

CONTROL AND OPTIMAL MANAGEMENT OF HYBRID PV-WIND INTEGRATED CHARGING STATION FOR ELECTRIC VEHICLES

by

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DECLARATION

I, Lindiwe Bokopane, student number #####, hereby declare that the work that is presented in the thesis titled **“Control and optimal management of hybrid PV-wind integrated charging station for electric vehicles”**, was carried out by me in the Department of Electrical, Electronic and Computer Engineering at the Central University of Technology Free State, for the degree Doctor of Engineering in Electrical Engineering, and that it complies with the Code of Academic Integrity, as well as other relevant policies, procedures, rules, and regulation of the Central University of Technology Free State.

The information derived from the literature is duly acknowledged in the text and a list of references is provided. No part of this project was previously presented for another degree at this institution or any other in fulfilment (or partial fulfilment) of the requirements for the attainment of any qualification.

L. Bokopane

Date: 24 June 2024

DEDICATION

I dedicate this work to my late mother, **Masentle Lorna Rasiile**.

May you continue to rest in power. Mbokodo, uyibekile induku ebandla. Uyidlalile eyakho indima
wena thonga elihle.

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ABSTRACT

Electric vehicles (EVs) are rapidly gaining popularity worldwide due to significant advancements in their technology; however, the development of their charging infrastructure remains a topic of interest. Historically, most EV charging requirements were fulfilled by the conventional alternating current grid. Extensive research has, however, been conducted over the years to explore the integration of renewable energies into electric vehicle charging stations (EVCSs). Most research studies focus on management, optimal control, charging schemes, charging strategies, and prosumer trade options. To date, limited research has been conducted on charging stations that incorporate a grid-integrated hybrid renewable energy system that utilises sources like wind and solar power. These charging stations typically utilise a central battery bank (CBB) and explore the implementation of a peer-to-peer (P2P) energy-trading model. The objective of this model is to enhance profitability for both the charging station and prosumers, who are consumers that also produce electricity. The aim of this research was to address the challenges posed by inadequate power systems in the country and to develop sustainable charging solutions for EVs. By leveraging renewable energy sources and facilitating energy trading, these charging stations aim to promote vast adaptation of EVs in a country with ailing energy-generation infrastructure while promoting a more sustainable approach to EV charging.

This work developed a well-coordinated charging scheme of EVs in a charging station while optimally managing the charging and discharging of the CBB (used for energy storage), as well as the power dispatch of a grid, wind, and photovoltaic (PV) charging station. The model maximises EV user satisfaction, meets all the charging requirements of the charging station, and offers cost-effective charging schemes such as the P2P energy-sharing model.

The first model was based on an optimisation approach and a modelling framework for a PV-grid-integrated EVCS with battery storage and P2P vehicle-charging strategies. The main objective was to optimise the system for reliability and profitability while minimising operational costs. The model considered factors such as energy demand, grid stability, battery health, and charging costs to efficiently utilise resources. A notable aspect of the proposed model is the introduction of a P2P energy-sharing mechanism. Prosumers are allowed to trade energy with one another, which enables

efficient utilisation of resources and fosters a collaborative energy ecosystem. The dynamic power demand and pricing environment facilitate fair and optimised energy exchanges. It outlines the development of a mathematical algorithm formulation for the proposed model and validates its effectiveness and performance using a real-world case study conducted at Nelson Mandela University in South Africa. This comprehensive approach considered daily varying weather and load conditions to ensure a realistic analysis of system performance and economic feasibility. The simulation results demonstrate significant energy demand cost savings, with a 38.14% reduction considering time-of-use (ToU) tariffs, and a 30.5% reduction in maximum demand through optimal control in comparison to the baseline model and it further conducts a detailed techno-economic analysis over a 20-year period. The results indicate substantial reductions in grid costs and a breakeven point within eight years, which highlight the economic advantages of the optimisation model. Furthermore, the results demonstrate significant cost savings, including energy demand cost savings and ToU savings.

The second model was based on the model predictive control (MPC) optimisation of a hybrid smart grid with PV-wind and a CBB incorporating demand-side management, a P2P charging scheme, as well as EVCS profitability. The aforementioned model maximised EV user satisfaction that meets all the charging requirements of the EVCS while offering cost-effective charging schemes such as the P2P energy-sharing model. The optimal power scheduling was modelled into a control problem to benefit from feedback advantages and predictions. The programming framework of the MPC model was linearized to accommodate two scenarios under scrutiny (with and without the occurrence of power cuts). The closed-loop MPC model further enhanced the open-loop optimal control with an additional 18.04%, which translated to an overall cost savings of 43.29% when compared to the baseline model. The lifecycle cost also saw a reduction of two years, which translated to reaching the breakeven point after six years.

The results proved the effectiveness and benefits of each optimal-control model, while displaying the robustness of the MPC closed-loop control model. This may assist in advancing the vast adaptation of EVs while displaying the profitability and reliability of the EVCS under the proposed scenarios.

Keywords: Electric vehicle charging station; peer-to-peer sharing; peer-to-peer energy sharing; open-loop optimal model; closed-loop MPC algorithm; time-of-use tariff structure

TABLE OF CONTENTS

DECLARATION.....	i
DEDICATION.....	ii
ACKNOWLEDGEMENTS.....	iii
ABSTRACT.....	v
LIST OF FIGURES.....	xiv
LIST OF TABLES.....	xix
LIST OF ABBREVIATIONS.....	xx
LIST OF SYMBOLS.....	xxii

CHAPTER I: INTRODUCTION

1.1 BACKGROUND	1
1.2 PROBLEM STATEMENT	2
1.3 RESEARCH OBJECTIVES.....	3
1.4 METHODOLOGY	3
1.4.1 Literature review.....	3
1.4.2 Stepwise process for system modelling and control.....	4
1.4.2.1 <i>System variable identification</i>	4
1.4.2.2 <i>Mathematical modelling and control</i>	5
1.4.2.3 <i>Simulation and verification</i>	5
1.5 CONTRIBUTION TO KNOWLEDGE	8
1.6 HYPOTHESES	9
1.7 DELIMITATIONS.....	10
1.8 PUBLICATIONS FROM THIS STUDY	10
1.9 THESIS ORGANISATION	11

CHAPTER II: A REVIEW OF THE IMPROVEMENT OF ELECTRIC VEHICLE CHARGING STATIONS (EVCSs) USING THE POET FRAMEWORK

2.1	INTRODUCTION	12
2.2	REVIEWED LITERATURE.....	12
2.2.1	Justification of the reviewed literature	21
2.3	POET STRUCTURED FRAMEWORK IN AN EVCS.....	22
2.3.1	POET structured performance of the infrastructural designs of an EVCS (according to the technical objective)	23
2.3.1.1	<i>Photovoltaic (PV) panel overview and selection justification</i>	23
2.3.1.2	<i>Wind turbine overview and selection justification.....</i>	24
2.3.1.3	<i>Battery bank technologies overview and selection justification</i>	25
2.3.1.4	<i>Energy management system (EMS) overview and selection justification.....</i>	26
2.3.1.5	<i>Charging point technologies overview and selection justification.....</i>	27
2.3.2	POET structured framework for an EVCS (according to the non-technical objective).....	29
2.3.2.1	<i>Infrastructural design of an EVCS</i>	30
2.3.2.2	<i>Optimal sizing of an EVCS.....</i>	31
2.3.2.3	<i>Resource availability and variability.....</i>	34
2.3.2.4	<i>Energy security</i>	35
2.4	KEY FINDINGS ON THE REVIEWED LITERATURE	35
2.4.1	POET perspective analysis	35

CHAPTER III: OPTIMAL POWER-DISPATCHING SCHEMES OF A GRID-INTEGRATED PV-WIND EVCS WITH BATTERY STORAGE AND PEER-TO-PEER (P2P) VEHICLE CHARGING STRATEGIES

3.1	INTRODUCTION	37
3.2	MODEL DEVELOPMENT.....	38

3.2.1	EVCS load profile description	38
3.2.2	Steps to obtain the EVCS load profile.....	40
3.2.3	Proposed system configuration and description	42
3.3	MATHEMATICAL MODEL FORMULATION.....	45
3.3.1	Objective function	45
3.3.2	Variable constraints	46
3.3.2.1	<i>Power flow balance</i>	46
3.3.2.2	<i>Inequality constraints</i>	46
3.3.2.3	<i>Variable boundaries</i>	47
3.3.2.4	<i>Exclusive power flows</i>	48
3.3.2.5	<i>Fixed-final state condition</i>	48
3.3.2.6	<i>Battery state of charge (SoC) limits</i>	49
3.3.2.7	<i>Solver selection</i>	50
3.3.3	PV power output.....	50
3.3.4	Wind power output.....	52
3.4	MODEL VALIDATION.....	53
3.4.1	Pre-existing system description.....	53
3.5	DETAILED DESCRIPTION OF THE MODEL VALIDATION PROCESS	57
3.5.1	Data collection.....	57
3.5.1.1	<i>EMS at the charging station (Uyilo at Nelson Mandela University [NMU] in Gqeberha)</i>	57
3.5.1.2	<i>EV-QC45 Standalone Quick Charging Station</i>	57
3.5.1.3	<i>DL 850 Scope Corder at NMU</i>	57
3.5.1.4	<i>2013 Nissan Leaf</i>	57
3.5.1.5	<i>South African Universities Radiometric Network (SAURAN)</i>	58
3.5.2	Mathematical formulation.....	62

3.5.3	Simulated results.....	62
3.5.4	Comparison and validation.....	62
3.6	CASE STUDY.....	65
3.6.1	Detailed system description.....	65
3.6.1.1	<i>PV system</i>	65
3.6.1.2	<i>Wind turbine</i>	65
3.6.1.3	<i>Battery energy storage system (BESS)</i>	65
3.6.1.4	<i>Hybrid inverter</i>	66
3.6.2	Load profile description.....	66
3.6.3	Overview of the process	67
3.6.3.1	<i>Representation of charging protocols</i>	67
3.6.3.2	<i>Time-of-use (ToU) shift</i>	68
3.6.3.3	<i>Performance analysis</i>	68
3.6.3.4	<i>Maximising profit</i>	68
3.6.4	Optimal system sizing	68
3.7	SIMULATION RESULTS AND DISCUSSION.....	70
3.7.1	Determination of an optimal maximum demand threshold for Scenario 1 (overcast day).....	70
3.7.2	Optimal power flow simulation for Scenario 1 (overcast day).....	71
3.7.2.1	<i>Analysis of the power flow during off-peak ToU intervals (00:00 to 06:00)</i>	74
3.7.2.2	<i>Analysis of the power flow during standard ToU intervals (06:00 to 07:00)</i>	74
3.7.2.3	<i>Analysis of the power flow during peak ToU intervals (07:00 to 10:00)</i>	75
3.7.2.4	<i>Analysis of the power flow during standard ToU intervals (10:00 to 18:00)</i>	79
3.7.2.5	<i>Analysis of the power flow during peak ToU intervals (18:00 to 20:00)</i>	80
3.7.2.6	<i>Analysis of the power flow during standard ToU intervals (20:00 to 22:00)</i>	80
3.7.2.7	<i>Analysis of the power flow during standard ToU intervals (22:00 to 24:00)</i>	81

3.7.3	Analysis of the power flow during power cuts / load shedding during work hours	81
3.7.3.1	<i>Analysis of the power flow during off-peak ToU intervals (00:00 to 06:00)</i>	<i>83</i>
3.8	ECONOMIC ANALYSIS OF THE SYSTEM.....	89
3.8.1	Daily operation cost savings.....	89
3.8.2	Monthly operation cost savings	91
3.8.2.1	<i>Solar irradiance.....</i>	<i>91</i>
3.8.2.2	<i>Ambient temperature.....</i>	<i>91</i>
3.8.3	Lifecycle cost analysis	92
3.8.3.1	<i>PV system</i>	<i>93</i>
3.8.3.2	<i>Wind turbine</i>	<i>93</i>
3.8.3.3	<i>BESS.....</i>	<i>93</i>
3.8.3.4	<i>Hybrid inverter.....</i>	<i>94</i>
3.9	CONCLUSION	96

CHAPTER IV: MODEL PREDICTIVE CONTROL (MPC) OPTIMISATION OF A HYBRID SMART GRID WITH PV-WIND-BATTERY STORAGE INCORPORATING DEMAND-SIDE MANAGEMENT

4.1	INTRODUCTION	97
4.2	MATHEMATICAL MODEL OF A HYBRID SMART GRID WITH PV-WIND-BATTERY STORAGE AND P2P ENERGY SHARING.....	101
4.2.1	Schematic model layout.....	101
4.2.1.1	<i>Grid power.....</i>	<i>102</i>
4.2.1.2	<i>Battery power</i>	<i>103</i>
4.3	DEMAND-SIDE MANAGEMENT MODEL.....	104
4.3.1	Optimisation problem	105
4.3.1.1	<i>Objective function</i>	<i>105</i>

4.3.2	Variable constraints	106
4.4	MPC ALGORITHM.....	107
4.5	MATHEMATICAL MODEL FORMULATION.....	110
4.5.1	Objective function	110
4.5.2	Equality constraints	110
4.5.2.1	<i>Constraints equations</i>	111
4.5.2.2	<i>Sub-matrices</i>	111
4.6	CASE STUDY.....	115
4.7	RESULTS AND DISCUSSION.....	116
4.7.1	Scenario 1 (uninterrupted power from the grid)	116
4.7.1.1	<i>Analysis of the power flow during off-peak ToU intervals (00:00 to 06:00)</i>	117
4.7.1.2	<i>Analysis of the power flow during standard ToU intervals (06:00 to 07:00)</i>	119
4.7.1.3	<i>Analysis of the power flow during peak ToU intervals (07:00 to 10:00)</i>	120
4.7.1.4	<i>Analysis of the power flow during standard ToU intervals (10:00 to 18:00)</i>	120
4.7.1.5	<i>Analysis of the power flow during peak ToU intervals (18:00 to 20:00)</i>	121
4.7.1.6	<i>Analysis of the power flow during standard ToU intervals (20:00 to 22:00)</i>	123
4.7.1.7	<i>Analysis of the power flow during standard ToU intervals (22:00 to 24:00)</i>	123
4.7.2	Scenario 1 (power outages / load shedding).....	125
4.7.3	Economics analysis of the system	128
4.7.3.1	<i>Lifecycle cost analysis</i>	128
4.8	CONCLUSION	130

CHAPTER V: CONCLUSION

5.1	SUMMARY AND CONCLUSION.....	132
5.2	SUGGESTIONS FOR FURTHER RESEARCH.....	133

5.2.1	Globally	133
5.2.2	Locally.....	133
REFERENCES.....		135
APPENDIX.....		159

LIST OF FIGURES

Figure 1.1:	Flowchart outlining the approach and structure of the research methodology.....	8
Figure 2.1:	Energy-efficiency components	22
Figure 2.2:	EV charging modes and connectors	28
Figure 3.1:	Slow-charging protocol setup.....	38
Figure 3.2:	Fast-charging unit charging protocol	39
Figure 3.3:	Load profile for each charging protocol at the station.....	39
Figure 3.4:	Minimum battery SoC for AC charging	41
Figure 3.5:	Minimum battery SoC for fast DC charging.....	41
Figure 3.6:	Power flow diagram of a smart grid-PV-wind EVCS with battery storage and P2P sharing...	44
Figure 3.7:	Initial design of the EVCS at NMU (Uyilo).....	54
Figure 3.8:	Current design of the EVCS at NMU (Uyilo)	55
Figure 3.9:	The wind turbine at the south campus next to the EVCS at NMU (Uyilo).....	55
Figure 3.10:	Irradiation for the selected scenario winter day.....	59
Figure 3.11:	Irradiation for the selected scenario spring day	59
Figure 3.12:	Ambient temperatures in °C for the selected winter day	60
Figure 3.13:	Ambient temperatures in °C for the selected spring day	60
Figure 3.14:	Wind speed for the selected winter day	61
Figure 3.15:	Wind speed for the selected spring day	61
Figure 3.16:	Simulated vs actual PV output for the selected winter day.....	63
Figure 3.17:	Simulated vs actual PV output for the selected spring day	64
Figure 3.18:	Dataset of the detailed EV charge records of a similar EVCS in Germany.....	66
Figure 3.19:	Customised load profile of an EVCS based on actual dataset from an EVCS in Germany.....	67

Figure 3.20: Grid power subjected to the proposed constraints: Simulated results for the selected spring day	72
Figure 3.21: PV power: Simulated results for the selected spring day	73
Figure 3.22: Wind power: Simulated results for the selected spring day	74
Figure 3.23: SoC for energy storage: Simulated results for the selected spring day	76
Figure 3.24: Grid power to energy storage: Simulated results for the selected spring day	77
Figure 3.25: Total power utilised from the grid subject to constraints for the selected spring day	77
Figure 3.26: PV power to BESS: Simulated results for the selected spring day	77
Figure 3.27: Wind power to BESS: Simulated results for the selected spring day	78
Figure 3.28: Supplied power to the load from all the resources at the EVCS: Simulated results for the selected spring day	78
Figure 3.29: Excess power sold to the grid: Simulated results for the selected spring day	79
Figure 3.30: Grid power during load shedding: Simulated results for the selected spring day	82
Figure 3.31: SoC for energy storage during simulated load shedding for the selected spring day	83
Figure 3.32: Grid power to BESS: Simulated results for the selected spring day during a load-shedding scenario.....	84
Figure 3.33: PV power to BESS: Simulated results for the selected spring day during a load-shedding scenario.....	84
Figure 3.34: Wind power to BESS: Simulated results for the selected spring day during a load-shedding scenario.....	85
Figure 3.35: Total power from the grid: Simulated results for the selected spring day during a load-shedding scenario.....	85
Figure 3.36: Excess power sold to the grid: Simulated results for the selected spring day during a load-shedding scenario.....	86
Figure 3.37: Supplied power to the load from all the resource at the EVCS: Simulated results for the selected spring day during a load-shedding scenario.....	87
Figure 3.38: P2P sharing to supplement the EVCS during load shedding (seller's battery SoC).....	88

Figure 3.39: P2P sharing to supplement the EVCS during load shedding (buyer's battery SoC).....	88
Figure 3.40: Optimal savings for Scenario 1 (overcast day).....	90
Figure 3.41: Monthly average solar irradiance for the year 2020 at Gqeberha	91
Figure 3.42: Monthly average ambient temperature for the year 2020 at Gqeberha	92
Figure 3.43: Breakeven point analysis between the baseline and the open-loop optimal-control models ...	95
Figure 4.1: Schematic of a grid-integrated PV-wind system with battery storage and a P2P energy-sharing scheme	102
Figure 4.2: ToU for low and high demand seasons for 2020/2021 at Gqeberha	105
Figure 4.3: Structure of an MPC-based control approach.....	107
Figure 4.4: Closed-loop model for a smart grid PV-wind hybrid system.....	109
Figure 4.5: Grid power from the MPC: Simulated results for the selected spring day	117
Figure 4.6: Power supplied by the grid to battery storage from the MPC: Simulated results for the selected spring day	118
Figure 4.7: PV power to battery storage from the MPC: Simulated results for the selected spring day	118
Figure 4.8: Wind power to battery storage from the MPC: Simulated results for the selected summer day	119
Figure 4.9: Load supplied by all the resources from the MPC: Simulated results for the selected spring day	121
Figure 4.10: Power supplied by the battery storage to the EVCS from the MPC: Simulated results for the selected spring day	122
Figure 4.11: Battery storage from the MPC: Simulated results for the selected spring day	122
Figure 4.12: Total power supplied by the grid from the MPC: Simulated results for the selected spring day	124
Figure 4.13: Total power sold to the grid from the MPC: Simulated results for the selected summer day	124
Figure 4.14: Simulated results of the MPC grid power during load shedding for the chosen summer day	126

Figure 4.15: Simulated results of the MPC power supplied to the load during load shedding for the chosen spring day	126
Figure 4.16: Simulated results of the MPC P2P sharing to supplement the load during load shedding for the chosen spring day (seller's battery SoC).....	127
Figure 4.17: Simulated results of the MPC P2P sharing to supplement the load during load shedding for the chosen spring day (buyer's battery SoC).....	127
Figure 4.18: Breakeven point analysis between the baseline, open-loop optimal control, and closed-loop MPC optimal-control models.....	128
Figure A1: PV energy generation: Simulated results for the selected winter day.....	159
Figure A2: Wind energy generation: Simulated results for the selected winter day.....	159
Figure A3: Power supplied to the load from all the resources at the station for the selected winter day	160
Figure A4: Grid power subjected to the proposed constraints: Simulated results for the selected winter day	160
Figure A5: Grid power: MPC simulated results for the selected winter day.....	161
Figure A6: SoC for energy storage: Simulated results for the selected winter day.....	161
Figure A7: Battery storage: MPC simulated results for the selected winter day.....	162
Figure A8: Wind power to the EVCS: Simulated results for the selected winter day	162
Figure A9: Wind power to EVCS: MPC simulated results for the selected winter day	163
Figure A10: PV power to the ESS: Simulated results for the selected winter day	163
Figure A11: PV power to the ESS: MPC simulated results for the selected winter day	164
Figure A12: Wind power to the ESS: Simulated results for the selected winter day	164
Figure A13: Wind power to the ESS: MPC simulated results for the selected winter day	165
Figure A14: Power supplied by the battery storage to the EVCS: Simulated results for the selected winter day	165
Figure A15: Power supplied by the battery storage to the EVCS: MPC simulated results for the selected winter day	166

Figure A16: Power supplied by the battery storage to the EVCS: Simulated results for the selected winter day	166
Figure A17: Power supplied by the battery storage to the EVCS: MPC simulated results for the selected winter day	167
Figure A18: Load requirements at the EVCS for the selected winter day	167
Figure A19: Total power utilised from the grid subjected to the constraints for the selected winter day..	168
Figure A20: Total power utilised from the grid subjected the constraints for the MPC for the selected winter day	168
Figure A21: Optimal savings for the selected winter day	169
Figure A22: Total power from the grid: Simulated results for the selected winter day during a load-shedding scenario	169
Figure A23: Optimal savings for the selected winter day during a load-shedding scenario	170
Figure A24: Simulated results of P2P sharing to supplement the load during load shedding for the chosen winter day (seller's battery SoC)	170
Figure A25: Simulated results of the MPC P2P sharing to supplement the load during load shedding for the chosen winter day (seller's battery SoC)	171
Figure A26: Simulated results of P2P sharing to supplement the load during load shedding for the chosen winter day (buyer's battery SoC)	171
Figure A27: Simulated results of the MPC P2P sharing to supplement the load during load shedding for the chosen winter day (buyer's battery SoC)	172
Figure A28: Total power sold to the grid: Simulated results for the selected winter day	172
Figure A29: Total power sold to the grid: MPC simulated results for the selected winter day	173

LIST OF TABLES

Table 2.1:	Summarised literature on work done on EVCSs	13
Table 3.1:	Simulation parameters	69
Table 3.2:	Investment costs of an open-loop system.....	94
Table 3.3:	Total energy cost comparison between the baseline and open-loop models with optimal-control system.....	95
Table 4.1:	Investment costs of a closed-loop system.....	130
Table 4.2:	Total energy costs comparison between the baseline, open-loop, and closed-loop systems.....	130

LIST OF ABBREVIATIONS

\$	Dollar
°C	Degree(s) Celsius
5G	Fifth generation
AC	Alternating current
AI	Artificial intelligence
BESS	Battery energy storage system
BSS	Battery storage system
BSS2G	Battery storage system-to-grid
BSS2V	Battery storage system-to-vehicle
CALC	Actor-critic learning algorithm
CBB	Central battery bank
CHAdemo	CHARGE de Move
CIGS	Copper indium gallium selenide
COVID-19	Coronavirus disease of 2019
DC	Direct current
DHI	Diffuse horizontal irradiance/irradiation
DNI	Direct normal irradiance/irradiation
e-KYC	Electronic know your customer
eMPC	Explicit model predictive control
EMS	Energy-management system
ESS	Energy storage system
EV	Electric vehicle
EVCS	Electric vehicle charging station
G2BSS	Grid-to-battery storage system
G2V	Grid-to-vehicle
GHI	Global horizontal irradiance/irradiation
GIS	Geographic Information System
IEEE	Institute of Electrical and Electronics Engineers
IEMS	Intelligent Energy Management System

kW	Kilowatt(s)
kWh	Kilowatt-hour(s)
kWp	Kilowatt peak
m	Metre(s)
MILP	Mixed-integer linear programming
MIMO	Multiple input multiple output
MISOCp	Mixed-integer second-order cone programming
MPC	Model predictive control
NMU	Nelson Mandela University
NSGA-II	Non-Dominated Sorting Genetic Algorithm
P2P	Peer-to-peer
PHEV	Plug-in hybrid electric vehicle
POET	Performance, operation, efficiency, and technology [framework]
PV	Photovoltaic
PWT	Wind turbine power
RER	Renewable energy resources
RES	Renewable energy sources
ROI	Return on investment
SAURAN	South African Universities Radiometric Network
SCA	Smart charging algorithm
SoC	State of charge
SOCp	Second order cone programming
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solutions
ToU	Time-of-use
US	United States
V2BSS	Vehicle-to-battery storage system
V2G	Vehicle-to-grid
V2V	Vehicle-to-vehicle
W	Watt(s)
Wp	Watt-peak
ZAR	South African rand

LIST OF SYMBOLS

α	Temperature coefficient of the photovoltaic (PV) module
α_G	Grid availability parameter where +1 represents normal operation and power-outage periods
β	Tilted angle measured in degrees
δ	Hourly self-discharge rate
η_{ch}	Charging efficiency
η_{dsch}	Discharging efficiency
η_{INV}	Efficiency of the inverter
η_{mod}	Module efficiency percentage
∞	Represents the uncapped scenario of no limitation on the amount of energy when the grid is permitted to act as a mode of supply
ρ	Air density
ρ_o	The cost of energy purchased from the grid during the off-peak period tariff structure
ρ_p	The cost of energy purchased from the grid during the peak period tariff structure
ρ_s	The cost of energy purchased from the grid during the standard period tariff structure
σ	Reflectance factor of the surrounding area
θ_β	Angle of incidence on a tilted surface measured in degrees
A	The swept area of the wind turbine rotor in permissible metric measurement (square metre/centimetre)
A_1	Scale parameter of the Weibull distribution in m/s
A_{eq} and b_{eq}	Correspond to equality constraints
$C_{initial}$	Initial cost of implementing the proposed system
C_{OM}	Operating and maintenance costs incurred over the project lifetime
C_{EC}	Energy cost component, which includes the cost of energy consumed by the system over the project lifetime
D_d	Distance driven in miles since the energy storage was full
D_{rb}	Distance in miles of the range buffer required by the driver
En	Nominal capacity of the energy storage system

EV_{BSS}	Stored energy available from the electric vehicle (EV) as DC kWh to the inverter
E_w	Energy contained in wind
f	Objective function for the open-loop model
f^T	Objective function for the closed-loop model
h_1	Reference height
h_2	Hub height
I_{DNI}	Direct normal irradiance
I_{DHI}	Diffuse horizontal irradiance
I_{GHI}	Global horizontal irradiance
I_{total}	Total irradiance on a tilted surface
j	Denotes different control variables at each sampling interval
k	Shape parameter of the Weibull distribution
L_b	Lower bounds for variables
N_c	Control horizon
N_{PVp}	Number of PV panels connected in parallel
N_{PVs}	Total number of parallel-connected PV strings
P_{ch}	Charging power
P_D	Power demand
P_{dsch}	Discharging power
P_{EV}	Maximum power from an EV in kW
$P_{Grid(t)}$	Power from the grid at any interval with accordance to the permissible hierarchy
$P_{i(j)}^{max}$	Maximum power limit for each resource (PV and wind)
$P_{i(j)}^{rated}$	Rated power of a battery or grid
$P_{G-B}(j/k)$	Grid power to a battery storage system
$P_{G-L}(j/k)$	Grid power to the load
P_{PV}	PV output power, which is the desired quantity to be calculated
$P_{PV-G}(j/k)$	Power generated from the PV supplied to the grid
$P_{PV,STC}$	Rated power of the PV module under standard testing conditions
$P_{W-G}(j/k)$	Power generated from the wind supplied to the grid
$SoC_{n(0)}$	Initial state of charge (SoC) of the battery at the start of every sampling time

$SoC_{n(max)}$	Maximum SoC of the battery at the start of every sampling time
$SoC_{n(min)}$	Minimum SoC of the battery at the start of every sampling time
t	Volume of air passing through A (which is considered perpendicular to the direction of the wind)
T_{amb}	Ambient air temperature
T_{cell}	Temperature of the PV module's cell in °C
T_{NOC}	Nominal operating temperature of the PV cell in °C
t_s	The time the vehicle's stored energy is dispatched in hours
U_b	Upper bounds for variables
v	Wind speed in m/s
v_1	Reference wind speed
v_2	Wind speed at hub height
X	Vector containing all the control variables relevant to the optimisation challenge

CHAPTER I: INTRODUCTION

1.1 BACKGROUND

Transportation is a critical sector in South Africa's economy, and its reliance on fossil fuels, particularly imported crude oil, has significant implications [1]. The limited domestic reserves of crude oil and the rise in global oil prices have led to the country's growing dependence on external sources for its energy needs [2–3]. Historically, crude oil prices have been influenced by market performance, which is often tied to the performance of the United States (US) dollar. Fluctuating exchange rates, particularly the weaker performance of the South African rand (ZAR), have led to higher import costs for crude oil, which further impacts fuel prices domestically [4–6]. The COVID-19 pandemic and conflicts among major crude oil exporters have contributed to the volatility of fuel prices both locally and globally. These fluctuations, along with power outages and fuel price increases, can affect the economic stability of the country [7–13]. In context, the need for alternative solutions to supplement and sustain the country's economic backbone becomes crucial. Electric vehicles (EVs) emerge as a potential option for South Africa's economic emancipation. The popularity of EVs is increasing globally, and current trends suggest their dominance in the near future [14–15]. Their introduction was aimed at reducing the world's dependency on fossil fuels and decreasing external costs of road transport. However, their charging strategies, as well as charging options, restrict their popularity. The uneven distribution of chargers and charging infrastructure is a concerning factor to potential EV owners in South Africa [16–17]. As it stands, Eskom has a capacity challenge, whereby supply and demand need to be constantly matched and balanced. This tends to be a challenge during the night when demand is at its lowest, and the excess generated energy is wasted. This is due to the fact that most of Eskom's energy generation is from coal-fired power stations where instant on/off switching is not achievable with this type of station as it takes time to power up/down [18–19]. EVs could be charged during the night when the electricity tariffs are cheaper and assist the utility to store the excess energy during off-peak hours. Using the grid for all the charging requirements of EVs will only operate as a load balancing/shifting mechanism for Eskom.

