being truncated due to the imposition of the smaller converter. The 13 kW converter therefore only serves to accommodate peak discharge power of the system. 4.10c shows the hours of operation at each power bin for the charging of the Corsham battery which is the same with and without any imposed power limit.

A further analysis can suggest that using a converter power limit on the battery input and output allows more efficient use of the energy transfer due to the shape of the efficiency curve of the power converter. Converters operate at maximum efficiency closest to their rated power, therefore if the converter is rated for the maximum battery discharge power as shown in figure 4.11b, it would have operated at maximum efficiency for only a few hours a year. This can be seen from the blue bars in figure 4.11c which depicts the hours of operation at each power bin for the discharge of the Corsham battery without any imposed power limit. The blue bars on the higher power end show negligible hours of operation for the battery at those higher power levels.

On the other hand, if the discharge power is capped as described previously, the hours of operation at the maximum efficiency point increases significantly, as can be seen from figure 4.11b and the pink bars of 4.11c. This allows running the converter close to its maximum efficiency for a significant number of hours throughout a year and thereby reduces conversion losses in comparison to using converters which allow the full range of discharge power.

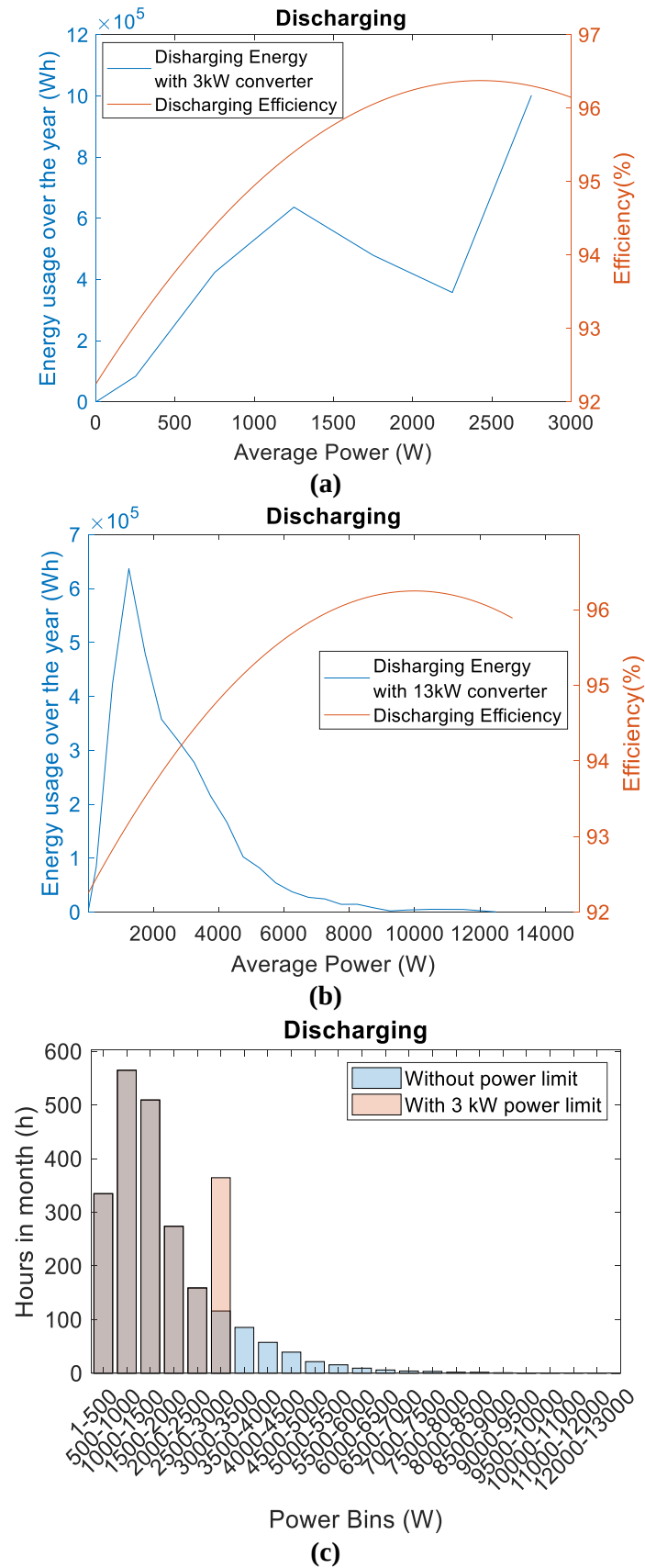


Figure 4.11: Discharging energy used by battery against average operating power, overlaid with 3 kW converter efficiency curve for (a), and 13 kW converter efficiency curve for (b), and hours of operation at each power bin with and without 3 kW converter rating (c), for a 13 kWh battery

A further detailed analysis has been made in order to see the financial benefits of using a reduced power converter limit for lowest payback period as opposed to using a converter limit which accommodates the whole range of charging and discharging power. The difference in energy discharged by employing the smaller power converter – and therefore the unachieved reduction in grid import, during mid and high tariff bands – is calculated. This is achieved by running the CPF algorithm for the 9 properties of the Corhsam community, and recording the total energies discharged per converter size. Calculations then give energy and monetary losses incurred due to a smaller converter size, shown in table 4.8.

In the worst-case scenario, the lost discharge capability due to the converter limit would have been imported during the low tariff band resulting in lower import cost. The price difference in import electricity purchase within the TIDE tariff scheme is calculated between the mid and low tariff band, as well as between the high and low tariff band, as shown in table 4.7. This is then multiplied with the lost energies from the respective tariff bands to find the increase in import cost due to a smaller converter employment. Equation (4.23) shows how to calculate the increase in import cost when the smaller power converter rating, given by the lowest payback period is used instead of a larger power converter which is rated by the highest power in or out of battery.

$$\begin{aligned} & \text{Total increase in import cost if smaller converter used} = \\ & (HT - LT) * (E_{HT1} - E_{HT2}) + (MT - LT) * (E_{MT1} - E_{MT2}) \end{aligned} \quad [4.23]$$

In (4.23), HT, MT, and LT are the electricity import cost in p/kWh for high tariff band, mid tariff band and low tariff band respectively for the TIDE tariff scheme. E_{HT1} and E_{HT2} are the energy discharged by the battery in the high tariff band for a larger power converter rating (defined by the highest power in or out of the battery) and a smaller power converter rating (given by the lowest payback period) respectively. E_{MT1} and E_{MT2} are the energy discharged by the battery in the mid tariff band for a larger power converter and a smaller power converter rating respectively. Table 4.7 lists the various import price differences and Table 4.8 shows the differences in energy discharged by the 13 kWh battery in different tariff bands for a larger and smaller power converter rating along with calculations of cost-benefit achieved by using reduced converter size for the Corsham community. The negative value for the reduction in battery discharge energy during mid tariff band for the Corsham community signifies

Table 4.7: Differences in import prices between tariff bands in TIDE scheme

TIDE tariff Bands	Import Price (£/kWh)
High and Low tariff difference (HT-LT)	0.24
Mid and Low tariff difference (MT-LT)	0.08

Table 4.8: Analysis of cost saving achieved by using reduced converter size given by lowest payback converter size instead of converter size which can accommodate maximum battery power.

	EmPower Community 13 kWh Batt.
Maximum battery power rating (kW), Converter-1	13
Lowest Payback converter rating (kW), Converter-2	3
Reduction in battery discharge energy during High Tariff Band (kWh), $E_{HT1} - E_{HT2}$	138.20
Reduction in battery discharge energy during Mid Tariff Band (kWh), $E_{MT1} - E_{MT2}$	-114.3
Total increase in import cost if smaller conv. used (£/year)	£23.89
Total reduction in capital cost if smaller converter used (£)	£1,570
Payback years	66

that discharge during mid tariff band actually increased for a smaller converter. This has resulted due to the second mid tariff band in the TIDE tariff scheme appearing after the peak period is complete, where any remaining energy within the battery is emptied to reach the minimum battery SOC at the end of the day. For a lower converter size, the energy remaining within the battery at the end of the peak period is higher since less energy is discharged during the peak period compared to a converter with a higher maximum rating.

The total increase in import cost due to using a smaller converter is compared with the purchase cost saved by using the smaller converter as opposed to the larger converter. The purchase cost is calculated per kW, where the cost of power converters is assumed to be £157/kW, based on an average drawn from available converters from Fronius and SMA in the market, the details of which can be found in Appendix B, as mentioned earlier in the chapter. A payback period is calculated for using a larger converter instead of a smaller converter, by taking the capital cost saving over the reduced economic benefit of battery operation. A large payback period signifies that using a larger converter rating will take a long time to pay off the additional purchase cost using the economic benefit from reduced peak-period import, whereas a shorter payback period means that the additional peak period savings using a larger converter is substantial enough to pay for the additional purchase cost over a short period of time.

The payback period for the Corsham community is calculated to be 66 years (see Table 4.8), which is a large time period, since the overall life of the batteries tend to be much shorter than the calculated value (e.g. Tesla Powerwall

2 warranty has a capacity retention of 80% after 10 years and an operating limit of 37.8 MWh of aggregate throughput which is approximately 8-9 years of operation if cycled once daily) [116].

To put this into perspective, sizing up the converter to 13 kW incurs an additional £1,570 which more than offsets the gain of allowing a slightly bigger discharge from the battery and saving only an additional £24 over the year. It can therefore be concluded that using a 3 kW converter instead of a large converter that accommodates the whole range of charging and discharging demand for the EmPower battery is justifiable.

4.5 Effects of Application of Designed CPF Battery Algorithm onto the Community of Project EmPower

The original load and PV generation data obtained from the properties in the Corsham trial have been isolated in order to test with the battery algorithm designed in this work. Since the work in this thesis does not incorporate DSM, comparisons are made only for the effect of energy management through battery deployment.

One complete month of data from three different seasons gathered from 8 properties in Corsham used in the EmPower project are extracted to ensure continuity of the minute-wise data throughout the month. These data sets were analysed to compare and contrast the battery energy management algorithm developed in this work against the issues seen from the results in chapter 3 which employed the EmPower battery management algorithm.

It was also possible to extract data for four properties in the community over one complete week for nine different months throughout the project trial.

This allowed the evaluation of the battery management algorithm and sizing methodology designed in this work using real community data. The missing data from Corsham trial (April, May, June, and the three remaining weeks of all other months) were approximated from the 9 weeks of available data to make a whole year in order to complete the evaluation.

The monthly data completed by assuming that the savings on the three unknown weeks of the month were the same as that of the known week. The savings of April were assumed to equal that of March (both falling close to spring equinox), and the data of June was deemed the same as June (summer pattern). The saving for May was considered to be an average of that of April and June. The following sections address both this analysis and the comparison between the two sets of energy management schemes. The battery capacity for each of the analysis is considered to be 13 kWh for the CPF-BMS, with a 3 kW converter.

4.5.1 Results to illustrate superior performance of CPF based battery management system, over EmPower EmPower Battery Management System

In chapter 3, a few examples were presented for poor battery performance in terms of charging and discharging patterns. Taking the same data set of PV generation and load consumption as used in chapter 3, a new set of results is obtained by replacing the original EmPower BMS with the CPF BMS. For each presented figure of results, the original results from Chapter 3 are reproduced for ease of comparison.

Figure 4.12 depicts the battery charge profile (blue) over the first week in October 2015 for the EmPower community, in relation PV generation (red), and TIDE tariff levels (black) using the CPF BMS. The first and the last day in the plot are weekends which is depicted by the Import Tariff Level having only two levels, and no peak tariff. It can be seen that charging takes place during

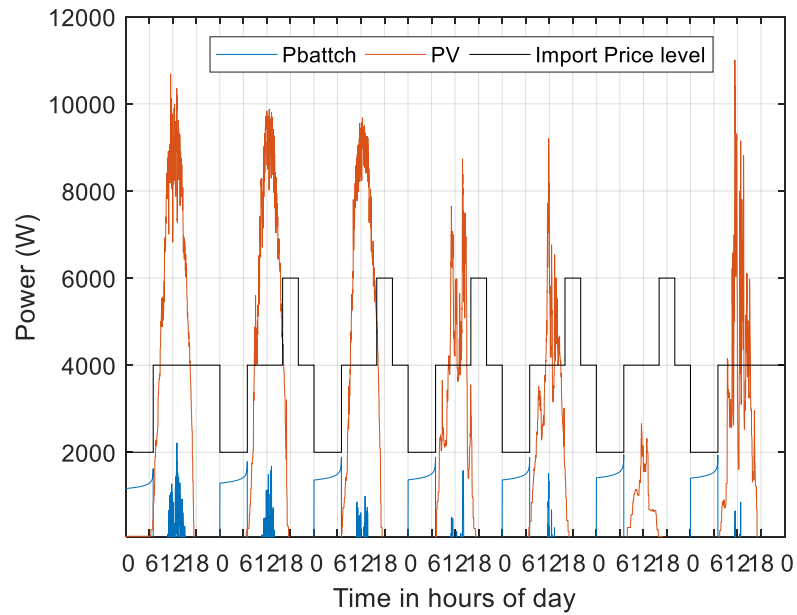


Figure 4.12: Battery charging profile in relation to net power profile, battery SOC and TIDE tariff levels, over 1st to 7th October 2015

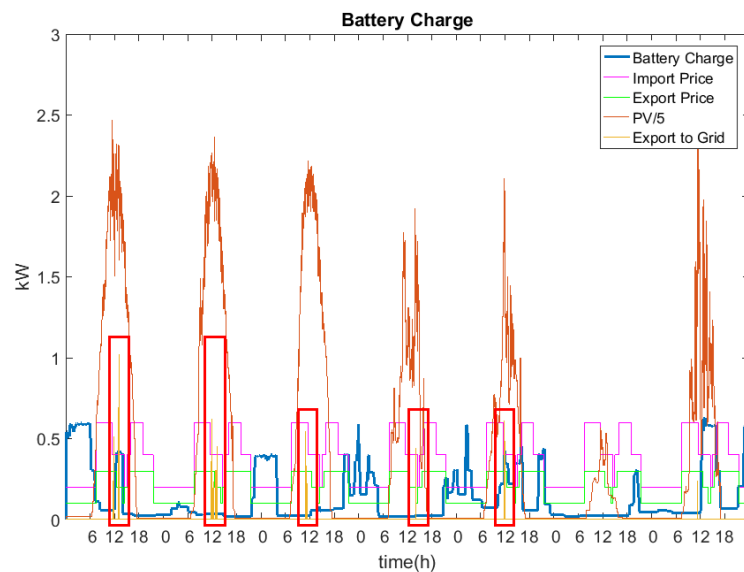


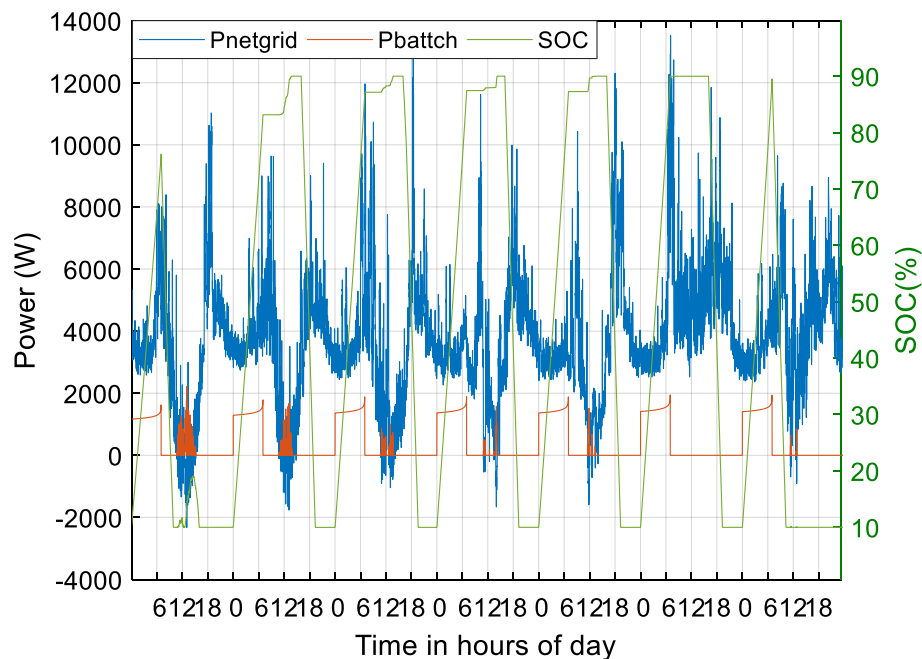
Figure 3.14 (Reproduced): Battery charging profile in relation to PV generation, grid export and tariffs, over Week-1 in October.

Table 4.9: Total export over 1st to 7th October, before and after employing CPF BMS.

Energy Management System	Export (Wh)
EmPower BMS	425
CPF BMS	0

low tariff periods and during PV availability, as opposed to the EmPower BMS (3.13) which was unable to charge the battery during PV generation resulting in unwanted exports. Table 4.9 reiterates this and shows that all the previously exported energy has now been used up to charge the battery, which will be released later during high tariff periods.

Figure 4.13 shows the battery charge profile (red) over the same week in October 2015 for the EmPower community, in relation to net grid demand (blue) and battery SOC (green) using the CPF BMS. As mentioned previously, whenever the net demand is negative, there is excess PV generation which should charge the battery unless the battery SOC is at its maximum. The profile above confirms this by depicting that charging has taken place whenever the net

**Figure 4.13: Battery charging profile in relation to net power profile and battery SOC, over 1st to 7th October 2015**

demand has become negative. If the net demand is positive, the unmet load is supported either through battery discharge (during peak tariff period) or by the grid if the battery has reached its minimum SOC.

The CPF BMS also dictates that during the early morning hours of cheap electricity tariff, the battery will charge to its maximum SOC, leaving capacity for any PV export throughout the day, irrespective of a positive net demand during those hours. From figure 4.12 and 4.13 again we can see that this is being established by the battery every day from 00:00 to 07:00 hours in the morning. In days with no export (6th day in fig. 4.12), the battery charges to the maximum 90% SOC between 00:00-07:00 hrs (6th day in fig. 4.13), while on the other days when there is excess PV generation during day-time, the morning charging is capped to a lower SOC which allows for the exports to be captured into the battery. By running the CPF battery algorithm in MATLAB and recording the charging energy at every time step 't', the total energy charged by the battery over the week is found to be **73 kWh** for a 13 kWh battery with 3 kW converter, which is more than twice the energy charged into the combined original 6 kWh 0.5 kW batteries (which comprised of three 2 kWh batteries of 0.5 kW power rating each). Separation of improvement due to increased battery capacity from improvement due to change in algorithm alone is covered later in the chapter.

It can also be noted that the batteries behave differently during weekends due to the different TIDE tariff levels offered over the weekend. There are only two tariff levels offered over the weekend with a cheap period from 00:00-07:00 hrs and a moderate tariff for the remainder of the day. The battery is designed to charge during the cheap periods and discharge for the net positive load as

soon as the cheap period is over since there is no need to store charge for peak period discharge. Details of the battery design over weekends are presented in section 5.5.2.

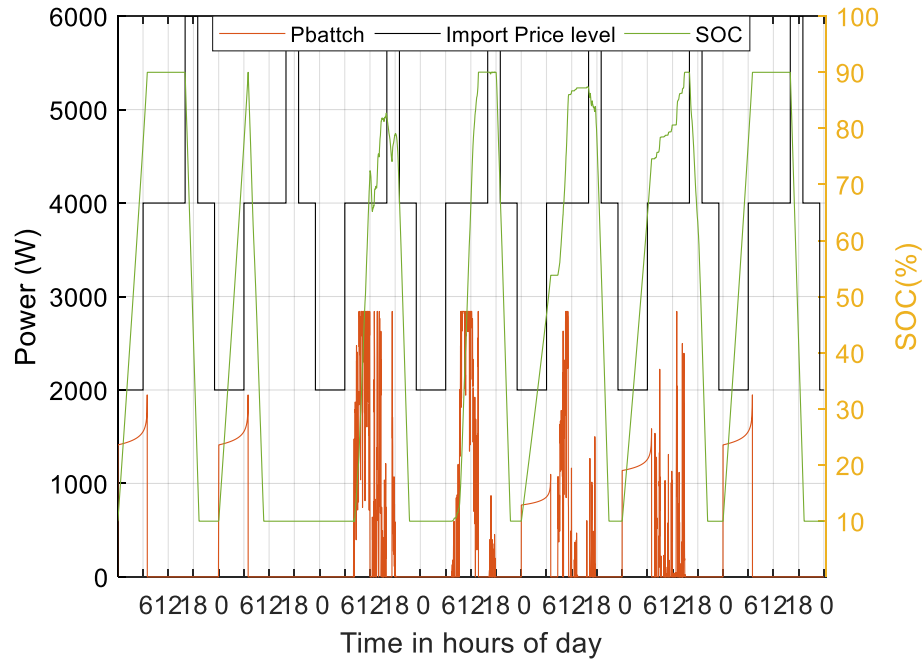


Figure 4.14: Battery charging profile in relation to net power profile, battery SOC and TIDE tariff levels, over 13th to 19th August 2015

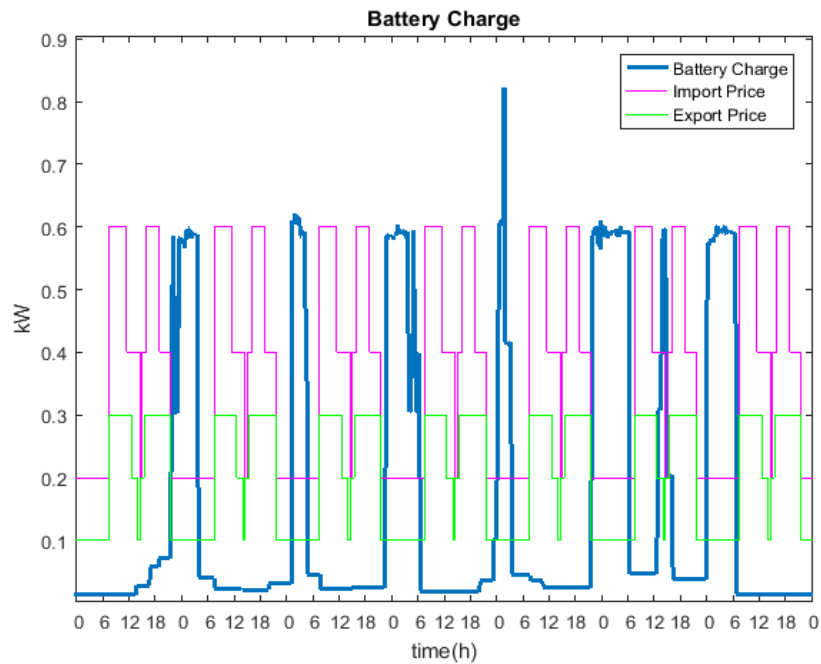


Figure 3.16 (Reproduced): Battery charge profile over 13th - 19th August.

Another set of data examined earlier in chapter 3 was the week of 13th to 19th August 2015 for the EmPower community. Results are seen in figure 4.14. The battery charges from the grid only during the low tariff hours of midnight till 7 am. On the 3rd and 4th day when excess PV generation exceeds the total storage capacity of the battery, the battery does not charge at all during the early morning hours to be able to store and make use of the free PV energy during the day: this is more cost-effective than low tariff charging. This self-consumption has resulted in the exports being reduced to nearly one-sixth from 60 kWh to 11 kWh over the week, as recorded in table 4.10.

Note that export is not completely eliminated as the battery capacity is too small to cope with the individual days. As discussed earlier, the battery sizing is a compromise between accommodating maximum PV exports versus the actual utilisation of the battery over the whole year. If the battery was sized according to accommodating the largest PV export during the summer day with the highest generation, it would sit idle through most of the remainder of the year without being utilised and therefore without coming into any reasonable cost benefits.

The battery discharge profile over the same week, given in Figure 4.15, shows that discharge begins only during the high tariff period from 4 pm to 7 pm, and continues to discharge until the battery SOC reaches its set minimum of 10%. The battery only discharges when the net demand is positive and when

Table 4.10: Total export over 13th to 19th August, before and after employing energy management scheme developed in this work.