A transition to EVs will reduce the country's dependency on imported fossil fuels for transportation. EVs offer the potential for a cleaner and more sustainable mode of transportation, as

they produce zero tailpipe emissions when powered by renewable energy sources (RES). Additionally, the development of a local EV industry can contribute to job creation and economic growth [20–22].

The rise of EVs globally is driven by factors such as environmental concerns, technological advancements, and supportive government policies. South Africa can leverage these trends and develop a comprehensive strategy to promote the adoption of EVs. This includes the development of charging infrastructure, incentives for EV purchases, and the establishment of partnerships between the government, private sector, and academia to foster research and development in the EV sector. By embracing EVs and diversifying transportation energy sources, South Africa can work towards reducing its reliance on imported fossil fuels, enhancing energy security, and mitigating the environmental impact of transportation.

1.2 PROBLEM STATEMENT

Most of the electric vehicle charging stations (EVCs) that have been implemented are in developed countries that have a stable and reliable utility grid. As such, most of the work done on these stations promotes load shifting, optimisation schemes, as well as the use of RES in EVCs for EV charging to navigate problems associated with the impact of load spectrum on the grid. However, no work has combined a grid-integrated system powered by renewable energy such as wind and photovoltaic (PV), which combines a central battery bank (CBB), as well as applying peer-to-peer (P2P) sharing of energy among EVs at EVCs for the sustenance and profitability of the stations and EV prosumers.

The following notable sub-problems were identified:

- Sub-problem 1: Due to the stability and reliability of the utility in developed countries, most of the research conducted on grid-integrated PV- or wind-charging stations do not employ the use of a CBB as a supplementary power supply during peak hours and power outages, or when the charging requirements of the EV exceeds the available power from the RES at the station.
- Sub-problem 2: No work has been done on the design and implementation of a P2P energy-sharing model among EV owners at charging stations in a dynamic power demand and pricing environment where power cuts are the norm. The work done is usually on the mode of sharing (such as game-based and blockchain trading), while neglecting the profitability of the EVCS.

1.3 RESEARCH OBJECTIVES

This research study focused on prioritising the reduction of EVCSs' operational costs while ensuring a reliable energy supply and optimal battery state of charge (SoC). The aim of this project was to develop an optimal energy management model to minimise the charging costs of an EVCS that comprises a grid-integrated PV and wind EVCS with a CBB and a P2P energy-sharing model.

The objectives of the research study were therefore set as follows:

- To design the proposed system using Nelson Mandela University's (NMU) EVCS (Uyilo, a PV grid-tied system with a battery energy storage system [BESS]) as the baseline for the proposed system. The proposed model includes the integration of a wind turbine located 600 meters away from the station. Although the wind turbine is not directly connected to the EVCS, its incorporation in the proposed model aims to demonstrate its potential contribution to the overall energy mix of the EVCS.
- To develop and simulate an open-loop optimal-control and optimisation model to coordinate the charging and discharging schemes of EVs based on demand-response ancillary services on the utility grid, CBB, P2P charging scheme, and charging activities at the EVCS.
- To develop and simulate a model predictive control (MPC)-based closed-loop optimal-control model for the energy management of the proposed system with a P2P energy-sharing model among EVs.
- To conduct a detailed techno-economic analysis of over 20 years for the open- and closed-loop models.

1.4 METHODOLOGY

To achieve the abovementioned objectives, the following methodology was applied:

1.4.1 Literature review

A comprehensive review of EVCSs focusing on technological advancements of major components and the implementation of an effective energy management system (EMS) for efficient charging using the POET (performance, operation, efficiency, and technology) framework was undertaken. This

included a thorough review of literature related to the operation and control of an energy mix with a storage system and a P2P-sharing scheme. The proposed review analysed these components comprehensively and proposed viable charging options for enhanced performance.

1.4.2 Stepwise process for system modelling and control

System modelling and control involve a stepwise process that encompasses several key stages. Below is an outline of the steps involved in system modelling and control.

1.4.2.1 System variable identification

The initial model entails an open-loop optimal-control and optimisation model of a grid-integrated PV-wind EVCS with a CBB and a P2P charging scheme (referred to as the first model), while the alternative model is an MPC-based closed-loop optimal control to enhance the initial open loop and further reduce the costs associated with the utility grid under applicable constraints. The variables involved in the analysis with respect to the developed models were independent, control, and variable state.

The data-collection process for this study involved the compilation of various input variables from diverse sources. The following sources were employed to gather data, which comprised the following input variables:

- Energy generated from solar resources over the course of the two-day study period.
- Solar data, encompassing measurements of global horizontal irradiance (GHI), direct normal irradiance (DNI), and diffuse horizontal irradiance (DHI).
- Wind speed and wind direction measurements.
- Ambient air temperature at the university in the Gqeberha area, Eastern Cape province.
- Time-of-use (ToU) electricity tariff information.
- Other input parameters, such as Weibull distribution parameters, hub height, climatic conditions, and optimal sizing.

These diverse data sources and input variables were employed in conducting a comprehensive case study. The analysis focused on evaluating the performance and optimisation of the hybrid smart

grid system integrated with PV-wind-battery storage. The study considered factors such as demand-side management, prosumers, and the profitability of the EVCS.

1.4.2.2 Mathematical modelling and control

- Models of the EVCS, which are connected to the university's charging station, were formulated and developed.
- Optimal energy management algorithms were created to economically dispatch power, reduce operational energy costs, increase profitability, and implement a P2P charging scheme. MATLAB software was employed for this purpose.
- The devised optimal energy management algorithm was specifically designed to minimise energy costs by considering the ToU tariff pricing structure and maximum demand charges. Simultaneously, it aimed to ensure user satisfaction, promote prosumer engagement, and enhance the profitability of the EVCS.
- The collected data were utilised to simulate the operation of baseline systems and to compare them with optimal-control cases for the first model, as well as MPC scenarios for the second model.

1.4.2.3 Simulation and verification

In the context of the first model, which posed a mixed-integer and non-linear multivariable optimisation challenge, the chosen solver from the MATLAB Optimization Toolbox was `fmincon`.

Specifically designed for finding the minimum of a constrained non-linear multivariable function, this solver excels in handling intricate optimisation problems with constraints and is well suited for non-linear programming challenges. The `fmincon` solver proved to be an efficient and versatile tool capable of managing objective functions focused on minimising energy costs and incorporating considerations such as the ToU tariff pricing structure. Through proper formulation of the optimisation problem, and defining the objective function, constraints, and relevant parameters, `fmincon` adeptly explored optimal solutions that adhered to specified constraints while minimising energy costs.

Leveraging the capabilities of the fmincon solver for the first model enabled effectively addressing the complexities inherent in the mixed-integer and non-linear optimisation problem associated with this particular model.

To assess the techno-economic analysis in an open-loop model, the system's performance was evaluated in terms of its ability to meet load requirements while minimising costs. The baseline model at Uyilo was used as a reference model and was used in conjunction with the open-loop model. The two were subjected to the same load requirements and climatic conditions to directly compare their financial and economic outcomes. The analysis focused on the reduction in grid costs for the EVCS and BESS achieved by the proposed open-loop model. This reduction was attributed to the optimisation techniques and strategies employed in the model. By considering factors such as energy consumption, peak demand management, and grid interaction, the economic benefits were quantified, evaluated, and implemented in the proposed model. Through this comparison, the financial viability of the proposed model was assessed by considering factors such as return on investment (ROI), payback period, and overall cost savings. The economic advantages of the optimisation model were examined to determine its potential for cost reduction and improved efficiency compared to the baseline model.

In the case of the second model, which involved addressing a multi-stage non-linear MPC problem, the fmincon solver from the MATLAB Optimization Toolbox was selected. From a control perspective, the system was conceptualised as a multiple-input multiple-output (MIMO) system. The proposed closed-loop MPC model represents an enhancement over the open-loop optimal control, which incorporates a feedback system to adapt to variable demand patterns and external disturbances. The modelling of the microgrid-connected PV-wind-grid system, integrated with P2P interactions and energy storage, was executed using a linear programming framework.

The techno-economic analysis of the closed-loop model involved the utilisation of an MPC optimisation control. The MPC was employed to improve performance and cost reduction compared to the open-loop model. The model took real-time feedback into account and adjusted its control actions based on the current system state. This dynamic adjustment allowed for better response to disturbances and uncertainties, which led to enhanced control performance. The evaluation of the cost-reduction capabilities of the closed-loop model compared it with both the baseline and the open-

loop models. The comparison involved analysing various performance metrics such as system stability, control accuracy, response time, and overall cost. The demonstration of the superiority of the closed-loop model over the baseline and open-loop models is meant to highlight the benefits of employing MPC optimisation control in terms of cost reduction.

Figure 1.1 outlines a flowchart that details the research modelling process for each model. The initial stages involved the identification of input variables and the collection of relevant data. Subsequently, initial values were assigned to the state variables. The culmination of the process involved solving the optimal-control problem in the final step.

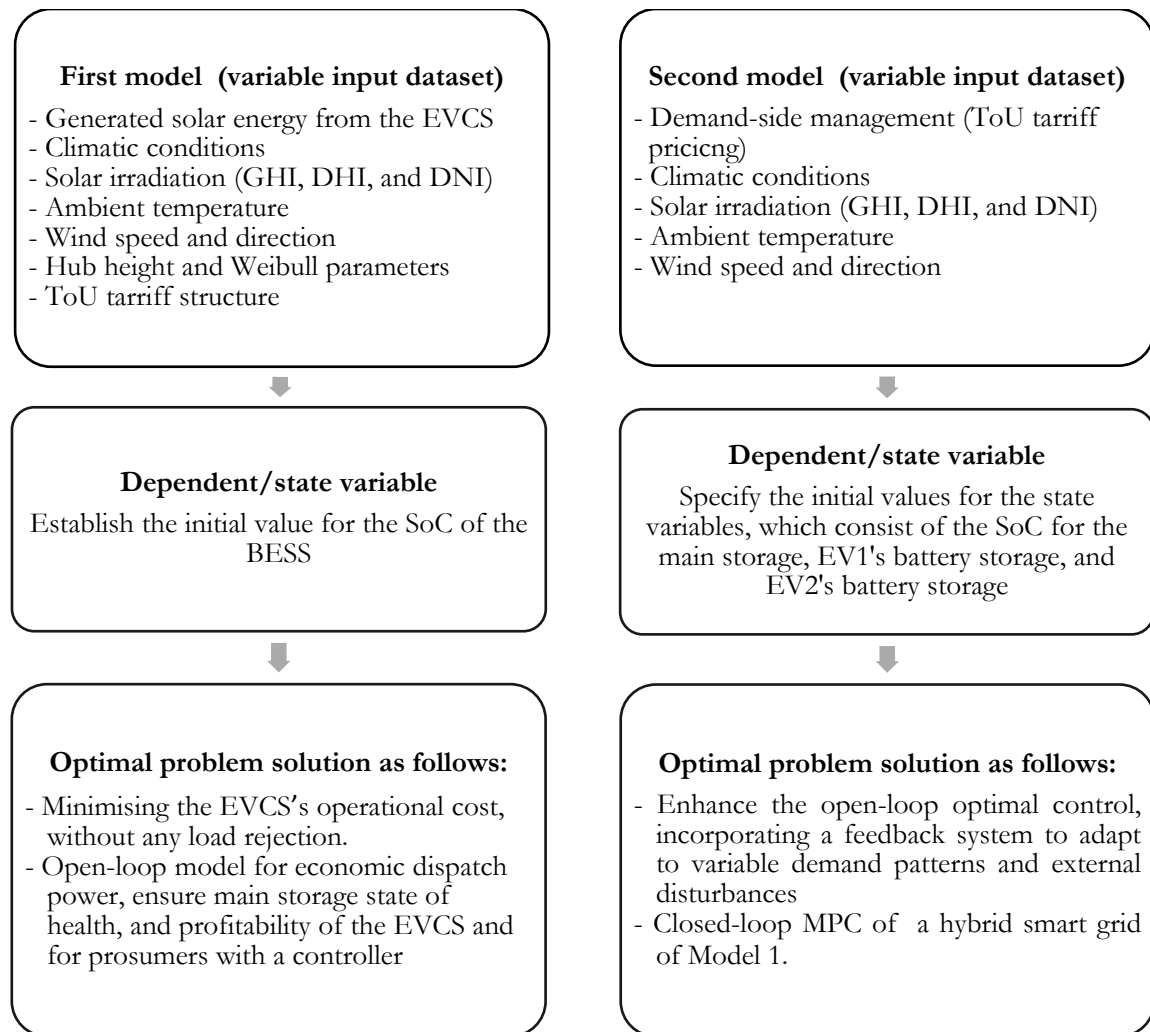


Figure 1.1: Flowchart outlining the approach and structure of the research methodology

1.5 CONTRIBUTION TO KNOWLEDGE

In comparison to the scope of research available on EV charging infrastructure, the key contributions of this work are as follows:

- Most of the solutions provided by previous work done on EVCSs indicated that the system's operation was primarily based on assumptions of EV users' ToU and charging requirements. Their research objectives were met by formulating an optimisation scheme to maximise RES and minimising battery and grid energy usage, while others shifted load and promoted coordinated charging dispatch based on EVCS algorithm.
- These studies hardly indicated the financial benefits to EV users and the cost reduction of running the EVCS and the backup energy storage to assist the system's reliability and to manage electricity prices to be cheaper even during peak hours by promoting P2P /vehicle-to-vehicle (V2V) sharing among EV users. However, this work employed a non-linear optimisation approach to address power dispatch and control optimisation problems and to reduce the operational cost associated with the grid tariff structure through the two models specified below.

Model 1 is an open-loop optimal power dispatch of an EVCS microgrid comprising PV-wind-energy storage and P2P for a campus EVCS (Chapter III):

A validated mixed-integer of a linear model of a PV-wind system, with energy storage that considered both the ToU tariff, grid conditions, and cost-effective charging scheme, including P2P sharing during peak hours without compromising the storage system's state of health, was utilised. This model focused on the following factors:

- Optimally managing the charging and discharging of the EV's on-board BESS, as well as power dispatch of the grid and renewable energy system.
- This coordinated approach ensured efficient utilisation of energy resources while meeting the charging requirements of the EVCS.

- This model considered various factors such as EV charging requirements, grid conditions, and cost-effective charging schemes, including P2P energy sharing during peak hours.
- By considering these factors, the model can offer charging schemes that prioritise user satisfaction while minimising costs and optimising energy utilisation.

Model 2 – A closed-loop MPC model of a hybrid smart grid with PV-wind-battery storage incorporating demand-side management, prosumers, and EVCS profitability (Chapter IV):

A notable contribution is the development of an MPC-based closed-loop optimal-control model for energy management of the proposed system with a P2P energy-sharing model among EVs (the novel approach is a combination of two elements: MPC-based energy management and P2P energy sharing to address challenges such as optimising energy usage, balancing energy demand, and enhancing overall system efficiency in EV networks).

Finally, a detailed techno-economic analysis of over 20 years was conducted for two days for the open- and closed-loop models.

- The purpose of this enhancement was to compare the baseline, open-loop, and closed-loop models in terms of their cost-reduction capabilities. A comparison to the baseline model subjected to the same load requirements and climatic conditions for the open-loop model was also conducted.
- The analysis assessed the financial viability and economic benefits of the proposed model, with a focus on a reduction in grid costs for the charging station and BESS. By investigating the economic advantages of the optimisation model, the potential for cost savings and improved efficiency is demonstrated.

1.6 HYPOTHESES

The study's hypotheses are as follows:

- The open-loop optimal power dispatch model will reduce the operational cost associated with the grid tariff structures and provide uninterrupted power supply with any load rejection at any interval with a suitable storage power loss model to preserve the BESS lifespan of the EVCS.

- The predictive control model will further enhance the operation cost of the model through problem-based optimisation while adhering to the set constraints.

1.7 DELIMITATIONS

This study focused on EVCS infrastructure, its optimal operation, EMS, BESS, and a P2P energy-sharing model, and not on the impact of temperature as a result of charging and discharging.

The study focused on the simulated results of the EVCS, as well as the simulated optimisation model.

1.8 PUBLICATIONS FROM THIS STUDY

Conference papers:

- L. Bokopane, K. Kusakana and H. J. Vermaak (2018, October). Energy management of a grid-integrated hybrid peer-to-peer renewable charging station for electric vehicles. *Open Innovation Conference (OI)*, pp. 275-280.
- L. Bokopane, K. Kusakana and H. J. Vermaak (2019, October). Is the South African electrical infrastructure ready for electric vehicles? *Open Innovation Conference (OI)*, pp. 127-131.

Journal articles:

- L. Bokopane, K. Kusakana and H. J. Vermaak (2020). POET structured energy management and efficiency improvement of a grid-integrated electric vehicle energy charging station. *Journal of Physics, Conference Series*, 1577(1), 012052.
- L. Bokopane, K. Kusakana and H. J. Vermaak (2024). Optimal power dispatching schemes of an EVCS microgrid that comprises of grid-PV-wind energy with a battery storage and peer-to-peer charging scheme. *Journal of Energy Storage* 96, 112435
- L. Bokopane, K. Kusakana, K.P Ndwali, and P.A. Hohne (2024). Model Predictive Control for Optimal Scheduling of a PV-Wind-Grid Hybrid System with Energy Storage, and Peer-to-Peer Energy Sharing under Time-of-Use Tariffs (under review in Sustainable Energy, Grids and Networks journal, Elsevier).

1.9 THESIS ORGANISATION

This thesis is structured into five chapters, each focusing on specific aspects of the research:

Chapter I presents an introduction to the research work, elucidates the underlying issues, and outlines the research objectives, methodology, contribution to knowledge, research hypotheses, and the delimitations of the study.

Chapter II presents a literature review on the stance of charging infrastructure around the world, which showcases various technologies and charging strategies while investigating the possibility of improvement and analysing how these strategies can be implemented and advanced in an ailing utility such as in South Africa.

Chapter III describes the development of an optimal dispatch scheme for a PV-wind grid-tied system with a BESS and P2P charging scheme at a charging station. The Uyilo's EVCS at NMU served as the baseline for the proposed system. Additionally, a modelling framework is presented, which is accompanied by the formulation of a mathematical algorithm for the proposed model.

Chapter IV describes the diverse types of controllers, their strategies, and optimisation approaches. It also introduces a modelling framework and formulates a mathematical algorithm to develop and simulate an MPC-based closed-loop optimal-control model for the proposed system to enhance the model in Chapter III and to further reduce the operational cost of the proposed model.

Chapter V concludes the thesis and underscores potential areas for future research and development related to the topics explored in the study.

CHAPTER II: A REVIEW OF THE IMPROVEMENT OF ELECTRIC VEHICLE CHARGING STATIONS USING THE POET FRAMEWORK

2.1 INTRODUCTION

Charging strategies and charging modes are discussed in this chapter, with a holistic approach to the improvement of EVCSs. The POET energy management framework was methodically selected due to its success rate in the evaluation and overall improvement of the efficiency of large-scale energy systems that possess various loads. The aforementioned framework is known for its energy savings and improvements based on its four levels, namely conceptual, active, technical, and further improvement. For the purposes of this study, three processes of POET were selected, namely energy audit, target, and planning on the fourth level (which is an engineering level in an attempt to improve the efficiency and economical nobility of the system). The layout of this chapter is as follows: Section 2.2 presents a comprehensive review of key study cases, as well as the justification of the study. Section 2.3 presents the POET structured framework in the EVCS. Section 2.4 outlines the key findings of the reviewed literature and concludes the chapter.

2.2 REVIEWED LITERATURE

Design and analysis, including the feasibility assessment of various charging system designs, have become essential. Many research studies and solutions for EVCSs have focused on optimising the operation of the system based on assumptions about EV users' ToU and charging requirements. Table 2.1 presents an overview of the findings presented in the literature over the years.

Table 2.1: Summarised literature on work done on EVCSs

Ref. no.	Publication year	Type of system presented	Strategy utilised to meet the objective	Outcome of research
[23]	2021	Impact of EVs on a Swedish power grid	Summarised reports of various studies conducted by members of the Electric Power Engineering Group in Sweden.	Presented valuable evidence and insight regarding the impacts of e-mobility on the electrical system that highlighted power-quality challenges, the need for grid infrastructure adaptation, and the importance of proper planning to ensure a smooth transition to widespread EV adoption in Sweden.
[24]	2023	Impact of EVs on the utility grid of India	A comprehensive investigation into EV technologies and their associated aspects.	Explored the impact of EVs on the utility grid and discussed potential solutions to mitigate any adverse effects. The evaluation included several power management and control strategies and assessed their effectiveness.
[25]	2020	Grid-tied PV system with energy storage	Assessment of the potential impact of EVs on distribution networks, considering their current widespread use and expected exponential growth in the future.	Presented sustainable mobility and optimal network management, resulting in fewer power losses and reduced costs, creating a virtuous circle that benefits the environment.
[26]	2015	Generalised utility grid	A review and analysis of the deployment of EVs in a vehicle-to-grid (V2G) system emphasising the benefits and overheads offered by such a system.	Presented an improvement of major factors of electric grid / distribution network such as reliability, efficiency, losses, and stability of a grid, and explained the major requirements, advantages, and challenging issues for V2G implementation.
[27]	2022	Generalised utility grid	A review of the potential impacts of EV charging on electricity distribution systems and described methods from the literature to efficiently integrate EVs into distribution systems.	Recommended that EVs should be considered in conjunction with other distributed resources and all elements of power supply to maximise the benefits and to foster successful integration.
[28]	2018	Proposed EVCS supplied by the grid	Optimal siting and sizing of EVCSs by considering the economic benefit as the primary objective of life-cost analysis.	Presented an economic planning method that considered net present value and lifecycle cost to optimise the siting and sizing of charging stations.

Ref.: no.	Publication year	Type of system presented	Strategy utilised to meet the objective	Outcome of research
[29]	2017	Generalised utility grid in China	Multiple objectives and incorporating stochastic traffic flows and innovative volume-delay functions.	Addressed the collaborative planning problem of EVCSs and the power distribution system. Presented a multi- objective planning model that considered uncertainties in charging loads, utilising stochastic models and traffic assignment techniques.
[30]	2018	Grid-power EVCS case study of Jiangsu, China	Multiple types of charging facilities in EVCS planning using a two-step equivalence approach and exact relaxation techniques, the optimisation model was transformed into a mixed- integer second-order cone programming (MISOCP) through second-order cone programming (SOCP).	Highlighted the benefits of mixed installation of different types of charging facilities in EVCSs. Provided an efficient and precise solution for the optimal planning problem with two-step equivalence and exact SOCP relaxation.
[31]	2021	Inverter-based renewable energy resource EVCS	An optimisation technique that considered the uncertainty in the generation profiles of PV and wind energy units, the total load demand, the operation capability of Distributed Static Compensators in PV- and wind- generation units.	Demonstrated the effectiveness of the proposed method for designing RES and managing EVs in achieving autonomous microgrids with interconnected PV- and wind-generation units and EVCSs. The method outperformed existing approaches, with a 57% reduction in voltage deviation and an 81% reduction in tie-line power.
[32]	2023	Grid-tied PV-wind EVCS with a base load (residential area)	By utilising an optimal planning approach (utilising an optimiser called Jaya-based Search Optimisation) for allocating EVCSs with controllable charging and hybrid renewable energy resources (RER) within multi- microgrids.	Introduced an efficient approach that integrates a large number of EVCSs and RERs to address various operational challenges. The simulated results highlighted the superiority of integrating EVCSs and RERs with controlled charging and discharging strategies, resulting in significant reductions in voltage deviations, energy not supplied, and total cost. The optimiser also demonstrated superior performance compared to other algorithms in solving the allocation problem of EVCSs and RERs.

Ref.: no.	Publication year	Type of system presented	Strategy utilised to meet the objective	Outcome of research
[33]	2019	Multi-source EVCS with battery storage system (BSS)	Integrating stationary and in-vehicle energy storage systems (ESSs) which can store energy during off-peak hours and make it available during peak hours to a multi-source EVCS.	Presented a comprehensive approach to real-time control of a multi-source EVCS, considering degradation costs and prioritising different system sources.
[34]	2021	Microgrid EVCS that incorporates PV and BSS	Utilising a grid-able EV's on-board Intelligent Energy Management System (IEMS) to support the microgrid charging station.	By offering a comprehensive solution for real-time control of a multi-source EVCS, considering degradation costs and prioritising system sources.
[35]	2020	Grid-integrated EVCS PV system with battery storage	Utilising a flexible and efficient solution for controlling a residential EVCS to minimise grid dependency, maximise EV owner satisfaction, and optimise the use of RES.	Presented an energy management framework and the utilisation of the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) approach contributed to the efficient integration of grid-able EVs into microgrid charging stations, which enabled optimal energy utilisation, active power regulation, and effective communication and pricing negotiations.
[36]	2018	Grid-integrated hybrid (PV and wind) with P2P charging scheme and battery storage	Using a well-coordinated charging scheme for EVs in an EVCS to optimise the management of the charging and discharging of the CBB, as well as the power dispatch from the grid, wind, and PV charging sources.	Presented the operational cost reduction and charging efficiency of the grid-integrated PV/wind EVCS with a CBB.
[37]	2010	Energy efficiency and control systems	POET framework as a unifying classification for energy efficiency.	Presented a new classification of energy-efficiency components (which include performance, operation, equipment, and technology efficiency) to encompass various aspects of energy efficiency and to be applied to practical demand-side management problems.
[38]	2010	Generalised system energy audit	Framework for energy auditing based on the POET classification system.	Illustrated how the POET-based energy audit could be implemented in practice and highlighted its effectiveness in identifying energy-efficiency improvement opportunities.

Ref.: no.	Publication year	Type of system presented	Strategy utilised to meet the objective	Outcome of research
[39]	2012	Energy management activities of a financial service company in South Africa	Utilising the POET framework to analyse the energy management activities of a financial service company's commercial buildings in South Africa and discussed the sustainability of energy management programmes within the framework.	Presented enhanced and comprehensive coverage of potential energy-saving measures and valuable insight into energy-efficiency improvement opportunities.
[40]	2020	Grid-integrated EVCS with PV-wind and battery storage	A review of the effectiveness of the POET energy management framework in evaluating and improving the efficiency of large-scale energy systems.	Presented a review based on a holistic approach to the further improvement of an EVCS and measurable amount of efficiency improvement in the EVCS.
[41]	2014	Distributed generation	Utilised a market framework that coordinated the actions of EV owners, fleet operators, and the distribution system operator.	Presented a flexible and scalable solution, with potential for enhancing congestion prevention in the scheduling period and congestion relief in real time.
[42]	2011	Generalised EVCS	By exploring the relationship between feeder losses, load factor, and load variance in the context of coordinated plug-in hybrid electric vehicle (PHEV) charging.	Presented efficient and real-time dispatching to PHEVs to help mitigate potential negative effects on the power system.
[43]	2019	Generalised grid-powered EVCS	Using a hierarchical mixed-variable optimisation problem, considering the interdependencies among the station selection, charging option selection at each station, and charging amount settings.	Addressed the challenging problem of EV charging scheduling for battery-limited EVs by presenting a hierarchical mixed-variable optimisation problem, considering station selection, charging option selection, and charging amount settings.

Ref.: no.	Publication year	Type of system presented	Strategy utilised to meet the objective	Outcome of research
[44]	2023	Generalised grid-powered EVCS	Using a two-phase coordinated charging scheduling solution in an energy market environment, focusing on profit maximisation for EV aggregators.	Three key findings based on the case study. Firstly, the bidding strategy of EV aggregators is influenced by the grid connection time of EVs and the clearing prices. Secondly, the day-ahead bidding strategy is heavily influenced by the difference between day-ahead clearing prices and real-time clearing prices. Thirdly, the proposed method enables EV aggregators to schedule the charging loads of EVs to align with the day-ahead bidding energy, resulting in reduced operational costs. The study also demonstrated that using four real-time clearing scenarios for optimal bids is more efficient than considering a large number of historical real-time clearing scenarios.
[45]	2015	Centralised charging strategy in a grid-powered EVCS	Using a novel centralised charging strategy for EVs in the context of battery swapping. An evaluation using an IEEE 30-bus test system and algorithms using swarm optimisation and genetic algorithm.	Presented a centralised EV charging strategy that incorporated battery-swapping technology under a spot pricing-based electricity market environment.
[46]	2018	Centralised charging strategy in a grid-powered EVCS	Introduced a dynamic pricing scheme and a time-window method to prevent interruptions in battery charging. An evaluation using IEEE 33-bus test system and algorithms using NSGA-II algorithm.	Presented a BSS algorithm that optimised both cost-related goals and the technical performance of the grid.
[47]	2019	Centralised charging strategy on a grid-powered EVCS	Utilised a periodic fluid model that captured the time-varying demand for battery swapping and time-varying prices for charging empty batteries.	Offered insight into battery purchasing and charging decisions for EV BSSs. It emphasised the benefits of operating in an environment where demand and electricity price functions are asynchronous.

Ref.: no.	Publication year	Type of system presented	Strategy utilised to meet the objective	Outcome of research
[48]	2021	Grid-powered EVCS with battery storage	Utilisation of retired batteries from EVs as retired BESS at battery- swapping and charging stations to improve their economic profitability and operational flexibility.	Presented a dynamic charging and discharging-based optimisation framework for retired BESS-incorporated battery- swapping and charging stations, aiming to maximise annual economic benefits. Also demonstrated the effectiveness of the proposed method in improving economic benefits and operational flexibility.
[49]	2023	Electricity-hydrogen hybrid charging station	A bi-level strategic operation framework for an integrated energy system with an electricity-hydrogen hybrid charging station.	Illustrated a model that incorporated a hierarchical game to capture the competitive interaction between the integrated energy system and hybrid charging station. Additionally, a data-driven two-stage distributionally robust energy trading model was developed to address uncertainty in EV types and to optimise energy trading decisions.
[50]	2021	Smart online charging algorithm for EVs	Actor-critic learning algorithms (CALC) and smart charging algorithm (SCA).	Presented SCA and CALC to solve the offline EV charging-scheduling problem. The algorithms achieved significant improvements in energy cost compared to existing methods, with SCA demonstrating better convergence and CALC offering higher computational efficiency.
[51]	2023	Grid-tied EVCS	PROLIFIC deep reinforcement learning to determine the optimal charging strategy.	Demonstrated the ability of a PROLIFIC strategy to identify patterns in order distribution and charging station availability, enabling informed decisions about optimal charging times and locations, thereby improving overall service efficiency.

Ref.: no.	Publication year	Type of system presented	Strategy utilised to meet the objective	Outcome of research
[52]	2022	Smart grid EVCS coupled with PV and energy storage	A multi-agent deep reinforcement learning approach with centralised training and decentralised execution.	Presented a multi-agent deep reinforcement learning technique to solve the charging scheduling problem of multiple EVs in a smart grid by formulating the problem as a sequential decision- making problem and utilising advanced algorithms such as multi-agent deep deterministic policy gradient and counterfactual multi-agent, the study achieved superior performance compared to existing methods.
[53]	2023	EVCS with V2G scheme	An iterative multi-stage optimisation method.	Presented an innovative technique for integrating EVs into the V2G concept, and addressed constraints often overlooked by existing methods.
[54]	2024	Optimal PV/BESS- integrated EVCS	Hybrid modelling techniques for PV power prediction using mixed-integer linear programming (MILP).	Illustrated optimal capacity configuration and scheduling of PV/BESS-integrated EVCSs that demonstrated improvements in net present value, carbon emissions reduction, and system performance.
[55]	2022	Hydrogen fuelling station with P2P energy trading	A collaborative framework with P2P energy trading in a hydrogen fuelling station-coupled power-traffic system.	Presented reduced operational costs and the improvement of interactive efficiency by enabling direct energy transactions and promoting cooperative behaviour between the networks.
[56]	2022	P2P smart grid EVCS with PV-wind and biomass using electronic know your customer (e-KYC) with blockchain and a truthful double auction	A combination of blockchain technology and truthful double auction strategy to address energy management and incorporating 5G networks to reduce latency.	Presented an integrative scheme that combines blockchain and a truthful double auction strategy for trusted energy transactions in EVs. It addressed scalability and reliability through the use of Inter- Planetary File System and a 5G-assisted network.
[57]	2022	Grid-tied EVCS with BESS	P2P trading of charging quota between a fast-charging station as an alternative approach to load management.	Illustrated optimised load distribution and congestion alleviation, and improved the overall efficiency of the charging infrastructure.
[58]	2023	Grid-tied PV EVCS with battery bank and secondary-life storage	The optimal design and control of PV- powered EVCSs with energy storage.	Presented an analysis of the environmental sustainability of an EVCS, using a bi-level optimisation approach to determine the optimal configuration.

Ref.: no.	Publication year	Type of system presented	Strategy utilised to meet the objective	Outcome of research
[59]	2023	Artificial intelligence (AI) techniques for EV charging and discharging scheduling, as well as dynamic pricing	A review that focused on EV charging- and discharging-related studies and classified them into three main categories: forecasting, scheduling, and pricing mechanisms.	Illustrated the provision of accurate forecasting, efficient scheduling, and well-designed dynamic pricing strategies for optimising EV charging and discharging.
[60]	2023	Active distribution grid with PV and BESS integration	Genetic algorithm and IEEE 33-bus grid model data in Zones 1 to 5.	Showcased a significant reduction in total power loss of 33%.

The studies included in the literature list had distinct research objectives and sought to tackle various challenges. These challenges encompassed optimising the utilisation of RES, reducing the consumption of battery and grid energy, and facilitating coordinated charging dispatch [27–31]. Techno-economic analyses, simulation software, and real-time optimisation tools were utilised to evaluate system reliability, sustainability, net present cost, ROI, and levelised cost of energy [32–37].

As much as the standalone EVCS eliminated grid utilisation, it had numerous challenges; ranging from the variability of resources, location, and accessibility, charging time, the station's capacity to handle peak charging requirements and accommodate future technological advancements, to the battery bank's state of health [38–42]. Battery-swapping EVCS offered shorter charging times compared to traditional charging methods. The traditional charging times can range from 20 minutes for fast charging to eight hours for the longest charging sessions, depending on the charging level and voltage specifications. Battery-swapping stations are an alternative approach to charging EVs that allow owners to minimise the time spent at the EVCS. Instead of waiting for their EVs to charge, users can quickly swap out their depleted battery with a fully charged one, which reduces the charging time significantly. Previously, the battery-swapping process took around 10 minutes, during which the driver was expected to exit the vehicle. However, technological advancements have reduced the swapping time to approximately five minutes, which makes it comparable to refuelling an internal combustion engine vehicle. However, battery compatibility at this type of station was always a concern. Numerous factors need constant evaluation to ensure that the swapped battery is suitable for the specific vehicle and can provide the desired range and performance. Those factors include, but are not limited to, battery chemistry, capacity, age, and health.

In the context of grid-integrated stations, additional benefits can be achieved with the implementation of a proper EMS, control, and optimisation scheme to achieve effective charging [43–47]. Battery banks integrated with the grid can extend their lifespan by utilising grid power during night time or unfavourable weather conditions. Grid-integrated stations are seen as offering more attractive charging schemes, and an EMS, control, and optimisation scheme can provide effective charging. Battery banks integrated with the grid can enhance their lifespan by utilising grid power during off-peak hours and adverse weather conditions [48–60].

2.2.1 Justification of the reviewed literature

The evolving landscape of electric mobility in developed countries is shaped by a multifaceted approach that encompasses technology, infrastructure, policy, and environmental considerations. This approach is reflected in the trends observed in EVs, which highlight the interconnected nature of these factors and their collective contribution to the ongoing evolution of the electric mobility sector. Technological advancements, such as battery technologies, electronics improvement, vehicle design, reliable and efficient charging infrastructural designs, and the incorporation of autonomous features, have played a pivotal role in driving the extensive adoption of EVs overseas [42–48]. These innovations have significantly enhanced the appeal of EVs, making them more attractive to potential owners [49–51]. While developed nations experience a seamless integration of these innovations, the adoption of EVs in developing countries is influenced by a complex interplay of factors [52–55]. Challenges related to charging infrastructure and affordability persist, yet there is a growing awareness of the environmental and economic benefits associated with electric mobility [56–58]. With technological advancements and supportive policies, it is anticipated that the uptake of EVs in developing nations will significantly increase in the coming years. In order to align with the global surge in EV adoption, a significant enhancement of the power system is imperative to accommodate the escalating demand. The considerable increase in EV penetration and the prevalent issue of uncoordinated charging practices pose substantial threats to the stability of local grids. This scenario has the potential to trigger disruptive impacts on power distribution systems, particularly within the intricate framework of building power energy systems [59–62]. Addressing the challenges inherent in the widespread adaptation of EVs in the country necessitates the adoption of a suitable paradigm. In this context, the POET framework emerged as a pertinent choice. This paradigm relies heavily on

various crucial factors, including energy security, the availability of resources, infrastructural design, and efficient energy management, well-thought-out charging schemes, reasonable charging costs, and ensuring profitable margins for the operation of EVCSs [63–67]. The comprehensive consideration of these factors within the POET framework is instrumental in devising a strategic and sustainable approach to overcome the challenges associated with the expansive integration of EVs in the country. Section 2.3 presents the POET structured framework in the EVCS, while Section 2.4 outlines the key findings of the reviewed literature and concludes the chapter.

2.3 POET STRUCTURED FRAMEWORK IN AN EVCS

The POET framework, as first presented by Xia and Zhang, looks at two-part objectives, namely the technical and non-technical energy efficiency of a power system, as indicated by Figure 2.1. According to these authors, both the technical and non-technical can still be highlighted in the four words that make up the POET acronym, with different approaches [63–65]. The two approaches are further sprawled over three levels, namely the technical, active, and conceptual levels. The framework is then applied to an EVCS in an attempt to investigate further improvement of the infrastructure. This section highlights the efforts on further improving EVCS operations through the adaptation of the POET framework.



Figure 2.1: Energy-efficiency components [63]

The two authors regrouped the words in the acronym to present their specific application. Through that regrouping they denoted that the far-left group, which comprises all the words in the POET acronym, is dubbed the *energy group* due to their direct influence by the technology aspect. The second block is *time planning* since the use (operation and performance) of the equipment will be time based, while the second last block is *behavioural based* and the last one is *human-induced factors* such as loss and theft [63–65]. The following review tackles the words in the acronym in their hierarchy on the non-technical and technical performance objectives while showcasing different levels of this framework.

2.3.1 POET structured performance of the infrastructural designs of an EVCS (according to the technical objective)

There are presently several operational EVCSs around the globe. Their performance depends upon various factors such as resource availability, infrastructural design, accessibility, energy management, charging schemes, and environmental as well as financial implications. This section of the study investigates what other researchers have accomplished concerning the performance of EVCSs to address the aforementioned factors.

Whether it is a standalone EVCS or a grid-integrated EVCS, both types incorporate resources and storage systems that align with the system's nature. These components collaborate to create a system that is tailored to the infrastructure's specifications. The configuration and selection of these components may differ based on factors such as capacity, location, and charging station requirements. This section emphasises the technological progress of these components to establish a precedent to determine which ones are most suitable for enhancing the efficiency of an EVCS system.

2.3.1.1 Photovoltaic (PV) panel overview and selection justification

The improvement of PV-module technologies has been a core focus of many research studies. The efficiency of these modules makes a significant contribution to the daily operation of the system. There are numerous types of PV cell technologies to date, for both large-scale and small-scale applications with different materials and efficiency. Their materials have great implications for their performance, efficiency, and cost. Their aforementioned effects have a great potential to increase the overall efficiency of the system suited to their individual application. For the purposes of this study,

the focus is on the first- and second-generation classifications since these two are the types used to generate energy. These types of panels are manufactured by utilising semiconductor material such as silicon, amorphous silicon, and cadmium telluride and copper indium gallium selenide (CIGS) cells. They are made from a single silicon crystal (mono-crystalline) or cut from a block of silicon that is made up of many crystals (multi-crystalline) [68–71].

(a) PV panel technology analysis (first generation)

Numerous studies have been conducted with the sole purpose of investigating the efficiency of the first-generation PV module. A number of findings were made concerning their performance due to the variation in solar irradiation. A study conducted by Gulkowski et al, in Poland indicated that the second generation exhibited high resistance to temperature rise as compared to the first generation. CIGS (second generation) in turn produced more power than polycrystalline (first generation). A similar study conducted by Serameng et al, in South Africa also indicated that CIGS performed better than crystalline silicon technology in both fixed north-facing and east-west tracking configurations. Romero-Fiances et al, concluded that silicon crystalline was a better option in Lima due the low irradiation resources. The evidence in the three studies led to one conclusion, namely that thin-film/second-generation PV modules have much higher efficiency where high irradiance was detected, and as such they would be a logical choice in South Africa [72–75].

2.3.1.2 Wind turbine overview and selection justification

Numerous aspects contribute to the performance of wind turbines in an energy system. Some of the applications of wind energy include energy generation, water pumping, boat battery charging, etc. Wind turbines utilised in energy-generation systems are the core focus in this section. The type of wind turbine utilised differs for each application, and is classified according to design, size, configuration, and location [76–77]. Since the environment and location tend to be the biggest influencers of the energy generated at each station, the aerodynamic design of the wind turbine could be improved and optimised to enhance wind turbine efficiency [78].

(a) Wind turbine technology analysis (aerodynamic improvement)

Rahman et al. investigated the performance improvement of the horizontal axis wind turbine. They noticed improved efficiency with three-bladed turbines as compared to two and five blades. Their study also showed that the type of material used for the blades also made a significant difference in the turbine's efficiency and performance [79]. Meana-Fernández et al, also emphasised the importance of aerodynamic design to improve the efficiency of a turbine [80]. Besides technological and design improvements, location and environment play a significant role in the overall performance of a wind turbine. Wind speed in a coastal site is significantly higher as compared to inland. It has been established through many studies that the placement of a wind turbine and turbulence have an impact on the turbine's performance [81–83].

2.3.1.3 Battery bank technologies overview and selection justification

The BESS plays a pivotal role in the optimisation of an EVCS. The storage-selection process depends on what the designer intended to accomplish in the design. There are different types of storage to date that possess different behaviour and performance criteria. Battery banks are the dominant storage of choice in EVCSs due to their versatility and quick charging and discharging response. Their performance criteria include specific power, typical voltage, amp hour efficiency, energy efficiency, commercial availability, cost, operating temperatures, self-discharge rates, number of lifecycles, and recharge rates [84]. The use of this storage option has been widely implemented and has been discussed by numerous researchers.

Eid et al. conducted a study on battery storage functionality in an EVS. In their study the battery storage was optimised through the use of the Gorilla Troops Optimizer to control the power flow inside the distribution system and to enhance its performance through the minimisation of the proposed fitness [85]. Sarker et al, showcased the profitability aspect of incorporating a BESS to arbitrate energy and to balance out the time variant, as well as uncertainties in the energy demand [86]. Li et al, conducted a study on the utilisation of grid energy to satisfy the energy demand of EVCSs. The study proposed a contract-capacity-optimisation algorithm to coordinate the exchange between the grid and charging facilities [87]. While a study by Radu et al, presented the promotion of

battery energy storage to support EVs' charging in smart grids, their study mitigated the excessive penetration of EVs in the power system by optimising the system through the use of renewable energy inclusion and a storage system [88].

2.3.1.4 Energy management system (EMS) overview and selection justification

An EMS acts as smart control strategy to employ apt functionality in an EVCS through proper communication between the resources, battery bank, charging point, and the grid while considering the EV's charging requirements. This effective communication within the EVCS has proven to be a game changer in the EVCS, as more activity in the EVCS can be achieved without compromising the energy supply, grid stability, and CBB SoC while minimising the charging cost of EVs [89]. The subsection below deals with EMS-applicable technologies that address the issue of EVCS dynamic pricing, while it constantly monitors the energy level in an EVCS and the EVs' charging/discharging requirements. However, the EMS requires a control system to successfully manage the energy from the RES to the EVCS, grid-to-EVCS, EVCS-to-grid, battery-to-EVCS, EVCS-to-battery, vehicle-to-EVCS, EVCS-to-vehicle, as well as P2P energy sharing. Charging infrastructure is an important component for the healthy growth of the EV industry [90].

(a) EMS analysis

Mumtaz et al, presented a paper on energy management and control of PHEV charging stations in a grid-connected hybrid power system. They designed an EMS for charging and discharging of five different PHEVs simultaneously to fulfil the grid-to-vehicle (G2V), V2G, grid-to-battery storage system (G2BSS), battery storage system-to-grid (BSS2G), BESS-to-vehicle (BSS2V), vehicle-to-energy (V2BSS), and V2V charging and discharging requirements of the charging station [91].

Huang et al, presented a paper on EMS optimisation of a drug store EVCS operation. Their paper proposed a strategy aimed at maximising the benefits of EVCSs based on the impact of weather and various uncertain factors using the MATLAB MILP toolbox [92].

Savio et al, presented a paper on a PV-integrated hybrid microgrid structured EVCS and its energy management approach. They proposed an EMS for a multiport battery-energy EVCS powered by a hybrid microgrid. Their proposed EMS maintained the direct current (DC) bus voltage irrespective of utility grid overloading caused either by the local load or meagreness of PV power [93].

Torreglosa et al, presented a paper on a decentralised energy management strategy based on predictive controllers for a medium voltage DC PV EVCS. Their study proposed a decentralised EMS for regulating the energy flow among the PV system, the battery, and the grid in order to achieve efficient EV charging [94].

Hassoune et al, conducted a study on the power-management strategies of an EVCS-based grid-tied PV-battery system. Their study presented a power predictive model to forecast EVs' power demand and to enhance EVCS performance, in order to avoid an extra burden on the grid during peak hours [95].

Amir et al, presented a study on IEMS-based coordinated control for reducing peak load in grid-connected PV-powered EVCSs. They proposed an IEMS-based coordinated control for PV-based EVCSs. Their proposed IEMS optimised the PV generation and grid power utilisation of EVCSs by analysing real-time meteorological and load demand data [96].

Wu et al, conducted a study on the real-time energy management of a PV-assisted EVCS through the Markov decision process. Their paper proposed a finite-horizon Markov decision process model for the optimal control of a PV-assisted EVCS on a university campus [97].

Cabrera-Tobar et al, conducted a study on the real-time EMS of a PV-based EVCS using explicit model predictive control (eMPC) to account for uncertainties. Their paper presented the use of eMPC in EVCSs based on PV and BESS, while considering the uncertainties. They used an explicit formulation that was based on the mapping of critical regions through the use of multi-parametric programming [98].

2.3.1.5 Charging point technologies overview and selection justification

The configuration of EVCSs varies from country to country depending on frequency, voltage, electrical grid connection, and standards [99], which in turn set precedents for the amount of power to be delivered through each mode of charging. There are several modes of charging, which are classified according to the power that they can deliver for a specified period. These charging modes have different connectors that can be connected to certain designs of socket. The subsection below discusses the available modes of charging, the connector standards, as well as their specific sockets.

Current type	Region			
	Japan	America	Europe, rest of world	China
AC				
Plug name:	J1772 (or Type 1)	J1772 (or Type 1)	Mennekes (or Type 2)	GB/T
DC				
Plug name:	CHAdeMO	CCS1	CCS2	GB/T

Figure 2.2: EV charging modes and connectors [100]

(a) Charging station modes and connector technologies analysis

Kumar et al, conducted a review on the standards for EVCSs in India. Their review examined the types of EVCSs, their charging methods, connector guns modes of charging, testing and certification standards, and the current status of Indian standards with respect to international standards. They recommended the use of a combined charging system for one-direction charging and CHArge de Move (CHAdeMO) for bidirectional charging [101].

Dericioglu et al, undertook a comprehensive review of the charging technologies for commercial EVs. Their review presented and described the charging technologies for commercial vehicles, related standards, charging levels, and charging modes. They documented some beneficial reports on charging technologies for commercial EV manufacturers interpreting various charging modes, levels, and types [102].

Savio et al, presented a paper on EVCS architecture, criteria, power converters, and control strategies in microgrids. Their review paper presented different RES-connected architecture and

control strategies used in EVCSs while highlighting the importance of different charging station architecture with current power converter topologies proposed in the literature. Additionally, they presented a comparison of microgrid-based EVCS architecture with their applicable energy management, control strategies, and charging converter controls. They presented challenges and opportunities in selecting adequate parameters for an EVCS [103].

Chamberlain and Al-Majeed presented a paper on the standardisation of British EV charging protocol, payment, and charge point connection. Their study analysed emerging standards for EV rapid charging and investigated how standardisation challenges affected stakeholders by reviewing the existing literature on single-mode and polymodal harmonisation. They also highlighted the importance of carefully reflecting on whether to introduce new processes and methods and to avoid being rushed by outcomes resulting from dormant modes, such as the continued roll-out of CHAdeMO relating to just one outgoing model by Nissan. They also found that the market-led combined charging system standard is rapidly becoming the de facto standard for all cars with a rapid-charge facility, with the exception of the CHAdeMO-based Nissan Leaf. Nevertheless, they observed that the CHAdeMO consortium has developed a new Far East standard named Chaoji that is gaining rapid acceptance in China and Japan [104].

Sachan et al, presented a comprehensive state-of-the-art bibliographical review of standards related to utility grid integration and best practices for EVCSs. Their study presented a systematic review of charging standards, highlighted challenges and barriers, and made recommendations on the integration of distributed energy resources and the grid [105].