Energy Management System	Export (kWh)
EmPower Original Battery	60
CPF-BMS	11

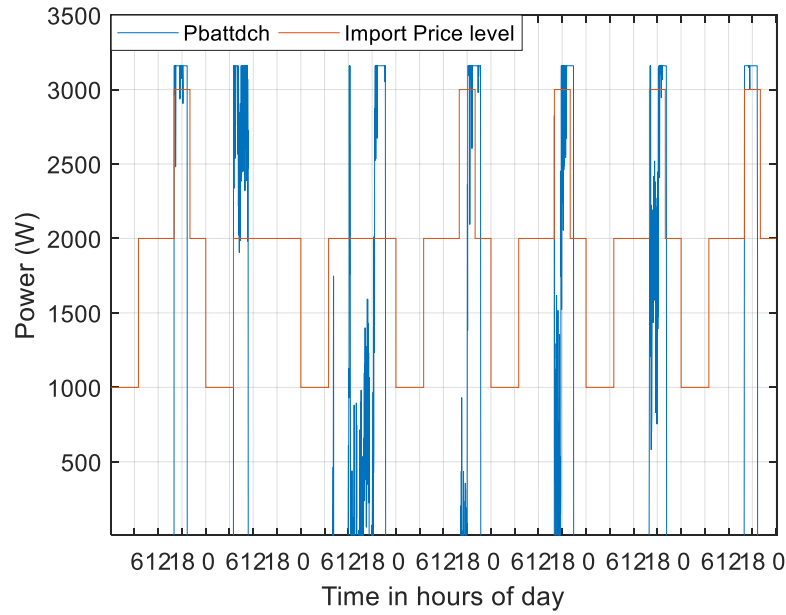


Figure 4.15: Battery discharging profile in relation to TIDE tariff levels, over 13th to 19th August 2015

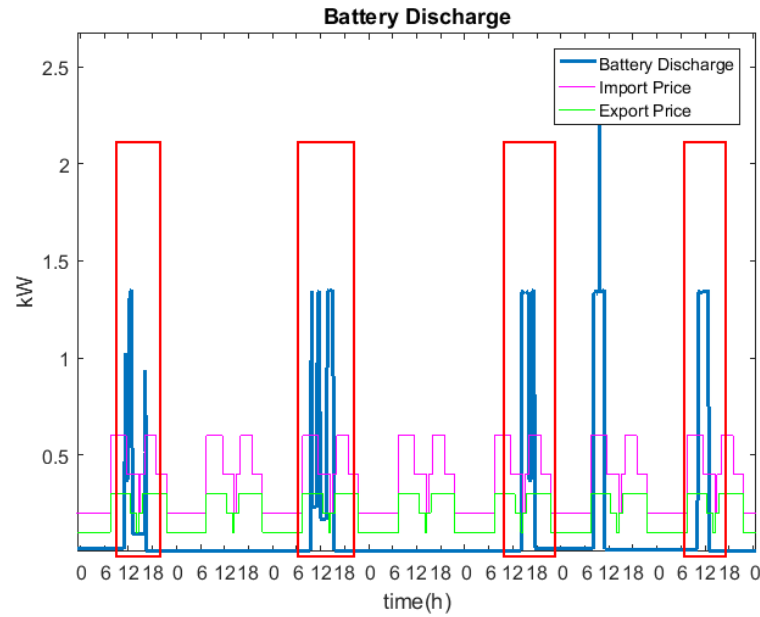


Figure 3.15 (Reproduced): Battery Discharge profile over 13th to 19th August

there is no excess PV generation. The second day in the figure is a weekend which explains why there is discharge before the 4 pm time band.

Similar profiles for the first week of December are presented in figures 4.16a and 4.16b. Since there was no PV generation throughout the month, the

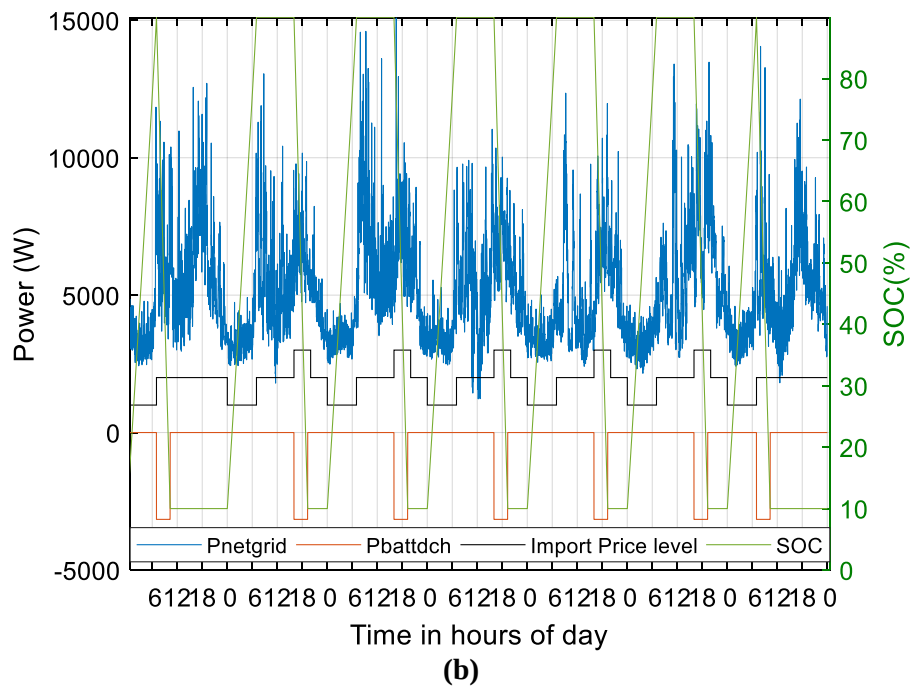
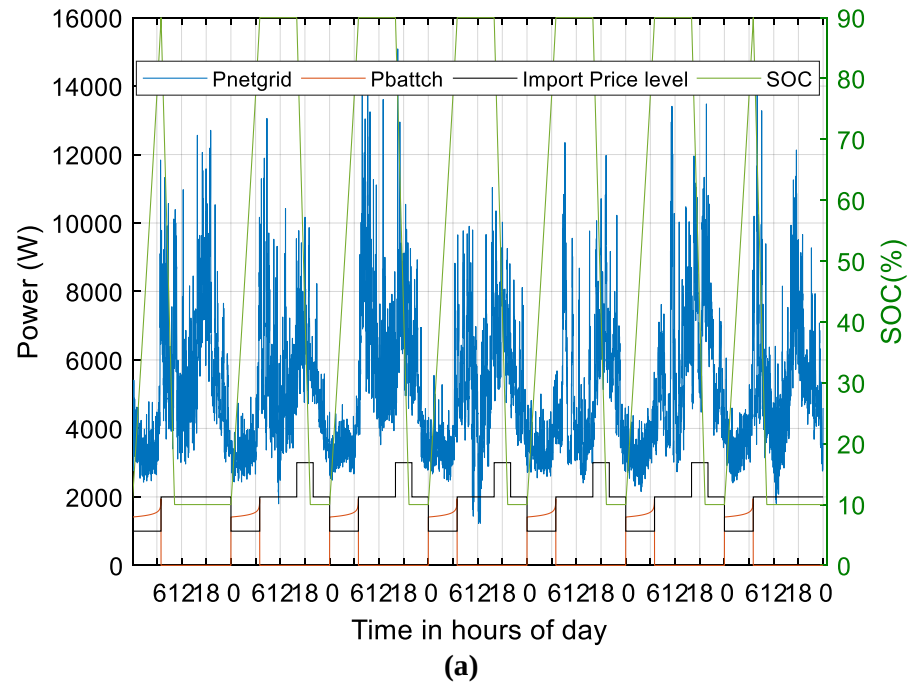


Figure 4.16: Battery charge (a) and discharge (b) profile over first week of December for Corsham community.

battery charged to maximum SOC over early morning hours and discharged all of that energy during evening peak hours to reach minimum SOC. As a result, the battery can be seen to be fully cycled once every day and therefore be well utilized over winter months.

The overall data for the complete months of August, October and December (representing summer, autumn and winter respectively) for the 8 properties of Corsham considered using the new CPF BMS can be further analysed by looking into the energy imported from the grid in each tariff period of TIDE, and contrasting with the import energy in the scenario without a battery, alongside the energy going into charging and discharging the battery in each of these periods, as shown in figure 4.17. The losses pertain to roundtrip efficiencies of the battery and converter system. It can be seen from these bar charts that no discharge takes place in the low tariff period, with most of the discharge taking place in the high tariff period. Charging primarily takes place overnight from the grid throughout the whole month for autumn and winter, however for summer charging during midday is also significant which would be on account of increased PV generation, as seen from the PV energy bars. In August alone, battery charging takes place during high tariff band due to the availability of PV in this period. Load demand during the winter month is the highest and during summer it is the lowest. The import from the grid is considerably reduced throughout all the months during the high tariff period. Since the whole battery algorithm is designed around shifting load away from the high tariff period, only the constraint of battery size and power converter limit has resulted in residual load demand from the grid during high tariff periods and export during summer months. With a significantly larger battery and converter size, all the load from high tariff region could have been removed, however, that would have resulted into operation of the battery below its optimum utilisation as well as unjustifiable cost.

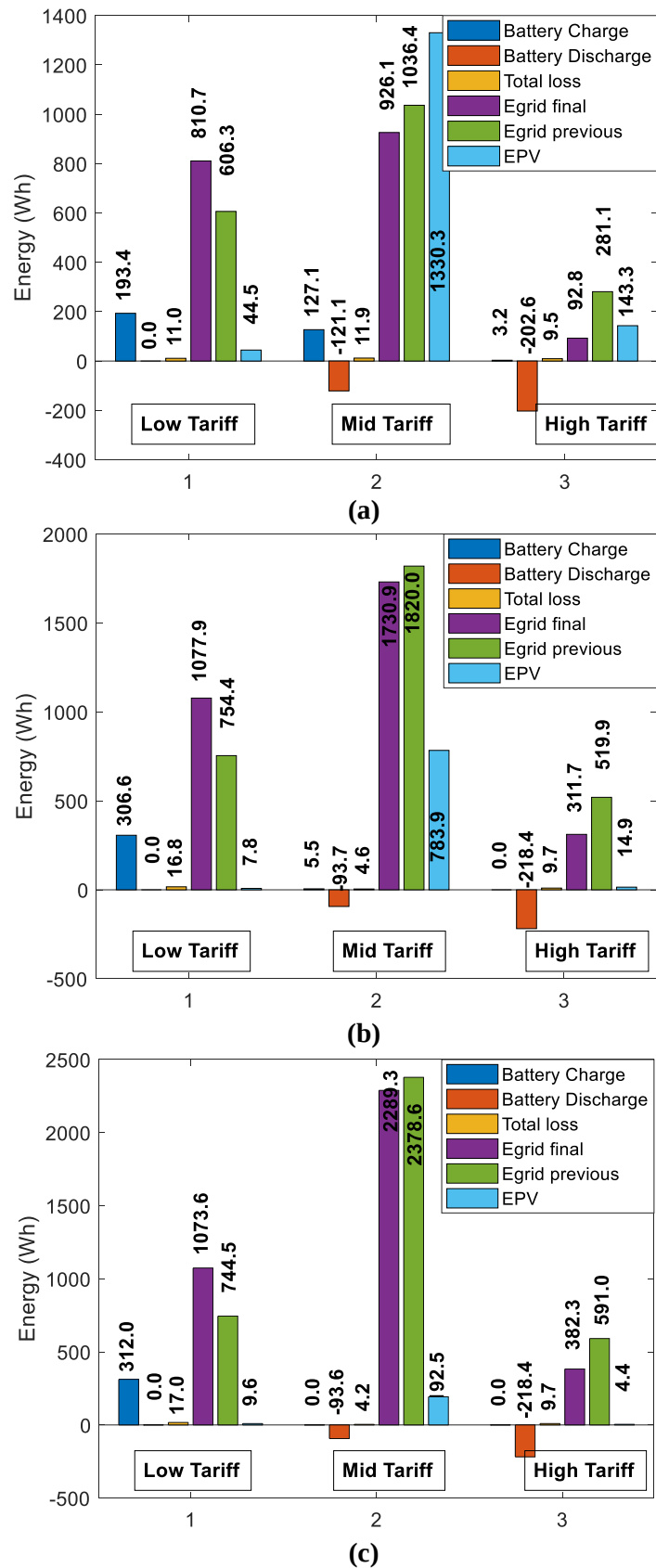


Figure 4.17: Energy imported from the grid in each tariff period of TIDE using CPF BMS (Egrid final) alongside the battery charging and discharging energy in each of these period, contrasted with the import energy in the scenario without a battery (Egrid previous), considered for the 8 properties of Corsham community for a) August b) October and c) December

The total amount of energy in kWh charged into and discharged from the battery over the three different months of August, October and December are tabulated in Table 4.11. This result can be contrasted with that of Table 3.4 in Chapter 3, reproduced here, which shows the lower efficiency of the EmPower BMS system.

The increase in self-consumption over the three months through the employment of the battery is portrayed in Table 4.12. It shows that during autumn, all the energy which would otherwise be exported without a battery is captured within the battery, while during summer about five-sixth of the original exports are used to charge up the battery for peak-time use. As a result, it can

Table 4.11: Total charge and discharge energy to and from the battery over summer, autumn and winter, in the Corsham community using CPF BMS

	Energy Charged (kWh)	Energy Discharged (kWh)	Efficiency (%)
August	337.3	304.0	90%
October	328.2	296.2	90%
December	328.1	296.2	90%

Table 3.4 (Reproduced): Monthly and annual battery energy storage in kWh for the community

	Energy Charged (kWh)	Energy Discharged (kWh)	Efficiency (%)
August	84.3	52.4	62
October	109.7	66.6	61
December	46.5	39.6	85
Yearly Extrapolation	1050.6	675.6	64

Table 4.12: PV energy exported to grid over three different months for the Corsham community with and without the designed battery.

Energy Management System	Export (kWh)		
	August	October	December
EmPower	188	6.2	0
CPF Controller	41	0	0
Community without battery	178	5.9	0

be said that energy has been successfully shifted in the day to low demand from high demand time, which eventually results in a reduction in electricity purchase cost for the property/properties.

For a closer look at what is happening to the grid energy, figure 4.18 is presented, which shows the energy imported from the grid with ($P_{gridfinal}$) and without ($P_{netgrid}$) employment of the battery, over the first three days of October for the Corsham community. It can be seen that during the peak tariff hours, the grid import reaches zero throughout the week, showing the desired performance of the battery algorithm.

For a comparison of the effectiveness of the battery algorithm alone (i.e. ignoring the derived battery and converter size from the sizing methodology), the next set of data considers a battery of 6 kWh and 0.5 kW converter in order to match the numbers with that of the three 2 kWh 0.5 kW Moixa Maslow

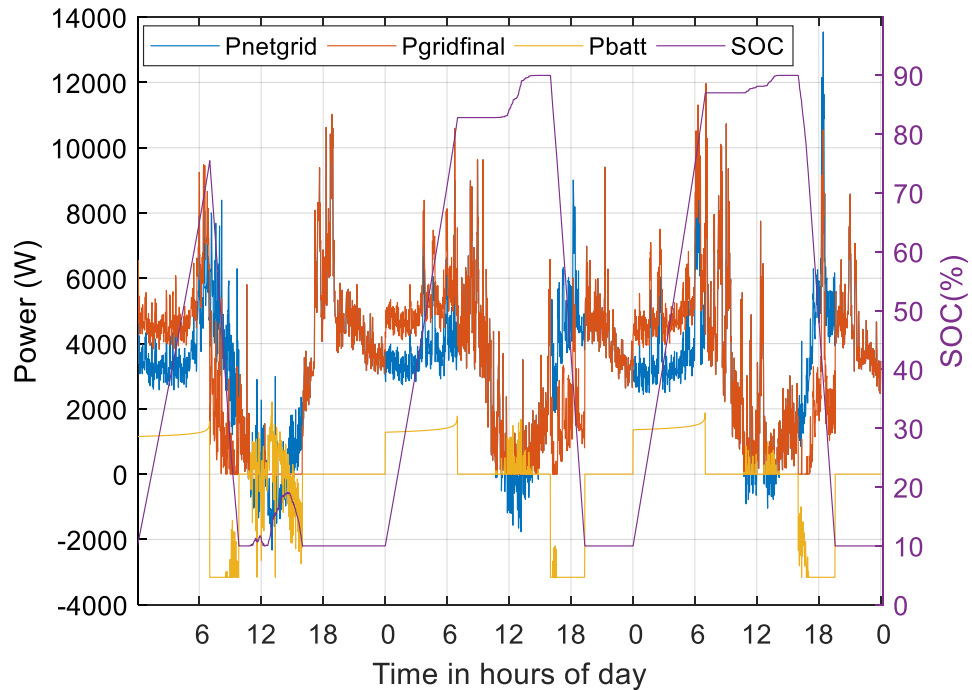


Figure 4.18: Oct 1st-3rd, 13 kWh batt, 3 kW converter

batteries within the 8 properties of the Corsham trial considered in the original tests. Table 4.13, shows the superiority of the CPF battery algorithm developed in this work in reducing overall import in summer, and shifting consumption throughout the three different months, with further reduction in import cost as a result of energy shifting throughout the day to beneficial hours, for both the 6 kWh and 13 kWh batteries.

The total import in October/December does not change much as PV is not abundant. Looking at the cost columns, it can be concluded that despite higher import energy from the EmPower BMS or no-battery scenario, the CPF algorithm has resulted in lower import costs which imply that the CPF-BMS has performed well shifting of energy from higher tariff bands to lower. For comparisons, the last column gives Import kWh and cost for the EmPower community with no energy storage systems. It can be seen that in all three of the months, the originally employed battery at EmPower in effect increases total grid import rather than reducing it compared to the case without any battery presence. As discussed in chapter 3, this was due to the battery discharging at unwanted times resulting in the energy from battery discharge being exported

Table 4.13: Import kWh and cost (£) over Aug, Oct and Dec for different battery scenarios

EmPower Community	IMPORT							
	EmPower BMS		CPF- BMS 6kWh/0.5kW		CPF-BMS 13kWh/3kW		w/o Batt	
	Wh	£	Wh	£	Wh	£	Wh	£
Aug	1966	£222	1891	£209	1830	£175	1924	£225
Oct	3136	£428	3101	£382	3121	£340	3094	£385
Dec	3770	£484	3724	£468	3746	£424	3714	£470

to the grid, along with the grid having to supply the high losses of the Moixa batteries. For the summer month of August when PV generation is plentiful, import has been significantly reduced for both the CPF controlled battery scenarios as a result of the battery self-consuming most of generated PV and using it to support load demand instead of importing from the grid. For the summer months, import is reduced also due to the battery not having to charge to maximum SOC during early morning hours, since it needs to keep available capacity for charging itself with the free PV energy generated throughout the day. For October and December, the 13 kWh 3 kW battery seems to slightly increase import kWh from no-battery condition, however looking at the import cost, it can be seen that the total cost has in effect been reduced as a result of the load and PV shifting and the increase in import kWh is due to overnight charging. It should be noted that the load consumption is the same for all scenarios, however, the import increases after battery additions due to feeding losses of the battery system. The tariff used in calculating import cost is the Green Energy UK TIDE tariff. It should be noted that EmPower battery algorithm was based on half-hourly ToU tariff further separated into three levels of cheap, average and expensive periods, based on +/- 10% deviation on either side of average daily value. However, the tariff patterns used are close to TIDE tariff, if not worse, hence TIDE is used to find the cost for all the scenarios.

The 6 kWh 0.5 kW CPF-BMS controlled battery has savings of 75 kWh, 35 kWh, 46 kWh over the original empower BMS for August, October, and December respectively. Taking an average of these values and multiplying for 12 months of the year, a total of 624 kWh could be saved with the new battery

without employing a sizing methodology. The monetary savings for this case is £13, £46, and £16 respectively for the three different months whose average gives a total of £300 over a year.

With the optimum battery size and converter rating introduced, savings of 136 kWh during summer, 15 kWh during autumn, and 24 kWh during winter can be obtained, compared to the EmPower battery. Taking an average of these values and multiplying to get the total over 12 months gives an annual saving of 700 kWh. In monetary terms, this is calculated as savings of £47, £88, and £60 for August, October and December respectively, whose average gives a total saving of £780 over a year. Comparing with the no-battery condition, a cost saving of £50, £45, and £46 is achieved for the three months, averaging it to £564 over the whole year.

It should be noted that the total import energy for the CPF BMS is higher than the case without any battery for some months, but the total cost of importing this energy is essentially lower. This is due to the fact that the CPF algorithm prioritizes shifting of import to cheap tariff bands rather than reducing import altogether, which it has successfully achieved.

4.6 Conclusion

This chapter has provided details of the development stages of an energy management system for community energy and presented results based on the real-life dataset of the Corsham community in the UK. An algorithm has been developed for the power-flow management of community battery storage systems and methodologies derived for sizing the battery for a community as well as sizing its power converter, based on historical consumption and

generation data. An efficient model in the form of the Community Power Flow Battery Management System (CPF-BMS) is demonstrated by controlling the charge/discharge patterns of the battery based on perfectly predicted PV generation data alongside instantaneous PV and load power data.

The validity of this CPF BMS is examined by comparing the simulation results obtained from this energy management model against the results obtained from the EmPower energy management project. From the simulation results obtained it has been shown that the EmPower community working together with the CPF BMS can reduce peak-tariff grid consumption, lower the cost of energy bills and improve self-consumption by employing community energy storage which better accommodates renewable energy generation sources such as PV, and makes use of varying Time-of-Day electricity tariffs to maximize benefits.

The total annual cost of electricity import for a community using the CPF BMS plotted against varying battery sizes in kWh, allowed the determination of an optimum battery size for the community using the knee-point detection. The relationship between the battery size and the annual electricity cost is found to be an exponential decay. The optimum battery size gives the best trade-off relationship between meeting peak-time load from the battery and minimizing the battery size and its capital cost.

Similarly, the effects on energy loss and cost saving by choosing a converter rating which is lower than the maximum power of the system is demonstrated and using the lowest payback period, the rating is determined. The effect of converter efficiency is included in the model and the losses resulting

from considering the varying efficiency with converter loading is shown. The minimum rating for the converter is determined according to the power required to charge the entire usable capacity of the battery over 7 hours in the early morning cheap tariff band. However, converter efficiency can also be improved by limiting the charging hours, i.e. if the battery discharging profile has high power instances compared to the charging profile and a larger converter is needed for effective discharging, the charging hours can be limited to a few hours every morning with higher power rather than charging with lower power over the total 7 hour duration. This effect was visible in comparing the results for a 3 kW and 13 kW rated converter, where the 13 kW converter (which could accommodate the whole range of discharging power) gave rise to higher charging losses since overnight charging was mainly taking place at power levels significantly lower than the 13 kW mark. Although this study has used the converter rating for optimum cost-saving results, the alternative of using larger converters with a cap at minimum charging can be explored further, which can both accommodate high power discharge demand, as well as limit losses due to low power charging.

Employing the battery and converter size using the proposed methodologies on the Corsham community has shown significant savings in electricity import cost for the community for three different seasons. The results have also shown that the CPF BMS is able to shift load by charging during early morning hours and during excess PV generation and discharging this energy during peak tariff band to reduce, if not eliminate import from the grid during that time. By employing the CPF BMS along with the sizing methodologies of

battery and power converter for the three months investigated in the EmPower project, energy consumption in the high-tariff band is reduced by 67% in August, 40% in October and 35% in December. Due to improved self-consumption, overall community export is reduced by 78% in August and 100% in October with December having no export with or without the battery. The average reduction in electricity import price over the year for the Corsham community, compared to the EmPower BMS, is found to be £780. The results verify that the CPF BMS meets the objectives to reduce high tariff band import and energy cost as well as increase self-consumption, through real-time scheduling of the load and PV source and battery storage system.

A comparison of these results with the same battery algorithm but different battery sizes for the community has shown that a battery with a larger capacity and converter rating, derived from optimum sizing, can save 89% more energy cost than a smaller battery with lower converter rating, as seen from the results of a 13 kWh 3 kW system as opposed to the 6kWh 0.5 kW system employed in the original project (cost savings increases from £300 to £780).

The results have justified the need and benefits of a new and improved battery algorithm for the community of Corsham. The analysis carried has also moved from designing energy management systems based on simulated models of data, to a management system which is based on real community data and the first multi-level electricity tariff scheme offered in the UK.

It should be noted here that the analysis made in this chapter considers perfect knowledge of the PV energy available throughout the day in order to set the SOC of the battery at the end of the morning low-tariff period. In reality,

however, there cannot be a perfect prediction of the energy which will be available throughout the day. Imperfect prediction of available PV energy may lead to either the battery not charging to maximum SOC before peak hours as a result of higher prediction of PV, or will result in the battery charging ‘too much’ during morning hours due to lower prediction of PV, which will reduce the ability to absorb all available exports. Different methods that can be adopted for predicting the daily PV energy and their effects on the results of the energy management system will be discussed further in chapter 6.