Rubino et al, presented a comprehensive overview of innovative plug-in EVs' charging architectures, devoted to the integration of sustainable mobility and distributed energy sources in a smart grid scenario. Their study paid specific attention to off-board DC fast-charging architecture, which plays a fundamental role in the integration of stationary BESS and RES with the main grid. Their review summarised and discussed a wide range of the most interesting applications, technical experiences, and international pilot projects, with specific references to new technologies [106].

2.3.2 POET structured framework for an EVCS (according to the non-technical objective)

The dawn of industrialisation and efforts to transform the world into a global village have seen an increase in energy requirements. Sustainable developments are necessary to meet future energy

requirements without compromising the stability of the power system [107–108]. The non-technical objectives as described by Xia and Zhang are basically efforts made to improve energy efficiency, and these efforts are not influenced by technology. They further elaborated that this can be achieved through tailored time planning and behaviour-based and human-induced factors [63–65].

This section of the chapter presents work that has been done in the non-technical sphere to further improve the energy efficiency of EVCSs. The optimisation of an EVCS requires a multidisciplinary approach that combines engineering, economics, environmental science, and policy considerations to achieve the desired balance between efficiency, reliability, and sustainability.

It can easily be linked to the non-technical aspect of the POET framework, since the aforementioned factors of optimisation rely on a proper coordination of renewable energy technologies to support the grid energy mix, load forecasting, demand-side management, and maintenance, reliability, and sustainability of the power system. In this context, the non-technical POET framework emerged as a pertinent choice. This selected paradigm relies heavily on various crucial factors, including infrastructural, energy security, efficient energy management, and well-thought-out charging schemes, reasonable charging costs, and ensuring profitable margins for the operation of charging stations [66–67].

2.3.2.1 Infrastructural design of an EVCS

Al-Hanahi et al, conducted a study on charging infrastructure for commercial EVs in terms of challenges and future work. Their study presented a comprehensive review and analysis of existing work on commercial vehicle charging. They reviewed two major charging strategies for commercial vehicles, namely the return-to-base model and the on-route charging model. They proposed that public charging stations for commercial EVs should be optimally located and dedicated to mitigating the aforementioned issues of charging heavy EVs. Moreover, optimal charging strategies need to be designed to coordinate the charging process of commercial EVs at different locations [109].

Maia et al, wrote a paper on infrastructure as a social catalyst for EVCS planning and deployment. Their paper described the planning, design, and deployment of a network of EVCSs in British Columbia from a synthetic human-centred design perspective. Their framework is adaptable to an evolving deployment, technology, and market timeline. The strategies adopted included context-

specific station phasing, regional network design, station design and branding, and a phased business model [110].

Domínguez-Navarro et al, presented a paper on the design of an EV fast-charging station with the integration of renewable energy and storage systems. In order to improve the profitability of fast-charging stations and to decrease the high energy demanded from the grid, the station includes renewable energy generation (wind and PV) and a storage system using generic algorithm [111].

Das et al, presented a technological review paper on EV standards, charging infrastructure, and impact on grid integration. Their paper introduced the current EV status, provided a comprehensive review of important international EV charging and grid interconnection standards, and discussed all the aspects of EV charging and grid-integration infrastructure [112].

Gupta et al, conducted research on the optimal allocation of EV charging infrastructure, policies, and future trends. Their paper presented the optimal allocation of rapid-charging stations based on economic benefits and grid impacts. Their study employed the use of MILP and k mean ++ optimisation [113].

2.3.2.2 Optimal sizing of an EVCS

The concept of EVCSs has been widely explored in the literature and in practice. The benefits and drawbacks have set the tone for more research to be conducted on the improvement of existing architecture. The practicality and feasibility of EVCS design vary due to various influential factors. These factors can include the geographical location and environment, consumer characteristics, economic factors, and technology. The technology factor is not discussed in this section as it forms part of the technical aspect, which was thoroughly discussed in that section. The other aforementioned factors are discussed in detail in the subsections that follow.

(a) Location and geographical environment factors

Ease of accessibility, EV traffic volume, and resource availability are critical in determining the sustainability and success of an EVCS project [114–115]. Site selection plays a pivotal role in maximising EV usage and can significantly impact the construction and operational costs of the EVCS [116].

Many studies have utilised Geographic Information System (GIS) as a tool for the optimal site selection of EVCSs. GIS helps to identify the distribution of charging demands based on land-use classifications and integrates economic, social, and technological variables. By employing GIS, researchers can analyse various factors and make informed decisions regarding the location of charging stations [117–118]. In recent research by Liu et al., a hybrid model combining GIS and Bayesian network was introduced. This approach focused on infrastructure considerations, GIS, conditional probability, and causal relationships among random variables at the EVCS (Bayesian network). By combining these approaches, a more comprehensive understanding of site selection can be achieved [119].

Another study by Zhang et al. integrated GIS with a multi-criteria decision-making approach, particularly the analytic hierarchy process. The study utilised quantitative and qualitative data to identify suitable EVCS station locations. By employing the analytic hierarchy process within GIS, a systematic evaluation of multiple criteria can be conducted to determine the optimal site [120]. Štilić and Puška's study combined GIS with the Technique for Order of Preference by Similarity to Ideal Solutions (TOPSIS), which is another multi-criteria decision-making technique. TOPSIS calculates the closeness of value for each location and ranks the most optimal site based on an integrated GIS analysis [121].

This approach allows for a comparative evaluation of different sites. In the case of Gqeberha, the environmental conditions, such as wind speed and irradiation, were considered using available data from the EMS at the station. Factors like humidity and ambient temperature were also considered, as they directly impact the performance of specific components. Air density affects wind power generation, as denser air allows for more intense contact with turbine blades. Ambient temperature affects the efficiency of PV panels, as higher temperatures can decrease module efficiency and rated power output.

(b) Consumer characteristic factors

Xiang et al, conducted research on the economic planning of EVCSs considering traffic constraints and load profile templates. Their study focused on the provision of a novel planning framework for determining the siting and sizing of charging stations by coupling the interactions between the distribution and transportation networks. They used temporal and locational methods to effectively

guide EV charging infrastructure planning without violating the constraints of both the power and transportation systems [122].

Another study by Shojaabadi et al, presented the optimal planning of a PHEV charging station in a distribution network considering demand-response programmes and uncertainties with the aid of a mathematical model. Optimal planning was done by considering the rate of customers' participation in demand-response programmes in the presence of some uncertainties associated with load values and the electricity market price [123].

Ucer et al, presented a paper on modelling and analysis of a fast-charging station and the evaluation of service quality for EVs. They developed a DC fast-charging station model and analysed three different DC fast-charging stations using charging and mobility data acquired from EVI-Pro. The model ran a thorough analysis of DC fast-charging station operations to understand statistical metrics such as peak demand power, customer service quality, and port utilisation [124].

Moon et al, conducted a study on forecasting the electricity demand of EVs by analysing consumers' charging patterns. Their study focused on estimating the changes in electricity charging demand based on consumer preferences for EVs, charging time of day, and types of EV supply equipment and elucidated the matters to be considered for constructing EV infrastructure. By applying consumer preferences for EVs, EV supply equipment, and charging patterns, they were able to analyse the environmental effect of EV diffusion [125].

Hardman et al's paper presented a literature review of studies that investigated infrastructure needs to support the market introduction of plug-in EVs. Their study focused on literature relating to consumer preferences for charging infrastructure and how consumers interact with and use this infrastructure [126].

(c) Economic factors

In developed countries, EVCS infrastructure and the generation, delivery, and mix of energy over the past century have evolved significantly. Their framework encourages power utilities to use sustainable and technological advancement to generate energy. They have also implemented policies to drive down energy prices. The introduction of renewable energies, storage systems, and EMSs has been successful in cost reduction at EVCSs. Studies on achieving a balance in energy mix and grid support

to provide sustainable energy support at EVCSs have seen significant results in cost reduction based on ToU tariff structures [127].

Hafez and Bhattacharya proposed an optimal design for EVCSs considering various energy resources systems to accomplish operational cost reduction. Their paper presented the optimal design and comparative studies for an isolated EVCS and a grid-connected EVCS as a smart energy hub configuration [128].

Yan et al, researched optimised operational cost reduction for an EVCS integrated with battery energy storage and PV generation. Their paper proposed an algorithm aimed at maximally reducing the customer satisfaction-involved operational cost considering potential uncertainties while balancing the real-time supply and demand by adjusting the optimally scheduled charging/discharging of EV mobile/local battery storage, grid supply, and deferrable load [129].

Luo et al, conducted a study on the optimal planning of EVCSs comprising multiple types of charging facilities. Their study proposed a new optimisation model for targeting and minimisation of the annualised social cost of a whole EV charging system. They employed the use of a two-step equivalence to process the scenario-based constraints and transforming the optimisation model into the type of MISOCP through an exact SOCP relaxation [130].

Adetunji et al, conducted a study on an optimisation planning framework for allocating multiple distributed energy resources and EVCSs in distribution networks. Their study presented a novel multi-phase planning framework for allocating PV-distributed generation, BESS, and EVCS facilities in distribution networks, using a recombination technique to find optimal locations while considering power loss reduction, voltage stability improvement, voltage deviation reduction, installation cost reduction, operational cost reduction, and emission cost reduction [131].

2.3.2.3 Resource availability and variability

The fluctuating nature of resources makes it difficult to sustain a balance between supply and demand. This variability in resources requires the implementation of additional measures to balance the system. Knowledge of this variability is important for improving the design of a system (by adding properly sized storage capabilities, for instance) and understanding the performance of a system.

Dharmakeerthi et al, studied numerous cases to analyse the influence of renewable energies and their storage systems in a fast-charging station and through that analysis noted that grid impact was

lowered when RER and a battery system were utilised. Similarly, Muratori et al, and Brunner et al, came to the same conclusion with regard to the use of renewable energy and the inclusion of a storage system to minimise grid utilisation, as well as to mitigate the variability associated with these resources by including a storage system (either battery or the grid) and an EMS for seamless integration of the resources [132–134].

2.3.2.4 Energy security

Both physical and cyber-attacks are significant factors that influence the reliability of EVCSs and their ancillary services. Physical attacks relate to the integrity of the infrastructure and its ability to meet the country's energy demand without any load rejection, which compromise the stability of the grid, uninterrupted energy supply, and affordability. Cyber-attacks usually happen in EVCSs that are equipped to communicate with consumers and prosumers. This open-access information sharing leaves EVCSs vulnerable to attacks. Over the years, both physical and cyber-attack detection tools have been implemented. Researchers such as Warraich et al, and Wang et al, have dissected threats that can compromise the reliability, performance, security, and stability of EVCSs and proposed ways to combat them. They developed a novel approach that uses machine learning to detect such attacks early. This approach directly reduces the strain on ageing assets and mitigates the risks associated with the denial of ancillary service provision. By promptly identifying and responding to attacks, this approach helps to prevent financial losses and power outages [135–136].

2.4 KEY FINDINGS ON THE REVIEWED LITERATURE

2.4.1 POET perspective analysis

Technological advancements in the major components as well as an effective EMS for efficient charging were reviewed with the intention to analyse and propose a viable charging option. Technological advancements and the type of material used in the manufacturing process of various components were viewed to be beneficial to the overall performance of EVCSs. The POET framework was applied to further improve the energy efficiency of EVCSs. This framework serves as a roadmap for energy management and facilitates the assessment of opportunities for energy and cost savings. Energy-efficiency initiatives and potential savings were identified across different stages,

encompassing conceptual (non-technical objectives) and active, technical, and ongoing improvement levels (under the technical objectives). The provision of remote control and configuration capabilities of a web-based energy-monitoring system such as real-time data tracking, scheduling and optimisation as well as integration capabilities offered the convenience, flexibility, and efficient management of a charging station's energy settings which in turn allowed the operators to adjust and monitor performance and optimise energy usage without the need for on-site visits, which reduces maintenance costs and enables more streamlined operations. This allows energy-efficiency improvement at the technical level.

CHAPTER III: OPTIMAL POWER-DISPATCHING SCHEMES OF A GRID-INTEGRATED PV-WIND EVCS WITH BATTERY STORAGE AND PEER-TO-PEER (P2P) VEHICLE CHARGING STRATEGIES

3.1 INTRODUCTION

This chapter proposes an optimisation approach and a modelling framework for a PV-grid-integrated EVCS with battery storage and P2P vehicle charging strategies. The main objective is to optimise the system for reliability and profitability while minimising operational costs. The model considers factors such as energy demand, grid stability, battery health, and charging costs to efficiently utilise resources. A notable aspect of the proposed model is the introduction of a P2P energy-sharing mechanism.

Prosumers are allowed to trade energy with one another, which enables efficient utilisation of resources and fosters a collaborative energy ecosystem. The dynamic power demand and pricing environment facilitates fair and optimised energy exchanges. This chapter outlines the development of a mathematical algorithm formulation for the proposed model and validates its effectiveness and performance using a real-world case study conducted at NMU in South Africa.

This comprehensive approach considered daily varying weather and load conditions to ensure a realistic analysis of system performance and economic feasibility. The simulation results demonstrate significant energy demand cost savings, with a 38.14% reduction considering ToU tariffs, and a 30.5% reduction in maximum demand through optimal control. A detailed techno-economic analysis over a 20-year period was conducted. The results indicate substantial reductions in grid costs and a breakeven point within eight years, which highlight the economic advantages of the optimisation model. Furthermore, the results demonstrate significant cost savings, including energy demand cost savings and ToU savings.

3.2 MODEL DEVELOPMENT

3.2.1 EVCS load profile description

Due to COVID-19 restrictions imposed at the time the study was conducted, the data acquired at the station did not have a load. The measurements were recorded for two different charging schemes: slow charging and fast charging. Both setups employed the use of a 2013 Nissan Leaf to plot the load profile. The setups for measuring the charging activity from the slow alternating current (AC) charging and fast unit are shown in Figures 3.1 and 3.2.



Figure 3.1: Slow-charging protocol setup

The measurements were taken using a DL 850V SCOPE CORDER, which is a portable data-acquisition device that is capable of capturing and analysing data over extended periods.

For the slow-charging scheme, measurements were taken at 30-minute intervals using the DL 850V SCOPE CORDER.



Figure 3.2: Fast-charging unit charging protocol

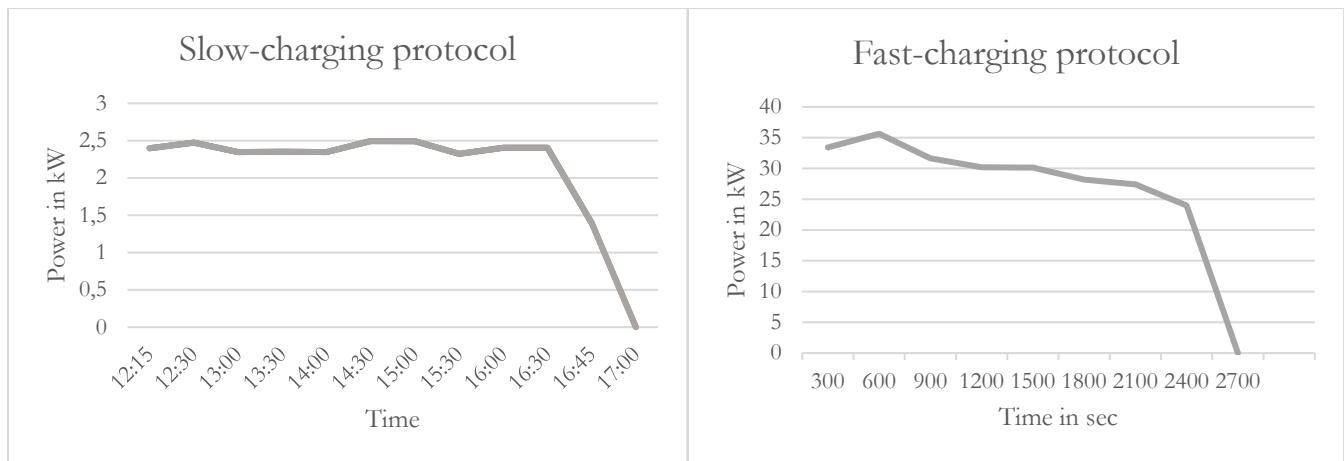


Figure 3.3: Load profile for each charging protocol at the station

Figure 3.3 represents the type of charging unit and the active charging of the Nissan Leaf utilised to plot the results of the charging activities illustrated in Figures 3.1 and 3.2. The Spy Leaf app was used to obtain readings from the on-board diagnostic adapter connected to the vehicle.

3.2.2 Steps to obtain the EVCS load profile

In a traditional charging station, the load profile is influenced by the volume of charging and the load requirements of each vehicle when it arrives. The availability of resources at the time of arrival determines the type and rate of charging that can be provided. This means that the load profile at a traditional charging station can vary depending on the charging demand and the capabilities of the infrastructure. In contrast, a campus setup for charging EVs may have a different load profile compared to a traditional EVCS. In a campus setting, charging events are typically more predictable and occur at specific intervals. This predictability stems from the fact that charging is often planned or scheduled in advance by the vehicle owners or operators on the campus. In a campus charging setup, the overall activity at the EVCS may be limited compared to a traditional charging station, which can experience charging events at random intervals throughout the day. The highest load demand at a campus charging station would typically occur when vehicles arrive with the lowest battery SoC. This is because vehicles with lower battery levels require more charging power and time to reach an acceptable charge level. The load evaluation in a campus charging setup would take into consideration the expected arrival times of vehicles, their battery SoC upon arrival, and the available resources at the charging station. This evaluation helps to determine the charging requirements and capacity needed to effectively meet the demand. It is worth noting that the specific details of the load profile and evaluation of a campus charging setup would depend on the characteristics of the campus, such as the number of vehicles, their charging patterns, the charging infrastructure in place, and any scheduling or management systems implemented. It is interesting to note that in both charging schemes, the charging protocol was designed to meet the same charging requirements, with the minimum SoC for each vehicle set at 15%. This requirement is indicated in Figures 3.4 and 3.5. Screenshots were taken from the Spy Leaf app communicating with an embedded LS091 Cloud Edge on-board the vehicle.



Figure 3.4: Minimum battery SoC for AC charging

The battery SoC for each vehicle under each protocol is displayed on a tablet on the Spy Leaf app as seen in Figures 3.4 and 3.5 respectively. The Spy Leaf app displays the battery SoC for each vehicle under each protocol. The results were collected and summarised to show the charging activity of both protocols.



Figure 3.5: Minimum battery SoC for fast DC charging

Despite the similarity in the load requirements, it is important to understand that this does not necessarily imply a uniform or coordinated charging scheme. Instead, it serves as a measuring tool to gather data for comparison purposes. This practical setup provides insight for selecting a suitable EVCS with adequate charging activity when analysing the load profile during a case study. The primary goal of this setup was to ensure a consistent charging process without any load rejection. The focus was on effectively managing the charging process to accommodate the evolving needs of the vehicles without overwhelming the available resources or causing disruptions. This approach aimed to strike a balance between meeting the charging demands and optimising the utilisation of resources.

By studying the load profile and analysing the collected data, researchers can gain insight into charging behaviour and patterns, as well as the ability to assess the feasibility and effectiveness of incorporating RES to meet the charging demand. It is understandable that in the current stage of e-mobility and associated infrastructure development in the country that the profitability of running an EVCS and reducing operational costs may not be the primary priority. Instead, the focus is on ensuring an adequate number of charging points available for future EV owners. This reflects the infancy stage of e-mobility in the country, which necessitates the development of robust charging infrastructure that is capable of supporting the growing number of EVs on the roads.

3.2.3 Proposed system configuration and description

The Eastern Cape province in South Africa has seen significant developments in wind farms and has garnered a substantial share of the country's wind energy allotments. It also has an abundance of solar energy. The Eastern Cape's favourable wind resources, along with government policies and incentives, have attracted investments in renewable energy projects, particularly in the wind power sector [137–139]. Gqeberha, which is situated in the Eastern Cape, is dubbed the windy city of the country, which translates to the abundance of this type of resource. Solar energy, with its storage options and year-round availability, has gained popularity despite the challenges associated with grid viability.

In addition to solar energy, wind energy is also abundant in South Africa, particularly in coastal areas like the Eastern Cape province. The Eastern Cape has received a significant allocation of wind farms, with 51% of South Africa's wind farms located there. Gqeberha benefits from the abundance of wind resources in the region. Wind energy is currently underutilised by smaller systems, primarily

due to noise emissions and aesthetic considerations. The introduction of silent turbines could address these concerns and increase the interest in wind energy for smaller applications. The proposed system is a P2P energy-sharing EVCS with a grid-integrated hybrid system. This system combines PV solar panels, wind energy, an EMS, and a BSS. Such a configuration is known for its efficiency, reliability, and potential energy cost savings. This type of system can be implemented at universities, taking advantage of shaded parking bays that can be converted into PV parking bays. Wind energy generation, on the other hand, may require a bit more space away from the parking bays to avoid shading that could significantly reduce PV generation.

Figure 3.6 provides a visual representation of the power flow between major components. The power generated from the PV and wind system in the proposed setup serves multiple purposes. Firstly, it is used to charge the EVs present at the station, providing them with renewable energy for their charging needs. Secondly, any excess energy generated by the PV and wind systems beyond the immediate charging requirements is stored in the BSS. It can provide additional power to meet demand and bridge the gap between the energy generation from renewable resources and the load requirements.

Furthermore, during periods of minimal activity at the station and when the BSS is fully charged, the excess power generated from the RER can be sold back to the utility grid. This allows for the monetisation of surplus energy and contributes to the overall financial viability of the system.

During peak periods when the combined output of the renewable resources and the BSS is insufficient to meet the changing requirements, the proposed system promotes P2P EV charging. In this mode, energy sharing occurs among the EVs themselves. An EMS plays a crucial role in managing this P2P sharing. The EMS constantly communicates with the EVs and evaluates their SoC.

Based on the SoC of each vehicle, the EMS makes decisions regarding whether a vehicle needs to be recharged or if it can participate in energy trading. This information is then communicated to the charging units, which address the specific charging requirements of each vehicle accordingly.

This P2P energy-sharing approach optimises the utilisation of available energy resources within the system by ensuring that EVs are charged efficiently while also balancing the load requirements. It enables effective management of energy distribution among the vehicles, considering their charging needs and available energy resources. Figure 3.6 depicts the proposed system.

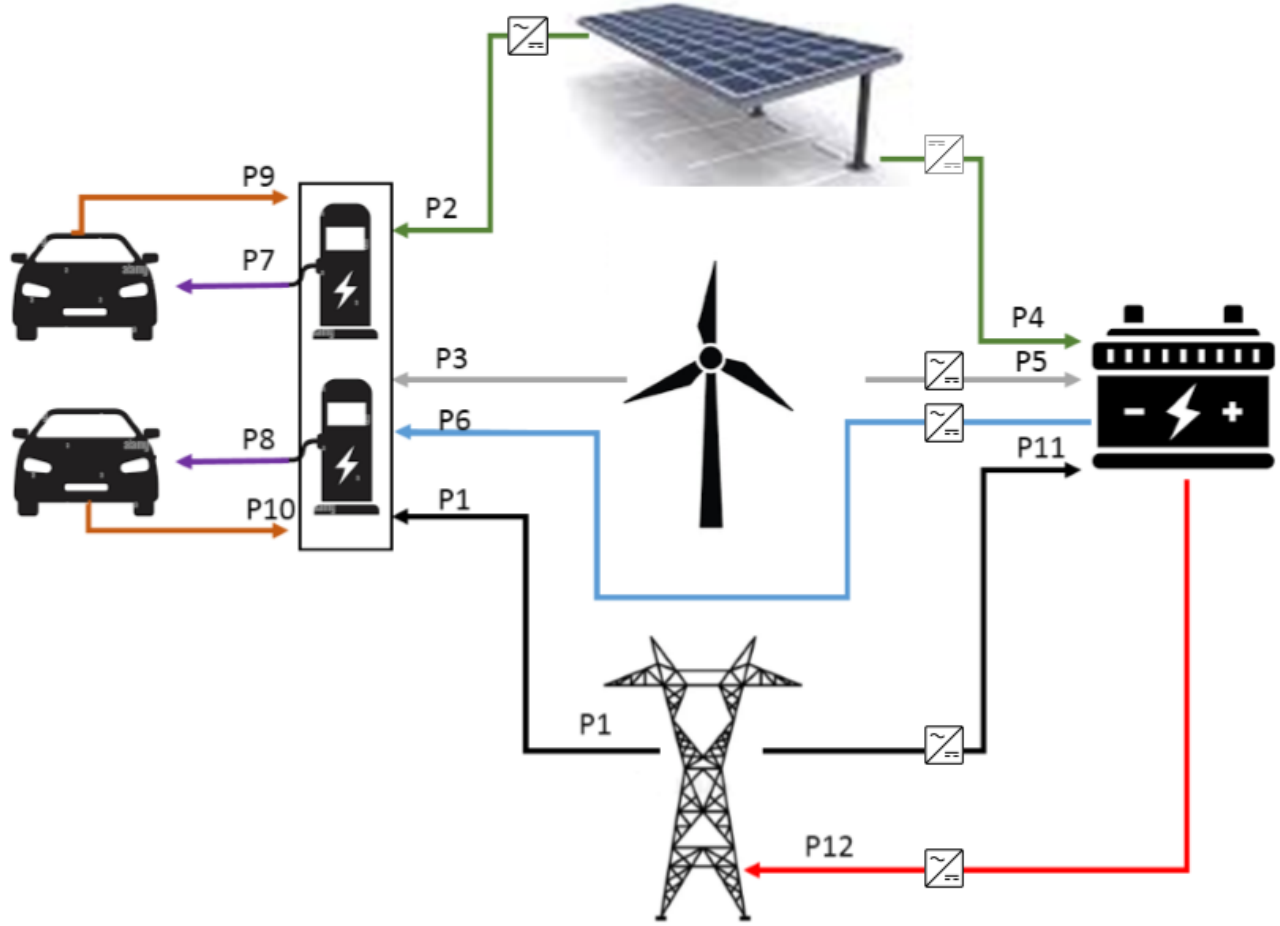


Figure 3.6: Power flow diagram of a smart grid-PV-wind EVCS with battery storage and P2P sharing

The different power flows from Figure 3.6 may be defined as follows:

- $P_{1(j)}$: Power from the utility grid during peak hours when the PV and wind are unable to meet the charging requirements at the station at any interval.
- $P_{2(j)}$: Output power generated from the PV supplied to the charging station upon availability of adequate irradiance in specific intervals in kW.
- $P_{3(j)}$: Output power generated from the wind turbine power (PWT) supplied to the charging station at any specific interval (j) in kW.
- $P_{4(j)}$: Excess power generated from the PV stored in the BESS at any specific interval (j) in kW.

- $P_{5(j)}$: Excess power generated from the wind turbine stored in the BESS at any specific interval (j) in kW.
- $P_{6(j)}$: Power stored in the battery used to supply the load when the PV and wind cannot meet the load, subject to the battery's constraints of discharging at any interval (j) in kW.
- $P_{7(j)}$: EV1 charging at the charging station at any interval (j) in kW.
- $P_{8(j)}$: EV2 charging at the charging station at any interval (j) in kW.
- $P_{9(j)}$: P2P energy sharing between EV1 and EV2 through the EMS when the demand exceeds the supply, and the energy storage is at minimum SoC at any interval (j) in kW.
- $P_{10(j)}$: P2P energy sharing between EV2 and EV1 through the EMS when the demand exceeds the supply, and the energy storage is at minimum SoC at any interval (j) in kW.
- $P_{11(j)}$: Power from the grid to the EVCS when the PV, PWT, and battery are in a deficit at interval (j) in kW.
- $P_{12(j)}$: Power sold to the grid when the BESS is fully charged and the PV and PWT are generating excess energy at interval (j) in kW.

3.3 MATHEMATICAL MODEL FORMULATION

3.3.1 Objective function

The main objective of the pre-existing system was to minimise the use of the battery with an optimum algorithm to maximise the use of the PV system. The proposed multi objective model with a primary and secondary cost function is aimed to firstly minimise the use of the grid with an optimum algorithm to maximise the use of renewable energy such as PV and wind while promoting P2P energy sharing among EV prosumers as indicated by Equation 3.1. And then secondly to maximise the use of renewable energy (as indicated by Equation 3.2) to cater to the load demand, as well as to promote P2P sharing among EV owners when the renewable energy system cannot fully meet the load requirement (Equations 3.3 and 3.4).

$$f_1 = \min \sum_{j=1}^N (\rho_j (P_{1(j)} + P_{11(j)})) \Delta t \quad (3.1)$$

$$f_2 = \max \sum_{j=1}^N (P_{2(j)} + P_{3(j)} + P_{12(j)}) \Delta t \quad (3.2)$$

$$f_3 = \max \sum_{j=1}^N (P_{8(j)} + P_{10(j)}) \Delta t \quad (3.3)$$

$$f_4 = \max \sum_{j=1}^N (P_{9(j)} + P_{11(j)}) \Delta t \quad (3.4)$$

3.3.2 Variable constraints

3.3.2.1 Power flow balance

For the proposed system the load is unknown. Additionally, the EV's battery acts as storage and its role in the station shifts according to its SoC. Various factors were predetermined to establish the role of the EV upon entry to the station, while ensuring that simultaneous charging and discharging do not occur. However, the predetermining factor for either action of the EV in most studies are closely related. These factors include, but are not limited to, power availability, the range travelled, range buffer, and dispatch time [140].

$$P_{EV} = \frac{\left(EV_{BSS} - \frac{D_d + D_{rb}}{\eta_{EV}} \right) \eta_{INV}}{t_s} \quad (3.5)$$

Where:

- P_{EV} is the maximum power from the EV in kW;
- EV_{BSS} is the stored energy available from the EV as DC kWh to the inverter;
- D_d is the distance driven in miles since the energy storage was full;
- D_{rb} is the distance in miles of the range buffer required by the driver;
- η_{EV} is the vehicle driving efficiency in metres/kWh;
- η_{INV} is the electrical conversion efficiency of the DC-to-DC inverter (dimensionless); and
- t_s is time the vehicle's stored energy is dispatched in hours.

3.3.2.2 Inequality constraints

At any sampling time (j), the sum of the power flows from the PV and wind system to the BESS and the critical load should not exceed the power produced by the PV and wind system. At any sampling time (j):

- The power flows from the utility grid that supplies the load (at the charging station) should be less or equal to the maximum power supplied by the grid.
- The sum of the power flows from the PV system to the charging station and stored in the BESS should not exceed the power produced by the PV system.
- The sum of the power flowing from the wind turbine system to the charging station and stored in the BESS should not exceed the power produced by the wind turbine system.
- The power supplied from the PV and wind turbine system and stored in the BESS should not exceed the permissible maximum capacity of the BESS.
- The charging and discharging requirements of the EVs should not exceed the permissible maximum (when recharging) and minimum (discharging) capacity.

$$P_{1(j)} + P_{11(j)} \leq P_G^{rated} \quad (3.6)$$

$$P_{2(j)} + P_{4(j)} \leq P_{PV(j)}^{max} \quad (3.7)$$

$$P_{3(j)} + P_{5(j)} \leq P_{PW(j)}^{max} \quad (3.8)$$

3.6 represents the powerflow of the grid while 3.7 and 3.8 respectively are for the pv and wind power flow representation.

3.3.2.3 Variable boundaries

The manufacturer provided the specification of each design, and these specifications were utilised as boundaries of operation for each power flow. Both components are modelled in accordance with their minimum and maximum boundaries as provided by the manufacturer. These are the main components' control variable limits at any sampling interval j .

$$0 \leq P_{i(j)} \leq P_{i(j)}^{max} \quad (3.9)$$

$$0 \leq P_{i(j)} \leq P_{i(j)}^{rated} \quad (3.10)$$

j denotes different control variables at each sampling interval; $P_{i(j)}^{max}$ is the maximum power limit for each respective system, depending on the resource(PV and wind), while $P_{i(j)}^{rated}$ represents the rated power of a battery. Since the battery is subject to perform within specific boundaries, its operation is capped at specific states stipulated by the manufacturer to preserve its lifespan. Equations 3.11 to 3.13 indicate the operational boundaries for the CBB and the EVs' batteries respectively [141].

$$SoC_0^{min} \leq SoC_{(j)} \leq SoC_{(j)}^{max} \quad (3.11)$$

$$SoC_{EV1}^{min} \leq SoC_{(j)} \leq SoC_{EV1(j)}^{max} \quad (3.12)$$

$$SoC_{EV2}^{min} \leq SoC_{(j)} \leq SoC_{EV2(j)}^{max} \quad (3.13)$$

3.3.2.4 Exclusive power flows

At any interval, power flows are one directional, as charging and discharging in a BESS cannot be executed at the same time. The product of the two states of the BESS (charging and discharging) should always be zero [142].

$$(P_{6(j)}) \times (P_{3(j)} + P_{5(j)} + P_{11(j)}) \quad (3.14)$$

$$(P_{7(j)}) \times (P_{9(j)}) \quad (3.15)$$

$$(P_{8(j)}) \times (P_{10(j)}) \quad (3.16)$$

3.3.2.5 Fixed-final state condition

To demonstrate the consistent implementation and efficient control of the hybrid EVCS model, it is desirable for the State of Charge of the BESS at the end of the control horizon to be equal to its SoC at the beginning of the control horizon. This can be expressed mathematically as follows [141].

$$\sum_{j=1}^N ((P_{3(j)} + P_{5(j)} + P_{11(j)}) - P_{6(j)}) = 0 \quad (3.17)$$

$$\sum_{j=1}^N P_{7(j)} - P_{9(j)} = 0 \quad (3.18)$$

$$\sum_{j=1}^N P_{8(j)} - P_{10(j)} = 0 \quad (3.19)$$

It is worth noting that to accommodate the different types of generated power (AC and DC), a converter is incorporated into the system. This converter plays a crucial role in converting the power to AC when it needs to be sold to the grid or for slow charging purposes. Conversely, it converts the power to DC for fast charging requirements.

3.3.2.6 Battery state of charge (SoC) limits

The battery storage rated capacity is the backbone of the battery-management system and the only variable state in the system. The operating limit of the battery is a critical component for both the systems [141].

BESS of the EVCS:

$$SoC_{(j)} = SoC_{(j-1)} + \frac{\Delta t}{E_n} \times \left(\eta_{ch} \sum_{j=1}^N P_{4(j)} + P_{5(j)} + P_{11(j)} - \frac{\sum_{j=1}^N P_{6(j)} + P_{12(j)}}{\eta_{Dsch}} \right) \quad (3.20)$$

BESS of the EV (P2P):

$$SoC_{EV1(j)} = SoC_{EV1(j-1)} + \frac{\Delta t}{E_n} \times \left(\eta_{ch} \sum_{j=1}^N (P_{7(j)}) - \frac{\sum_{j=1}^N (P_{9(j)})}{\eta_{Dsch}} \right) \quad (3.21)$$

$$SoC_{EV2(j)} = SoC_{EV2(j-1)} + \frac{\Delta t}{E_n} \times \left(\eta_{ch} \sum_{j=1}^N (P_{8(j)}) - \frac{\sum_{j=1}^N (P_{10(j)})}{\eta_{Dsch}} \right) \quad (3.22)$$

Where $SoC_{n(0)}$ is the initial SoC of the battery at the start of every sampling time, $E(n)_n$ is simply the nominal capacity of the BESS, while the charging and discharging efficiency are represented by η_{ch} and η_{dsch} respectively.

At any sampling time (j):

- The power flows from the utility grid that supply the load (at the charging station) should be less or equal to the maximum power supplied by the grid.
- The sum of the power flows from the PV system to the charging station and stored in the BSS should not exceed the power produced by the PV system.

- The sum of the power flowing from the wind turbine (PWT) system to the charging station and stored in the BESS should not exceed the power produced by the PWT system.
- The power supplied from the PV and PWT system and stored in the BESS should not exceed the permissible maximum capacity of the BESS.

The charging and discharging requirements of the EVs should not exceed permissible maximum (when recharging) and minimum (discharging) capacity.

3.3.2.7 Solver selection

The selection of `fmincon` as the solver using the quasi-Newton method was aimed at efficiently searching for the optimal solution that minimises a non-linear objective function while satisfying the specified non-linear constraints. The `fmincon` solver employs an iterative approach to update the solution by adjusting the variables in each iteration, with the goal of minimising the objective function. It uses the quasi-Newton method to approximate the Hessian matrix of the objective function, which allows for efficient optimisation without explicitly computing the Hessian. During the optimisation process, `fmincon` will iteratively update the solution by adjusting the variables to improve the objective function value, while ensuring that the constraints are satisfied. This iterative process continues until convergence is reached, or until a termination condition is met [143].

3.3.3 PV power output

Equation 3.23 represents a commonly used formula to calculate PV output power. The equation calculates the PV output power by multiplying the rated power of the PV module under standard testing conditions with factors such as the number of modules in parallel, the number of parallel-connected strings, and the total solar irradiance. It also considers the effect of temperature on the PV module's performance through the temperature coefficient and the actual operating temperature. Finally, the module efficiency is considered to reflect the conversion efficiency of the PV module [141].

$$P_{PV} = P_{PPV,STC} \cdot N_{PVp} \cdot N_{PVs} \cdot \frac{I_{total}}{1000} [1 - \alpha(T_{cell} - 25)] \cdot \eta_{mod} \quad (3.23)$$

Where:

- P_{PV} is the PV output power, which is the desired quantity to be calculated;
- $P_{PV,STC}$ is the rated power of the PV module under standard testing conditions;
- N_{PVp} is the number of PV panels connected in parallel;
- N_{PVs} is the total number of parallel-connected PV strings;
- I_{total} is the total irradiance on a tilted surface;
- α is the temperature coefficient of the PV module;
- T_{cell} is the temperature of the PV module's cell in °C; and
- η_{mod} is the module efficiency percentage.

Most of the parameters in Equation 3.23 were either given or selected at the designer's discretion. However, two parameters needed to be calculated, which were the cell temperature and the total irradiance on the tilted surface. Equation 3.24 provides a formula to calculate the total irradiance on a tilted surface [141]:

$$I_{total} = I_{DNI} \cos \theta_{\beta} + I_{DHI} \left(\frac{1 - \cos \beta}{2} \right) + \sigma I_{GHI} \left(\frac{1 - \cos \beta}{2} \right) \quad (3.24)$$

The second parameter to be calculated, which is the cell temperature of a PV module, can be determined by using the following standard formula [142]:

$$T_{cell} = T_{amb} + \frac{I_{total}}{800} (T_{NoC} - 20) \quad (3.25)$$

Where:

- I_{DNI} , I_{DHI} , and I_{GHI} are the irradiance (DNI, DHI, and GHI respectively);
- β and θ_{β} are the tilted angle and the angle of incidence on a tilted surface (both measured in degrees);

- σ is the reflectance factor of the surrounding area;
- I_{total} is the total irradiance on a tilted surface, calculated using Equation 3.24;
- T_{amb} is the ambient air temperature; and
- T_{NOC} is the nominal operating temperature of the PV cell in °C.

3.3.4 Wind power output

Wind power as one of the most prominent resources in the country has gained momentum due to its abundance in nature, most particularly in the coastal areas [144]. The availability and variability of this resource throughout the day would yield a different power output. Due to that reason, the hourly output power of the wind system is expected to be different, and it will therefore be determined by the average hourly wind speed at hub height and the characteristics of the wind turbine [145–146].

The general formula for the wind velocity at the hub height is as follows [147]:

$$v_2 = v_1 \left(\frac{h_2}{h_1} \right)^{\gamma} \quad (3.26)$$

Naturally, the wind's speed continually varies. To predict a wind turbine's production, it is necessary to know precisely how often the wind blows strongly. The frequency distribution of wind speeds provides information about the likelihood of observing different wind speeds, while the estimation of energy contained in the wind requires integrating the wind energy equation over the wind speed distribution. The Weibull distribution is commonly used as an approximation for the wind speed distribution at a specific site and can be expressed as follows [148]:

$$f(v) = \frac{k}{A_1} \left(\frac{v}{A_1} \right)^{k-1} \exp \left(- \left(\frac{v}{A_1} \right)^k \right) \quad (3.27)$$

In function of this wind speed and the Weibull distribution, the general formula used to calculate the output power P_w is then denoted as follows [148]:

$$E_w = \frac{1}{2} A t \rho v^3 \quad (3.28)$$

Where:

- v_1 and v_2 are the wind speed at reference and hub height respectively;
- h_1 and h_2 are the reference and hub height respectively;
- γ is the wind shear exponent;
- E_w represents the energy contained in the wind;
- ρ is the air density;
- A is the swept area of the wind turbine rotor in permissible metric measurement (whereby square metres/ centimetre are the common types);
- v is the wind speed in m/s;
- t is the volume of air passing through A (which is considered perpendicular to the direction of the wind);
- A_1 is the scale parameter of the Weibull distribution in m/s; and
- k is the shape parameter of the Weibull distribution.

3.4 MODEL VALIDATION

3.4.1 Pre-existing system description

The EVCS's initial design was focused on a PV-grid system with a BESS; however, over the past few years, the system underwent redesign and modification to achieve optimal generation and efficiency. These modifications included resizing the inverter to accommodate future extensions while avoiding issues such as clipping and overlocking. The EMS and battery storage solution were also upgraded to enhance the system's performance. Additionally, changes were made to the direction and angle of the PV panels to optimise the overall system performance.

To ensure the accuracy of the simulated results and to provide an accurate representation of the charging station's operation, various factors were taken into consideration during the model development stages. Historical data obtained from the EMS at the NMU south campus, located at coordinates 34.0085907°S, 25.6652031°E, were used. These data were utilised to validate the accuracy of the simulated results by comparing them to the actual operation of an EVCS.

Initially, the station had a maximum generation capacity of 12.8 kW_p, consisting of 50 PV panels with a power rating of 250 W each. These panels faced north and were mounted on a corrugated roof pitched at an angle of 30°. However, the system was later upgraded to a generation capacity of 29.42 kW_p, which included 55 PV panels with a power rating of 525 W each. The storage capacity was increased to almost 100 kW, utilising second-life EV batteries. The inverter size was upgraded to a hybrid 100 kW in order to accommodate the increased capacity. Additionally, there is a 2.8 kW wind turbine next to the life science building at NMU, which was incorporated into the proposed model. The wind turbine is located approximately 600 m from the EVCS and was initially installed to supplement the grid on campus. While it is not directly integrated into the EVCS, it was included in the proposed model due to the abundance of wind energy resources at NMU.



Figure 3.7: Initial design of the EVCS at NMU (Uyilo) [149]

These design changes and upgrades aimed to optimise the generation capacity, efficiency, and overall performance of the EVCS to ensure that it can meet the demands of EV charging while utilising RES and maximising the use of available resources. Figures 3.7 and 3.8 show the previous and current design of the EVCS selected in this research study, while Figure 3.9 shows the wind turbine.



Figure 3.8: Current design of the EVCS at NMU (Uyilo) [150]



Figure 3.9: The wind turbine at the south campus next to the EVCS at NMU (Uyilo) [151]

The validation process involved recreating a mathematical model using the same solver that would be used for the proposed system. This approach allowed for simulation and comparison of the

simulated results with the data collected from the actual charging station, which enabled an assessment of their similarities. To evaluate the impact of different weather patterns on the system's viability, two typical weather scenarios were selected: a day with no clouds and a cloudy day. These scenarios were chosen to assess the system's performance under different conditions, as weather patterns can significantly affect renewable energy systems such as solar charging stations. The mathematical formulation used in the simulation enabled a direct comparison between the actual system and the simulated system. Highlighting the similarities between the two validates the applicability of the same formulation for the proposed system. This step is crucial in ensuring the accuracy and reliability of the simulation model. To ensure the accuracy of the simulation model, the components of the system were sized in line with the base model. This means that the specifications and capacities of the components in the simulation model matched those of the actual system. Aligning the sizes of the components ensured that the simulation accurately represented the behaviour and performance of the proposed system.

The historical data from the upgraded model at Uyilo, as well as the simulation results from MATLAB, were the focal points for comparison. The same simulation package used for the base model was employed for the proposed model, and the parameters used in the simulation were consistent with the ones outlined in Table 3.1. For comparison purposes, two days, 17 July and 10 September 2020, were selected from the dataset of the EMS and weather station. These days were chosen because they represented different weather patterns in different seasons, providing clear records of the microgrid status stored on the university's server. It is worth noting that the summer tariff structure is applied to the month of September, and subsequently, the tariff structure will be addressed according to the prescribed guidelines. This particular date, 10th September, was chosen as it exhibited the most significant deviation from the overall patterns observed during the year 2020.

The data from the weather station and EMS, including solar irradiance (DNI, DHI, and GHI), zenith and azimuth angles, wind speed and direction, ambient temperature, and battery SoC, were substituted into the equations at each interval for simulation purposes. By comparing the simulated results with the actual data collected from the EVCS, the accuracy and reliability of the simulation model could be assessed.

3.5 DETAILED DESCRIPTION OF THE MODEL VALIDATION PROCESS

The mathematical formulation was used to compare the actual and simulated systems by quantitatively assessing the similarities and differences between their performances. An overview of how the formulation was utilised follows.

3.5.1 Data collection

Historical data from the actual system, including weather conditions (solar irradiance, wind speed, and ambient temperature) and system parameters (battery SoC), were collected and logged at regular intervals (e.g., every 30 seconds) for a duration of 24 hours. This dataset provided the basis for comparison. The data-collection process for this study involved the compilation of various input variables from diverse sources. The following sources were employed:

3.5.1.1 EMS at the charging station (Uyilo at Nelson Mandela University [NMU] in Gqeberha)

Real input variable data were gathered from the EMS, which actively monitors the operational activities of the charging station.

3.5.1.2 EV-QC45 Standalone Quick Charging Station

Data pertinent to the fast-charging protocol were collected using the EV-QC45 Standalone Quick Charging Station.

3.5.1.3 DL 850 Scope Corder at NMU

Data for the slow-charging protocol were obtained from a DL 850 Scope Corder instrument stationed at NMU. This instrument served the purpose of data acquisition and analysis.

3.5.1.4 2013 Nissan Leaf

Data on charging a 2013 Nissan Leaf EV were collected, using the setups shown in Figures 3.1 to 3.5. This dataset encompassed information pertaining to both slow- and fast-charging protocols.

3.5.1.5 South African Universities Radiometric Network (SAURAN)

Data were acquired from SAURAN's website before its permanent closure. This dataset included GHI, DHI, DNI, wind speed, and ambient temperature data for the station.

It is important to note that the actual dataset was collected at a 30-minute interval, and this specific time resolution will be maintained and presented in the thesis. The decision to present the actual dataset in its original 30-minute intervals is justified by the need to accurately represent the real-world data and capture the dynamics of the microgrid system. On the other hand, the simulated values generated using MATLAB will be presented at a 24-hour interval. This choice is justified by the desire to provide a more concise and easily interpretable representation of the simulated data. By aggregating the simulated values into 24-hour intervals, it allows for a broader overview of the system's behaviour and simplifies the presentation without compromising the essential insights gained from the simulation.

Therefore, the distinction in presentation between the actual dataset and the simulated values is based on the need to balance the granularity of real-world data with the clarity and comprehensibility of the simulated results.

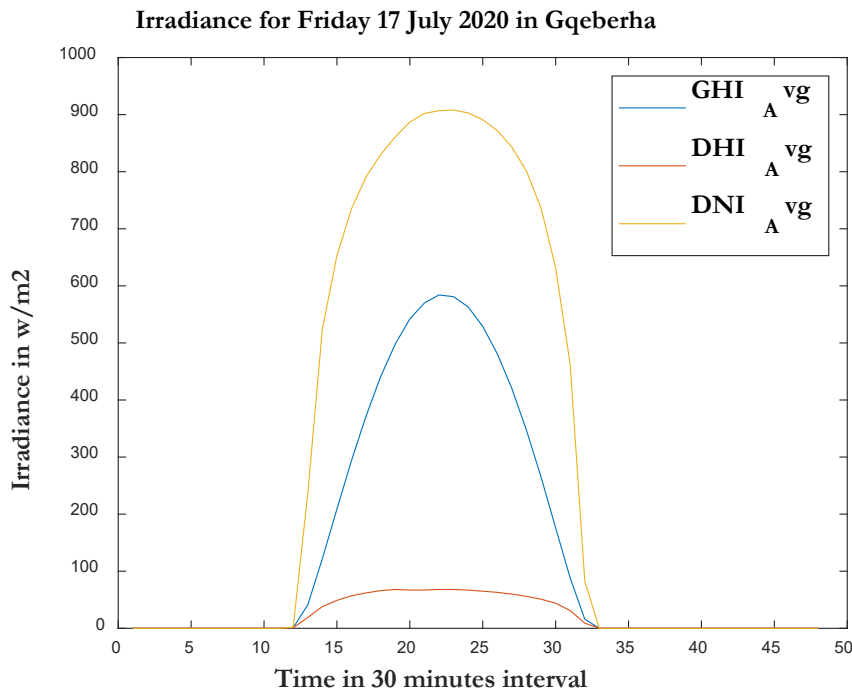


Figure 3.10: Irradiation for the selected scenario winter day

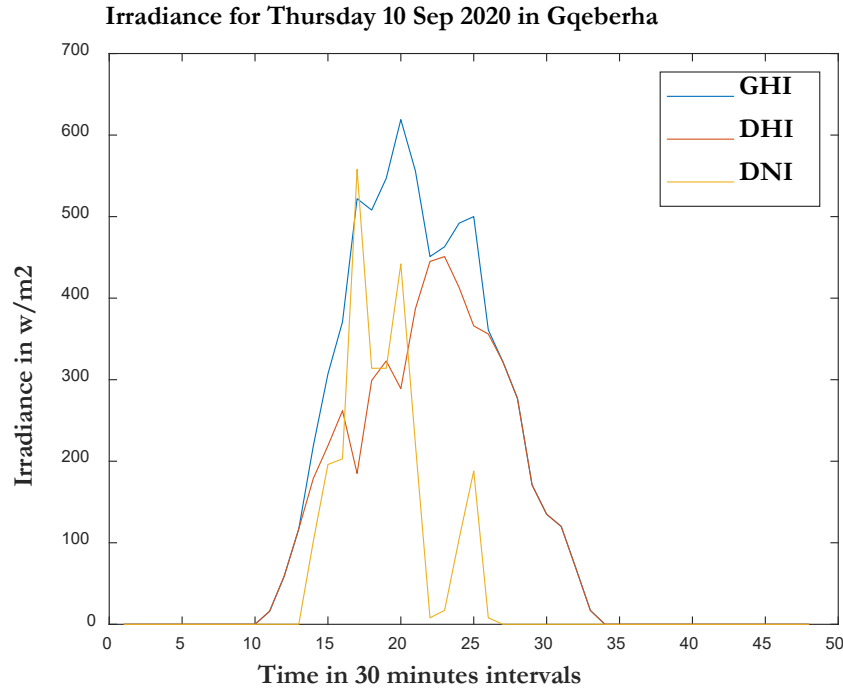


Figure 3.11: Irradiation for the selected scenario spring day

Figures 3.10 and 3.11 display the spectral distribution of irradiation during the winter and summer of 2020, respectively, at NMU in Gqeberha. The observed irradiation played a crucial role in establishing the viability of the design.

The collected data from the weather station and EMS were substituted into the mathematical formulation or equations used for the simulation. The inputs included solar irradiance values (DNI, DHI, and GHI), zenith and azimuth angles, wind speed and direction, ambient temperature, and battery SoC at each interval.

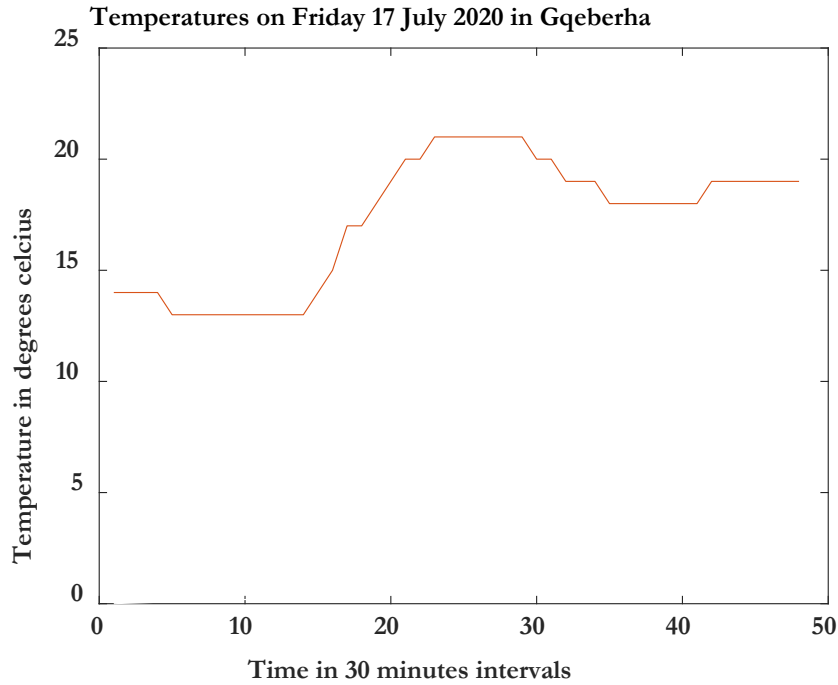


Figure 3.12: Ambient temperatures in °C for the selected winter day [152]

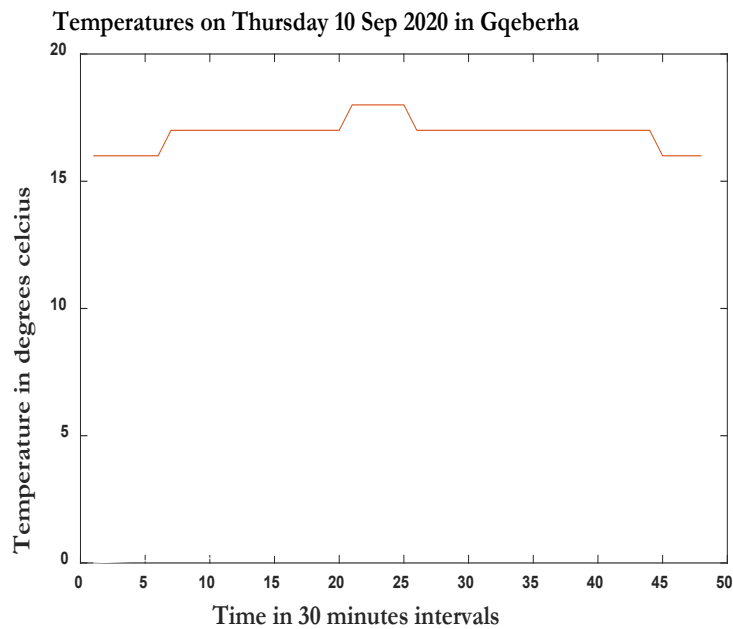


Figure 3.13: Ambient temperatures in °C for the selected spring day [152]

Figures 3.12 and 3.13 depict the ambient temperatures recorded during the specified period. Analysing the data variation on these specific dates was crucial for a comprehensive analysis that

would guide the decision-making process regarding a system that is suitable for both worst-case and acceptable scenarios in terms of resource availability.