In the following chapter, the CPF controller will be further verified through additional communities from Carbon Legacy clients and Milton Keynes in the UK, with more thorough and complete dataset which allows a better evaluation of the results.

5 EVALUATION OF CPF CONTROLLER ENERGY MANAGEMENT SYSTEM THROUGH ADDITIONAL COMMUNITIES

5.1 Introduction

The CPF controller algorithm for energy management systems developed in the previous chapter has been designed not only for the framework of the Corsham community but can operate under any different system configuration with PV generation and battery storage. Its implementation is dependent on the availability of an instantaneous value of power flow in the system. Since the model has been developed based on the real-life data of the Corsham community, further real-life households and communities are studied for the development and testing of the CPF controller algorithm taking into account different operating characteristic and limitations of each of the participatory DER. The aim here is to confirm that communities working together can save energy and reduce bills by employing community energy storage which in turn can better accommodate collective or individual

renewable energy generation sources, and utilise ToU tariff differences between peak and off-peak electricity prices by load shifting to beneficial tariff bands.

Both domestic electricity demand and PV generation for the households vary considerably during the course of the day. Household loads are characterized by low values during the night followed by comparatively high values in the mornings and evenings when there is more active occupancy in the dwelling. The electricity used in a single household depends on a number of factors including the number of people residing in the house, set of appliances in the household and their individual electricity demands, and the frequency of use of the appliances. Solar energy, on the other hand, is also highly variable and intermittent throughout the day, and this temporal variation of solar irradiation has a direct influence on the generated power. While seasons follow a general pattern of irradiation, the day-to-day PV generation can vary significantly. Different mathematical models and simulation models such as the CREST demand model [117], stochastic generation of high-resolution series data [118], load-shape synthesis approach [119], PVSyst photovoltaic software [120], etc. have been used to generate load and PV generation data, however the considerable variability of the data makes it challenging to derive an accurate and realistic model. As a result, testing and evaluating the CPF controller system through data from real-life communities were deemed more effective and conclusive in verifying the energy management model.

This chapter will outline the evaluation of the CPF controller battery management algorithm based on instantaneous load and PV generation data from two different real-life communities along with ToU electricity tariff rates,

in increasing self-consumption, reducing consumption during peak periods, and overall reducing the import cost of the communities. The same energy management algorithm developed in Chapter 4 will be utilised for the study and results will be displayed to justify that the aims of the energy management system are being successfully met. Again it has been assumed that perfect prediction is available. The more realistic non-perfect prediction will be examined in the next chapter.

The methodologies to optimally size battery and power converter are more accurately established in this chapter due to the presence of more reliable and longer year-wide datasets for both consumption and generation data of the communities. The energy saving established by the battery algorithm when paired with the optimum battery size and converter rating for individual properties as well as relative energy savings as a community is to be evaluated to show merits of the battery algorithm on its own and further benefits for community energy.

The remaining parts of this chapter are organised in the following way. Section 5.2 describes the details about the real communities whose data has been used to design and evaluate the battery management algorithm. Section 5.3 discusses the sizing of optimal battery capacity using the annual data of both communities, followed by the detailed procedure and results for power converter sizing in section 5.4. The effects of application of the designed CPF controller battery algorithm onto the two new communities of Milton Keynes and Carbon Legacy and the results of energy shifting and energy cost savings achieved by the combined battery algorithm and sizing techniques have been

presented in section 5.5. Section 5.6 presents the analysis of results based on the operation as a community as opposed to individual energy management and highlights some notable benefits of the former. Finally, section 5.7 draws some comparison with the results of the EmPower community from Chapter 4 and summarises the key results obtained in this chapter.

5.2 Communities used for Load and PV Generation Data

As mentioned previously in Chapter 4, consumption and PV Generation data for several properties in different communities are collected in order to form the inputs for the design and evaluation of the battery management algorithm.

Another project measured electricity use with a one-minute resolution in 22 dwellings in the East Midlands, UK, over the complete year of 2008 [77]. Each dwelling was fitted with a single high-resolution meter covering electricity use of the whole dwelling, whereby, the one-minute resolution allowed the switching of individual domestic appliances to be observed. The meters measured true active power and a survey form for each dwelling detailed its characteristics and the types of appliances and lighting installed.

The second source of data came from collaboration with an energy consultant company (Carbon Legacy). This resulted in the acquiring of client data in the East Midlands, UK area, for hourly consumption and PV generation. The annual data of the four residential properties investigated spanned over October 2016 to September 2017 monitored by PowerRouter from Nedap [103].

WEEKDAY			
13%	Low Tide	00:00 – 07:00	6.41p
24%	Tide Weekday	07:00 – 16:00	14.02p
19%	High Tide	16:00 – 20:00	29.99p
16%	Tide Weeknight	20:00 – 00:00	14.02p

WEEKEND			
5%	Low Tide	00:00 – 07:00	6.41p
24%	Tide Weekend	07:00 – 00:00	14.02p

Figure 4.2: Multi-level TIDE tariff rates in p/kWh offered by Green Energy

This set of data was very reliable in terms of consistency of data and unbroken communication to a storage server at mypowerrouter.com.

For each of these two different datasets, analysis has been carried out for individual properties as well as the properties grouped together as a community to test and evaluate the validity of the developed CPF controller scheme on wider communities. To be considered as a community, the individual consumption and generation data were summed to give the combined kWh for the community, and the battery was sized and managed accordingly. All input data are converted to minute-wise data to make the algorithm uniform over all scenarios investigated. It may be noted that the original rate of receiving and recording samples by their respective controllers was 1 hour for the Carbon Legacy and roughly 10 minutes for the EmPower data.

The tariff model used remains the same as the three-level ToU TIDE tariff scheme currently offered by Green Energy UK. For convenience, figure 4.2 which shows the prices in p/kWh offered by TIDE scheme for the three different tariff bands are reproduced in this chapter.

5.3 Battery Sizing Methodology

The availability of load consumption and PV generation data for a complete year for both the Milton Keynes and Carbon Legacy communities allows a more rigorous analysis of battery sizing methodology and a better formulation of a rule of thumb in sizing batteries based on annual consumption and PV data of any given property or communities.

The battery sizing methodology is based on the results of the CPF algorithm detailed in chapter 4. By recording the amount of energy imported by households/communities in each tariff band and calculating the total import energy cost based on the TIDE tariff for different battery sizes as was given by equation (4.19).

$$\begin{aligned}
 & \textit{Total Cost Saving}_k \\
 &= [(T1 \times L1) + (T2 \times L2) + (T3 \times L3)]_{\textit{without battery}} \\
 &\quad - [(T1 \times L1) + (T2 \times L2) + (T3 \times L3)]_{\textit{with battery } k} \\
 & \hspace{15em} [4.19]
 \end{aligned}$$

Where T1, T2, and T3 are the Low, Medium and High TIDE tariffs respectively and L1, L2 and L3 are the load consumption during the low, medium and high tariff bands respectively.

For both the communities, the annual total import cost savings are plotted against evenly spaced battery sizes until the plateau point ‘A’ where the cost saving ceases to increase, as given earlier in figure 5.1. This plateau occurs at a battery size of 80 kWh for the dataset of both the communities, while the knee point ‘B’, defined earlier as the point giving the optimum battery size, occurs at 26.2 kWh for the Milton Keynes community and 26.9 kWh for Carbon Legacy community, calculated as the point in the curve with maximum vertical distance to the cost slope. These optimum sizes denote the battery size which would give the highest additional benefits per kWh compared to the battery size

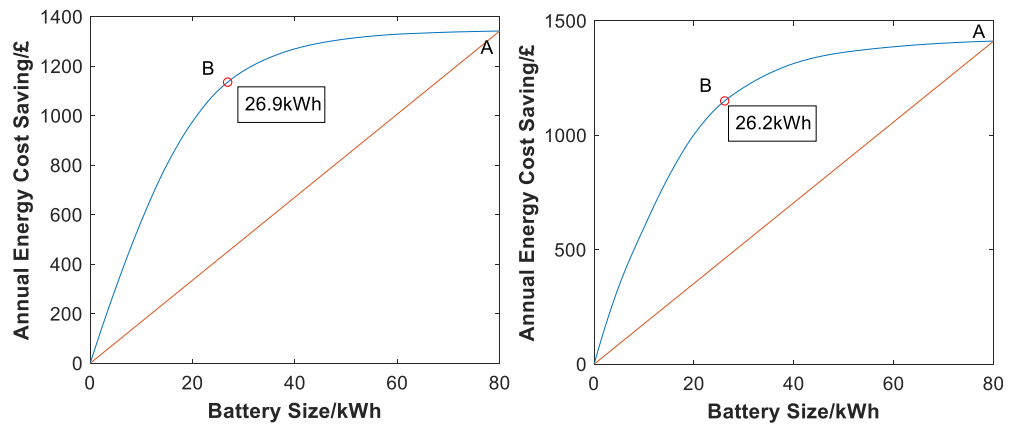


Figure 5.1: Plot of annual import energy cost saving against battery sizes in kWh, showing the knee-point of Carbon Legacy community at 27 kWh (left) and Milton Keynes community at 26 kWh (right).

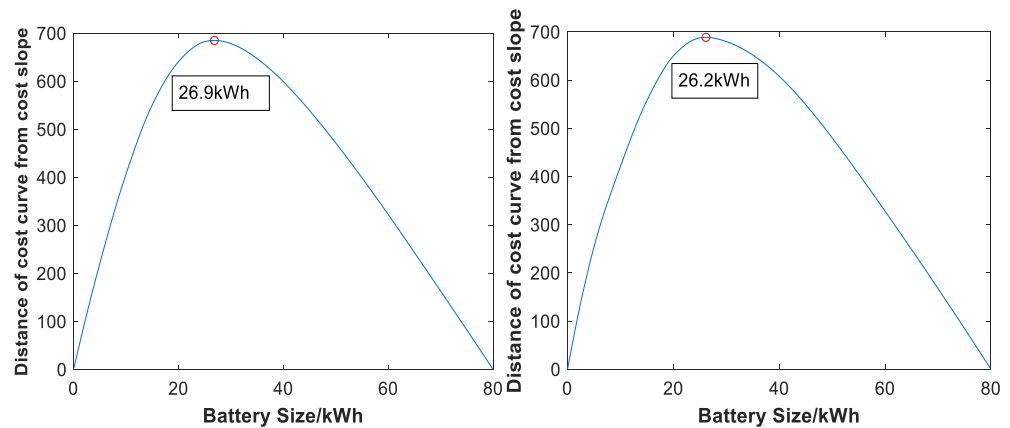


Figure 5.2: Curve showing distance of points on cost curve from straight line in order to identify Knee-point for Carbon Legacy (left) and Milton Keynes (right) communities

which has the maximum annual cost saving at point 'A', and beyond which no further benefit to cost reduction is added with increasing battery size. Figure 5.1 shows the plots of annual import energy cost saving against battery sizes in kWh for Carbon Legacy and Milton Keynes community (left and right respectively) showing the knee-point for the optimum battery size and cost-saving marked at point 'B'. Figures 5.2 verifies points 'B' as the knee-points by showing their vertical distance with the cost slope indicating the maximum difference between revenue and the cost of the battery. Considering that battery units come in fixed unit sizes, the optimum battery size numbers will be rounded up to the nearest integers. No power converter limit was put in for the communities in their respective CPF algorithms which derived the import energy costs for battery sizing estimation.

The Carbon Legacy and Milton Keynes communities will therefore operate with 27 kWh and 26 kWh batteries respectively, centrally for all its properties for the most optimum energy and cost saving. Once the optimum battery size is identified using the knee-point over a known data set of one complete year, a general rule of thumb is now to be formulated which can identify the days in the year most representative, in terms of load, to the optimum battery size. In other words, looking at the load demand in kWh for certain days of the year, an estimation can be made about the optimum battery size, without having to calculate the import costs and knee points.

Since the primary objective of the CPF BMS relies on shifting away grid import during peak tariff band, the battery size should be represented relative to the energy consumption or load demand during those hours. For every month

of the year, the mean load demand during the high-tariff band hours is calculated along with the highest peak period consumption of those months, and the mean of the 5 highest peak-period consumptions for each month, which can be derived from equations (5.1) - (5.4). These values are compared with the usable capacity in kWh (found by (5.5)) of the optimum battery size given by the knee-point.

$$E_H = \sum_{m=961}^{m=1200} (Load_m - Generation_m) \quad [5.1]$$

$$Mean E_H = \frac{\sum_{n=1}^N E_{H,n}}{N} \quad [5.2]$$

$$Max E_H = \max_{n \in [i]} (E_{H,n}) \quad [5.3]$$

$$5 Max E_H = \frac{\sum_{n=1}^5 E_{H,max,n}}{5} \quad [5.4]$$

$$Usable Battery Capacity = Optimum Batt. Cap. by Knee Point \times Usable SOC \times Battery \eta \quad [5.5]$$

Where $m=961$ signifies the first minute of the high tariff period for the TIDE tariff (4 pm) and $m=1200$ denotes the last minute for this tariff band (8 pm). N is the total number of days in the month and $E_{H,n}$ is the load demand during the peak hours of the n th day of the month. $Max E_H$ denotes the highest peak period load consumption of a month which is derived through the equation where $[i]=\{1, \dots, N\}$. $E_{H,max,n}$ is the n th highest energy consumption of a month during peak hours. The usable SOC of the battery is between 10% to 90%, i.e. 0.8, and the battery η is 0.9. Tables 5.1a and 5.1b tabulate these values for the Milton Keynes and Carbon Legacy communities respectively.

Table 5.1: Identification of representative peak-period load consumption representative of optimum battery size found through knee-point detection for community a) Milton Keynes and b) Carbon Legacy

Milton Keynes	Mean E_H (kWh)	Max E_H (kWh)	5-max E_H (kWh)
Month			
Jan	19.4	30.4	25.7
Feb	17.0	25.5	22.1
Mar	14.0	23.6	18.8
Apr	6.5	16.1	12.4
May	4.5	11.2	9.9
Jun	2.7	17.1	8.5
Jul	1.3	4.4	4.1
Aug	4.1	11.5	8.4
Sep	9.3	15.0	13.5
Oct	14.5	24.1	20.4
Nov	16.8	27.5	22.9
Dec	18.9	33.3	25.7
Yearly Mean	10.8	20.0	16.0
Mar/Oct Average			19.6
Usable Battery Capacity (given by Knee-Point)		18.7	

(a)

Carbon Legacy	Mean E_H (kWh)	Max E_H (kWh)	5-max E_H (kWh)
Month			
Jan	16.0	29.2	23.3
Feb	15.8	29.6	23.6
Mar	13.7	21.9	20.2
Apr	10.6	20.7	18.2
May	6.9	13.2	11.6
Jun	6.1	12.4	11.4
Jul	6.1	13.8	10.5
Aug	7.5	13.9	12.6
Sep	9.7	15.9	13.1
Oct	14.5	21.9	19.7
Nov	17.6	26.5	24.8
Dec	10.8	19.0	15.5
Yearly Mean	11.3	19.8	17.0
Mar/Oct Average			19.9
Usable Battery Capacity (given by Knee-Point)		19.4	

(b)

In table 5.1a, values which are close to the 18.7 kWh optimum battery size of Milton Keynes community are highlighted in blue and red boxes. The

values in Max E_H column for each month will be disregarded for representation of battery size since those values signify the load demand of just one day in the whole year and could not be taken as a reliable representative value. However, the average of the Max E_H over the 12 months can be considered for a more representative result and is seen to give a value close to the optimum usable battery capacity given by the knee-point.

Looking at the mean E_H column, it can be seen that the mean load demand of the months of January and December come close to representing the optimum battery size found earlier. Since this column gives mean values of all the days of the month, this could be taken as a reliable representation. However further communities need to be analysed to see whether this representation is correct and consistent across a majority of communities to be established as a rule of thumb.

Other values close to the knee-point of Milton Keynes is given by the mean of the 5 highest load consumption days of March and October (E_H). These values are again used to find an average of the load demand of 10 days of the year comprising of the 5 highest peak-period demands of March and October, and can potentially be a reliable representative after it is verified by additional communities.

Similarly, in table 5.1b, values which are close to the 19.4 kWh optimum usable battery size of Carbon Legacy community are highlighted in blue and red boxes. The mean load demand of the month of January and December are no longer close to the optimum battery size found earlier, which makes them unsuitable as representative values.

Both the individual and average of the mean of the 5 highest load consumption E_H of March and October, bordered by the red boxes, still holds the closest value to the cost-saving knee-point of 18.7 kWh usable capacity for the Carbon Legacy community. The average of the Max E_H over the 12 months is also consistent with having a close match with the knee-point capacity suggestion. These values therefore need to be further checked against additional communities or individual properties in order to establish it as a representative for the optimum battery size for the given dataset.

Data from five individual properties of the Milton Keynes community and four properties of the Carbon Legacy customers are analysed in order to validate the assumption that the yearly average of the Max E_H and the mean of the 5 highest load consumption E_H of March/October can give a good estimation of the optimum usable battery size suggested by the knee-point. The results are tabulated in Table 5.2.

It can be seen that for all the properties listed, the values in the columns for 'Usable Optimum Battery Size given by Knee-point' and 'Mean 5-max E_H of Mar/Oct' match up with a difference of less than 1 kWh. Majority of the properties listed also match the 'Max E_H Yearly mean', except M3, M19 and ES highlighted in red, which give differences slightly higher than 1 kWh, and AH gives the highest difference, of approximately 2 kWh, from the knee-point. However, since the battery capacity suggested by the 'Max E_H Yearly mean' are all slightly higher than the Knee-point, this marginal over-sizing can be utilised in times of expansion within the energy community. The downside to using this rule of thumb is that the consumption and generation data for a whole

Table 5.2: Table showing consistency of mean of the 5 highest load consumption E_H of Mar/Oct month with optimum battery size given by knee-point calculation.

Community	Property	Usable Optimum Battery Size given by Knee-point (kWh)	Max E_H (Yearly mean kWh)	Mean 5-max E_H of Mar/Oct (kWh)
Milton Keynes	M3	3.4	4.6	4.3
	M7	4.7	5.1	4.8
	M13	4.0	4.8	3.3
	M14	5.5	5.7	4.9
	M19	6.6	7.9	7.2
Carbon Legacy	AH	8.2	10.3	8.9
	ES	3.2	4.2	3.9
	JF	7.6	8.3	7.8
	W123	4.5	5.4	5.2

year for any given property would be required in order to estimate the optimum battery size of that property or community.

It can therefore be concluded that an average of the five highest peak energy consumption days of March and October can be a good indicator to sizing the battery to get maximum import cost saving for a minimum battery size and therefore cost. Appendix C, which provides the detailed chart of maximum and mean peak-consumption for the analysed properties, shows that no other consumption pattern has been consistent in representing the knee-point, other than the mean of the March/October 5 maximum E_H (kWh), closely followed by Max E_H Yearly mean in the tables. As a result, estimating the battery optimum size through the mean load demand of specific months, mentioned earlier has also been discarded.

5.4 Power Converter Sizing Methodology

The best size for the power converters for the communities of Milton Keynes and Carbon Legacy are identified in this section using the methodology

of converter sizing from Section 4.4 which relies on deriving the lowest payback period for a converter rating, given the battery size.

For the optimum battery size given by the sizing methodology from Section 5.3, the CPF battery algorithm is run with different power limits and the associated efficiency of the power converters which are functions of the power going in and/or out of the converter. Note that the efficiency curves for power converters result in increasingly poor efficiency as load power decreases from the rated power. As a result, a large converter will give high losses if the system operates in power levels much lower than the rated power of the converter.

The energy savings achieved by the CPF BMS while employing each of the converters is calculated, along with the resulting energy cost savings. The payback period of the system, where the converter size is the only variable, is calculated based on the energy cost savings and the battery and converter capital costs. The cost of the battery is considered based on the price of the 13.5 kWh Tesla Powerwall II battery, the different components of which are reproduced in Table 5.3 (following from Table 4.4). A linear relationship is considered for the price per unit of battery kWh which was then used to derive the cost for the

Table 5.3: Battery cost calculation based on Tesla Powerwall II

Type	Battery Size	Cost (£)	
Tesla Powerwall II	13.5 kWh	Component	Cost
		Battery kit	4773
		Labour	160
		Bits	75
		Sales fee	300
		OHP	1061.6
		Vat @ 20%	1273.92
		Total	£7,643.52
		Unit	£566.19
Milton Keynes	26 kWh	£14,720.85	
Carbon Legacy	27 kWh	£15,287.04	

optimum battery sizes for the Milton Keynes and Carbon Legacy communities. These values are also presented in Table 5.3. The unit cost of power converters is assumed to be £157/kW, based on an average drawn from available converters from Fronius and SMA in the market. The details of this calculation can be found in Appendix B. The calculation of payback period in years for each converter size was given by equation 4.19 which is reproduced below for convenience. In the equation, the battery size is fixed for each community or dwelling.

$$\text{Payback Period} = \frac{(\text{Battery Size} \times \text{£566.19}) + (\text{Converter Size} \times \text{£157})}{\text{Annual Saving on Energy (£)}}$$

[4.19]

The results of equation 4.19 are presented in table 5.4 and figure 5.3 in order to derive the minimum payback period for the capital cost of the converter and battery system through energy savings achieved by the CPF BMS algorithm. It can be seen that the lowest payback period for the Milton Keynes community occurs for a converter rating of 6 kW, while for the Carbon legacy community occurs for a converter rating of 6 kW, while for the Carbon legacy

Table 5.4: Payback period for different converter sizes for Milton Keynes and Carbon Legacy communities while installed with their respective optimum battery capacities.

MK Converter Size kW	Annual Saving £ on Energy	Battery +Converter cost PB Period
1.5	568.2	26.32
3	901.3	16.86
5	1053.7	14.72
6	1083.7	14.47
9	1102.1	14.64
10	1103.1	14.77
11	1106.4	14.87
12	1106.4	15.01
13	1104.8	15.17
14	1102.8	15.34
15	1102.3	15.49
18	1100.2	15.95

CL Converter Size kW	Annual Saving £ on Energy	Battery +Converter cost PB Period
1.5	608.3	25.52
2	759.0	20.55
3	975.2	16.16
4	1051	15.14
5	1069.7	15.07
6	1072.9	15.13
7	1078.0	15.20
8	1070.0	15.46
9	1064.8	15.68

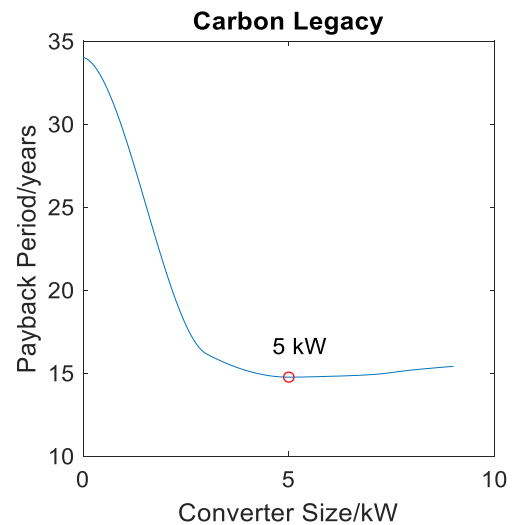
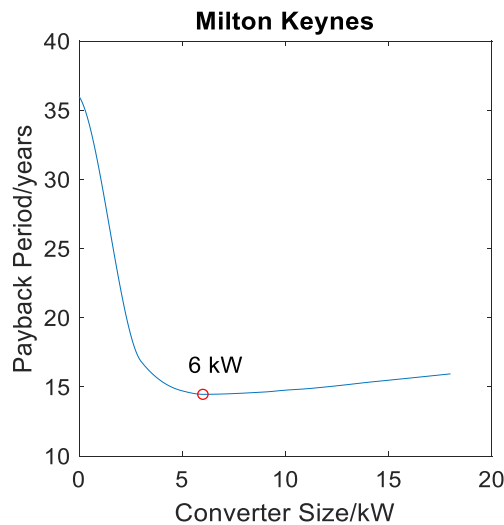


Figure 5.3: Payback period for different converter sizes for Milton Keynes and Carbon Legacy communities while installed with the optimum battery capacity

Table 5.5: Comparison of charging and discharging capability lost due to smaller converter cut-off power limit in relation to a converter which encompasses the entire charging and discharging power range (Includes losses due to converter efficiency, for both small and large converter).

Community	Milton Keynes Community		Carbon Legacy Community	
Battery Size	26 kWh		27 kWh	
Useful Battery Capacity	18.7 kWh		19.4 kWh	
Power Limit	18k	6k	9k	5k
Charging energy lost (kWh)	366.1	1357.1	362.3	556.7
Charging energy lost (%)	5.2	19.2	4.9	7.5
Discharging Energy lost (kWh)	382.8	1046.8	345.5	640.1
Discharging Energy lost (%)	5.6	15.2	4.7	8.8

community it takes place for a converter size of 5 kW. These values will be used in the remainder of the chapter to derive energy saving calculations and comparisons. However, it should be noted from the figures in 5.3 that the payback period after the mentioned power ratings flattens out resulting in very less increment in payback period despite increased converter rating and capital cost. This suggests that it can be beneficial for communities to invest in the converters with higher power rating, which would allow future expansions of both PV and additional participants, without drastically increasing the payback period, as well as have the flexibility to incorporate different tariff scenarios which may become available in the future.

The average total capability lost over the year for both charging and discharging for the communities, if the lowest payback period converter rating is used instead of a converter limit which accommodates the whole range of charging and discharging power, is derived for the different battery capacities and shown in Table 5.5. The reduced power converter limit for the Carbon Legacy and the Milton Keynes community are 5 kW and 6 kW respectively. The converter limit which accommodates the whole range of charging and

discharging power for Carbon Legacy community is 9 kW, and that of the Milton Keynes community is 18 kW.

The presented converter losses incorporate lost capability due to truncated power exchange as a result of the converter maximum limit as well as the efficiency losses which vary according to the converter rating and their input power. Note that a larger power converter operates at a lower efficiency when operating well below rated power. As mentioned earlier, power converters come in fixed sizes and therefore in this analysis, the minimum payback points are truncated to nearest integer kW. It should also be re-emphasized that the battery efficiency is considered to be constant at 90% round-trip for all the systems as mentioned previously. This is due to the rapidly developing and changing battery technologies which have not stabilised enough to include specific details within their models. Any change in loss incurred for the considered scenarios are therefore affected only by converter sizing and their efficiency variation alone.

The calculated percentage charging and discharging capabilities lost by limiting the battery for the lowest payback rating is recorded in table 5.5. For the community of Carbon Legacy, the losses are higher for the smaller 5 kW converter which incorporates both the power capability lost due to the maximum cut-off limit as well as converter efficiency. The larger 9 kW converter losses only incorporate the efficiency losses as its large value does not have any limiting effect on the power flow. It can be seen that the total increment of losses resulting from an imposed converter limit of 5 kW, including the converter efficiency losses are below 10 % for both charging and

discharging scenarios with a loss increment of 2.6 % for charging and 4.1% for discharging with the 27 kWh battery going from 9 kW to 5 kW due to the unmet peak power. The loss increment therefore seems to be reasonable to justify the converter size chosen by the lowest payback converter rating. It can also be noted that, with the smaller converter, the percentage energy lost from total discharging instances are higher than those of charging which is due to the load having higher power demand than the grid and PV charging.

For the Milton Keynes community, the percentage loss differences are larger for operating with a smaller converter instead of a converter which accommodates the entire operational power range of the community. A major reason for the difference is that charging power is heavily affected by the converter maximum limit in the Milton Keynes community as the PV data used for this community had particularly high power instances as can be seen from figure 5.4, which depicts battery charging and discharging energy demand at different power bins (denoted by the average power of each bin) over a year. As a result, the percentage charging capability lost is higher than the discharge capability lost when the smaller 6 kW converter is employed. In the figure, a second spike at a higher average power is visible for the charging profile of Milton Keynes, at approximately 9 kW, caused due to high power PV charging during the day. A loss increment of 14% is seen for the 26 kWh battery going from 18 kW to 6 kW for the total charge scenario, and 9.6% for the discharge scenario due to the unmet peak powers. This is a large increment for losses, however further analysis will be carried out to see whether the economic benefit still justifies the use of the smaller converter.

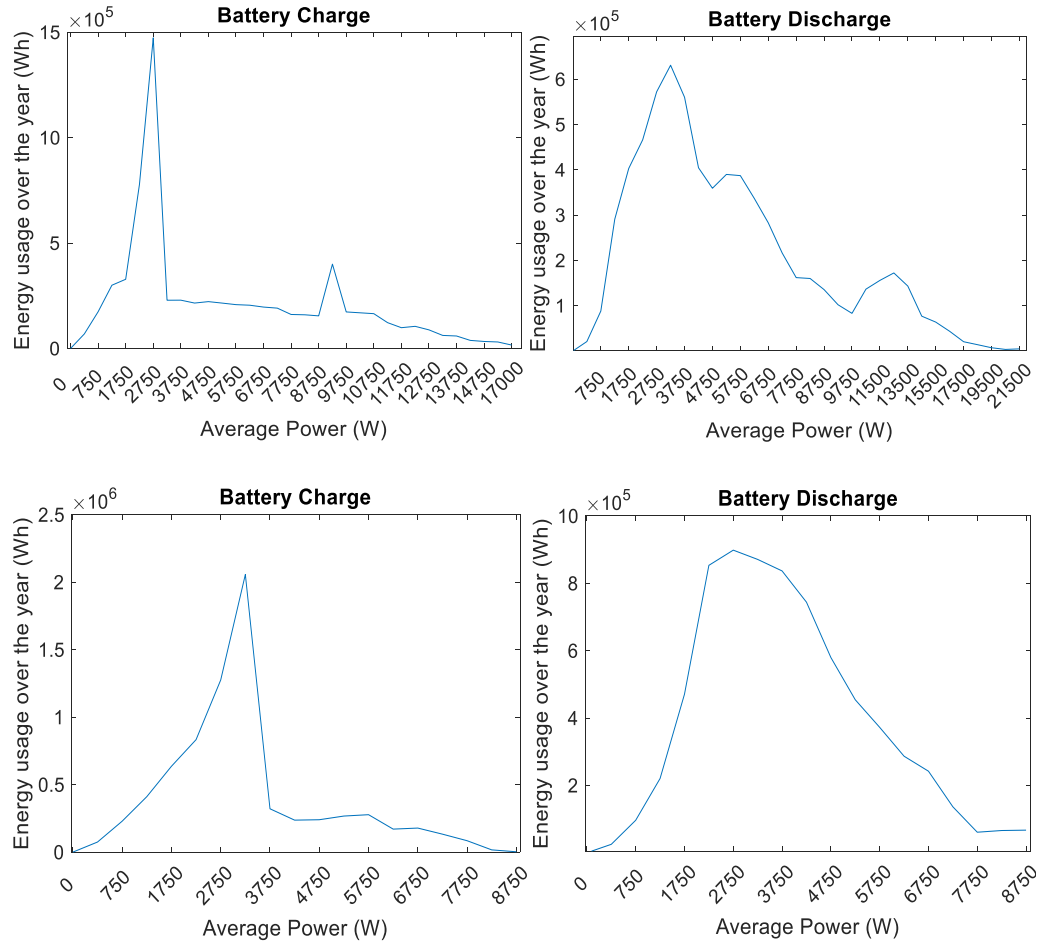


Figure 5.4: Charging and discharging power demand at respective average power bins for Milton Keynes (top) and Carbon Legacy (bottom) communities, employing the optimum battery sizes without any converter limit.

A further detailed analysis has been made in order to see the financial benefits of using a reduced power converter limit for lowest payback period as opposed to using a converter limit which accommodates the whole range of charging and discharging power. The difference in energy discharged by employing the smaller power converter – and therefore the unachieved reduction in grid import, during mid and high tariff bands – is calculated. This is achieved by running the CPF algorithm for individual communities and recording the total energies discharged per converter size. Calculations then give losses incurred due to a smaller converter size, shown in Table 5.7 later.

In the worst case scenario, the lost discharge capability due to the converter limit would have been imported during the low tariff band resulting in lower import cost. The price difference in import electricity purchase within the TIDE tariff scheme is calculated between the mid and low tariff band, as well as between the high and low tariff band, which is then multiplied with the lost energies from the respective tariff bands to find the increase in import cost due to a smaller converter employment. Equation (4.20) earlier showed how to calculate the increase in import cost when the smaller power converter rating, given by the lowest payback period is used instead of a larger power converter which is rated by the highest power in or out of battery. The equation is reproduced below for convenience.

$$\text{Total increase in import cost if smaller converter used} = (HT - LT) * (E_{HT1} - E_{HT2}) + (MT - LT) * (E_{MT1} - E_{MT2}) \quad [4.20]$$

In (4.20), HT, MT, and LT are the electricity import cost in p/kWh for high tariff band, mid tariff band and low tariff band respectively for the TIDE tariff scheme. E_{HT1} and E_{HT2} are the energy discharged by the battery in the high tariff band for a larger power converter rating (defined by the highest power in or out of the battery) and a smaller power converter rating (given by the lowest payback period) respectively. E_{MT1} and E_{MT2} are the energy discharged by the battery in the mid tariff band for a larger power converter and a smaller power converter rating respectively. Table 5.6 lists the various import price differences and Table 5.7 shows the differences in energy discharged by the 18 kWh battery in different tariff bands for a larger and smaller power converter rating along

Table 5.6: Differences in import prices between tariff bands in TIDE scheme

TIDE tariff Bands	Import Price (£/kWh)
High and Low tariff difference (HT-LT)	0.24
Mid and Low tariff difference (MT-LT)	0.08

Table 5.7: Analysis of cost saving achieved by using reduced converter size given by lowest payback period instead of converter size to accommodate maximum battery power.

	Milton Comm. 26 kWh Batt.	Carbon Comm. 27 kWh Batt.
Maximum battery power rating (kW), Converter-1	18	9
Lowest Payback converter rating (kW), Converter-2	6	5
Reduction in battery discharge energy during High Tariff Band (kWh), $E_{HT1} - E_{HT2}$	231.7	176.10
Reduction in battery discharge energy during Mid Tariff Band (kWh), $E_{MT1} - E_{MT2}$	10.4	-148.6
Total increase in import cost if smaller conv. used (£/year)	£55.43	£30.22
Total reduction in capital cost if smaller converter used (£)	£1,884	£628
Payback years	34	21

with calculations of cost-benefit achieved by using reduced converter size for the communities of Milton Keynes and Carbon Legacy. The negative value for the reduction in battery discharge energy during mid tariff band for the Carbon Legacy community signifies that discharge during mid tariff band actually increased for a smaller converter. This has resulted due to the second mid tariff band in the TIDE tariff scheme appearing after the peak period is complete, where any remaining energy within the battery is emptied to reach the minimum battery SOC at the end of the day. For a lower converter size, the energy remaining within the battery at the end of the peak period is higher since less energy is discharged during the peak period compared to a converter with a higher maximum rating.

The total increase in import cost due to using a smaller converter is compared with the purchase cost saved by using the smaller converter as opposed to the larger converter. The purchase cost is calculated per kW, where the cost of power converters is assumed to be £157/kW, based on an average drawn from available converters from Fronius and SMA in the market. The details of this calculation can be found in Appendix B. A payback period is calculated for using a larger converter instead of a smaller converter, by taking the capital cost saving over the reduced economic benefit of battery operation. A large payback period signifies that using a larger converter rating will take a long time to pay off the additional purchase cost using the economic benefit from reduced peak-period import, whereas a shorter payback period means that the additional peak period savings using a larger converter is substantial enough to pay for the additional purchase cost over a short period of time.

For both the Milton Keynes and Carbon Legacy communities, the payback periods are calculated **to be 34 and 21 years** respectively (see Table 5.7 and equation 5.6), which are large time periods, since the overall life of the batteries tend to be much shorter than the calculated values (e.g. Tesla Powerwall 2 warranty has a capacity retention of 80% after 10 years and an operating limit of 37.8 MWh of aggregate throughput which is approximately

8-9 years of operation if cycled once daily), as mentioned earlier in Chapter 4, [116].

The same analysis is made for several other individual properties within the communities, mentioned earlier in Table 5.2. All of them have shown a payback period much greater than 10 years, as can be seen from Table 5.8 which lists the individual properties of the Milton Keynes and Carbon Legacy communities. It can therefore be concluded that it is economically beneficial and technically viable to use the lower power converter limit as opposed to a rating of the maximum power exchange within the battery, for the CPF BMS, suggested by the lowest payback period converter rating for the battery.

Table 5.8: Analysis of cost benefit achieved by using reduced converter size given by lowest payback period instead of converter size to accommodate maximum battery power.

Properties	Milton Keynes			Carbon Legacy		
	M7-7kWh	M13-6kWh	M14-8kWh	AH-7kWh	ES-3kWh	JF-8kWh
Maximum battery power kW, Converter-1	8	14	14	8	4	5
Lowest Payback converter kW, Converter-2	2	2	3	2	1.5	2
Reduction in battery discharge energy during High Tariff Band (kWh), $E_{HT1} - E_{HT2}$	93	50.00	94.00	111	9.0	93.0
Reduction in battery discharge energy during Mid Tariff Band (kWh), $E_{MT1} - E_{MT2}$	-46	60	70	-79	-5	-74
Total increase in import cost if smaller conv. used (£/year)	£18.4	£16.4	£27.5	£20.1	£1.7	£16.3
Total reduction in capital cost if smaller converter used (£)	£942	£1,884	£1,727	£942	£393	£471
Payback years	51.1	115.2	62.8	46.7	225.4	28.9

5.5 Effects of Application of Designed CPF Battery Algorithm onto the Communities of Milton Keynes and Carbon Legacy

Load consumption and PV generation data from the properties in the communities of Milton Keynes and Carbon Legacy, along with the calculated battery sizes (kWh) and converter ratings (kW) found in the previous sections of this chapter are fed into the CPF algorithm in order to test the effectiveness of the CPF BMS in energy shifting (load and PV shift) and achieving economic benefits through battery deployment. Figure 5.5 shows the summary of energy shifting achieved for the two communities of Milton Keynes and Carbon Legacy after running the CPF BMS for 1 complete year for each of the communities, analysed according to the tariff periods of the TIDE scheme. The losses shown with the ‘yellow’ bars are due to the non-unity roundtrip efficiencies of the battery and converter system.

It can be seen from figure 5.5 that for both communities, during the low tariff band the grid import increases due to CPF BMS (shown by green bars) compared to the original grid import (shown by orange bars), as a result of heavy battery charging (represented by the indigo bars) during this period. A total import increment of 2367 kWh for Milton Keynes and 4256 kWh for Carbon Legacy community has taken place during the low tariff band. This increment is much lower than the import reductions which have occurred due to load shifting and PV self-consumption in the two other tariff bands, as will be discussed in the following paragraphs. There is no battery discharge

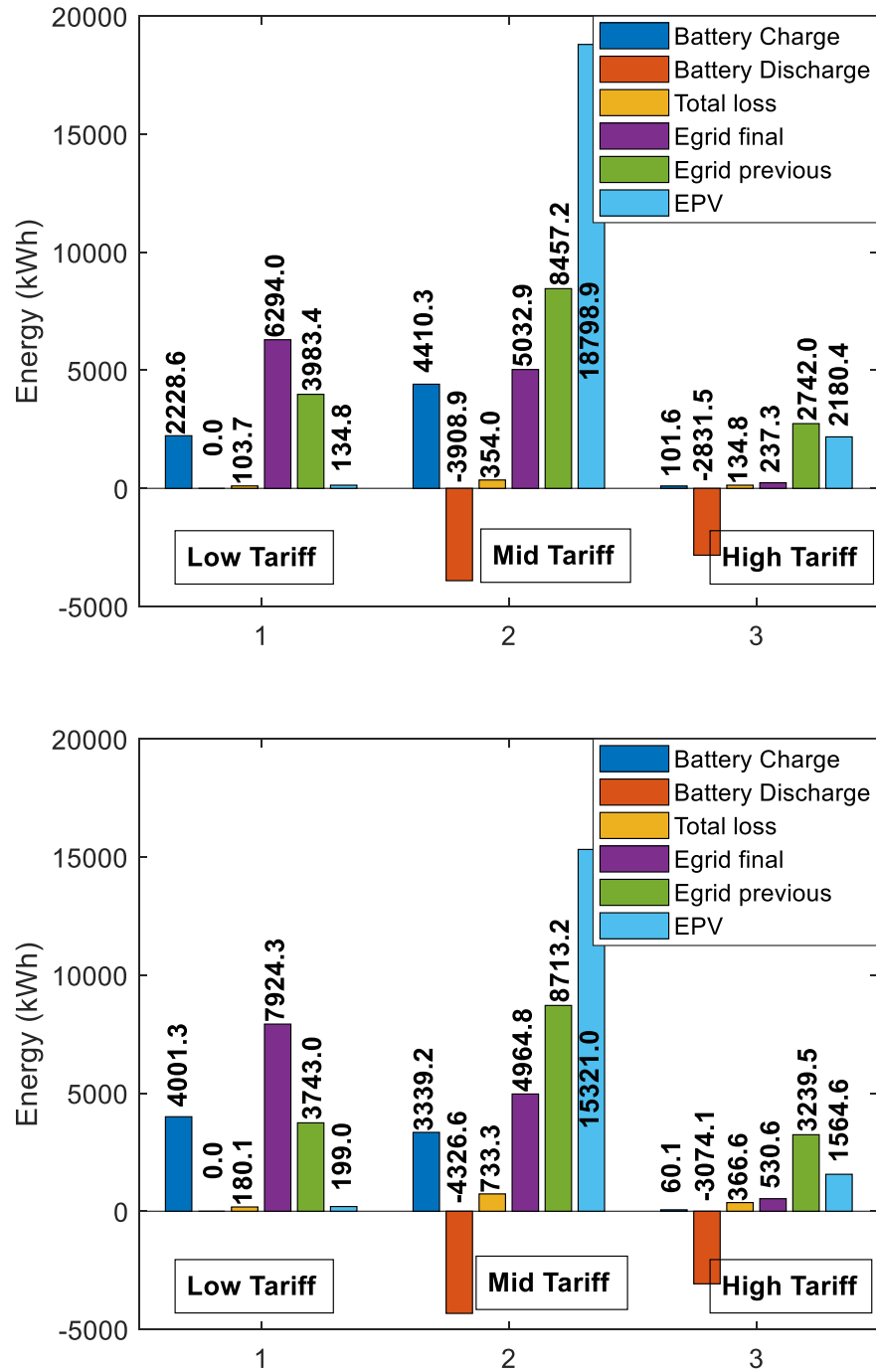


Fig 5.5: Annual energy imported from the grid in each tariff period of TIDE using CPF BMS (Egrid final) alongside the battery charging and discharging energy in each of these period, contrasted with the import energy in the scenario without a battery (Egrid previous), for communities of Milton Keynes (top) and Carbon Legacy (bottom)

(represented by orange bars) for either community during the low tariff period.

This shows that the CPF BMS is fulfilling its aim for the low tariff band

operation throughout the whole year for both the communities.

For the high tariff band, the import energy can be seen to be drastically reduced by CPF BMS for both the communities. A total import of **2505 kWh** for the Milton Keynes community and **2709 kWh** for the Carbon Legacy community are shifted away from the peak period. Ideally, the import during high tariff region should be zero, however, due to limiting battery size and converter power rating, there will be some remaining load in high tariff band, which would have to be supplied by the grid.

Import from the grid is also reduced during mid tariff band as seen from figure 5.5. A total import of **3444 kWh** for the Milton Keynes community and **3766 kWh** for the Carbon Legacy community are reduced or shifted away from the mid tariff band. Both charging and discharging is taking place to/from the battery during this period. Since there is a large amount of PV energy (sky blue bar) available during this period, most of the charging energy is attributed to PV charging. The discharge mainly occurs during the second half of the mid tariff band (8 pm to 12 midnight) when any remaining charge in the battery is drained out to take the battery to minimum SOC, ready to begin charging the next day with lower import prices.

Table 5.9 tabulates the total import costs for each community, with the new CPF BMS, compared with no battery deployment as well as against the original battery management system of the Carbon Legacy clients.

For the Milton Keynes community, a total of **3619 kWh** (15183 – 11564 kWh) of grid import can be reduced over a year by CPF BMS, along with a saving of **£1084** (£2263 - £1180) for the year by means of improved PV self-

Table 5.9: Summary of import and export kWh and cost (£) over one year for different battery management scenarios for Carbon Legacy and Milton Keynes communities.

Community			Carbon Legacy	Milton Keynes
Import	Original Battery	kWh	15203	-
		£	2302	-
	CPF BMS	kWh	13420	11564
		£	1363	1180
	w/o Battery	kWh	15696	15183
		£	2433	2263
Export	Original Battery	kWh	3892	-
	CPF BMS	kWh	1358	9705
	w/o Battery	kWh	4914	14411

consumption and load shifting throughout the days. PV self-consumption is increased by **4706 kWh** over the year as calculated from the table.

For the Carbon Legacy community, a total of **2276 kWh** ($15696 - 13420$ kWh) of grid import can be reduced over a year by the CPF BMS, compared to no battery employment in the community, along with a saving of **£1070** ($£2433 - £1363$) for the year by means of improved PV self-consumption and load shifting throughout the days. PV self-consumption is enhanced by **3556 kWh** over the year as calculated from the table.

The differences in the grid import reduction and self-consumption increment are a result of the combined battery and power converter losses. Hence, without the battery and converter losses, the self-consumption increment for the communities would have been the same as the grid import reduction.

It should be noted that the exports under CPF BMS are not reduced to zero due to the limitations of battery and converter size. Given a battery size and converter rating which could accommodate the entirety of the PV surplus

generation would have resulted in zero export, however it would have been an impractically large and uneconomic size of battery capacity and power converter rating.

Another comparison can be made for the results of CPF BMS for Carbon Legacy community by comparing the CPF based BMS to the behaviour of the commercial BMS embedded in each of the batteries themselves. The CPF BMS achieved a PV self-consumption increment of **2534 kWh**, and by load shifting away from peak period, an import price reduction of **£939** over a year is accomplished. Grid import is also reduced by **1789 kWh** by the CPF BMS compared to the original BMS deployed for the clients of Carbon Legacy.

5.5.1 Energy Shifting Patterns through CPF BMS

A closer look is taken into the energy traces for the communities over a small duration, i.e. a couple of days, in order to understand the flow of energy within the CPF BMS. Figure 5.6 shows the battery and import energies for the Milton Keynes community over four days in the month of January. A battery size of 26 kWh and converter rating of 6 kW is used for the CPF BMS.

The patterns in the graph show how the battery is charging and discharging according to the net consumption (P_{netgrid}) of the community, which is given by load consumption minus total PV generation at each sample time. For the first day, it is seen from figure 5.6 through perfect prediction that there are no projected PV exports during the day (i.e. P_{netgrid} is always positive). As a result, the battery charges throughout the low tariff period from 00:00 midnight to 7 am in the morning, resulting in the battery nearly reaching its maximum

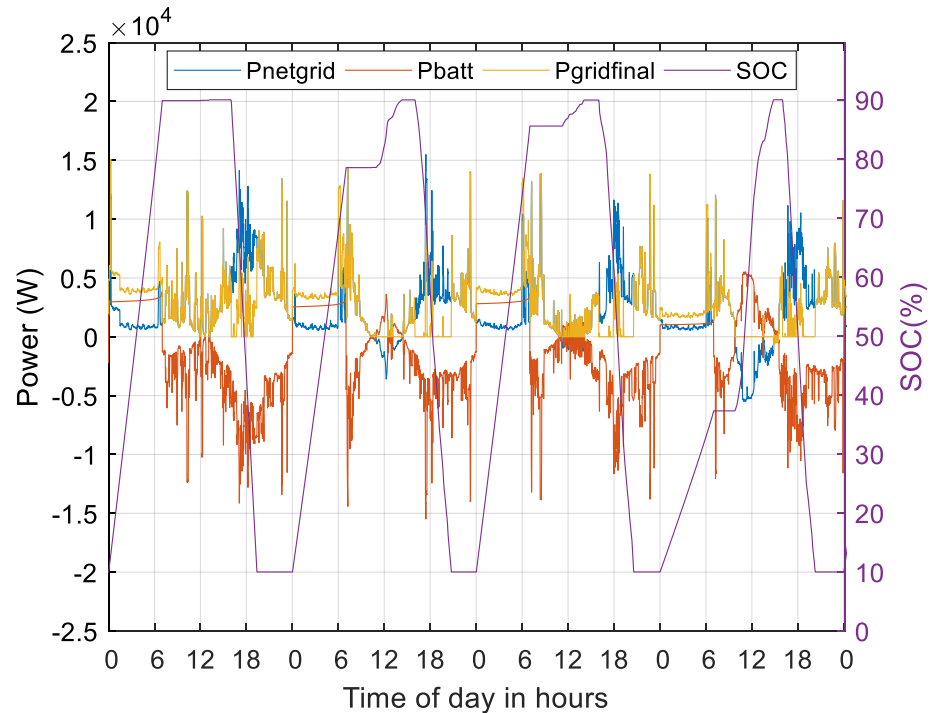


Figure 5.6: Energy flow from grid and to and from battery for Milton Keynes community over four days in the month of January

SOC at 90%. This energy is held throughout the mid-tariff band and is only discharged during the peak period starting from 4 pm until the battery reaches its minimum SOC at 10% close to 8 pm. There is no more discharging throughout the remainder of the day since the battery has reached its minimum SOC, and there is no charging until the beginning of the next low tariff period the next morning.