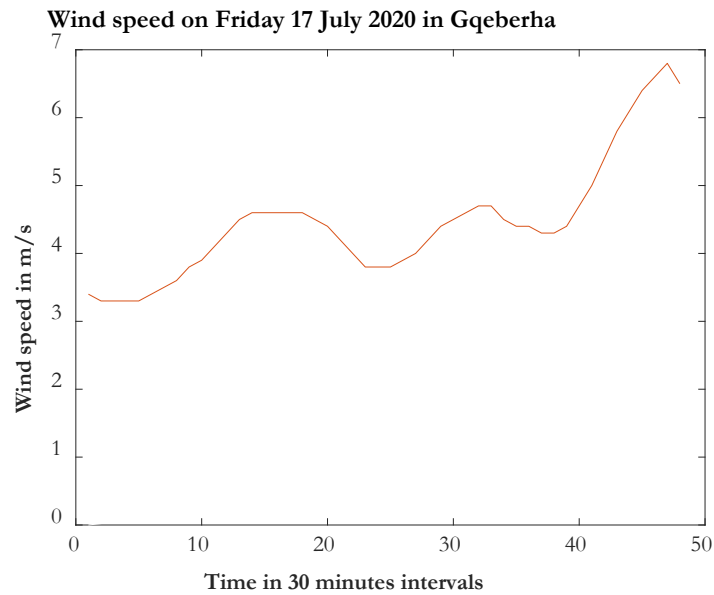


Figure 3.14: Wind speed for the selected winter day [152]

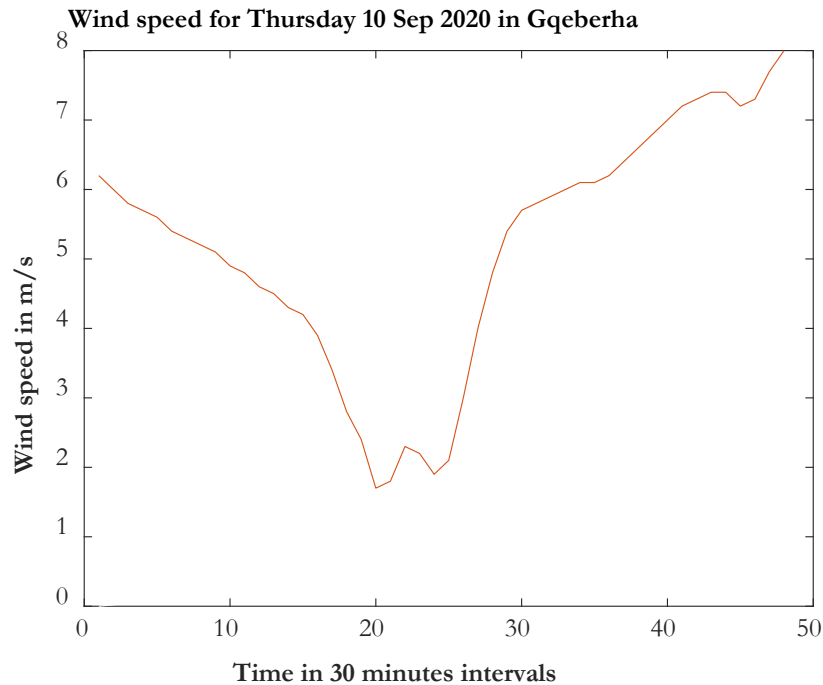


Figure 3.15: Wind speed for the selected spring day [152]

Figures 3.14 and 3.15 show the fluctuation in wind speed observed on the chosen days. The accurate representation of wind speed is essential for effectively modelling a wind system. Analysing the data presented in these figures can provide valuable insight to inform the development and optimisation of wind energy systems. Comprehending fluctuations in wind speed facilitates the identification of suitable turbine designs, the anticipation of power generation, and the evaluation of the overall viability and effectiveness of wind energy production. By incorporating this information into the modelling process, the design and operation of wind systems can be optimised to harness the available wind resources efficiently and reliably.

3.5.2 Mathematical formulation

The mathematical formulation consisted of equations (e.g., Equations 3.23 to 3.28) that represented the behaviour and performance of the system components, such as PV panels, wind turbines, battery storage, and charging units. These equations took into account the inputs mentioned above and described how the system would respond to different weather conditions and operational parameters.

3.5.3 Simulated results

By solving the mathematical formulation with the substituted inputs, the simulation package produced results that represented the simulated system's performance. These results included variables such as power generation from PV and wind sources, battery charge and discharge levels, and overall system efficiency.

3.5.4 Comparison and validation

The simulated results were compared with the actual data collected from the charging station. Statistical analysis and metrics were used to assess the degree of similarity between the two sets of results. This comparison aimed to validate the accuracy and reliability of the simulation model by verifying if the simulated system's performance closely matched the actual system's behaviour.

By utilising the same mathematical formulation and substituting actual data into the simulation model, the comparison allowed for a quantitative evaluation of the simulated system's accuracy and its ability to replicate the actual system's performance under different weather conditions.

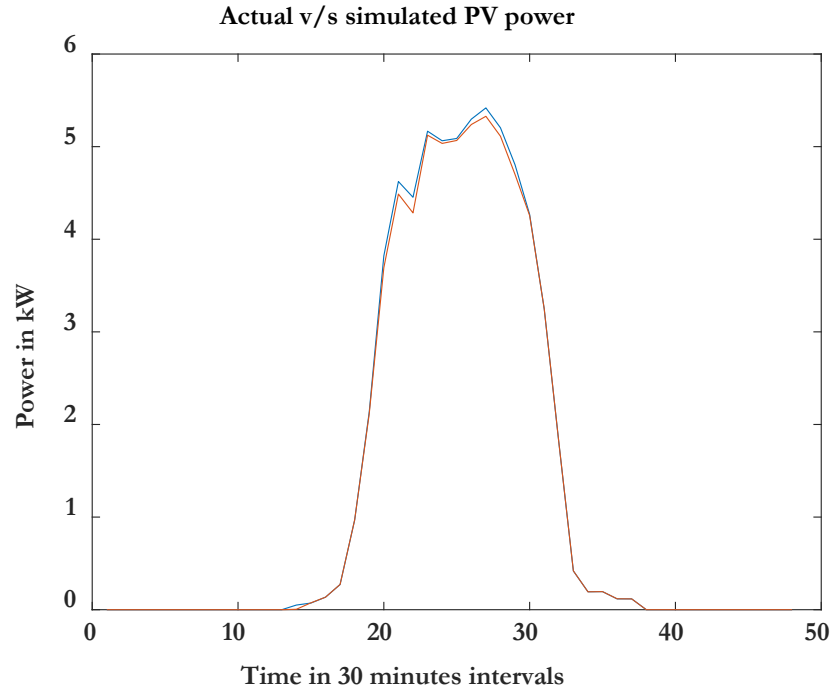


Figure 3.16: Simulated vs actual PV output for the selected winter day

The two days under scrutiny for validation purposes can be noted from Figures 3.16 and 3.17, which depict how the two days vary in terms of temperature, wind speed, and climatic conditions. These days were selected due to the availability of data when the EMS at the station was still operational. The data were limited to a couple of months during the peak of the pandemic and were validated against the simulation variables taken from the SAURAN website before its permanent closure. Based on the provided information, Figures 3.16 to 3.17 provide a graphical representation of the actual system compared to the simulated model in winter and spring respectively. The results obtained from the simulation show a high degree of similarity to the actual system, with only slight variations. These variations can be attributed to factors such as temperature effects and the specific orientation of the actual system, as depicted in Figures 3.11 to 3.15.

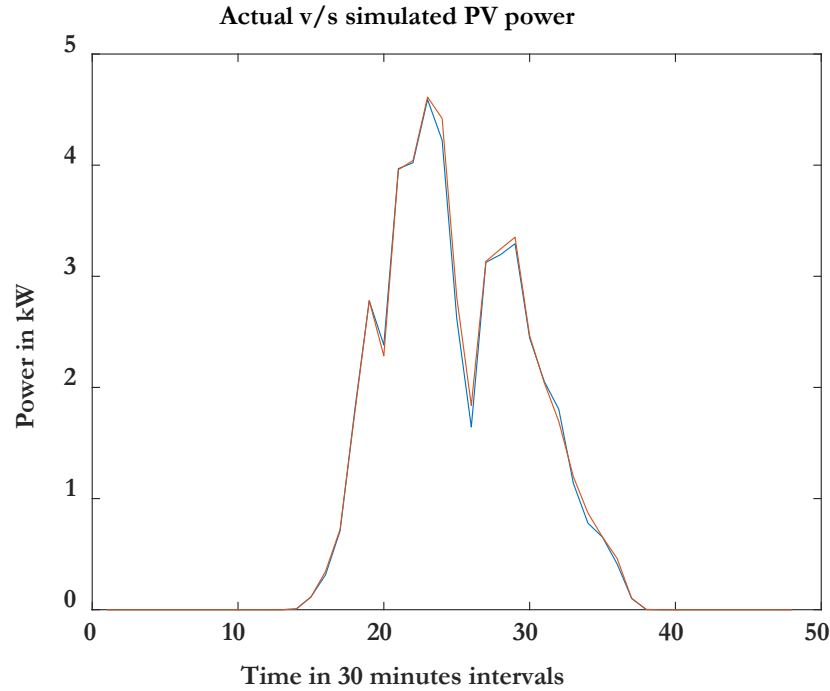


Figure 3.17: Simulated vs actual PV output for the selected spring day

Despite these slight differences, the variation between the simulated and actual results fell within acceptable ranges. The day without cloud cover exhibited a notable error of 7%, while the cloudy day had a slightly lower error of approximately 2.1%. These results indicate a promising level of accuracy and similarity between the simulated and actual values, which suggests that the same mathematical formulation can be applied to larger-scale systems. Figures 3.16 and 3.17 further validate the use of the same solver by demonstrating realistic power-output predictions. These figures provide additional evidence of the accuracy and reliability of the simulation model in replicating the behaviour and performance of the actual system. The two scenarios of a clear (winter) and an overcast day (spring) depict the impact of atmospheric effects on solar radiation. A visible reduction in the generated power on a cloudy spring day is evident due to the level of absorption, scattering, and reflection in the atmosphere. While the disparity in errors can be attributed to the simulation's underestimation of the actual power generation from the hybrid energy system, which arose due to discrepancies in the specific atmospheric conditions and solar radiation levels experienced on that particular day.

3.6 CASE STUDY

This case study focuses on the development and validation of a model to accurately represent the economic dispatch of power in a proposed hybrid energy EVCS located in the Gqeberha area of South Africa. The primary objective is to optimize the power generation and utilization within the hybrid energy system, considering various renewable energy sources and storage technologies.

To evaluate the performance of the system under realistic operational conditions, the hybrid energy system will undergo simulation for two distinct scenarios throughout the year 2020. These scenarios include a winter clear day and a spring day with overcast. By simulating these scenarios, the study aims to assess the system's capability to handle daily fluctuations in weather conditions and load demands.

3.6.1 Detailed system description

3.6.1.1 *PV system*

The PV system consists of 55 solar panels, each with a power rating of 535 Wp. The cost included the panels themselves, as well as mounting equipment such as rails, brackets, stands, and concrete foundations.

3.6.1.2 *Wind turbine*

The hybrid system incorporates a 2.8 kW wind turbine. The initial implementation cost covered the turbine itself, along with any necessary infrastructure and installation expenses.

3.6.1.3 *Battery energy storage system (BESS)*

The BESS comprises multiple LiFePO₄ battery banks with a total capacity of 100 kWh. The cost associated with the battery bank included the batteries, cabling, data-monitoring hardware, and software for logging purposes.

3.6.1.4 Hybrid inverter

The hybrid system incorporates a 100 kW inverter. The initial implementation cost covered the inverters with smart-charge capability, along with the necessary infrastructure and installation expenses.

3.6.2 Load profile description

In an EVCS, the load profile is mobile and depends on the energy requirements of EV drivers. Unlike stationary loads, which may have load profiles associated with specific seasons or appliances, EVCS load profiles can be similar across different days and seasons. A single load profile is therefore used to represent this scenario. Due to the lack of activity at the station in Gqeberha, a detailed data record of a similar EVCS in Germany was taken from a study conducted by Hecht et al. [153].

It is worth noting that the dataset (shown in Figure 3.18) from this charging station from Hecht et al.'s study was customised to suit the charging requirements of a university setup, as seen in Figure 3.19. Figure 3.18 is a small setup to indicate the similarity of two datasets (fast charging and slow charging). As can be seen, the slow-charging protocol in Figure 3.18 is under 4 kW (presented by the blue colour), which correlates to the values in Section 3.2.2. Similarly, the power consumption of a fast DC charger (represented by the red colour) is within the same range as that in Figure 3.19.

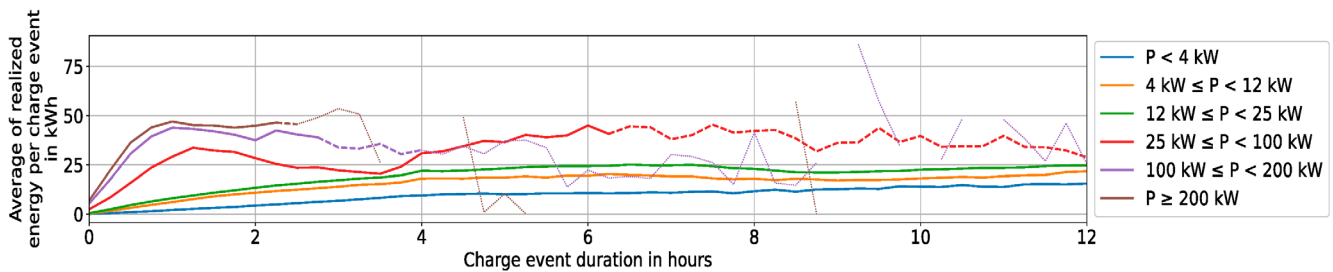


Figure 3.18: Dataset of the detailed EV charge records of a similar EVCS in Germany [153]

The dataset from the charging station in Figure 3.18 was customised to suit the charging requirements of a university setup. The various loads from the previous figure were added to create a single load profile in Figure 3.19. Since most charging activities would take place during normal working hours at a university (with the provision that late classes end at 19:45), night charging was neglected in the representation, as indicated below.

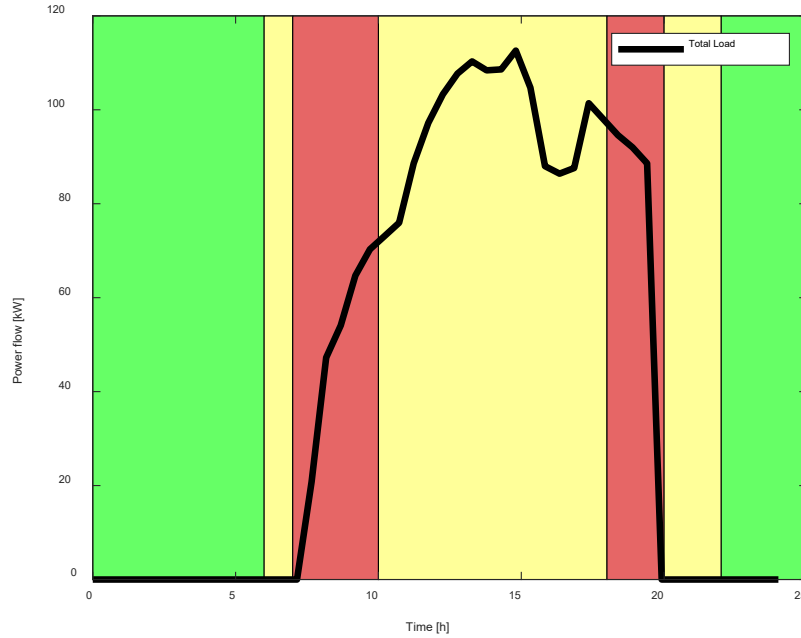


Figure 3.19: Customised load profile of an EVCS based on actual dataset from an EVCS in Germany

The real-time communication of the EMS will enable a dynamic adjustment of the power-sharing allocations based on the changing conditions between prosumers, charging units, and the central control system. By effectively managing the power allocation, the EMS ensures efficient utilisation of available resources, optimal charging of EVs, and overall grid stability. The research study makes the recommendation that the maximum power discharge for an EV's battery should be capped at 30%. This percentage is not a standard but rather a guideline to ensure the longevity and health of the EV battery.

3.6.3 Overview of the process

3.6.3.1 Representation of charging protocols

MATLAB was used to represent each charging protocol from the dataset for different ToU periods. This representation allowed for a detailed analysis of how the EVCS operates during specific time intervals and how and when P2P energy sharing can be implemented.

3.6.3.2 Time-of-use (ToU) shift

In the case of a university setup, the charging protocols' time period (as indicated in Figure 3.19) was shifted to match the normal operating hours from 07:00 in the morning to 20:00 at night.

This adjustment aligned the charging activities with the standard working hours of the university. Available power from renewable energy and ESS were assessed during specific ToU periods and optimised in a MATLAB environment to minimise reliance on the grid during peak periods as a means to reduce electricity costs and to maximise profit.

3.6.3.3 Performance analysis

The system's performance was constantly monitored to evaluate how much power is generated between 07:00 and 20:00 and what resources are best suited for recharging EVs at a lower cost without escalating the operational costs at the station.

3.6.3.4 Maximising profit

An analysis was conducted to achieve maximum profit under the given scenario. The analysis considered the standard ToU tariff structure of Eskom (indicated in equation 3.29 and 3.30 respectively), the national electricity utility in South Africa. The maximum demand was observed to occur during the specified standard ToU period, which coincided with the reasonable energy yield from the renewable energy system. This observation indicates the potential for leveraging the renewable system's output to meet the high demand during the peak tariff period, thereby optimising cost efficiency and profit.

3.6.4 Optimal system sizing

The concept of EVCS sizing has been widely explored in the literature and in practice. Its benefits and drawbacks have set the tone for more research to be conducted on the improvement of existing architecture. However, the practicality and feasibility of EVCS design are reliant on various influential factors that are unique to each site. Those factors may include, but are not limited to, the geographical location and environment, consumer characteristics, state of the utility grid, economic factors, as well as the technology.

The components are tabulated in Table 3.1 for the provision of a strategic and systematic dispatch of each component within the system. The ToU tariff at the selected location (Gqeberha) for the studied year is depicted in Figure 3.20. This figure shows the variation in electricity prices throughout the day, typically with higher prices during peak demand periods and lower prices during off-peak hours. The costs associated with the ToU tariff are likely correlated with the component sizes discussed in Table 3.1; thus reflecting the relationship between pricing and the optimal sizing of the EVCS components.

Table 3.1: Simulation parameters

	Original system	Upgraded system	MATLAB system
PV size	Fifty 255 Wp panels facing north	Fifty-five 535 Wp panels facing east	55 of 535 Wp panels facing east
Battery size	36 kWh storage capacity	36 kWh storage capacity	36 kWh storage capacity
Inverter size	70 kWh grid-tie inverter	100 kWh grid-tied inverter	100 kWh grid-tied inverter
ToU summer			
Peak	R1.42/kWh		
Off-peak	R0.68/kWh		
Standard	R0.97/kWh		
ToU winter			
Peak	R4.12/kWh		
Off-peak	R0.77/kWh		
Standard	R1.32/kWh		
Demand charge per kVA (above 200 kVA)	R107.94/kWh		
Initial SoC	46%		
Maximum SoC	100%		
Minimum SoC	30%		
Charging efficiency	95%		
Discharging efficiency	97%		

Equations 3.29 (winter) and 3.30 (summer) are mathematical representations of the cost of energy purchased from the grid per ToU tariff in Gqeberha, South Africa. These equations are part of the mathematical model shown in Figure 3.6, which illustrates the cost of energy based on different time periods during low and high demand seasons [144].

$$\rho(t) = \begin{cases} \rho_p; t \in P_g, P_g = [(7,10)(18,20)]; \\ \rho_o; t \in P_g, P_g = [(0,6)(22,24)]; \\ \rho_s; t \in P_g, P_g = [(6,7)(10,18)(20,22)]; \end{cases} \quad (3.29)$$

$$\rho(t) = \begin{cases} \rho_p; t \in P_g, P_g = [(6,9)(17,19)]; \\ \rho_o; t \in P_g, P_g = [(0,6)(22,24)]; \\ \rho_s; t \in P_g, P_g = [(9,17)(19,22)]; \end{cases} \quad (3.30)$$

Where: ρ_p , ρ_o , ρ_s represents the cost of energy purchased from the grid at a specific time (t) at peak, off-peak, and standard tariff structure periods.

3.7 SIMULATION RESULTS AND DISCUSSION

It is worth noting that the results depicted in this chapter are for the selected spring day, while the results for the winter day are depicted in the appendix.

3.7.1 Determination of an optimal maximum demand threshold for Scenario 1 (overcast day)

A significant reduction in energy costs can have a positive impact on the profitability of an EVCS. Introducing an optimal dispatch scheme is crucial to achieving cost reductions. By analysing the ToU tariff structure and load demand, the maximum demand threshold can be determined. Constraints are placed to limit the amount of energy supplied from the grid to the station, particularly during peak periods. This ensures that primary resources such as solar PV, wind power, and EV prosumers can meet the load requirements of the station. Several factors can impact the performance of an EVCS, and it is important to identify the most influential ones. Sensitivity analysis methods, such as local sensitivity analysis and global sensitivity analysis, can help with this task.

Global sensitivity analysis is particularly suited for systems that integrate RES. These analyses allow for the quantification of uncertainties in input parameters such as variable load, energy-generation cost, and renewable energy-generation capacity. In order to accurately conduct a sensitivity analysis, appropriate sampling methods were employed. This method was used to quantify uncertainties in input parameters. By varying limits or boundaries in 5 kW steps, an optimal point of 80.7957 kW was identified as the maximum threshold for energy cost savings. An analysis was conducted over two days with the same rand-to-dollar exchange rate, which made it easier to compare the savings. However, if there were variations in the exchange rate, it could have been used to assess the savings in an unstable economy. By conducting sensitivity analysis and considering factors such

as cost reductions, optimal dispatch schemes, and exchange rate fluctuations, it is possible to enhance the economic performance of an EVCS and maximise cost savings.

3.7.2 Optimal power flow simulation for Scenario 1 (overcast day)

In order to maximise profit and optimise the operation of the EVCS, various factors must be taken into consideration, including charging protocols, ToU shifts, and Eskom's tariff structure. The goal is to identify the optimal combination of these factors to achieve the highest profitability while efficiently utilising available resources. The EMS plays a crucial role in achieving this optimisation. It utilises sophisticated algorithms to determine the appropriate power sharing among prosumers in the EVCS. By considering the specific needs and conditions of each EV, the EMS ensures that each prosumer contributes the right amount of power without compromising their own battery integrity.

To minimise the costs associated with maximum demand, a sensitivity analysis was conducted to identify the optimal cost-saving point. The analysis involved varying parameters and thresholds to assess their impact on costs associated with maximum demand. By setting a specific grid threshold of 80.7957 kW, the computational load and simulation time for a day or month of operation were reduced. This optimisation helped to streamline the analysis process and provided insight into cost-saving opportunities. The results of the optimal-control simulation are presented in Figures 3.20 to 3.22.

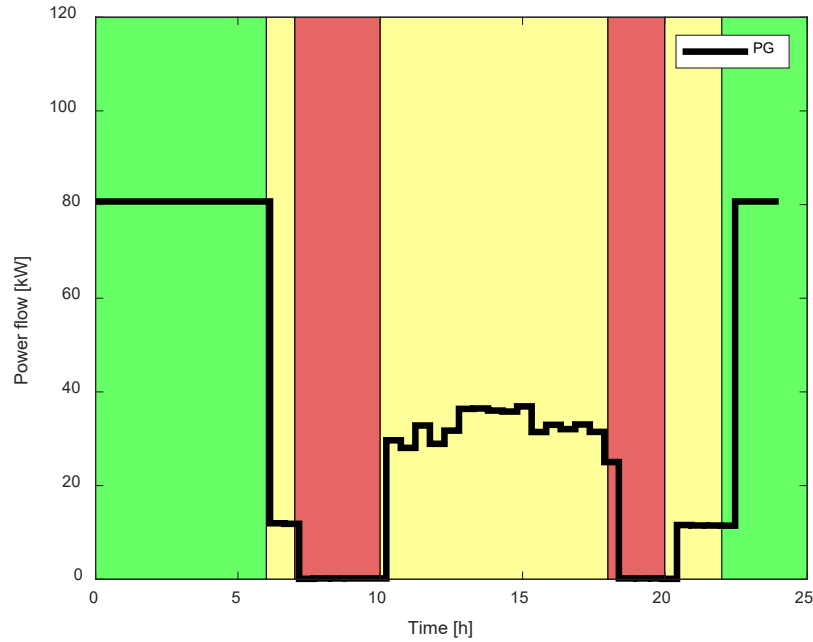


Figure 3.20: Grid power subjected to the proposed constraints: Simulated results for the selected spring day

Figure 3.20 illustrates the power from the grid subjected to the constraints and hierarchy structure. Two cases, winter (a day with the lowest solar insolation) and summer (an overcast day), were considered in the simulation. These scenarios helped to evaluate the EVCS's performance under different weather conditions and solar and wind energy availability. By analysing the results of these scenarios, it is possible to understand how the system adapts and operates optimally in varying conditions.