Over the next two days in figure 5.6, there is some excess PV projected during the day. During the low tariff period, the battery therefore charges to a SOC which leaves enough capacity to be filled by the excess PV during later part of the day. Between 10 am to 4 pm, we can see the battery charges up through the excess PV and reaches its maximum 90% SOC, which is then discharged over the peak period until the battery is drained to minimum SOC.

For the last day shown in figure 5.6, there is abundant excess PV during the day which can cover half of the battery charging in order to meet the peak period consumption of the day. As a result, due to considering perfect prediction, the battery charges only up to approximately 40% SOC during the midnight to 7 am off-peak hour, and keeps its remaining capacity available to be charged by PV energy. Between 10 am to 4 pm, it can be seen that the battery charges up to 90% SOC through all the available PV charging, which is then released to support all the load consumption during peak tariff period.

It can therefore be concluded, looking at the charging/discharging patterns and the SOC of the battery in relation to TIDE tariff bands and net consumption that the CPF BMS is successfully performing the energy shift for the communities according to the established set of rules and aims.

5.5.2 Battery Control Strategy for Weekends

As mentioned previously in chapter 4.2.6, the energy management algorithm for the battery system during weekends comprises of only two tariff bands with an off peak-period from midnight till 7 am in the morning, and a moderate tariff band applied for the remainder of the day from 7 am till midnight. Since there is no peak-tariff throughout the weekends, the CPF BMS no longer needs to prioritize on reducing import during the peak-tariff band, rather it would directly aim to minimize import cost and maximize self-consumption. The weekend control strategy could therefore be defined by any one of the following strategies and the option with the highest cost saving and self-consumption is chosen.

- a. Control Strategy-1: 00:00 – 07:00 hrs as Low-Tariff, 07:00 – 00:00 as Mid Tariff-1.
- b. Control Strategy-2: 00:00 – 07:00 hrs as Mid-Tariff1, 07:00 – 00:00 as Mid Tariff-1.
- c. Control Strategy-3: 00:00 – 07:00 hrs as Low-Tariff, 07:00 – 00:00 as Mid Tariff-2.

Control Strategy 1 allows the battery to charge to maximum SOC from the grid during the overnight period of low tariff electricity until 7 am, leaving spare capacity to accommodate the PV generation of the day. If the control strategy similar to Mid Tariff-1 band of weekdays is followed, the battery will hold the charge for the remainder of the day, not discharging for any load condition, and charging only from surplus PV. It can already be realised that this is a not a good idea in terms of minimizing grid import energy and cost

since the battery will remain unused in terms of supplying load and the charged energy during the early morning of the first day of the weekend will only be used once the weekdays start again. The grid meets all the net load demand during the weekend with this control strategy.

Since there is no peak-tariff for weekends, Control Strategy 2 explores the idea of using only surplus PV energy throughout the weekend to charge the battery, and not discharge it until the peak-tariff period is back on Monday. This causes the grid to support all the net load during the weekend at the low and mid tariff rates, and the self-consumed free PV energy is held back to provide for load during high tariff bands only. Over the course of one year, this control technique may make significant savings when the peak demand of 52 Mondays (total number of weeks in a year) are supported from free PV energy rather than low-tariff grid import discharged from the battery.

For Control Strategy 3, the overnight energy flow algorithm for the battery remains the same. After 7 am, all available battery energy is discharged to meet load since there is no 'peak tariff' to hold the battery capacity for. The battery charges only if there is surplus PV energy. The grid supplies load consumption only when battery SOC falls lower than its minimum 10%.

Table 5.10: Import cost and total export of the communities of Milton Keynes and Carbon Legacy over one complete year using the three different energy flow control strategies (CS) for the weekends.

Control Strategy	Milton Keynes		Carbon Legacy	
	Import Cost Saving (£)	Export Energy (kWh)	Import Cost Saving (£)	Export Energy (kWh)
CS-1	880	11468	882	2817
CS-2	895	11238	901	2541
CS-3	1082	10236	1068	1998

Table 5.10 presents the savings in import cost and total export of the communities of Milton Keynes and Carbon Legacy over one complete year using the three different energy flow control strategies for the weekends. It shows that for both communities, Control Strategy-3 results in the highest import cost saving and the lowest export (meaning highest self-consumption). It should again be noted that the exports under CPF BMS are not reduced to zero due to the limitations of battery and converter size, which would have been very large and cost-ineffective were it to accommodate all the surplus PV generation.

Choosing the control algorithms for the two tariff bands of weekends to correspond to ‘Low Tariff’ and ‘Mid Tariff-2’ are therefore justified as it maximizes load-support through battery from the cheapest electricity of off-peak times, as well as allows more available capacity for self-consumption of PV during the day.

5.5.3 Baseline Comparison of CPF BMS

In this section, the effects of deployment of a battery in a community which utilises dispatchable sources, such as PV generation, will be studied in terms of energy and cost. In particular, the analysis will compare the grid import

and electricity cost incurred by a community installed with PV generation and battery having CPF BMS versus the same community over the same days running with the same PV generation but without a battery. The former utilises the TIDE tariff scheme while the latter is assumed to operate on a standard flat-rate import tariff offered throughout the whole day, which is taken from an average of the rates offered by major UK electricity companies. A tariff rate for exports is also considered which allows the households/community to receive a flat-rate payment for every excess unit of generated PV that goes back into the grid.

The FIT scheme is a UK government programme designed to promote the uptake of small-scale renewable and low-carbon electricity generation technologies which requires participating licensed electricity suppliers (FIT Licensees) to make payments on both generation and export from eligible installations [121]. **However, we assume no FIT exist, and a fixed rate is paid only for exports to the grid.** Table 5.11 lists the different electricity providers and the flat-rate import tariff rates they offer, along with the export tariff from Ofgem [121] [122].

Table 5.11: Standard electricity import flat-rate tariff offered by different energy suppliers along with yearly standing charges and Feed-in-Tariff for export.

Provider	Standing Charge £/year	Standard Unit Rate p/kWh
British Gas	90.41	14.350
E.on	57.09	16.520
EDF Energy	80.92	16.670
nPower	55.01	17.620
Scottish Power	95.23	15.405
Average Import Price	75.73	16.113
Export (Ofgem)	-	5.24

Using the average tariff rate from table 5.11 and having calculated the total net consumption of communities from their available generation and consumption data, the total import cost, export revenue and using these the net electricity cost is calculated according to equations (5.6) to (5.8).

$$\text{Total Import Cost} = \text{Avg. std. unit rate} \times \text{Import kWh Energy} \quad [5.6]$$

$$\text{Total Export Cost} = \text{Standard export tariff} \times \text{Export kWh energy} \quad [5.7]$$

$$\text{Net Electricity Cost} = \text{Total Import Cost} - \text{Export Revenue} \quad [5.8]$$

Table 5.12: Comparison of annual import, export and net electricity cost and energy for communities without battery (standard flat-rate tariff) and with CPF BMS (TIDE Tariff)

Comm- unity	Battery System	IMPORT		EXPORT		Net	
		kWh	£*	kWh	£	kWh	£
Milton Keynes	CPF BMS	11564	1275	9705	508.5	1859	766
	w/o Batt	15183	2522	14411	755	772	1767
	Difference	3619	1247	4706	246	-1087	1001
Carbon Legacy	CPF BMS	13420	1458	1358	71	12062	1387
	w/o Batt	15696	2604	4914	258	10782	2346
	Difference	2276	1146	3556	187	-1280	959

* Includes standing charge in £/year. Standing charge for Baseline scenario is considered £75.73 per year and for TIDE tariff is 26.02 p/day [98]

Table 5.12 compares import energy and net electricity cost for both the scenarios of a community without a battery and the same community with CPF BMS driven battery. It can be seen that using a battery with CPF BMS saves a total of **£1001** and **£959** over a year on electricity costs for Milton Keynes and Carbon Legacy communities respectively. It can also be seen from the table that the net usage actually increases for battery deployment in the community (due to battery losses), however, due to successful energy shifting from higher to lower tariff bands and by increasing self-consumption, the total import cost is reduced in reality.

The reduction in electricity costs achieved by employing the CPF BMS in conjunction with the Green Energy UK TIDE tariff is a significant value and therefore can justify the incorporation of this energy management system in communities for notable economic benefits to users.

Another analysis has been made to see the effect of CPF BMS employment in the two communities considered when they do not have any PV generation. The results are displayed in table 5.13. It is seen that although CPF BMS increases kWh imported to the community from the grid (due to charging and discharging losses of battery and power converter) for both the Milton Keynes and the Carbon Legacy communities by **665 kWh** and **702 kWh**

Table 5.13: Effect of CPF BMS on community annual import in kWh and in £ for a scenario without PV generation. A standard flat-rate import price is used for the case ‘without battery’.

Community	Import			
		w/o Battery	CPF BMS	Difference
Milton Keynes	£	3602	2305	-1297
	kWh	21885	22550	665
Carbon Legacy	£	4566	3209	-1357
	kWh	27866	28568	702

respectively, it significantly reduces the import price by **£1297** and **£1357** for the two communities by shifting energy to cheaper periods alone. It can therefore be inferred that the employment of CPF BMS has a notable effect on the communities in reducing electricity import prices regardless of the community being equipped with distributed generation.

5.6 Community vs Individual results

As previously mentioned, the energy saving established by the battery algorithm when paired with the optimum battery size and converter rating for individual properties as well as relative energy savings as a community is evaluated in this section to show merits of the battery algorithm on its own and further benefits for community energy. A comparison is made between the savings achieved by individual households of the two different communities of Milton Keynes and Carbon Legacy as opposed to having the CPF BMS run on the properties summed together as a community, allowing a reduced number of higher capacity batteries and converters. This will also demonstrate the case for community energy being beneficial in terms of overall energy and cost savings and increased utilisation of renewable generation within the community.

Table 5.14 lists the optimum battery and converter size of each household in the community found using the sizing techniques described earlier in the chapter. The sum of these individual battery sizes of the properties of Milton Keynes community amounts to **35 kWh** battery capacity and **13 kW** total converter kW. For the Carbon Legacy community, this number amounts to **33 kWh** total battery capacity for all the properties and a total of **7.5 kW** converters.

For the Milton Keynes community, this is an increase of **35%** for the battery size in kWh and a **117%** increase for the converters kW. For Carbon Legacy community, the increase in battery size for individual operation as opposed to a community operation is **22%** and the converter kW is **50%** higher.

In terms of energy and cost savings, the community working together as a single unit in the BMS can make better utilisation of the battery and PV generation by self-consumption. It is likely that during the PV generation hours, even if there is no active occupancy at one given house, there could be load demand in another house within the community which can make use of the direct PV generation without having to export the PV back to the grid due to no demand, or without having to store the PV in the battery resulting in roundtrip losses.

This can be seen in the values tabulated in 5.14 where the community operating as a whole over one year can reduce exports by **448 kWh** (Milton Keynes) and **1561 kWh** (Carbon Legacy) compared to individual BMS operation. Having a large overall battery for the community also allows the battery to meet more of the peak-period demand. Grid import energy is also reduced due to enhanced self-consumption and is **866 kWh** and **1693 kWh** lower for community operation of the Milton Keynes and Carbon Legacy properties respectively. These energy savings are reflected in the grid import costs which are **£147** (Milton Keynes) and **£202** (Carbon Legacy) lower over the year compared to running the CPF BMS on a TIDE tariff scheme for individual properties.

Table 5.14: Energy and cost saving comparison for individual properties in a community versus saving achieved by the community as a unified system for Milton Keynes community (top) and Carbon Legacy community (bottom).

Property	M3	M7	M13	M14	M19	Sum	MK Community
Batt. size, Conv. size	5 kWh, 3kW	7 kWh, 2kW	6 kWh, 2kW	8 kWh, 3 kW	9 kWh, 3 kW	35 kWh, 13 kW	26 kWh, 6kW
Import £	86	176	216	259	296	1033	1180
Import kWh	960	2130	2796	2884	3660	12430	11564
Export kWh	2840	2155	2121	1607	1430	10153	9705

Property	AH	ES	JF	W123	Sum	CL Community
Batt size, conv size	11 kWh, 2kW	5 kWh, 1.5 kW	11kWh, 2kW	6 kWh, 2 kW	33 kWh, 7.5 kW	27 kWh, 5 kW
Import £	600	157	527	281	1565	1363
Import kWh	5183	1567	5638	2725	15113	13420
Export kWh	255	1008	318	1338	2919	1358

Since battery and converter purchase cost per kW is significant in any given BMS, and the community operation causes a notable percentage reduction in both of these costs, it can be said that differences in import energy cost mentioned above are increased further if the savings in battery and converter purchase are considered in terms of monetary saving. However since the price of batteries and converters in the market are subject to constant change, the gains are left in percentages for this discussion.

5.7 Conclusion

In this chapter, the CPF controller has been further verified through additional communities from Carbon Legacy clients and Milton Keynes in the UK, with a more thorough and complete dataset based on perfectly predicted PV generation

data alongside instantaneous PV and load power data, which allowed a better evaluation of the results.

The effects and methods of choosing a battery size which balances the trade-off between increasing battery impact and reducing system cost are demonstrated and their impact on the annual household electricity cost is shown. Due to the availability of a complete year of data consisting of all four seasons, battery and converter sizing has been achieved more precisely and additionally, a rule of thumb has been proposed to easily size batteries for any community, given available energy consumption and PV generation data for a year. This rule of thumb suggests that the battery size for optimum cost saving for a community, given by the knee-point analysis, is equivalent to the mean of the five highest peak consumption days of March and October.

Similarly, the effects on energy loss and cost saving by choosing a converter rating which is lower than the maximum power of the system is demonstrated and using a method of lowest payback period, the rating is determined. Although the cost analysis has shown that the smaller converter ratings give economic benefits, the large increments in lost capabilities for both charging and discharging (particularly for the Milton Keynes community) suggests that further studies can be made for investing in larger power converters in order to get more energy efficient systems, and as well allow for a flexible system for future expansions.

The annual energy consumption for the Milton Keynes and Carbon Legacy communities have been evaluated based on derived battery capacity, converter size and control algorithms and the superiority of the results are

compared to the scenarios without any batteries or with the originally deployed energy management scheme of the Carbon Legacy clients. The results show effective energy shifting from peak period to the off-peak period as well as enhanced self-consumption, resulting in both a decrease in grid import as well as a decrease in import cost achieved by energy shifting.

Two control scenarios have been considered where the baseline community is considered to be operating on an energy plan with flat-rate tariff scheme (found from averaging existing energy plans from major electricity suppliers in the UK) and no battery, as opposed to the same community operating with the TIDE tariff and CPF BMS. The results have confirmed that **£1001** and **£959** are saved for the Milton Keynes and Carbon Legacy community respectively by employing the CPF BMS in conjunction with the TIDE ToU tariff scheme.

Another scenario is considered where a comparison is made between a community without PV generation, operating on a flat-rate import tariff and no storage system, as opposed to the same community operating under the CPF BMS and variable TIDE tariff. The results show that despite an increase in import energy in kWh (since there is scope for enhancement of self-consumption in this case, and losses occur due to the battery and converter efficiency), load shifting alone by successful operation of the CPF BMS reduces import costs significantly over a year. This amount is approximately **£1300** for the two studied community and can be deemed as a notable saving.

The operation of loads clustered as a community has allowed for smaller optimum battery and converter sizes per household, which in turn allows better

energy and cost saving and higher utilisation of the battery. This has been demonstrated in the final section of the chapter where a comparison is made between the savings achieved by individual households of the two different communities as opposed to having the CPF BMS run on the properties summed together as a community, resulting in lower grid imports, lower overall import cost, and higher PV self-consumption. This can therefore establish the case for community energy being beneficial in terms of energy and cost savings.

In the following chapter 6, the effects of running the CPF BMS with an imperfect prediction of load consumption and PV generation will be studied. Data from the Milton Keynes community will be used due to its reliability and longer availability span. The study will give more realistic figures for achieved energy and monetary savings.

6 IMPERFECT PREDICTION OF DISTRIBUTED ENERGY RESOURCES

6.1 Introduction

A BMS is a recognized approach for optimizing renewable energy integration in communities and residential microgrids by enhancing self-consumption of distributed generation, load shifting to utilise ToU tariff schemes, peak shaving of load consumption, as well as limiting the variability and uncertainty of grid-connected renewable resources, etc. A BMS needs to have a control algorithm to provide a good estimation of the load on the grid at each time step along with the distributed generation. A load and generation forecast is necessary for efficient and optimized control of BMSs that are connected to the grid. The forecasting of domestic load and power generated by variable energy resources such as wind and solar has been the focus of academic and industrial research recently [123].

The analysis made in previous chapters, involving data from the communities of Corsham, Milton Keynes, and Carbon Legacy, considers perfect knowledge of the net load available throughout the day (after the morning off-peak hours) in order to control the power flow within the CPF BMS. In reality, however, there cannot be perfect prediction of the excess PV

energy which will be available throughout the day, due to the intermittent nature of renewable resources such as PV which faces constraints of meteorological forecasting, and due to the nature of variable consumption patterns within households which change from day to day depending on the occupants' behaviour.

A sensitivity analysis needs to be performed in order to demonstrate the impact on the results of the CPF BMS of forecast inaccuracies of the time-varying load and PV data as opposed to perfect prediction or actual data. This chapter provides this analysis and discusses the different methods that can be adopted for predicting the daily PV energy and their effects on the results of the energy management system for the communities considered. The individual effects of load prediction and PV generation prediction will also be studied which in turn can identify the more influential variable and thereby indicate better PV sizing.

The remaining parts of this chapter are organised in the following way. Section 6.2 describes the community considered and the types of forecast methods used for incorporation of imperfect prediction onto CPF BMS. Section 6.3 discusses the modified results of CPF BMS after incorporation of imperfect prediction. In section 6.4 the results of the battery algorithm using persistence forecast is compared against those with the actual data. Section 6.5 discusses the results of the preferred forecast method chosen based on the analysis in the previous section. The chapter finally ends with section 6.6 summarising the results of the CPF BMS based on predicted daily export data rather than actual export data.

6.2 Communities and types of forecasts used for incorporation of imperfect prediction onto CPF BMS

Data from the two communities of Milton Keynes and Carbon Legacy communities have been utilised to draw the analysis for using imperfect prediction of load consumption and PV generation on the CPF BMS. These two communities are chosen due to having a more thorough and complete dataset of instantaneous PV generation and power consumption which allows for more reliable results.

Prediction comes into play when the estimated kWh of excess PV energy throughout the day is used to set the target SOC of the battery at 7 am, the end of the morning off-peak period, each day. The predicted excess PV energy is found by subtracting the predicted load demand of the community from the predicted PV energy generated and is essentially the predicted energy exported from the community to the grid in the absence of storage availability. Equation (6.2) expresses the value of excess PV energy of the day in kWh, where ‘d’ is the day of the year, $t=421$ and $t=1440$ denotes time in minutes for 7 am in the morning and midnight respectively. The ‘Excess PV Power’ is given by (6.1) for every minute ‘t’ of the day, and only its positive values are considered to calculate the excess PV energy.

$$ExcessPV_Power_t = PV_t - L_t \quad (6.1)$$

$$ExcessPV_Energy_d = \sum_{t=421}^{1440} ExcessPV_Power_t \quad (6.2)$$

$$\{ExcessPV_Power \in \mathbb{R}, ExcessPV_Power \geq 0\}$$

Imperfect prediction of excess PV energy may lead to either the battery not charging to maximum SOC before peak hours as a result of higher prediction

of PV which in turn may cause the battery to run out of charge before the peak hours are over, or will result in the battery charging ‘too much’ during morning hours due to lower prediction of PV, which will reduce the ability to absorb all available exports and to benefit from self-consumption. (6.3) shows how the prediction of excess PV available throughout the day adjusts the power flow to and from the battery between midnight and 7 am and thereby sets the SOC of the battery at the end of the morning off-peak period at 7 am.

$$P_{Batt,t,d} = \frac{(Max.SOC - SOC_t) \times BatteryCapacity - ExcessPV_Energy_d}{420 - t + 1} \quad (6.3)$$

In the equation (6.3), ‘t’ ranges from 0 to 420 denoting the minute count from midnight to 7 am in the morning. Only positive values for the numerator are considered, which denotes the battery capacity to be filled by off-peak charging, after subtracting the excess predicted PV energy of the day, from the available empty battery capacity at the current SOC. Negative values may appear in the numerator when Excess PV Energy of the day is greater than the empty space available in the battery for charging at the beginning of the day, however the negative values are ignored which means battery will not charge at all during 00:00 hrs – 07:00 hrs if the export of the day is higher than the available capacity of the battery. The denominator is updated every time-step of the simulation to compute the optimal battery charging power at each time step over the low-tariff band based on the remaining free battery capacity and time remaining till the end of the off-peak period.

This is necessary for determining how much power is utilized from the controllable resources such as Energy Storage Systems

The following five different ‘look-ahead’ scenarios (also known as ‘persistence’ approach due to the usage of historical data) have been considered for estimating the excess PV energy (or export) throughout the day and determining how much power is utilized from the controllable resources such as the Energy Storage System.

1. Week-ahead load consumption profile (L_{Pred}), day-ahead PV profile (PV_{Pred}).
2. Day-ahead export
3. Week-ahead export
4. Week-ahead load consumption profile (L_{Pred}), actual PV generation profile (PV_{Actual}).
5. Day-ahead PV generation profile (PV_{Pred}), actual load profile load profile (L_{Actual}).

Although some link to forecast data is beneficial given the inherently unpredictable nature of UK weather, however, a ‘look-ahead’ forecasting is used for this study as it is simple to implement and does not rely on weather forecasts which may lead to further inaccuracy. The ‘week-ahead’ load and ‘day-ahead’ renewable energy forecasts schedule in advance the power charged/discharged by the storage devices, in an optimal manner. A ‘week-ahead’ load profile follows the basic assumption that consumption in households is identical for each day of the week. L_{Pred} can therefore be equated to historical data from the previous week with similar weekly indexes. A ‘day-ahead’ forecast uses measured PV output time series from the preceding day to obtain the PV generation estimation for the current day as PV_{Pred} . The main

assumption is that PV forecast is closer to the previous day, whereas load consumption has weekly rather than daily patterns.

The Day-Ahead Export utilises the previous day's PV exports to the grid as a measure for the current day's excess PV energy estimation, while the Week-Ahead Export estimation considers the current day's exports to equal the exports of the same day in the previous week. These two forecasting estimations are considered on the understanding that both load and PV energy are used to calculate exports which therefore can be estimated by either series or parallel forecasting.

The remaining two forecast evaluations consider one set of an inaccurate forecast for either load or PV (LPred or PVPred), and keeps the other variable in the set as actual data (PV_{Actual} or L_{Actual}). This allows the comparison of the two different dataset variables individually to see which has a higher influence on the BMS performance should they have inaccurate forecasts. In the next section, quantitative analysis is carried out on the forecast-based operation strategies for the CPF BMS.

6.3 Effects of Imperfect Prediction on the results of CPF Battery Algorithm onto the communities of Milton Keynes and Carbon Legacy

This section investigates the impact of the five different forecast techniques, incorporated into the BMS, outlined in the previous section. The effects of imperfect forecast inaccuracies on the performance of CPF BMS are assessed from the energetic and economic perspective. Simulations with a one-

minute resolution are carried out over a period of one year for the Milton Keynes community having a 26 kWh battery and 6 kW power converter, and for Carbon Legacy community fitted with a 27 kWh battery and 5 kW power converter. The prediction of the very first day for PV generation or the first week of load consumption in the dataset is taken from the last day or the last week of the previous year. The simulation takes into account measured PV power outputs and load forecasts, and results are presented in Table 6.1 for each forecast scenario, using the same methodology as described in section 4.2.6.

The annual import cost saving (£) and resulting additional grid import (kWh) by employing the forecast-based CPF BMS is calculated for the five different data prediction strategies. The additional yearly exported energy and the additional peak period grid consumption in kWh which could not be shifted away from high-tariff by battery discharge due to prediction is also calculated and displayed alongside. The imperfect forecasts are compared with the cost savings and energy reductions achieved by the CPF BMS when actual load and PV generation is used.

Table 6.1: Total yearly import cost saving (£), additional import kWh, and export kWh for five different scenarios of excess PV prediction, contrasted with that of actual scenarios (top), for Carbon Legacy (middle) and Milton Keynes (bottom) communities.

Actual Scenario	Saving (£)	Import kWh	Export kWh	E _{HT} reduction kWh
CL- 27 kWh- 5 kW	1070	13420	1358	2709
MK- 26 kWh- 6 kW	1084	11564	9705	2505

CL- 27 kWh- 5 kW	Saving (£)	Additional Import due to Prediction kWh	Additional Export due to Prediction kWh	Additional peak period grid consumption due to Prediction, kWh
PV _{Actual} , L _{pred}	1013	201	274	107
Day ahead Export	946	755	902	153
Week ahead Export	939	756	907	180
PV _{pred} , L _{pred}	904	808	991	294
PV _{pred} , L _{Actual}	896	858	1057	294

MK- 26 kWh- 6 kW	Saving (£)	Additional Import due to Prediction kWh	Additional Export due to Prediction kWh	Additional peak period grid consumption due to Prediction, kWh
PV _{Actual} , L _{pred}	1067	73	93	35
PV _{pred} , L _{Actual}	1004	416	484	156
Day ahead Export	1001	437	517	139
PV _{pred} , L _{pred}	998	412	486	181
Week ahead Export	953	583	693	298

From table 6.1, it is seen as expected that the highest cost saving, and lowest import/export energy is achieved when forecasts of load and PV generation energy are perfect (i.e. actual data used), which allows the morning battery SOC to be set to a value which accommodates all available PV energy of the day, reducing as many exports as the battery capacity allows, thereby maximizing self-consumption. It also charges all the remaining battery capacity from low-tariff electricity allowing the amount of peak tariff energy purchased

to be minimum. If the battery is fully charged, any remaining excess PV power will be injected into the grid.

The values for actual scenarios are closely matched by the scenario with an actual PV data and a ‘week-ahead’ load forecast. Savings on import cost reduce only by 5.3% (£1070-£1013=£57) and 1.6% (£1084-£1067=£17) per year for Carbon Legacy and Milton Keynes respectively, compared to actual scenario while self-consumption is reduced (exports increased) by 20.1% (274 kWh) and 1% (93 kWh) annually.

On the other hand, actual load data and a ‘day-ahead’ PV generation forecast results in the poorest performance of the CPF BMS in terms of import cost saving and self-consumption, for the Carbon Legacy community. The results for this scenario have the biggest difference from that of the actual scenario with a reduction in import saving of 16.3% (£1070-£896=£174) per year while self-consumption is reduced by 77.8% (1057 kWh) annually.

For the Milton Keynes community, the most deviated results are found for the scenario for Week-ahead Export Prediction, with a 12.1% (£1084-£953=£131) reduction of import cost saving per year and a 7.1% (693 kWh) increase in exports.

These values suggest that the effect of week-ahead load forecast inaccuracies have no major impact on the CPF BMS results, while the day-ahead PV forecast inaccuracies have a significant or higher effect in deteriorating the performance of the CPF BMS. Load prediction by the parallel week-ahead estimation for residential communities can therefore be considered

as a good forecast assumption, while the use of day-ahead measured PV data as prediction may require further improvements.

For the real-life scenario where both PV energy and load demand needs to be predicted in advance in the CPF BMS, the three strategies which can be used are: a combination of L_{Pred} and PV_{Pred} , Day-ahead exports, or Week-ahead exports. As understood from the previous paragraph, due to forecast inaccuracies of PV_{Pred} , the combination of L_{Pred} and PV_{Pred} also results in comparatively poor performance of the CPF BMS resulting in import cost saving of £904 (Carbon Legacy) and £998 (Milton Keynes) and additional exports of 991 kWh (Carbon Legacy) and 486 kWh (Milton Keynes) which are 73% and 5% increments respectively (meaning lower self-consumption). The cost savings are 15.5% (£166) and 8% (£86) lower compared to the actual scenario for the two mentioned communities.

A closer performance to the actual data incorporated CPF BMS is shown by the ‘Day-ahead exports’ for both the communities. For the Carbon Legacy community, cost savings in imports are reduced by **11.6%** (£1070-£904=£124) and self-consumption is reduced by **66%** (902 kWh) for this control strategy. The savings for ‘Week-ahead exports’ are also comparable to the Day-ahead export, achieving a 12.2% (£1070-£939=£131) cost saving and reducing self-consumption by 66.8% (907 kWh).

For the Milton Keynes community, the cost savings amounts to **7.7%** (£1084-£1001=£83) for the Day-ahead export with a self-consumption reduction of **5.3%** (517 kWh). It can be seen that the Day-ahead export forecasts fare better than the Week-ahead export forecasts in terms of cost savings for

both communities, and especially for the Milton Keynes community where the differences are more notable. This may be due to the fact that PV forecast inaccuracies impact more on the performance than load forecast inaccuracies, as seen above, and the week-ahead export calculation may result in more inaccuracies in PV forecast as opposed to day-ahead predictions.

It can be concluded therefore that the Day-ahead export forecast strategy results in the CPF BMS performing closest to the scenario with actual data or perfect prediction, giving considerable import cost saving and self-consumption among the three different forecast strategies. The results of operating the CPF BMS Algorithm having incorporated the Day-ahead export forecast strategy is further described in the following sections.

A better method of forecasting PV energy generation for the day needs to be identified, which may be in the form of taking the average of the three preceding days' PV energy, getting online access to the meteorological forecast of the current day and calendar timer etc. These possibilities are further studied in the next section along with a comparison of the persistence approach with no-forecast scenarios.

6.4 Algorithm using Persistence Forecast vs. No Forecast

A BMS can also be operated without requiring predicted PV generation and load consumption data for setting the overnight charging level. Different control methods have been applied in the past to set the battery SOC at the end of the overnight charge period [124]. They are discussed below.

A simple control approach uses constant overnight charging, where the battery charges from 00:00 hrs to 07:00 hrs (for the TIDE Tariff scheme) to a pre-set SOC throughout the whole year. This requires no historical power profiles or weather forecasts. The overnight charging level may be chosen according to the peak power levels of the PV system installed.

Another control strategy is to set the overnight charging level for the battery separately for every season in order to optimize seasonal benefits of the BMS. It was assumed that a calendar timer was connected to the meter between the ESS and the power grid in order to change the charging level at the beginning of each season. The best overnight charging level for summer tends to be lower due to the abundance of PV energy throughout its longer days which can fill up the battery with ‘free’ energy rather than ‘cheap’ energy. On the other hand, during winter, the battery is set at a higher SOC at the end of its morning off-peak period since there is less sufficient PV energy through its short days to fill up the battery and supply load during the peak period.

Both these control strategies can, in turn, be adjusted according to the size of the battery employed in the system. Generally, for small batteries, due to their restricted capacity, a higher SOC can be set at the end of the overnight charging period irrespective of the season. This is because smaller batteries discharge quickly and therefore can capture surplus PV when it is available. On the other hand, the pre-set SOC for larger batteries must be smaller in order to leave enough space for surplus PV storage during the day. The SOC level can also be determined according to the installed PV peak power, whereby a lower overnight charging is set for higher power PV systems and a higher overnight

charging is set for smaller PV systems. Overall, as the battery and PV size increases, the optimal charging level decreases for all seasons [125].

Simulations have been made with a minute sample rate in order to obtain results for the CPF BMS that operates using a seasonal fixed pre-set SOC for the battery after over-night charging. The pre-set SOC's are varied between 10% to 50% for the six months of summer (from April to September inclusive) and between 50% to 90% for the six months of winter (October to March) following British Summer Time [125]. The highest savings were achieved for a pre-set 7 am SOC of 90% during winter for both the communities and for pre-set SOC's of 10% and 20% during summer seasons for Milton Keynes and Carbon Legacy community respectively.

Comparisons are made for these results against the CPF BMS performance using predicted forecast using day-ahead exports. Table 6.2 gives results of the comparison and shows that while the import cost savings for the Milton Keynes community remains identical for both seasonal fixed SOC (£1004) and Day-ahead-export forecast scenario (£1001), for Carbon Legacy

Table 6.2: Summary of import and export kWh and cost saving (£) over one year for different battery control scenarios for Carbon Legacy and Milton Keynes communities

CL-27kWh-5kW	Saving (£)	Import kWh	Export kWh	Ehigh reduction (kWh)
Actual Scenario	1070	13420	1358	2709
Day ahead Export	946	14175	2260	2556
Seasonal fixed SOC	978	14095	2137	2616

MK-26kWh-6kW	Saving (£)	Import kWh	Export kWh	Ehigh reduction (kWh)
Actual Scenario	1084	11564	9705	2505
Day ahead Export	1001	12001	10222	2366
Seasonal fixed SOC	1004	13107	11215	2509

community, the forecast scenario gives a 3.3% (from £978 to £946) lower import cost saving compared to the fixed SOC scenario. However, for the Milton Keynes community, both imports and exports are lower for the control strategy which applies persistence approach, implying that the forecast strategy operates a more intelligent control which prioritises self-consumption and attempts to use off-peak imports only after allowing the utilisation of all possible PV.

Cost savings of summer and winter have been analysed separately to identify the cause of higher cost saving of fixed seasonal SOC for the Carbon Legacy community. The primary reason for the savings being high for the fixed SOC case is its ability to meet a larger amount of high-tariff demand as opposed to the prediction control strategies. During winter, the fixed SOC control strategy invariably keeps the battery charged to maximum SOC at 90% when the peak-tariff period begins. This results in the maximum possible shift of high-tariff energy to low-tariff band resulting in a sharp cut-down in cost.

For the predictive cases however, it is unlikely that the prediction would match the actual PV generation accurately, thereby resulting in either over-prediction or under-prediction of PV energy availability of the day. This is shown in figure 6.1, which records the difference in energy between predicted PV export (using average of 3-day ahead daily export energies) and actual PV export of each day. It can be seen from the figure that the forecast of days alternates between over-predictions (positive values) and under-prediction (negative values). The total difference in energy for the Milton Keynes community is 6114 kWh (which is 63% of the actual export of 9705 kWh) while

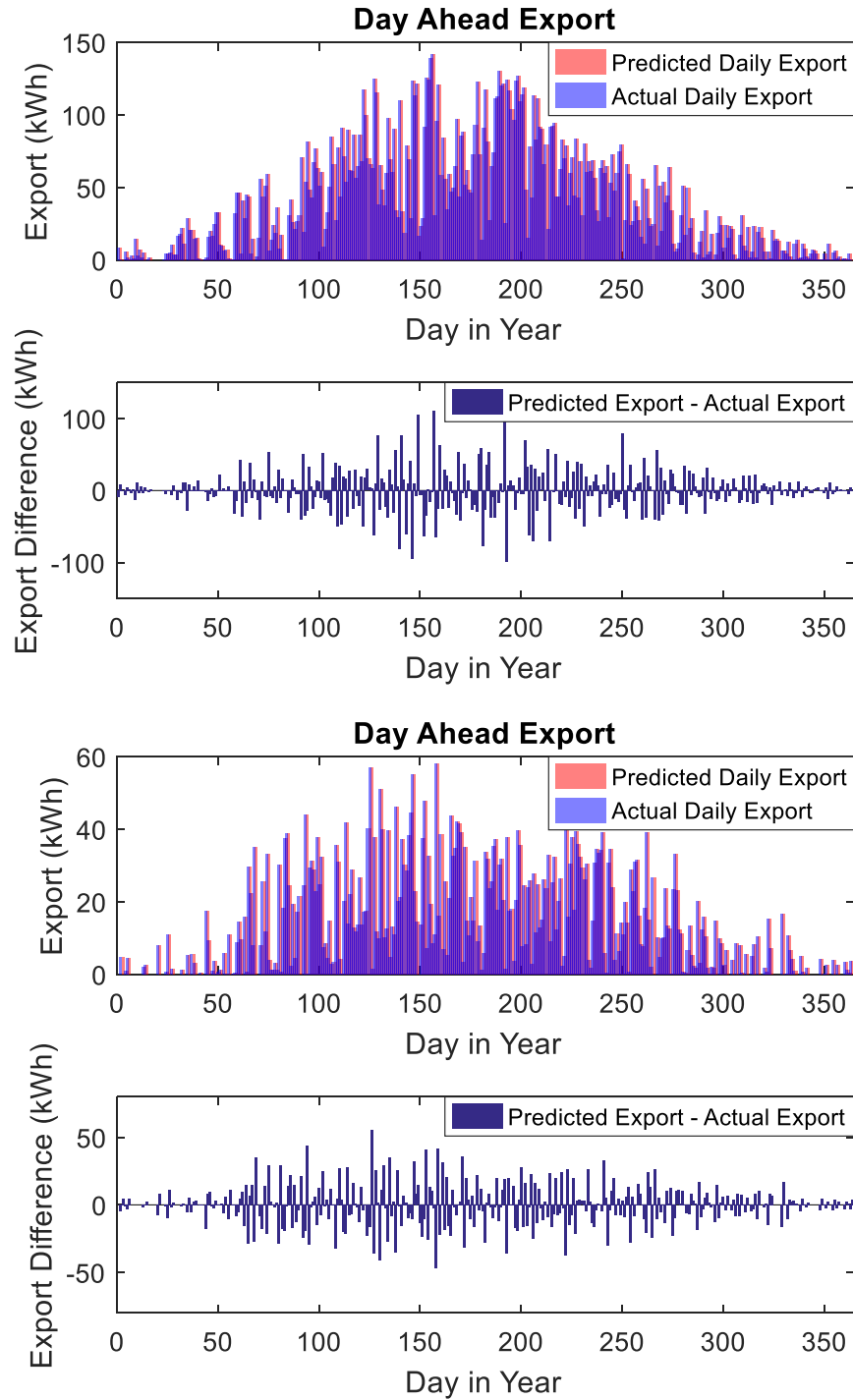


Figure 6.1: Difference in energy between predicted PV export (using average of 3-day ahead daily export energies) and actual PV export of each day for Milton Keynes (top) and Carbon Legacy (bottom).

for Carbon Legacy community, the prediction energy difference is by 2458 kWh (which is 181% of the actual export of 1358 kWh) over the complete year.

A large percentage of days resulted in over-prediction of PV generation for the day as can be seen in figure 6.2, where although the overnight import and therefore import cost was much lower, the battery was not charged to maximum capacity before the start of the peak period and therefore ran out of charge without being able to supply load during the entire peak-period. This resulted in the import of high-priced grid energy to supply the remaining load which slightly reduces the savings achieved due to lower overnight charging. It also reduces the import cost saving achieved during days of under-prediction which results in lower overall import cost than fixed SOC scenario.

During summer, the PV data for the year has shown a large amount of PV generation which has allowed the battery to be filled up to maximum SOC when PV is available for discharge support during the peak-demand period,

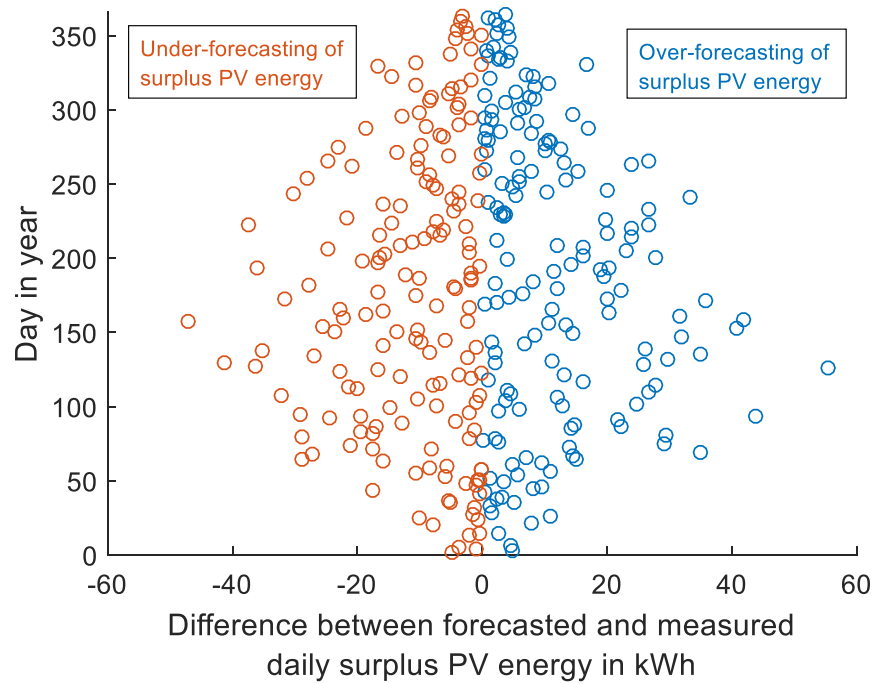


Figure 6.2: Count of under- and over-forecasted daily surplus PV energy based on Day-ahead export persistence forecasts compared to actual scenario, for Carbon Legacy community over one year.

despite the low SOC set at the end of overnight charging for the fixed SOC scenario. The results for the forecast and no-forecast scenario are therefore identical for the summer season, resulting in the winter operation making the final difference in cost saving for the community.

Due to the varying amount of export energy, as seen from figure 6.3, moving-average filters for a selected number of days have been applied to the Predicted Export Data in order to smooth the array of sampled data. The filter takes M samples of previous daily export (input) for each day and takes the average of those to produce a single output point to give the predicted export of the day. M is considered to be 3, 7, 15 and 30 days.

The same filtering technique is applied to obtain PV_{Pred} , resulting from the average of M samples of daily PV generation data, and used in conjunction with week-ahead load consumption data L_{Pred} to predict the net export energy of each day as opposed to predicting it through taking the average of the previous days' exports.

The 'Export average of M previous days' for the $(n+1)^{th}$ day is given by equation (6.4), where $DailyExportEnergy_m$ is the actual export energy in kWh of the m^{th} day of the year.

$$Export_{n+1} = \frac{\sum_{m=n}^{n+M} DailyExportEnergy_m}{M} \quad (6.4)$$

The 'M day average PV_{Pred} ' for the PV power profile prediction of the $(n+1)^{th}$ day is given by equation (6.5), where PV_m is the actual PV generation power profile of the m^{th} day. In both (6.4) and (6.5), M takes the values of 3, 7, 15 and 30 as the moving average window.

$$PVpred_{n+1} = \frac{\sum_{m=n}^{n+M} PV_m}{M} \quad (6.5)$$

Table 6.3 summarises the cost and energy results achieved using all the forecast methods utilising moving average filters for both Carbon Legacy and Milton Keynes communities. From the table it is seen that for the Milton Keynes community, the Week-ahead-load and 3-day-average-PV_{Pred} forecast holds the highest saving closest to the actual scenario, closely followed by Export average of 3 previous days, and Day-ahead-export. For the Carbon Legacy community, the forecast using the average of 15 and 30 previous days' export energy has the highest savings, which uses a 15 and 30-day moving average window respectively to filter the PV power profile for the prediction. The Seasonal fixed SOC savings are highlighted for ease of comparison with the forecast scenarios.

Table 6.3: Summary of cost saving and energy flow for Carbon Legacy (top) and Milton Keynes (bottom) communities resulted from forecast techniques using moving average filters.

CL- 27 kWh- 5kW	Saving (£)	Import kWh	Export kWh	Ehigh reduction
Actual Scenario	1070	13420	1358	2709
fixed SOC 0.9	978	14095	2137	2616
Export avg-15 prev day	969	13572	1687	2547
Export avg-30 prev day	968	13556	1677	2545
L_{Pred} , 30day-avg- PV_{Pred}	962	13988	2053	2550
L_{Pred} , 15day-avg- PV_{Pred}	961	13955	2027	2542
Export avg-7 prev day	959	13810	1904	2529
Export avg-3 prev day	959	13810	1904	2529
L_{Pred} , 7day-avg- PV_{Pred}	958	13996	2070	2545
Day ahead Export	946	14175	2260	2556
Week ahead Export	939	14176	2265	2529
L_{Pred} , 3day-avg- PV_{Pred}	933	14081	2171	2471
PV_{Pred} , L_{Pred}	904	14228	2349	2415

MK- 26kWh- 6kW	Saving (£)	Import kWh	Export kWh	Ehigh reduction
Actual Scenario	1084	11564	9705	2505
L_{Pred} , 3day-avg- PV_{Pred}	1006	11913	10130	2358
fixed SOC 0.9	1004	13107	11215	2509
Export avg-3 prev day	1002	11889	10130	2387
Day ahead Export	1001	12001	10222	2366
PV_{Pred} , L_{Pred}	998	11976	10191	2324
L_{Pred} , 15day-avg- PV_{Pred}	997	11865	10094	2311
L_{Pred} , 7day-avg- PV_{Pred}	995	11918	10146	2324
Export avg-15 prev day	992	11758	10020	2326
Export avg-7 prev day	991	11830	10085	2338
L_{Pred} , 30day-avg- PV_{Pred}	991	11876	10111	2294
Export avg-30 prev day	985	11745	10016	2301
Week ahead Export	953	12147	10398	2207

Since the two communities show quite some variability in the highest saving forecast strategy, a percentage loss in savings for each forecast strategy is calculated in comparison to the highest possible predicted scenario saving. The ‘Export average of 3 previous days’ filtered forecast method has been found

to give the least reduction in cost savings on average for the two communities. It reduces import cost savings by 1% for the Carbon Legacy community and by 0.4% for Milton Keynes community, compared to their highest possible saving scenarios of ‘Export-average-of-15-previous-days’ and ‘ L_{Pred} , 3day-average- PV_{Pred} ’ respectively.

The savings for the actual scenarios remains to be the highest since the control strategy ensures optimization of self-consumption leading to supplying the peak period demand from the virtually free energy of the sun, as opposed to energy from the grid purchased at off-peak tariff. This result again establishes that the CPF BMS is operating as it should under perfect conditions.

Despite the slightly lower savings achieved by the ‘Export average of 3 previous days’ forecast in contrast to the fixed SOC control strategy for the BMS, this control strategy is adopted for the CPF BMS due to its more general approach and adaptability to any PV generation and load pattern. Using the fixed SOC approach may need a readjustment of the fixed SOC, at the end of the off-peak period, every time there is a change of installed PV kW_s or meteorological variability as illustrated by the high PV generation during the summer of 2018) in PV generation of a year. Besides, the reduction in saving for the communities is less than 2% (for the use of Export-average-of-3-previous-days forecast as opposed to fixed SOC), warranting the use of the more dynamic 3-day-ahead export average prediction over the seasonal fixed SOC strategy.

6.5 Results of CPF BMS considering 3-Day-Ahead Average Export for PV Generation and Load Consumption Prediction

Load consumption and PV generation data from the properties in the communities of Milton Keynes and Carbon Legacy, along with the calculated battery sizes (26 kWh for Milton Keynes and 27 kWh for Carbon Legacy) and converter ratings (6 kW for Milton Keynes and 5 kW for Carbon Legacy) found in Chapter 5 are fed into the CPF algorithm to run the simulation on a one-minute resolution over a year. The 3-day-ahead-average export forecast strategy is incorporated into the algorithm in order to test the effectivity of the CPF BMS in energy shifting (load and PV shift) and achieving economic gains through battery deployment under the effect of inaccurate forecasts. A 3-day moving average export is particularly expected to produce better results in the UK due to the wide variability of solar radiation incident on the UK. Moving behind further than 3 days for data prediction may lead to vastly different weather patterns. For other locations with more consistent solar radiation, moving averages with higher number of days are likely to give better results.

Figure 6.3 and 6.4 shows the summary of energy shifting achieved for the two communities of Milton Keynes and Carbon Legacy respectively after running the CPF BMS for 1 complete year for each of the communities, analysed according to the tariff periods of TIDE scheme.

It should be noted that the primary change which occurs due to the incorporation of the 3-day-ahead average export prediction is the change in self-consumption since the knowledge of the export energy of the day directly influences how much capacity the battery leaves empty to be filled by surplus

PV energy. Low-tariff charging energy should also be altered since the amount of predicted export energy of the day dictates how much the battery charges during morning off-peak hours.