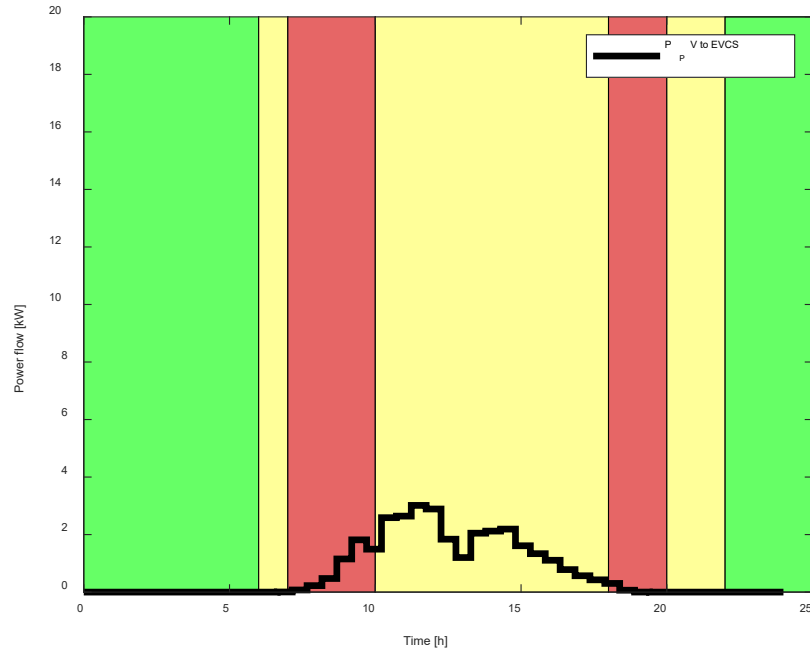


Figure 3.21: PV power: Simulated results for the selected spring day

Figures 3.21 and 3.22 depict the power output of PV and wind systems, respectively, in relation to the availability of resources on the specific days analysed in Gqeberha. These figures provide valuable insight into the performance and generation capacity of renewable energy systems in response to prevailing resource conditions.

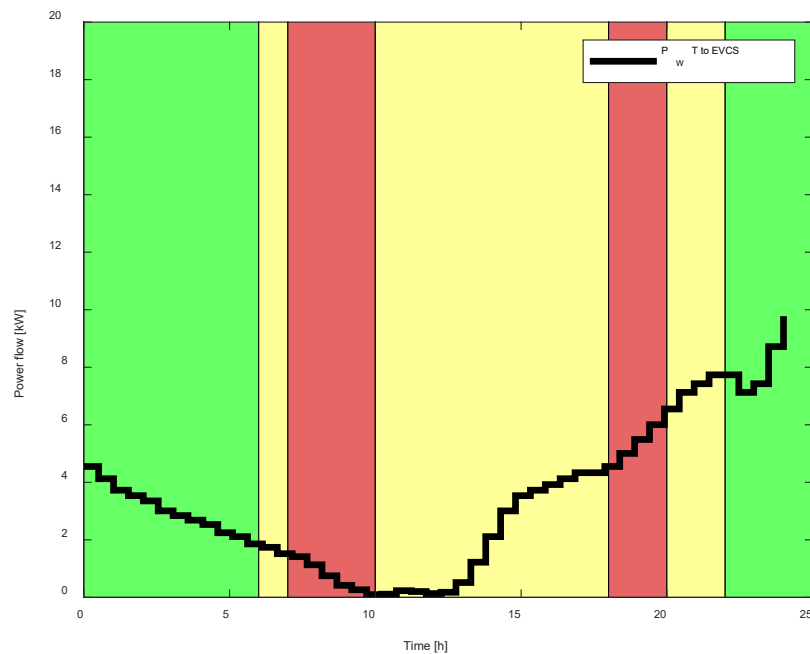


Figure 3.22: Wind power: Simulated results for the selected spring day

3.7.2.1 Analysis of the power flow during off-peak ToU intervals (00:00 to 06:00)

During the off-peak ToU period, which spans from 00:00 to 06:00, the power flow and operation at the EVCS exhibit specific characteristics. At this time, different tariff structures are in effect, and it may not always be possible to rely solely on RER to meet the load requirements. However, during this period, there is no activity at the charging station, which results in a load of 0 kW. Despite the absence of EV charging, power is still utilised during this time to charge the battery. The power used for battery charging is sourced from two different providers:

- **P₁ (grid power):** This denotes power supplied from the grid during the off-peak period. The maximum permissible grid-supplied energy is capped at 80.7957 kW, which indicates that the EVCS can draw a maximum amount of power from the grid during this time.
- **P₃ (wind power):** This represents the fluctuating power generated by the wind system. The wind system contributes to the overall power supply during the off-peak ToU period by helping to charge the battery.

By combining the power supplied from the grid (P_1) and the fluctuating power from the wind system (P_3), the battery is charged during the off-peak period, which ensures that energy is stored for future use when demand increases. It is worth noting that during this specific period, no EV charging activity takes place, but efforts are made to utilise available power sources, including the grid and the wind system, to charge the battery and to maximise the use of RER.

3.7.2.2 Analysis of the power flow during standard ToU intervals (06:00 to 07:00)

During the period from 06:00 to 07:00, which extends from the end of the off-peak period to the early morning hours, there is a minimal increase in power costs compared to the peak period. However, this increase is not a cause for concern since charging activities have not yet resumed at the station, which results in a load of 0 kW. During this time, the power for charging the battery is solely sourced from the wind system (P_3). The boundaries that have been set ensure that grid utilisation for battery charging is eliminated, as the actual EVs have not yet started charging. This means that the

power from the wind system is sufficient to meet the battery-charging requirements during this period.

It is important to note that the utilisation of standard tariffs is reserved for emergencies, and it is only used to charge EVs when the solar PV and wind systems are generating enough energy to satisfy the demand. Therefore, during this time frame, the EVCS relies solely on the power generated by the wind system for battery charging. It is worth mentioning that during this period, the energy generated by the wind system may start to depreciate as the temperature rises, which results in a decrease in humidity. These factors can impact the wind system's efficiency and output, potentially affecting the amount of power available for battery charging.

By considering these factors and utilising the available wind power during this time, the charging station optimises the use of RER and ensures that the battery is charged efficiently.

3.7.2.3 Analysis of the power flow during peak ToU intervals (07:00 to 10:00)

During the first peak period of the day, the solar PV system reaches its maximum production and generates a substantial amount of power. This indicates that the solar panels are operating efficiently and contributing significantly to the overall electricity supply. On the other hand, the wind system experiences a decrease in production during this time. Despite the decline in wind power generation, it is still utilised as the primary source of power to meet the load requirements of the EVCS. Figure 3.20 demonstrated that the total power supplied by the grid to the load (referred to as P_1) experiences a significant decrease. This reduction in grid power supply is primarily attributed to the higher electricity prices that prevail during the peak period. The higher electricity prices during the peak period can act as a deterrent for relying solely on grid power. As a result, the EVCS aims to minimise its reliance on grid electricity and to optimise the utilisation of RES, such as the solar PV system. The grid power supply is utilised only to compensate for any deficit in power supply from the solar PV system, thereby minimising reliance on non-RES and mitigating the impact of higher electricity prices. It is important to note that only 20% of the maximum permissible grid supply is utilised for a duration of 30 minutes due to the deficit in renewable energy supply. During this time, the power transferred from the BESS also termed ESS to the load (referred to as P_6) remains at zero. This is because the SoC of the battery has not yet sufficiently recovered to a level where it can actively supply power to the load, as shown in Figure 3.23. The prioritisation of power sources and the

avoidance of grid usage during this period align with the goal of maximising the utilisation of RER while minimising the costs associated with grid electricity. By optimising the utilisation of wind and solar power, the EVCS aims to maintain a reliable power supply and ensure that the battery's SoC is gradually restored for future use.

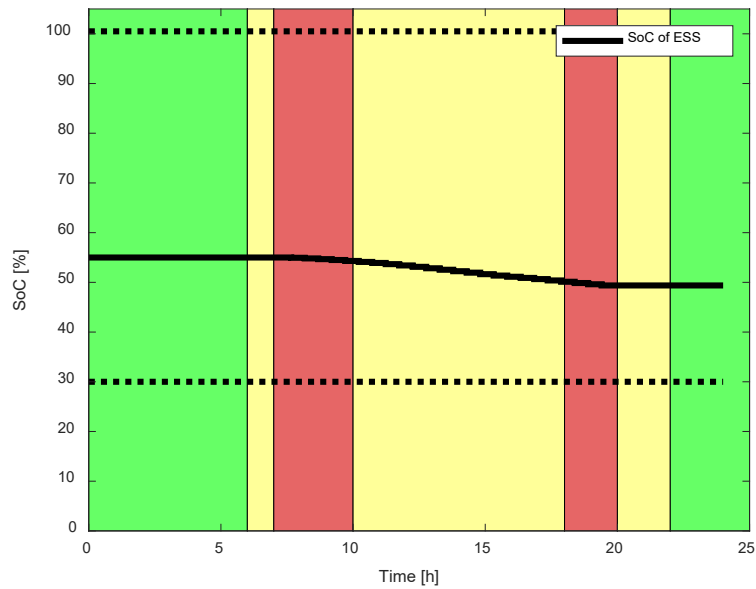


Figure 3.23: SoC for energy storage: Simulated results for the selected spring day

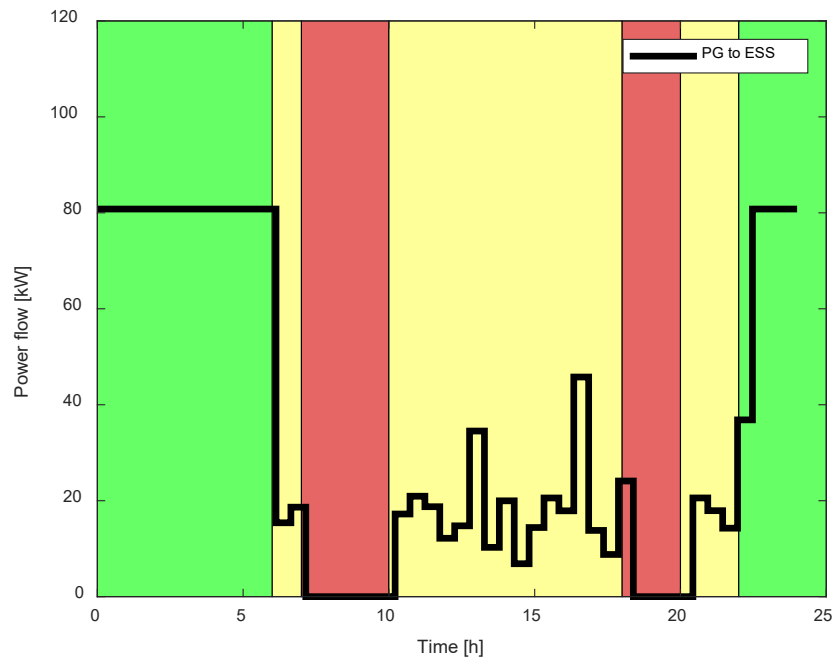


Figure 3.24: Grid power to energy storage: Simulated results for the selected spring day

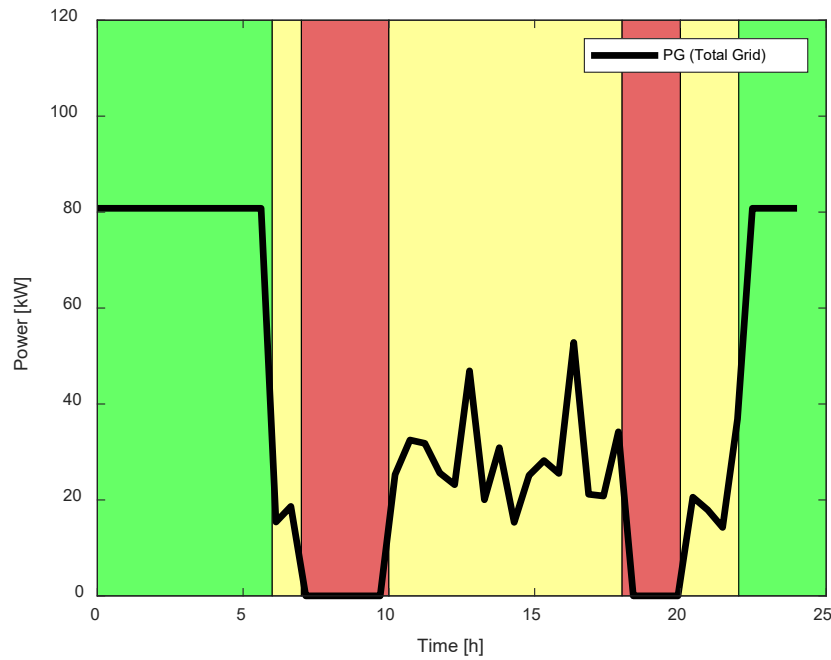


Figure 3.25: Total power utilised from the grid subject to constraints for the selected spring day

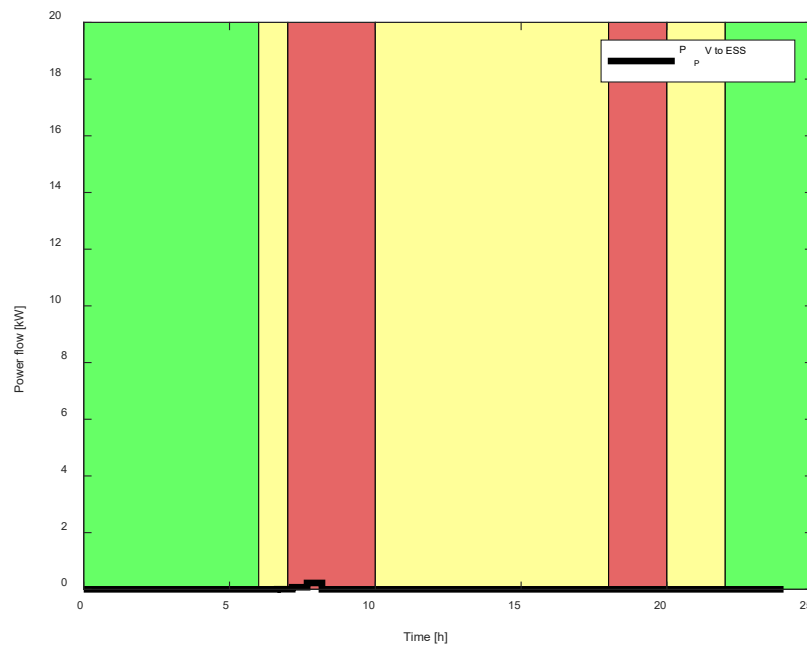


Figure 3.26: PV power to BESS: Simulated results for the selected spring day

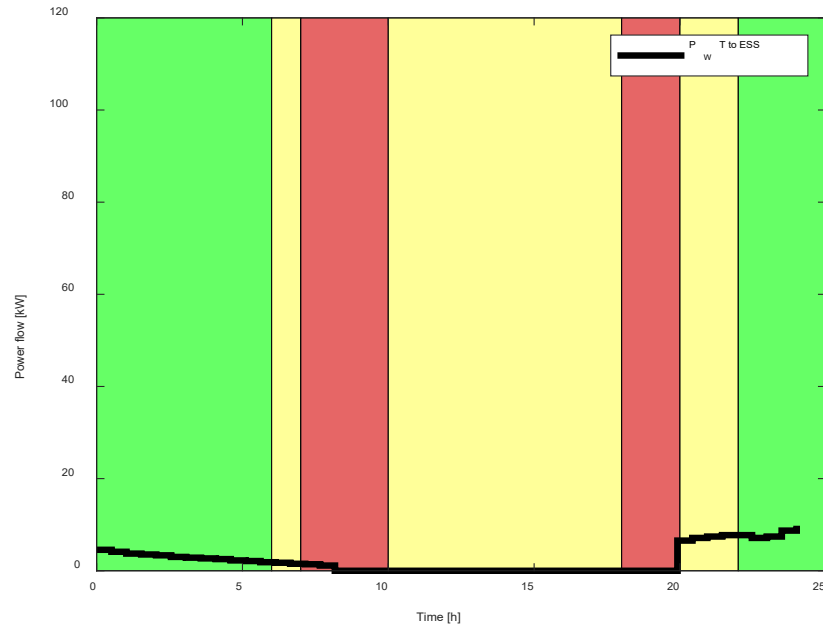


Figure 3.27: Wind power to BESS: Simulated results for the selected spring day

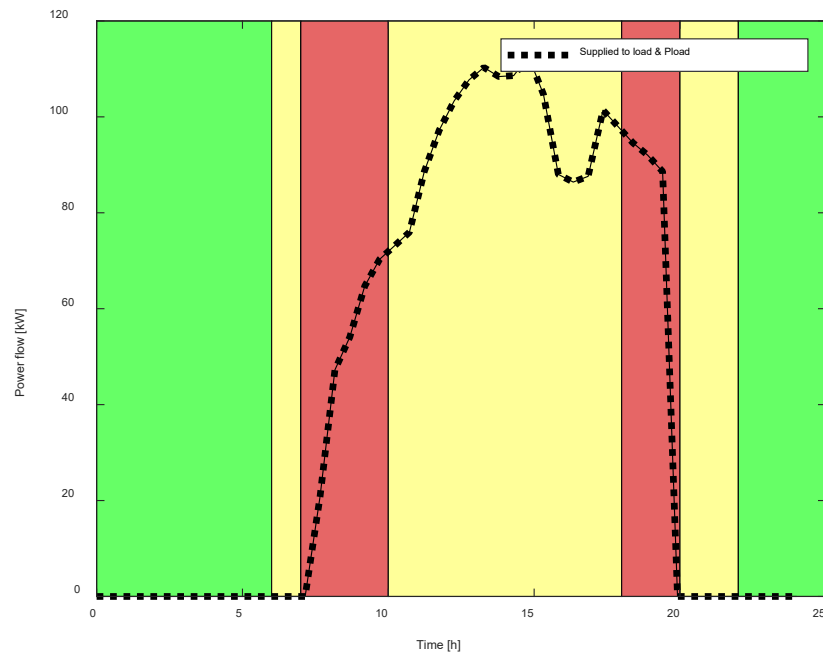


Figure 3.28: Supplied power to the load from all the resources at the EVCS: Simulated results for the selected spring day

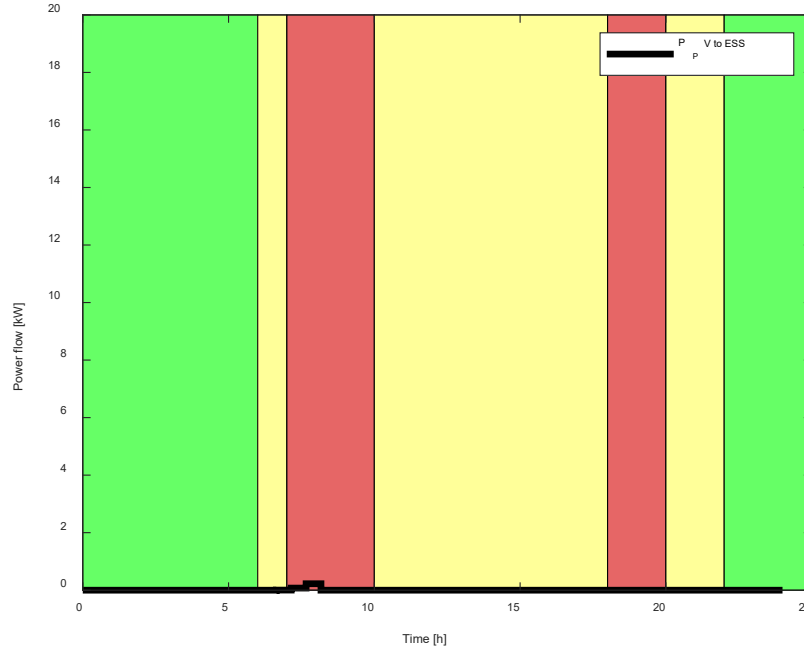


Figure 3.29: Excess power sold to the grid: Simulated results for the selected spring day

3.7.2.4 Analysis of the power flow during standard ToU intervals (10:00 to 18:00)

During the standard period, the EVCS experiences a considerable increase in energy costs as it relies on the grid to supplement the energy deficit from both the wind and PV systems. The amount of energy required varies depending on the load demand at the station. In this specific scenario, the PV system does not yield desirable energy production due to adverse climatic conditions such as rain and cloud cover; the energy therefore declines significantly. Unfavourable weather conditions affect the PV system's ability to generate sufficient power. Consequently, the EVCS becomes more reliant on the grid (P_1) and the PV system (P_2) to supply the growing load, as the wind system is hardly generating any energy due to the approaching rain. From 10:00 to 13:00, the wind energy produces approximately 0 kW. As the rain starts from 12:30 to 13:30, the production of the PV system drops further, while the wind system begins to pick up energy generation from 13:00 with a gradual increase every 30 minutes. During this time, a hierarchy-charging strategy is implemented at the station. This strategy primarily involves utilising RER ($P_2 + P_3$), BESS (P_6), and EV prosumers (P_7 and P_8) to meet the load demand. The grid becomes the last resort for energy supply. It is worth noting that the energy transferred from the RER to the battery becomes zero during this period, as depicted in Figure 3.26.

This is because charging and discharging of the battery are not permissible due to the exclusive power flow constraints in place. By managing the power flow hierarchy and considering the availability of RER, BESSs, EV prosumers, and the grid, the EVCS aims to optimise the use of renewable energy while minimising costs and ensuring a reliable power supply.

3.7.2.5 Analysis of the power flow during peak ToU intervals (18:00 to 20:00)

During the final peak period of the day, the PV system produces a minimal amount of energy for a duration of 30 minutes. Its production during this period is approximately 5% of its maximum generated energy throughout the day. This limited PV production necessitates the wind system (P_3), BESS (P_6), and EV prosumers (P_7 and P_8) to become the primary energy supply resources at the EVCS. This reliance on the wind system, BESS, and EV prosumers continues until 19:30. At that point, the grid (P_1) starts to supplement the remaining energy balance by supplying half of its permissible capacity. This is due to certain conditions imposed on EV prosumers, who are capped at supplying only up to 30% of their vehicles' energy, with the condition that their vehicles' batteries should be at least 65% charged. During this period, the BESS continues to discharge as the energy from the wind system is directed at the load. The grid is prevented from directly supplying the battery, but it is conditionally permitted to supply the load when the primary energy resources (wind, BESS, and EV prosumers) are not generating enough power to meet the demand. By prioritising the RER (wind and PV), the BESS, and the EV prosumers, the EVCS aims to make the most of available green energy. The grid is used as a backup or supplemental energy source when necessary to ensure that the load requirements are met while maintaining a focus on renewable energy utilisation. However, it is important to note that the grid is not directly used to recharge the BESS during this time. The priority is still given to the primary resources, and the battery continues to discharge as it supplies power to the load.

3.7.2.6 Analysis of the power flow during standard ToU intervals (20:00 to 22:00)

During the third and final standard period of the day, the grid is no longer supplying energy to the EVCS. This is because there is no load present or charging activity recorded beyond this point. Instead, the wind power generated is utilised to charge the BESS at the charging station. As the wind power is harnessed, the BESS's SoC continues to rise rapidly. This means that the BESS efficiently

stores the excess energy generated by the wind system during this period. The purpose of charging the BESS with wind power is to store the surplus energy for later use. The BESS serves as a means to store renewable energy and allows for its utilisation during times when the primary power sources, such as the wind system, are not generating enough energy or when the demand exceeds the immediate supply. By charging the BESS with wind power and increasing its SoC, the EVCS ensures the efficient utilisation of RER and prepares for potential future demands or contingencies. It is important to note that no further charging activity is recorded beyond this point, which indicates that the EVCS has completed its charging operations for the day.

3.7.2.7 Analysis of the power flow during standard ToU intervals (22:00 to 24:00)

During the final off-peak period of the day, the EVCS displays similar behaviour to the first off-peak period. This means that the EVCS operates in a similar manner during this time frame and exhibits comparable characteristics and patterns. In this period, the battery at the EVCS continues to charge due to ongoing charging activities. The charging station may be receiving EVs for charging or other devices that require power supply. The grid power is utilised to ensure that the battery receives sufficient energy to continue its charging process.

By adhering to the upper threshold of the maximum demand limit, the EVCS optimises its power consumption during the final off-peak period. This forces the system to remain within the specified limit while meeting the charging requirements of EVs, which helps to maintain the stability and reliability of the charging operations. During the off-peak periods, when the demand is relatively lower, the EVCS takes advantage of the grid power supply to charge the battery efficiently. This allows the station to store energy in the battery for future use or to meet changing demands during peak periods when RES may be insufficient.

3.7.3 Analysis of the power flow during power cuts / load shedding during work hours

This scenario describes a grid outage situation where the EVCS must rely solely on its renewable energy generation and battery storage to meet electricity demands. The battery is operated within certain constraints to balance the need for power delivery and the preservation of the battery's lifespan. The absence of grid power in the station would indicate that the storage components of the station failed to fully recharge as the grid is mainly used to recharge the storage during off-peak

periods. This situation forces the EVCS to look into other alternatives to ensure that charging activities are not disturbed by the lack of power availability. Figure 3.30 depicts the absence of grid power, which is a direct result of the battery's SoC. The battery barely has any backup to sustain the load, as can be seen in Figure 3.31. The energy delivered by the battery to the EVCS has been reduced by over 80% as compared to the power that was delivered in the absence of load shedding, as seen in Figure 3.28.