It can be seen by comparing the top left and bottom left bar charts from figure 6.3 for the Milton Keynes community that during the low tariff band the charging energy (given by the blue bars) has reduced by 238 kWh (from 2228.6 kWh in actual scenario to 1990.8 kWh in imperfect prediction) while the mid-

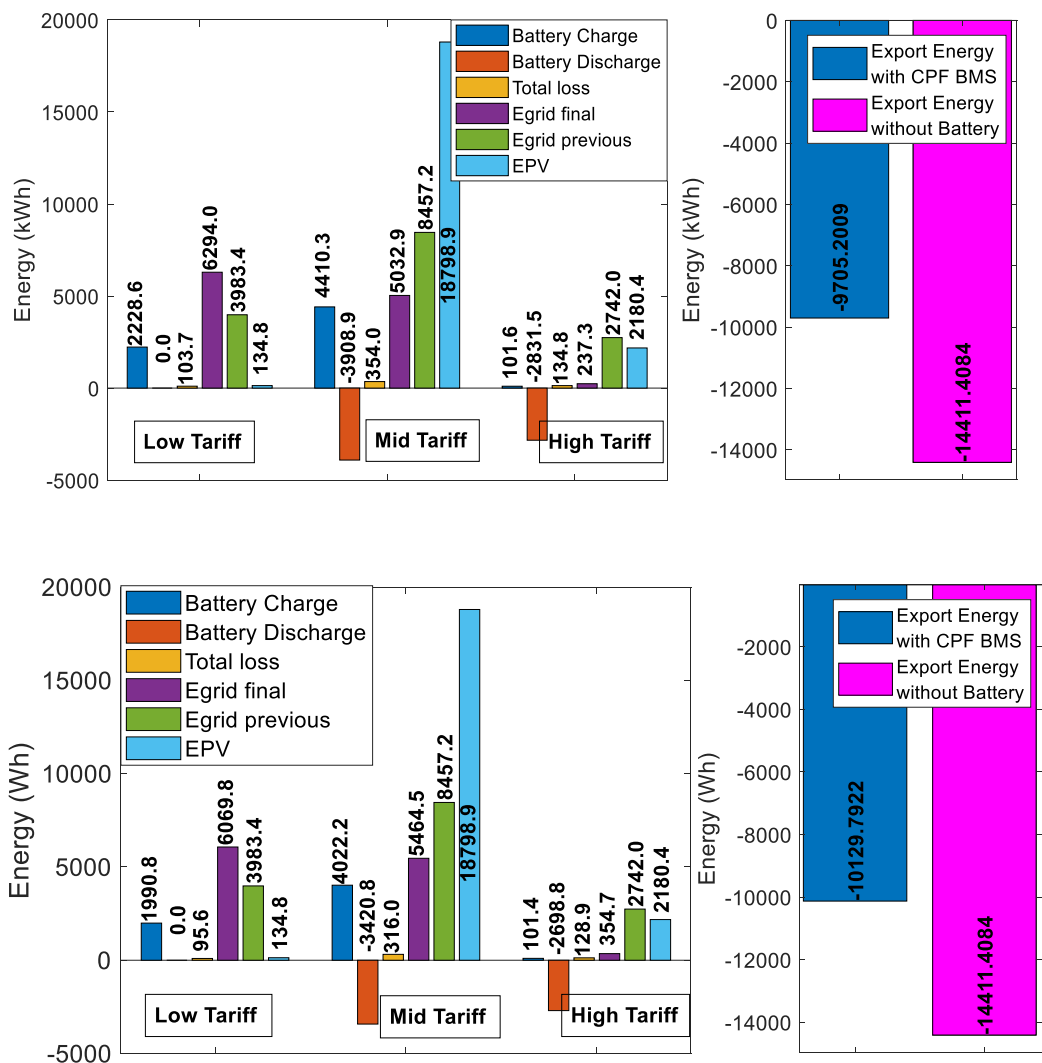


Figure 6.3: Milton Keynes Community Energy flow in different tariff bands for Actual Scenario (top, reproduced from figure 5.5), 3-Day-Ahead Export Prediction (bottom), both operating on CPF BMS

tariff charging is further reduced by 388 kWh (4410.3 kWh in perfect prediction to 4022.2 kWh in imperfect prediction) for the imperfect prediction scenario. This is a result of overprediction of export energy for the day. From the exports bar chart, it is seen that for imperfect prediction, export is increased by 425 kWh compared to the actual scenario considering perfect forecast, which is the amount that was failed to be captured into the battery due to incorrect prediction. The high tariff battery discharge is also reduced by 133 kWh due to the fact that, unlike the perfect forecast scenario, the battery may not have been at maximum SOC before the start of each peak period, resulting in the battery running out of charge before the end of the peak period.

The same is true for the Carbon Legacy community as seen in figure 6.4. Overnight battery charging energy reduces by 352 kWh for the imperfect forecast and charging during mid-tariff band is reduced by 516 kWh. This value is again reflected in the increment of exports by 546 kWh; the surplus PV energy that was not absorbed during mid-tariff band. Battery discharge during the high-tariff band is reduced by 202 kWh owing to the battery running out of charge before the end of the peak period as discussed earlier.

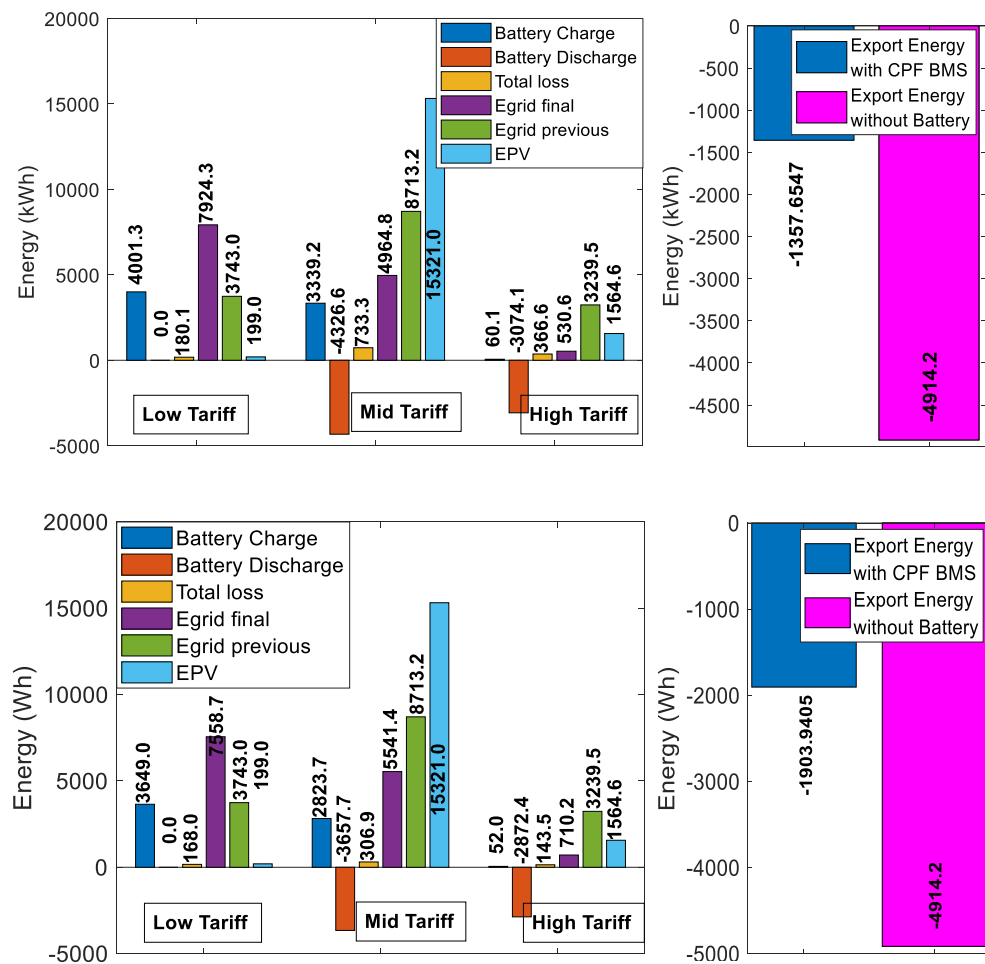


Figure 6.4: Carbon Legacy Community Energy flow in different tariff bands for Actual Scenario (top, reproduced from figure 5.5), 3-Day-Ahead Export Prediction (bottom), both operating on CPF BMS.

Table 6.4: Summary of import and export kWh and cost (£) over one year for different battery management scenarios for Carbon Legacy and Milton Keynes communities, where the Imperfect prediction is given by 3-Day-ahead-average export forecast.

Community			Carbon Legacy	Milton Keynes
Import	CPF BMS Actual	kWh	13420	11564
		£	1363	1180
	CPF BMS Imperfect	kWh	13810	11889
		£	1474	1262
	w/o Battery	kWh	15696	15183
		£	2433	2263
Export	CPF BMS Actual	kWh	1358	9705
	CPF BMS Imperfect	kWh	1904	10130
	w/o Battery	kWh	4914	14411

Table 6.4 tabulates the total import costs for each community, with the CPF BMS operating on an actual and imperfect 3-day ahead average export prediction algorithm, compared against no battery deployment.

For the Carbon Legacy community, a total of **1886 kWh** (15696 – 13810 kWh) of grid import can be reduced over a year by the CPF BMS Imperfect Prediction algorithm, compared to no battery employment in the community, along with a saving of **£959** (£2433 - £1474) for the year by means of PV self-consumption and load shifting throughout the days. PV self-consumption is enhanced by **3010 kWh** (4914-2351 kWh) over the year as calculated from the table. As discussed earlier, due to economic considerations which limit battery size, a larger battery capacity which could eliminate all export by self-consumption is not selected in the project.

For the Milton Keynes community, a total of **3294 kWh** (15183 – 11889 kWh) of grid import can be reduced over a year by CPF BMS, along with a

saving of **£1001** (£2263 - £1262) for the year by means of PV self-consumption and load shifting throughout the days. PV self-consumption is increased by **4281 kWh** (14411-10872 kWh) over the year as calculated from the table.

6.6 Conclusion

In microgrids with distributed generation and storage capabilities, the load demand or the renewable energy generation needs to be predicted in order to determine how much power is utilized from the controllable resources such as the battery. However, due to the intermittent nature of renewable resources such as solar energy and random consumption pattern of households, it is difficult to forecast solar power or load consumption accurately. This chapter has provided details of the effect of different forecast strategies on the performance of CPF BMS in real life scenarios when the total load and generation energy of each day are not known beforehand.

The CPF BMS algorithm is adjusted in order to incorporate different forecast strategies which are all based on the persistence approach and rely on historical power data and run for one complete year for the two communities of Carbon Legacy and Milton Keynes. The analysis has shown that load forecast based on the same weekday during the previous week gives results which are close to a perfect prediction, however, PV forecast based on the historical data of the previous day results in significant inaccuracy. In this particular BMS, the only variable required by the algorithm which needed prediction is the export energy of the upcoming day. As a result, another forecast technique which predicts the current day's export to be equal to the average of three previous days' export is considered. This prediction technique has shown satisfactory

results for both communities which are also comparable to the actual scenarios with perfect forecast. It gives an import cost saving of £959 and £1001 for the communities of Carbon Legacy and Milton Keynes respectively, compared to a system without any battery. It is also seen to achieve a self-consumption of 3010 kWh (61% of actual export without battery) and 4281 kWh (30% of actual export without battery) for the two communities.

The validity of the CPF BMS using the forecast controller approach is therefore examined and verified according to economic and energetic benefits achieved. From the simulation results obtained it has been shown that the communities in UK working together with an Export average of 3 previous days prediction of the current day's exports can continue to reduce peak-time grid consumption, save energy bills and improve self-consumption by employing community energy storage. It should be noted that more intelligent forecast techniques can be included in the algorithm in order to make more accurate and effective control decision of the battery power flow. Short-term renewable generation prediction for the day may be acquired through online access to a meteorological forecast of the current day and calendar timer etc. Progress in and application of artificial intelligence, machine learning etc. can also be utilized in more accurately predicting the required export of the day for the CPF BMS algorithm. However these mentioned techniques can require a lot of training and adjustment to exact operational scenarios. Therefore, despite inaccuracies, the 3-day-ahead export average CPF BMS is employed due to its convenience to better accommodate renewable energy generation sources such

as PV and make use of varying Time-of-Day electricity tariffs to maximize benefits, as opposed to systems without any BMS.

7 CONCLUSION

7.1 Introduction

The final chapter reviews the community energy management framework reported within this work and highlights the conclusions drawn based on the completed assessment. The chapter starts by explaining the conclusions derived in each part of the thesis encompassing the results obtained through different communities, control algorithms, sizing and forecasting strategies, in designing a novel battery management system for optimising the benefits of storage system within communities. It summarises the impact of the developed CPF BMS on the energetic and economic benefits to communities working together in generating, storing and using electricity.

This chapter is organised in the following way. Section 7.2 summarises the developed battery management system and its control framework and discusses the novelty of the work done, contrasting it to existing research within the area. Section 7.3 reports the analysed results based on the proposed CPF BMS and developed models in the work, through simulations carried out on a one-minute resolution over periods of one complete year and individual communities. The section highlights the effectiveness of the CPF BMS under different scenarios. Section 7.4 discusses the limitation of implementing community energy storage systems and presents some recommendations for moving this field forward. Finally, section 7.5 provides areas of further

improvement within the project in terms of future work and explores some alternative operational scenarios of community energy and storage systems which may be beneficial to electricity end-users and local suppliers.

7.2 Proposed Battery Management System and Control Framework

The aim of this project, as stated at the beginning of this dissertation, was to develop a management scheme for community battery storage systems based on currently available variable electricity tariff rates and battery systems in the market. An algorithm was to be developed which allows the capture of available energy from dispatchable sources for peak time usage as well as charging the battery at off-peak times to meet demand during peak periods in order to generate economic benefits for the electricity end-users working together as a community.

Familiarization with real community load and PV data was achieved earlier on in the research through the Corsham EmPower trial data and their challenges were identified. Learning from data analysis and the identified challenges were then used to propose a novel Battery Management System with Community Power Flow Controller (CPF-BMS) algorithm which is able to maximize economic and energetic benefits for electricity usage within communities through import cost reduction and enhanced self-consumption. A major contribution of this work in filling the gap in existing research is the use of data from real communities rather than using data acquired from simulated models such as CREST Demand Model, PVSyst etc.

In addition, a novel methodology is also developed to optimize the sizing of the battery for each community, along with models to choose the power converter rating of the system. The relative energy savings established by the battery algorithm for individual users vs. community usage was evaluated to show the merits of community energy. With new small-scale residential BESS such as Tesla Powerwall providing higher capacity energy storage systems (e.g. 13.5 kWh), the way to maximize these benefits through community operation seemed even more promising.

The CPF BMS introduced in this work was formulated based on known information of real time-varying load consumption and PV generation data, and available electricity tariff rates, in order to control the action of the battery storage unit for maximum cost benefits. In order for the CPF-BMS to be constructed the management framework was divided into different models including a battery with fixed round-trip efficiency, a controller for the power flow in and out of the battery, a bidirectional converter whose efficiency is dependent on input power and a ToU tariff scheme.

Based on these models, technical and economic evaluation is carried out, using simulations in one-minute resolution over a period of one year (when available), on real communities to demonstrate the impact of the proposed energy management. Comparisons are made with baseline scenarios where the community is considered to be operating on an energy plan with flat-rate tariff scheme and no battery, as opposed to the same community operating with the TIDE tariff and CPF BMS. A sensitivity analysis is also performed in order to

demonstrate the impact of imperfect forecasts of the time-varying load and PV data as opposed to actual scenarios.

Finally, the project was able to deliver a working battery management algorithm and battery sizing tool with the following outcomes for a community.

- ✓ Increment of energy self-consumption
- ✓ Reduction of energy consumption at peak tariff rates
- ✓ Reduction of electricity import cost for end-users
- ✓ Battery sized according to optimum cost saving
- ✓ Converter sized according to maximum cost benefits

After adjustment of the algorithm based on a limited economic size of battery and power converter, the project also offered conclusions based on the following evaluations.

- ✓ Evaluation of benefits of community operation
- ✓ Evaluation of results for imperfect data prediction scenarios

7.3 Summary of Simulation Results and Analysis for Developed Models

Analysis of data from the Corsham community in the EmPower project had been valuable in understanding the requirements of energy management systems to work with real-time data and actual communities, as opposed to simulated households, load profiles, and PV data.

A number of technical issues including battery charge and discharge patterns which needed more strategical adjustment to the deployed tariff schedule, effective shifting of energy to cheap period and away from peak periods all led to the designing a more robust battery management algorithm in

the form of CPF BMS. The validity of the CPF BMS is firstly justified by comparing the simulation results obtained from this energy management model against the results obtained from the EmPower energy management project, and later verified through additional communities of Milton Keynes and Carbon Legacy clients with a more thorough and complete dataset which allowed higher reliability of results.

The method of easily choosing a battery size for a community which balances the trade-off between increasing battery impact and reducing system cost is demonstrated, given available energy consumption and PV generation data for a year. A rule of thumb has been proposed which suggested that the battery size for optimum cost saving for a community, given by the knee-point analysis, is equivalent to the mean of the 5 highest peak-consumption of March and October month. Similarly, the effects on energy loss and cost saving by choosing a converter rating which limits the battery at the operational power given by lowest payback period instead of operating at the maximum power of the system is demonstrated and deemed to be economically beneficial and technically viable.

A comparison of the results of CPF BMS with the same battery algorithm but different battery sizes for the communities have shown that a battery with a larger capacity and converter rating, derived from the sizing model introduced in this work, can save more on import cost than a smaller battery with lower converter rating.

Results of employing the CPF BMS (considering perfect knowledge of the PV energy available throughout the day) along with the sizing

methodologies of battery and power converter for different communities in the UK have shown that energy consumption in the high-tariff band is reduced significantly as a result of battery discharge. Due to improved self-consumption, overall community export is reduced. This has allowed reduction in electricity import price over the year for the communities. Compared to baseline scenarios where communities are operating on an energy plan with flat-rate tariff scheme and with no batteries, load shifting alone by successful operation of the CPF BMS reduces import costs significantly over a year.

Individual operation of the households of the two different communities as opposed to having the CPF BMS run on the properties summed together as a community results in lower grid imports, lower overall import cost, and higher PV self-consumption. The community operating as a whole over one year can reduce exports by significant amount compared to individual BMS operation. Grid import energy is reduced due to enhanced self-consumption and is considerably lower for community operation

As a final analysis, the effect of different forecast strategies on the performance of CPF BMS in real life scenarios when the total load and generation energy of each day is not possible to be known beforehand is presented. In the CPF-BMS, the only variable required by the algorithm which needed prediction is the export energy of the upcoming day. Having explored different forecast strategies based on the persistence approach and relies on historical power data, a forecast technique which predicts the current day's export to be equal to the average of three previous days' export is considered. This prediction technique has shown satisfactory results for both communities

which are comparable to the perfectly forecasted scenario, resulting in the CPF BMS to better accommodate renewable energy generation sources such as PV and make use of varying Time-of-Day electricity tariffs to maximize benefits, as opposed to systems without any BMS.

The simulation results verify that the CPF BMS meets the objectives to reduce high tariff band import and energy cost as well as increase self-consumption, through use of existing Time-of-Day multi-level electricity tariffs to maximize benefits, and additionally establishes that operation of the BMS within energy communities are beneficial in terms of energy and cost savings.

7.4 Limitations and Recommendations

Although the technology is already in place for community energy, trading regulations and laws impede the implementation of the project in real life. The market rules and regulations are all designed for national-scale energy systems, which restrict the financial and legal expertise for community energy implementation.

One of the greatest barriers for community energy groups in recent times has been the removal of renewable energy subsidies by the government, in particular, the Feed-in Tariff (FIT). Barriers are also common due to the weaknesses in funding mechanisms for community energy projects as they tend to be higher risk with low returns on investment. The complexity, lack of certainty of outcome, and delays within the planning process and consent have limited organisations in adopting community energy. Since dedicated community energy groups usually do not own any building assets of their own,

access to suitable project sites is a further barrier to community energy project development. One of the key hurdles is therefore often negotiating access to land and the terms of leases and access rights with a landowner. Other regulatory barriers include uncertainty in government policy regarding the future price of energy, dependency on power purchase agreements with large commercial energy firms, the ease of connection to the grid, the future of the feed-in tariff and the level of support available for community schemes from the government. On top of that, there is also the uncertainty around the impacts of Brexit which brings additional challenges to the energy sector including community energy.

These are some of the challenges that are significant in the community energy sector in the current setup of UK's energy changing market. The opportunities raised by new and more decentralised technologies calls for a centralised forum that brings together both local and community ventures in developing longer-term strategies to deliver these projects. These strategies may include early-stage funding, financing support, and subsidy review. New collaborations and adaptive thinking need to be in place in order to sustain the sector with reduced government support.

Regulation may need to be in place to reduce entry barriers such that the choices of one consumer cannot constrain that of another. The impact on electricity users due to the risk introduced by these new approaches need to be assessed to see whether consumer groups should be segregated to bearing the failures and benefits. Government funding schemes need to ensure that access

for community and local energy projects is granted not only to deprived communities but to wider participatory groups.

Collaborations of local and community energy initiatives and organisations could lead the way to provide access to project management and delivery expertise which are currently lacking as well as pave the way for participation in larger projects.

7.5 Future Work

7.5.1 Areas of Improvement

The framework presented for the proposed novel CPF-BMS, as mentioned in chapter 4, takes as input instantaneous and historical consumption and generation data from a community, and consist of different component models including a tariff model, a battery model, a grid interface (converter) model, and a real-time battery and community power flow controller. The battery model within the CPF BMS algorithm is considered as a generic energy source and sink with a finite capacity in Wh, a fixed set of maximum and minimum SOC limits, and a constant one-way efficiency, since the electrochemical or the electrical circuit models are too complex and unjustified for this project.

While the general model allows the use of the model in a wide range of applications without restricting it to specific technologies, it also has scope for further improvement in terms of more accurate incorporation of losses and battery lifetime. The addition of cycle life degradation and calendar life degradation to the existing battery model will allow to predict battery lifetimes

for different usage patterns and give a more realistic measure of the actual energy that can be processed by the battery day-to-day and over its lifespan.

The converter rating in this study is determined by optimum cost-saving results. An alternative would be to explore the use of larger converters with a cap at minimum charging, which will accommodate high power discharge demand as well as limit losses due to low power charging. The minimum rating for the converter is determined according to the power required to charge the entire usable capacity of the battery over 7 hours in the early morning cheap tariff band. However, as discussed in chapter 4, converter efficiency can also be improved by limiting the charging hours, i.e. if the battery discharging profile has high power instances compared to the charging profile and a larger converter is needed for effective discharging, the charging hours can be limited to a few hours every morning with higher power rather than charging with lower power over the total 7 hour duration. Until established guidelines are laid down on how energy communities can get access to ToU and further benefits and cost reductions, this area will remain to be definitely determined.

The variation of discharge behaviour of batteries can be incorporated by accounting for the non-linear effects such as the rate capacity effect and recovery effect [128]. In non-ideal batteries, rate capacity effect is defined by the voltage drop during discharge which lowers the effective capacity for high discharge currents. Recovery effect allows some of this lost battery capacity to be retrieved during periods of no or very low discharge. In this way, the effective capacity and battery lifetime are affected by discharge patterns.

Another area of improvement within the management algorithm is the inclusion of more intelligent prediction techniques for forecasting renewable energy generation and load consumption of each day. A smarter way to predict data can lead to more effective decision making in charging and discharging the battery.

Since the primary discrepancy was in forecasting PV generation, alternative prediction methods may include short-term renewable generation forecast for the day, getting online access to a meteorological forecast of the current day and calendar timer etc. Numerical weather prediction (NWP) models are based on dynamical equations that predict the variation of the atmosphere up to several days ahead from initial conditions. The best day-ahead solar and PV forecasts combine NWP forecasts with post-processing of these forecasts in order to improve them, by comparing to measured data during a training period which is used to develop corrected forecasts. This type of approach is often referred to as Model Output Statistics or MOS. Various other MOS-based approaches have been developed to forecast PV power, including autoregressive methods, artificial intelligence methods including artificial neural networks, support vector machines etc. [129]. This can make better use of the locally generated renewable generation and enhance CPF control in capturing the surplus PV and providing support all throughout the peak hours.

More sophisticated load prediction is focused on a short-term forecast, with a window of two days or less. Classical short-term forecast techniques include regression models, auto-regressive models (ARIMA), time series models, Kalman filtering methods etc. These models perform satisfactorily

under normal conditions but can become unreliable if sudden changes are introduced. External factors such as human impact, social events and meteorological variabilities such as relative humidity of temperature and wind speed can influence significant errors in these forecast methods [130].

In recent years, machine learning and artificial intelligence forecasting technology have been deemed to have more notable benefits than the classical techniques, while neural network approaches combined with fuzzy methods and deep learning are making their place.

Extensive training and data gathering are needed for the implementation of these more intelligent and complex prediction methods. However, these methodologies are likely to become invalid with any new significant addition into the electric system such as electric cars, heat pumps, etc., due to the use of specific knowledge of consumer requirements/constraints. Hence the simpler, more flexible prediction strategy is used in this project under the persistence approach umbrella.

It may also be worth considering running simulation work with 1s sample time to make sure that the algorithm is operating correctly and is able to handle short, high power load such as electric shower, kettle, fan heater etc. Further work can be done to assess the responsiveness of the battery to these short, high power loads and the financial outcome of battery operation under these scenarios.

7.5.2 Alternative Operational scenarios

Alternative uses of community storage exist which have not been explored in this thesis, such as assessing the cost-benefit of installing larger batteries to do

business with higher level ancillary market. Larger batteries, having met the local demand of the community, can also be controlled to follow real Frequency Regulation Requests by the DNO for short-term frequency regulation to stabilize the grid. The fast responsiveness of battery storage systems means they can provide fast frequency control to power systems, and by only responding to fast and zero-mean frequency deviations in the grid, the ability of their limited capacity is enhanced [131].

Another market the large-scale community batteries can provide support to is the Short Term Operating Reserve (STOR). At certain times of the day transmission system operators may need access to sources of extra power to help manage actual demand on the system being greater than forecast or unforeseen generation unavailability [132]. The service is open to any technology with the ability to increase generation or reduce demand by at least 3 MW during pre-defined windows of a typically a morning and evening peak. Large community batteries should also be able to trade with the national grid in the Reactive Power Market, whereby the batteries will be contracted to deliver Enhanced Reactive Power Service [133].

Furthermore, suppliers and aggregators may choose to employ storage devices for Triad Avoidance. Large businesses aim to reduce consumption during the TRIADS or the three periods of peak demand during winter in a bid to save in Transmission Network Use of System (TNUoS) charges [134]. Triad management is however a complex business and relies on access to accurate forecasts.

Other markets may include services for the DNOs including Constraint Management, Demand Side Response, and Active Network Management (ANM) of curtailed Renewables, or further services for the transmission system such as Fast Start Reserve, Constraint Management, Energy Contracts etc. [135].

However, the execution of these functions must be limited to occasions of excessive generation so as not to be unsatisfactory for the electricity end-user by forfeiting their cost benefits. In this way, the controller will be able to provide both local and global services to the community.

The integration of Vehicle-to-Grid (V2G) would result in a notable rise of the total DER storage capacity available for CPFC operation. That, in turn, is expected to significantly enhance the control capability of CPFC, and it should therefore be considered in any future work [136].

Although present in the original management system of EmPower project, DSM techniques are neglected in developing the CPF BMS, due to its unfavourable outcomes seen from the assessment of the Corsham community results. However, further research can be done to implement more robust control and communication for DSM incorporated systems which can eventually lead to favourable results of the scheme. Creating awareness, training participants and gradually changing public habituation can play positive roles in making DSM more effective in achieving benefits for communities and individual electricity users.

Finally, larger communities with more diverse and non-residential loads such as schools, hotels, and universities should be incorporated which allows

assessing the performance of the CPF-BMS over a larger controlled area which can provide significant aggregation's influence.

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9 APPENDICES

Appendix A **241**

Appendix B **245**

Appendix C **246**

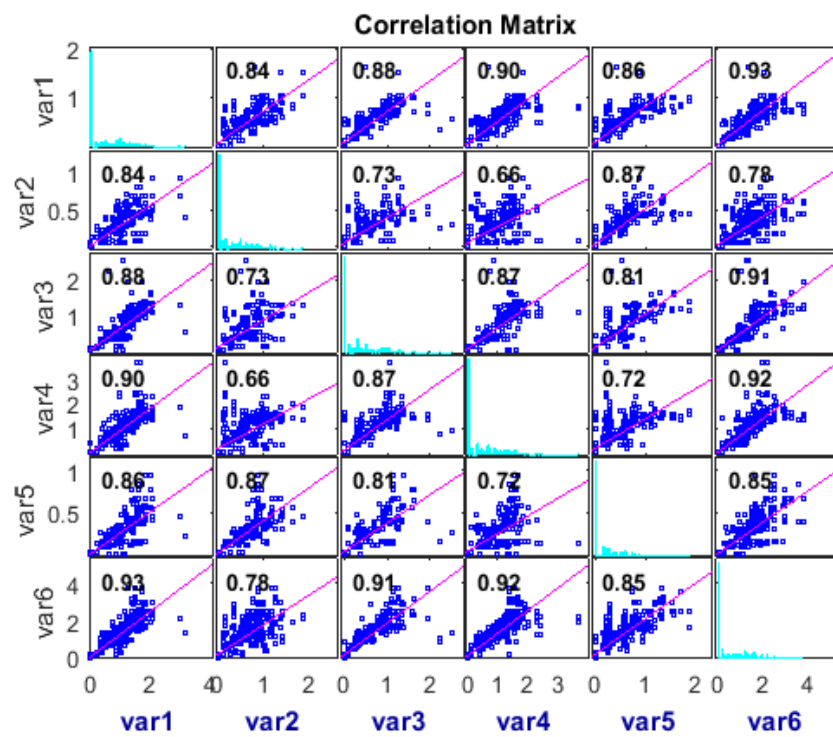
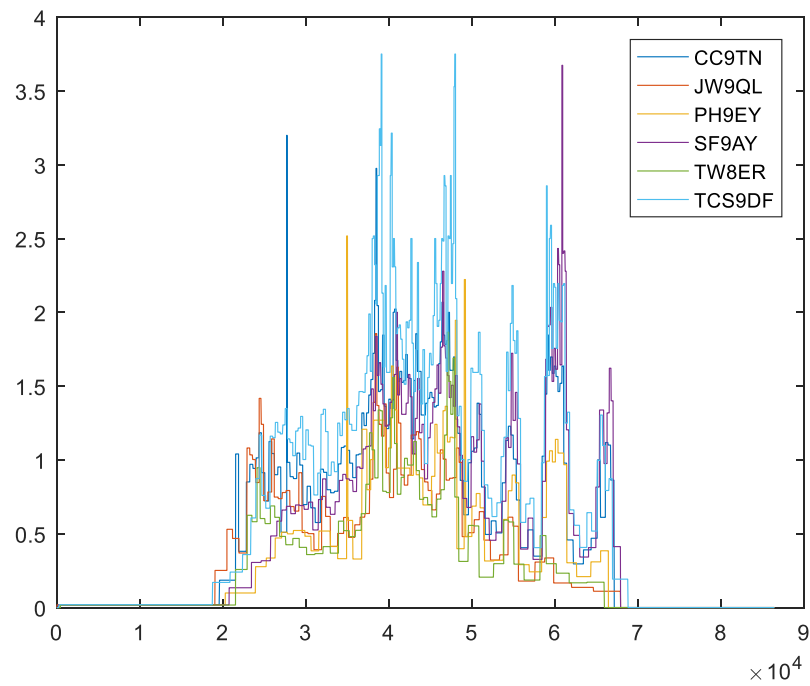
APPENDIX A

Correlation calculations are made between metered PV readings from the six different properties installed with PV generation. Differences seen are likely due to orientation and peak power of installed PV array, along with the fact that the dwellings in the ‘virtual community’ were not physically located at the same place. The tables show the installed peak PV kW_ps and correlation coefficient between the PV generation readings of the six dwellings.

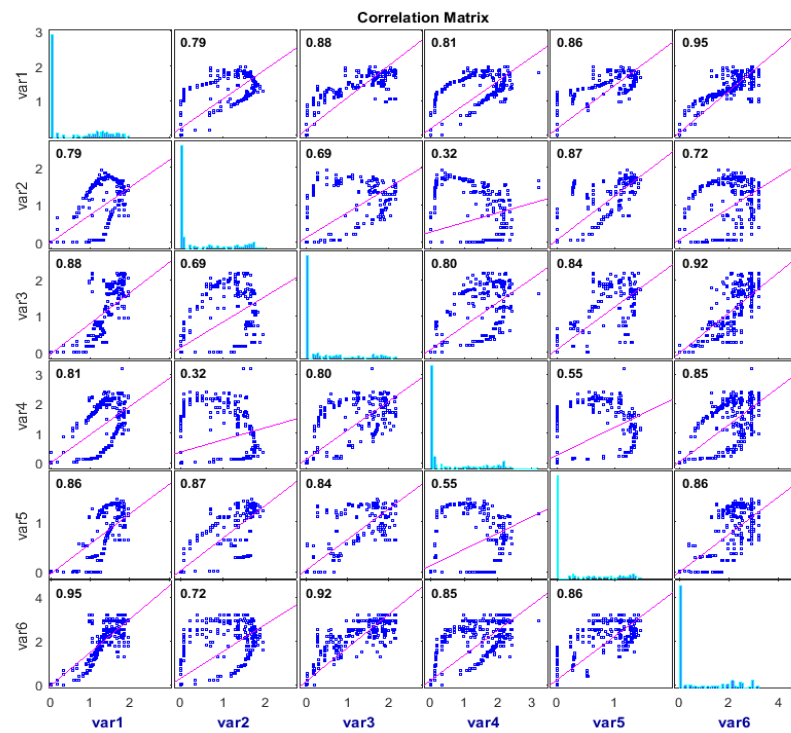
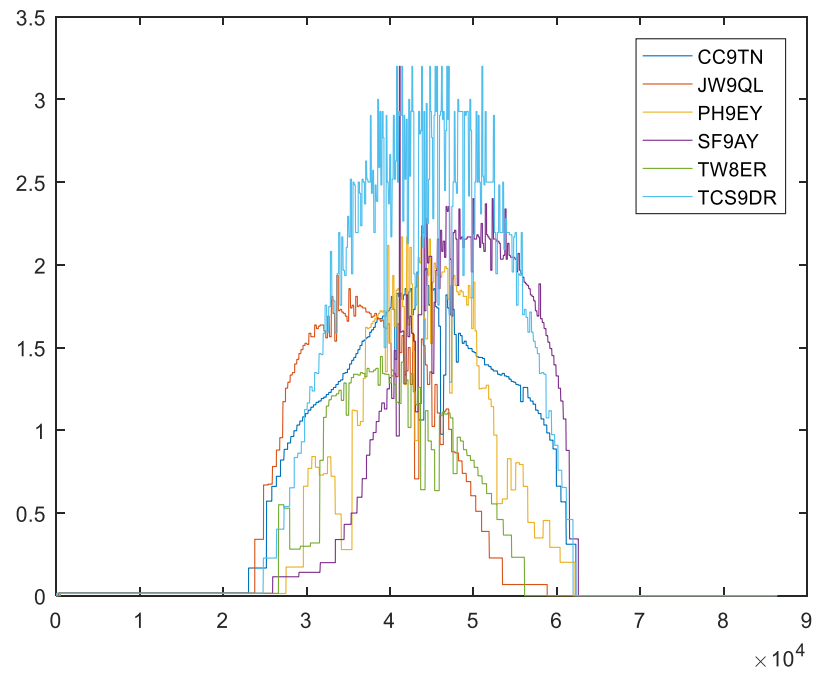
Property	SF9AY	TW8ER	CC9TN	JW9QL	PH9EY	TCS9DF
PV (kW _p)	3.75	2	3.2	2.58	2.6	50

Day of Month	August 1 st	September 30 th	December 1 st
Average Correlation Coefficient	0.86	0.82	0.81

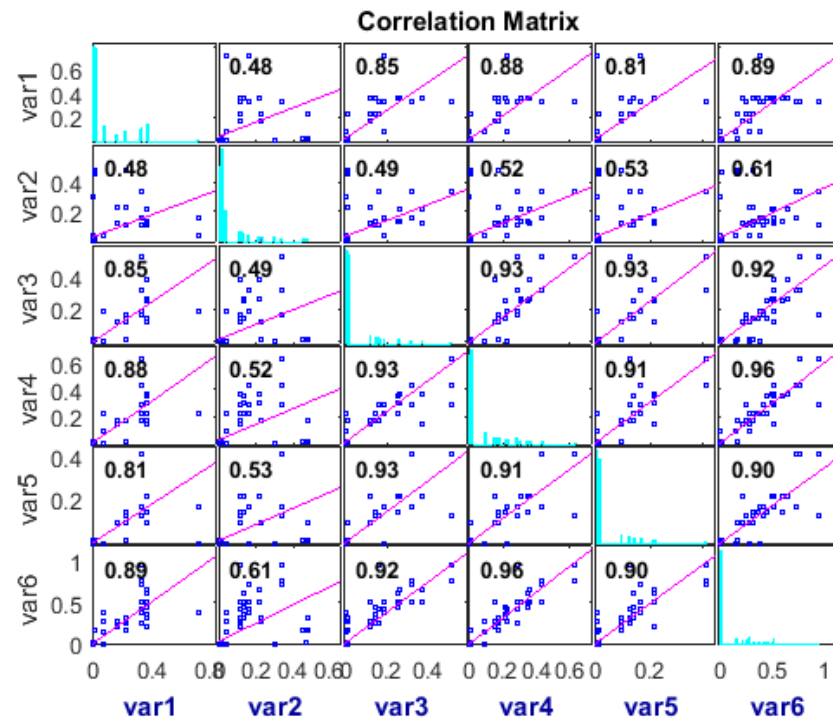
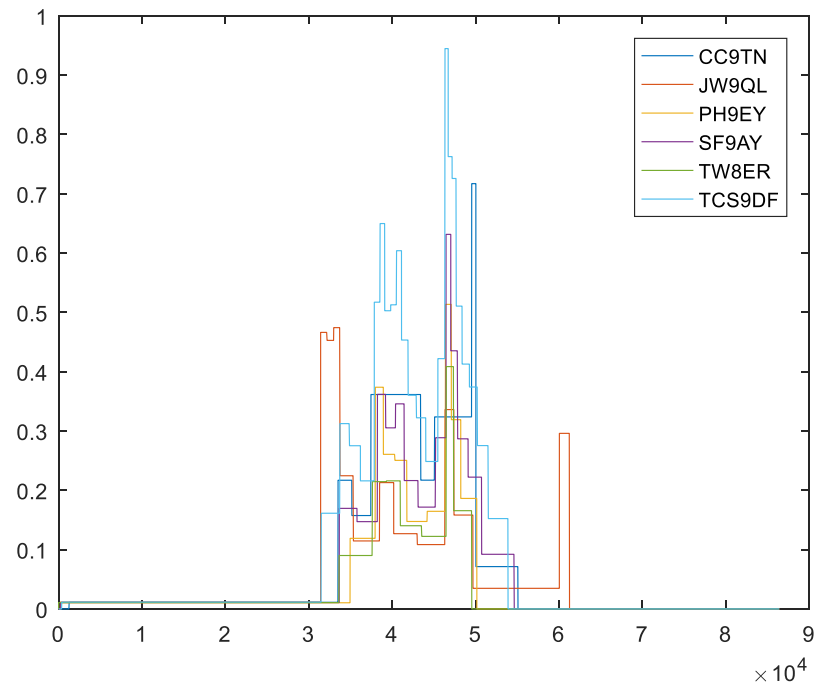
PV Correlation of 1st August 2015



PV Correlation of 30th Sep 2015

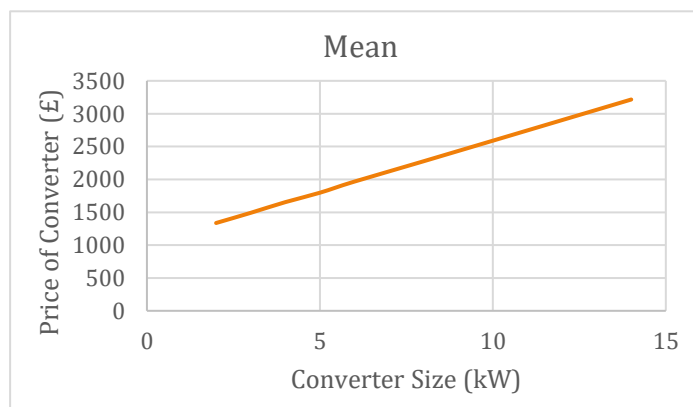
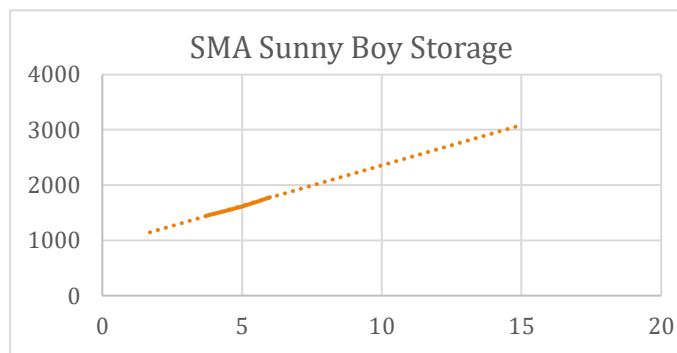
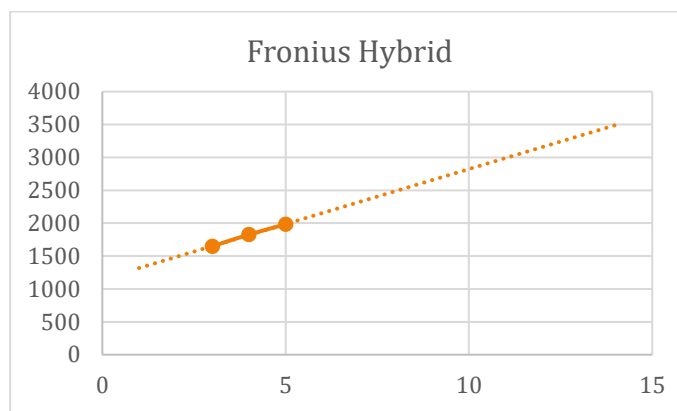


PV Correlation of December 1st



APPENDIX B

FRONIUS		SMA		Mean	
kW	£	kW	£	kW	£
2	1484.167	2	1189.162	2	1336.664
3	1647.5	3.7	1443.5	3	1491.292
4	1826.5	5	1612.5	4	1653.752
5	1982	6	1781	5	1797.25
8	2487.667	8	2064.689	6	1967.083
14	3491.167	14	2940.215	8	2276.178
6	2153.167	3	1335.083	14	3215.691
		4	1481.004		
gradient (£/kW):	167.25		145.9211		156.6591



APPENDIX C

M3 knee-point=3.4 kWh usable

M3	Mean E _H (kWh)	Max E _H (kWh)	5-max E _H (kWh)
Jan	1.9	5.1	3.3
Feb	2.2	6.3	4.2
Mar	1.8	5.7	4.4
Apr	1.4	6.9	3.2
May	0.5	1.7	1.4
Jun	0.5	2.3	1.6
Jul	0.3	2.6	1.5
Aug	0.6	2.1	1.8
Sep	1.3	3.4	2.6
Oct	2.1	5.7	4.3
Nov	2.2	7.7	4.6
Dec	2.1	6.1	5.1
Yearly Mean	1.4	4.6	3.2
Mar/Oct Average			4.3

M7 knee-point= 4.7 kWh usable

M7	Mean E _H (kWh)	Max E _H (kWh)	5-max E _H (kWh)
Jan	3.9	8.6	6.2
Feb	3.9	6.0	5.4
Mar	2.9	5.3	4.5
Apr	1.3	2.8	2.4
May	0.9	6.6	2.8
Jun	0.6	4.2	1.9
Jul	0.4	1.7	1.4
Aug	0.9	3.9	2.6
Sep	1.9	3.2	3.0
Oct	3.1	5.3	5.1
Nov	3.9	6.0	5.5
Dec	4.0	7.2	6.0
Yearly Mean	2.3	5.1	3.9
Mar/Oct Average			4.8

M13 knee-point=4 kWh usable

M13	Mean E _H (kWh)	Max E _H (kWh)	5-max E _H (kWh)
Jan	2.6	6.2	4.5
Feb	2.0	3.1	2.9
Mar	1.7	4.6	3.1
Apr	0.8	2.6	1.8
May	0.5	2.3	1.4
Jun	0.5	2.4	1.5
Jul	0.5	1.9	1.3
Aug	0.7	1.7	1.5
Sep	1.4	3.2	2.6
Oct	2.0	4.7	3.4
Nov	2.5	5.1	3.8
Dec	4.0	19.9	10.2
Yearly Mean	1.6	4.8	3.2
Mar/Oct Average			3.3

M14 knee-point= 5.5 kWh Usable

M14	Mean E _H (kWh)	Max E _H (kWh)	5-max E _H (kWh)
Jan	4.4	7.8	6.9
Feb	3.6	6.1	5.5
Mar	3.1	5.9	4.9
Apr	2.0	4.5	3.9
May	1.7	5.7	3.7
Jun	1.1	4.7	3.8
Jul	1.0	2.9	2.5
Aug	1.9	3.2	3.0
Sep	2.9	6.8	5.3
Oct	3.0	6.4	4.9
Nov	3.3	9.1	5.3
Dec	3.6	5.3	5.1
Yearly Mean	2.6	5.7	4.6
Mar/Oct Average			4.9

APPENDIX C- CONTINUED

AH knee-point=8.2 kWh usable

AH	Mean E _H (kWh)	Max E _H (kWh)	5-max E _H (kWh)
Jan	6.7	18.5	11.8
Feb	5.7	15.4	11.7
Mar	4.1	10.4	8.5
Apr	2.8	6.7	5.8
May	1.8	8.9	5.2
Jun	1.1	7.5	4.1
Jul	1.5	6.5	4.8
Aug	2.0	7.1	5.9
Sep	2.6	8.7	5.8
Oct	4.6	11.4	9.3
Nov	6.4	12.6	10.0
Dec	1.2	10.2	6.6
Yearly Mean	3.4	10.3	7.4
Mar/Oct Average			8.9

ES knee-point=3.2 kWh usable

ES	Mean E _H (kWh)	Max E _H (kWh)	5-max E _H (kWh)
Jan	2.2	4.0	3.1
Feb	2.4	5.2	4.0
Mar	1.8	5.6	3.7
Apr	1.6	3.6	3.0
May	1.1	3.5	2.5
Jun	0.9	2.7	1.9
Jul	0.9	3.7	2.3
Aug	1.0	2.4	1.9
Sep	1.6	6.0	3.4
Oct	2.1	5.6	4.0
Nov	2.0	3.8	3.2
Dec	2.5	4.4	4.0
Yearly Mean	1.7	4.2	3.1
Mar/Oct Average			3.9

JF knee-point= 7.6 kWh usable

JF	Mean E _H (kWh)	Max E _H (kWh)	5-max E _H (kWh)
Jan	5.7	10.8	8.7
Feb	5.7	9.6	9.0
Mar	5.5	9.5	7.9
Apr	5.4	12.9	11.5
May	2.6	7.5	4.8
Jun	2.8	5.6	5.2
Jul	2.7	4.9	4.4
Aug	2.4	5.7	4.5
Sep	3.7	7.0	5.7
Oct	5.5	8.5	7.6
Nov	4.2	7.7	6.3
Dec	5.6	9.7	8.6
Yearly Mean	4.3	8.3	7.0
Mar/Oct Average			7.8

W123 knee-pt= 4.5 kWh usable

W123	Mean E _H (kWh)	Max E _H (kWh)	5-max E _H (kWh)
Jan	1.6	2.3	2.1
Feb	2.2	6.9	4.5
Mar	3.0	6.1	5.9
Apr	2.7	6.8	5.5
May	2.5	6.0	5.1
Jun	2.5	5.1	4.7
Jul	2.2	4.7	4.2
Aug	2.9	5.4	5.2
Sep	2.2	5.4	4.4
Oct	2.6	4.8	4.4
Nov	3.2	8.4	6.8
Dec	1.6	2.5	2.2
Yearly Mean	2.4	5.4	4.6
Mar/Oct Average			5.2