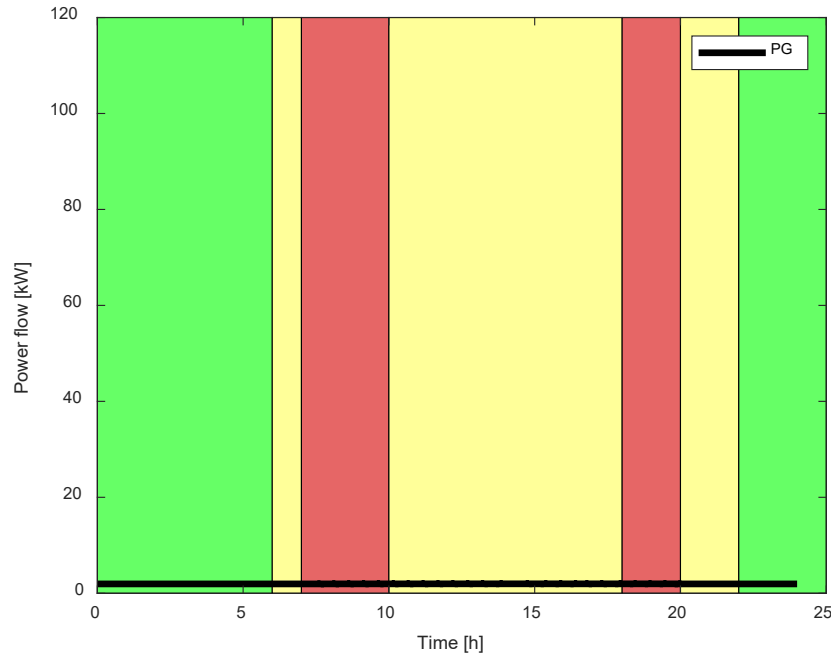


Figure 3.30: Grid power during load shedding: Simulated results for the selected spring day

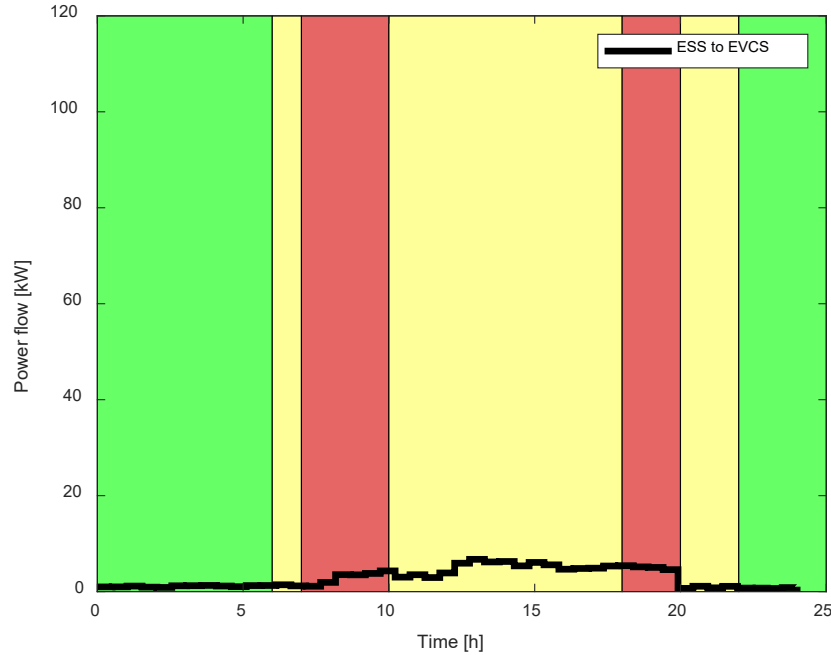


Figure 3.31: SoC for energy storage during simulated load shedding for the selected spring day

3.7.3.1 Analysis of the power flow during off-peak ToU intervals (00:00 to 06:00)

As previously alluded to, this period represents the first off-peak period of the day, when the battery was supposed to be charged with grid power due to the cost effectiveness of the arrangement. However, the situation is different due to power outages. In this case, the battery can only receive power from the wind as solar energy is not yet available in that duration.

- **P₁ (grid power):** This denotes power supplied from the grid during the off-peak period, which is 0 kW due to load shedding.
- **P₂ (PV power):** This represents PV power. The EVCS does not receive any power from the PV system because it is still early in the morning, and the sun has not risen yet, resulting in 0 kW of PV power being available.
- **P₃ (wind power):** This represents the wind power that contributes to the overall power supply during the off-peak ToU period and aids in charging the battery.

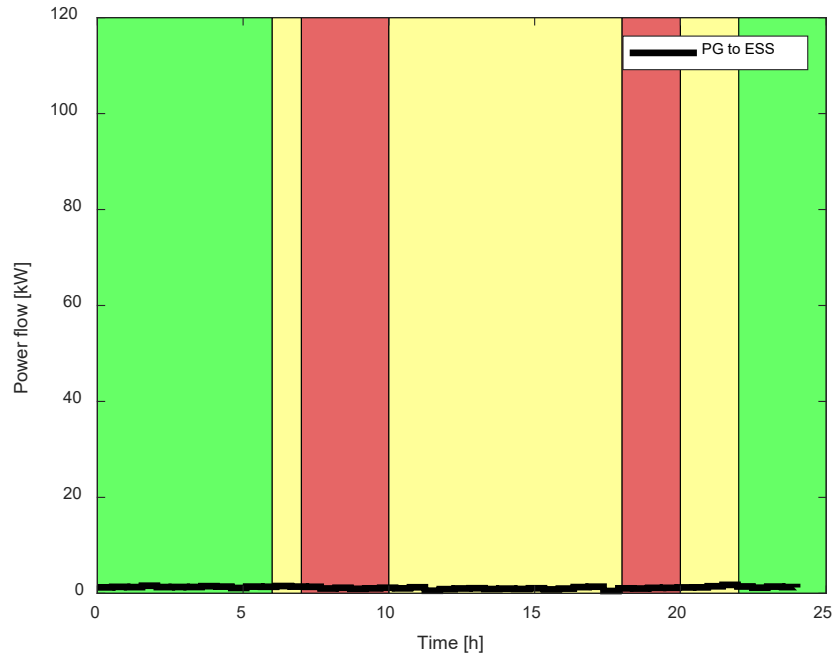


Figure 3.32: Grid power to BESS: Simulated results for the selected spring day during a load-shedding scenario

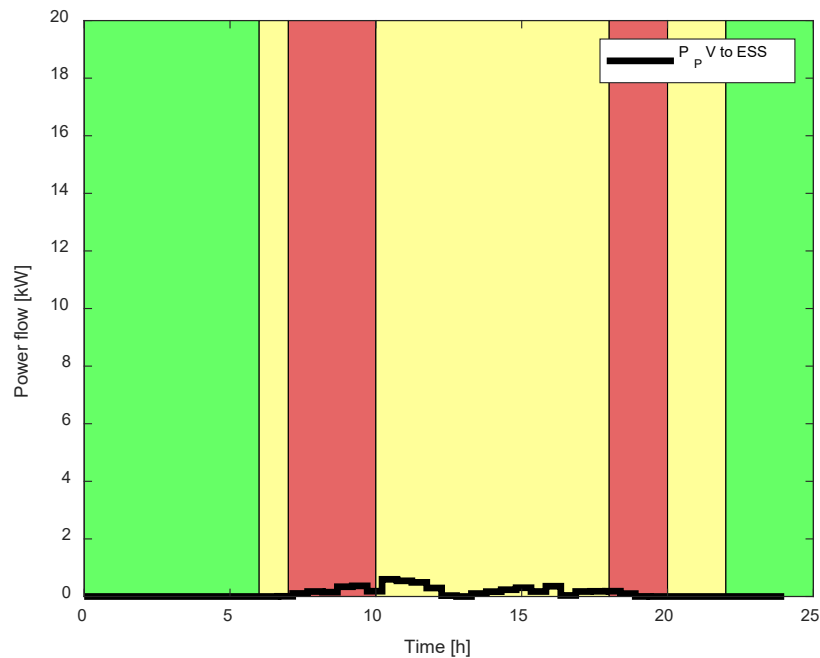


Figure 3.33: PV power to BESS: Simulated results for the selected spring day during a load-shedding scenario

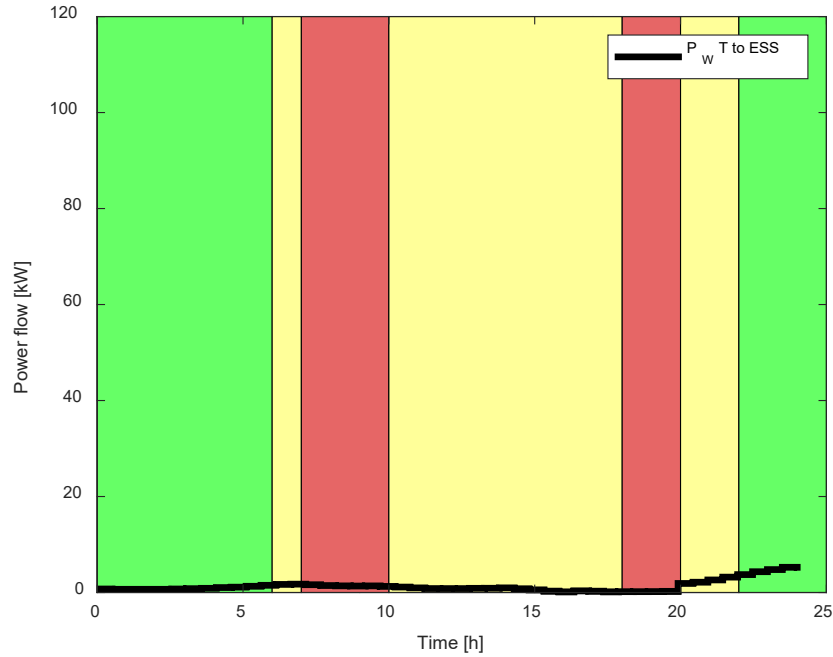


Figure 3.34: Wind power to BESS: Simulated results for the selected spring day during a load-shedding scenario

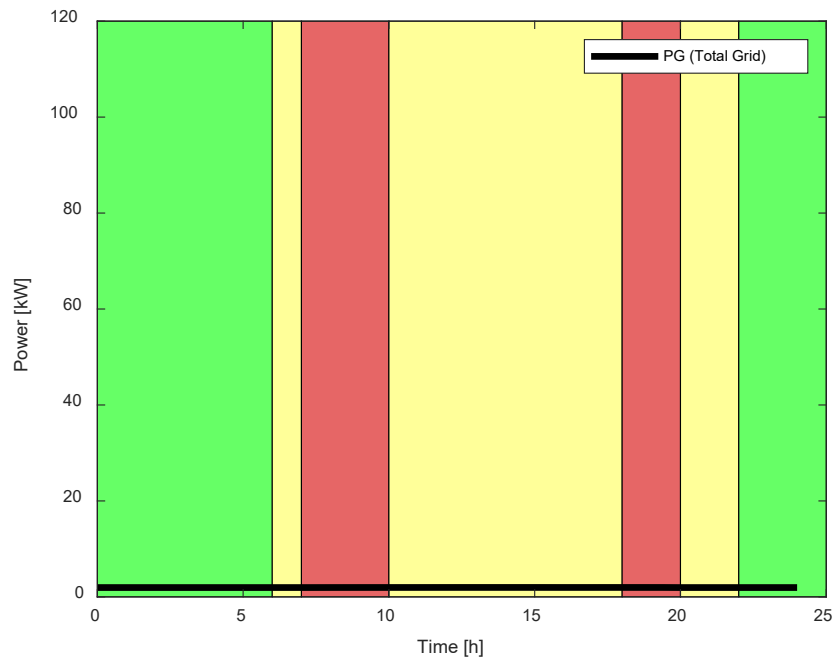


Figure 3.35: Total power from the grid: Simulated results for the selected spring day during a load-shedding scenario

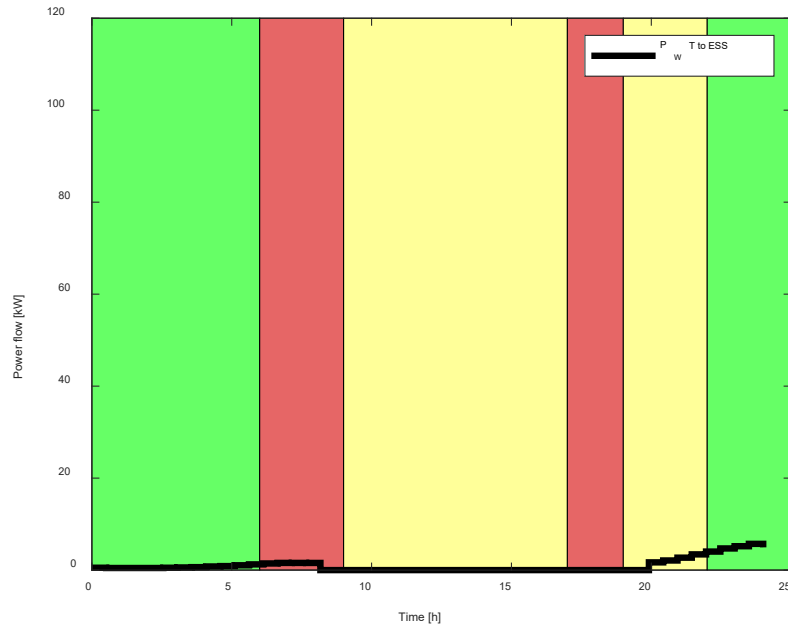


Figure 3.36: Excess power sold to the grid: Simulated results for the selected spring day during a load-shedding scenario

The charging requirements are left to the discretion of RER such as PV and wind. However, due to the size of the EVCS, RER are not able to meet the load demand, as indicated by Figure 3.37. The figure clearly indicates that the grid plays a significant role in contributing to the EVCS, thereby making the system more vulnerable during periods of load shedding. This observation validates the importance of utilizing the battery storage system more effectively and highlights the potential benefits of incorporating peer-to-peer sharing within this context.

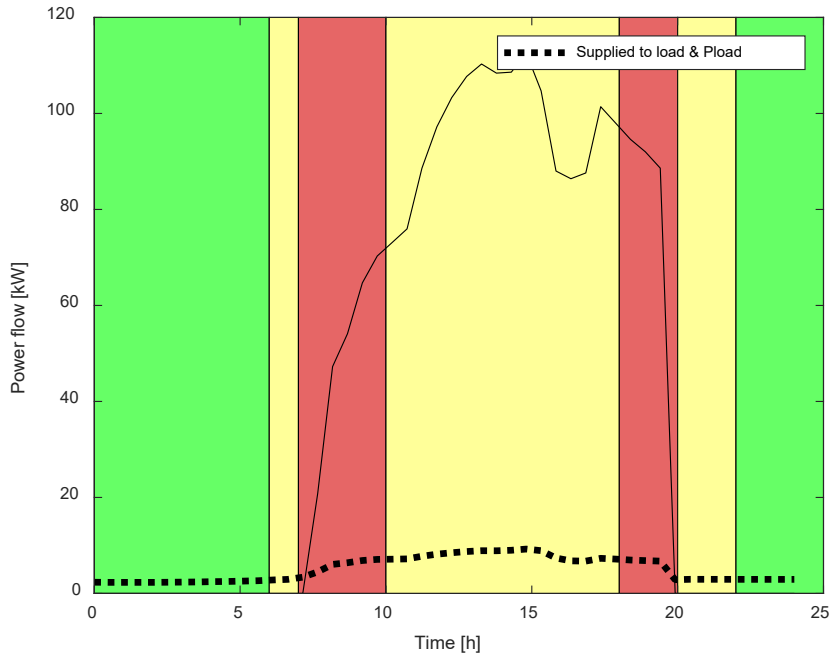


Figure 3.37: Supplied power to the load from all the resource at the EVCS: Simulated results for the selected spring day during a load-shedding scenario

During this interval, prosumers are the main suppliers at the EVCS, as indicated by Figures 3.38 and 3.39 respectively. Prosumers sell energy among one another through the EMS to ensure safety and the enforcement of dynamic selling/buying prices. A bidirectional charger is used to facilitate this type of transaction between prosumers. The prosumers are still subject to constraints that are meant to ensure that the seller has enough energy to make a trip to their next destination.

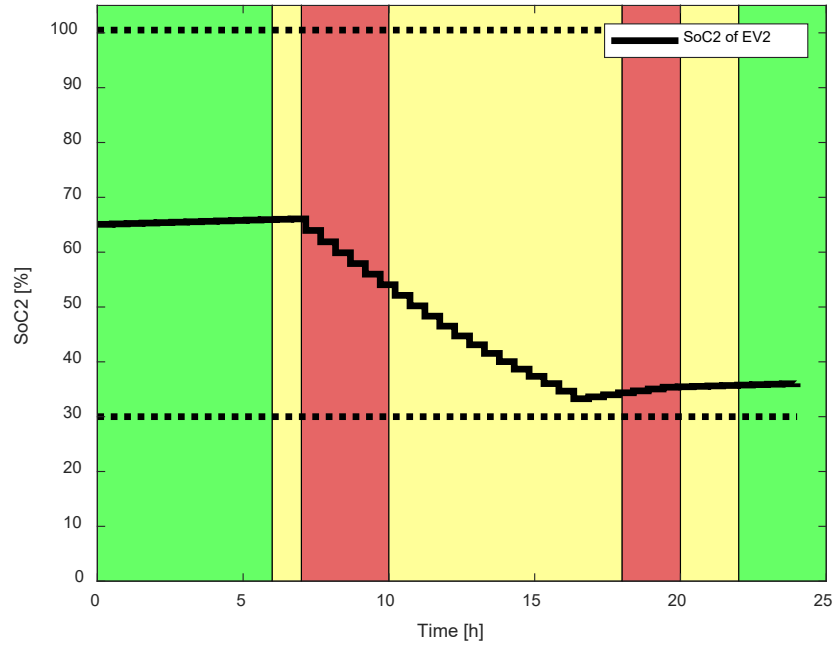


Figure 3.38: P2P sharing to supplement the EVCS during load shedding (seller's battery SoC)

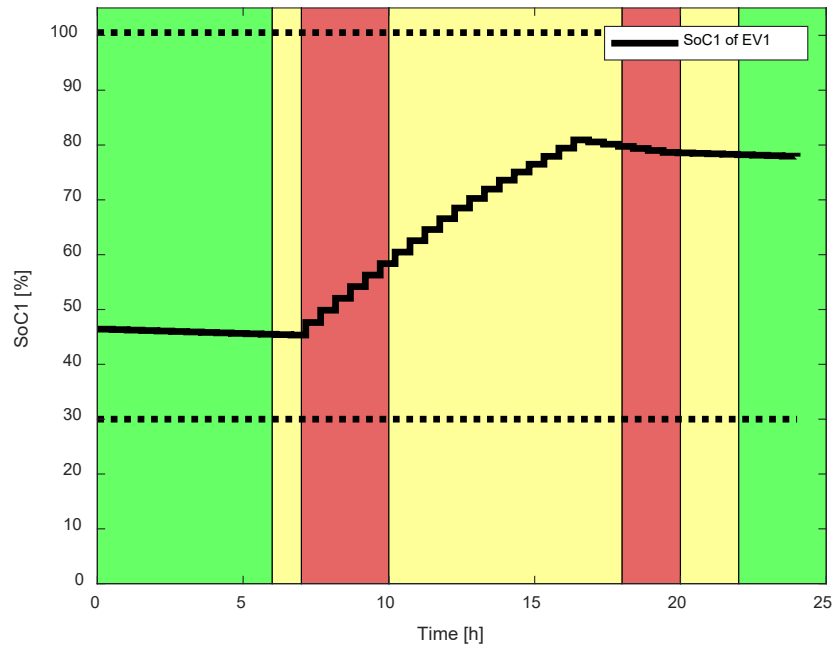


Figure 3.39: P2P sharing to supplement the EVCS during load shedding (buyer's battery SoC)

3.8 ECONOMIC ANALYSIS OF THE SYSTEM

3.8.1 Daily operation cost savings

The economic analysis conducted for a worst-case scenario day aimed to compare the potential energy savings of the proposed system with the baseline system. This analysis involved evaluating the cumulative energy costs of an optimally controlled system and the baseline system over the course of the day. Figure 3.40 illustrates the cumulative costs of the two systems by depicting how they evolve from the start of the day at 00:00. The graph demonstrates a noticeable divergence in cumulative costs between the two systems, with the optimally controlled system showcasing significant cost savings compared to the baseline system. This divergence in cumulative costs primarily stems from the dispatch of output power from the wind system to the battery in the optimally controlled system.

By utilising the excess wind power generated during the early hours of the day, the optimally controlled system can store energy in the battery, which results in cost savings. During the first peak-pricing period, there is a notable surge in energy cost savings for the optimally controlled system.

This surge can be attributed to the availability of both wind and PV output generation during this period. The combined contribution of these RES allows the optimally controlled system to rely less on grid power, which results in significant cost reductions. Figure 3.40 illustrates the economic benefits of the proposed system throughout the day and highlights the cost savings achieved through optimal control and utilisation of RES. These findings provide valuable insight into the potential financial advantages of implementing the proposed system compared to the baseline system. In the second peak period, the energy cost savings continue to rise due to no activity recorded at the charging station. Only a minimal amount of energy is purchased from the grid. The implemented hierarchy-charging scheme, which prioritises the use of renewable energies, supplemented by an ESS, and then P2P energy sharing, has resulted in significant daily cost savings. The observed daily cost savings of US\$20.48 and the calculated 38.14% savings for the selected simulation day indicate the effectiveness of the charging scheme in optimising energy usage and reducing reliance on the grid. Under the ToU tariff structure, renewable energies are utilised as a primary source, supplemented by stored energy from the ESS and P2P energy sharing, and the charging scheme strategically schedules EV charging during low-cost periods, thereby reducing electricity expenses. Additionally, the charging scheme's ability to prioritise renewable energies and stored energy from the ESS demonstrates a commitment

to sustainability and reducing reliance on the grid. By utilising these clean energy sources before resorting to grid power, the charging scheme contributes to environmental conservation and a lower carbon footprint. Furthermore, the charging scheme's inclusion of P2P energy sharing enables direct energy transfers between EVs, which promotes efficient use of available energy resources within the EVCS. This feature further optimises energy usage, especially during peak hours when grid electricity prices are typically higher. By leveraging P2P energy sharing, the charging scheme minimises the costs associated with maximum demand charges, which are often based on peak power consumption. Overall, the observed cost savings and the percentage of savings indicate the effectiveness of the implemented hierarchy-charging scheme in taking advantage of renewable energies, ESS, and P2P energy sharing under the ToU tariff and maximum demand charges. These results demonstrate the potential benefits of the proposed model in reducing operational costs, optimising energy usage, and promoting sustainability within EV charging infrastructure.

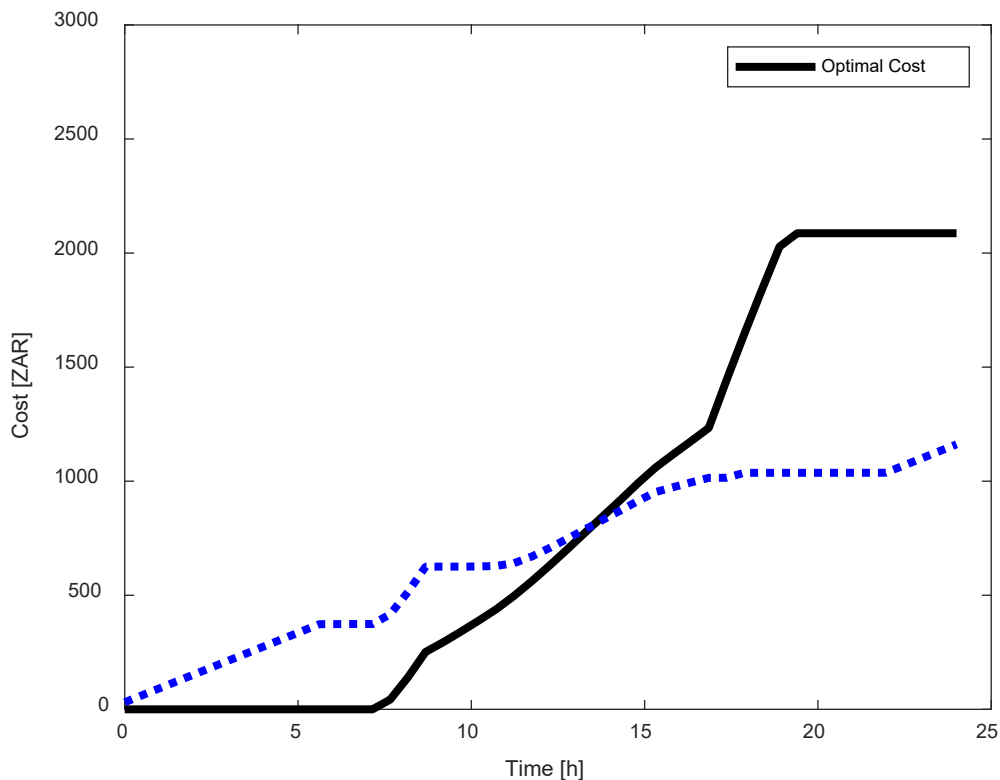


Figure 3.40: Optimal savings for Scenario 1 (overcast day)

3.8.2 Monthly operation cost savings

To thoroughly assess the feasibility and sustainability of the proposed model for a year, it is essential to consider the variations in resources such as solar and wind, as well as ambient temperature and wind speed. Figures 3.41 and 3.42 provide insight into these variations.

3.8.2.1 Solar irradiance

Figure 3.41 focuses on solar irradiance and depicts the average daily solar irradiance for each month in 2020. This information is crucial as solar irradiance directly impacts the power output of the PV system. The graph demonstrates that the total irradiance received from the sun decreases significantly during the winter season, as compared to the summer season. Understanding these variations in solar irradiance helps in accurately estimating the potential energy generation from the PV system and enables appropriate planning and optimisation of the proposed model to ensure its long-term feasibility and sustainability.

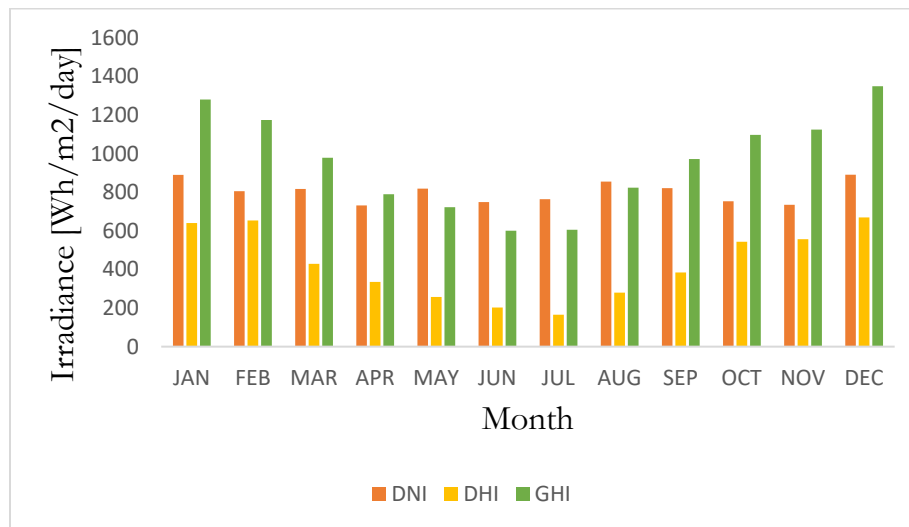


Figure 3.41: Monthly average solar irradiance for the year 2020 at Gqeberha

3.8.2.2 Ambient temperature

To accurately replicate the PV system's operation requires considering ambient temperature variations. The efficiency of PV cells is influenced by ambient temperature, as shown in Equation 3.23. Higher temperatures above 25 °C result in a decrease in efficiency and output power loss.

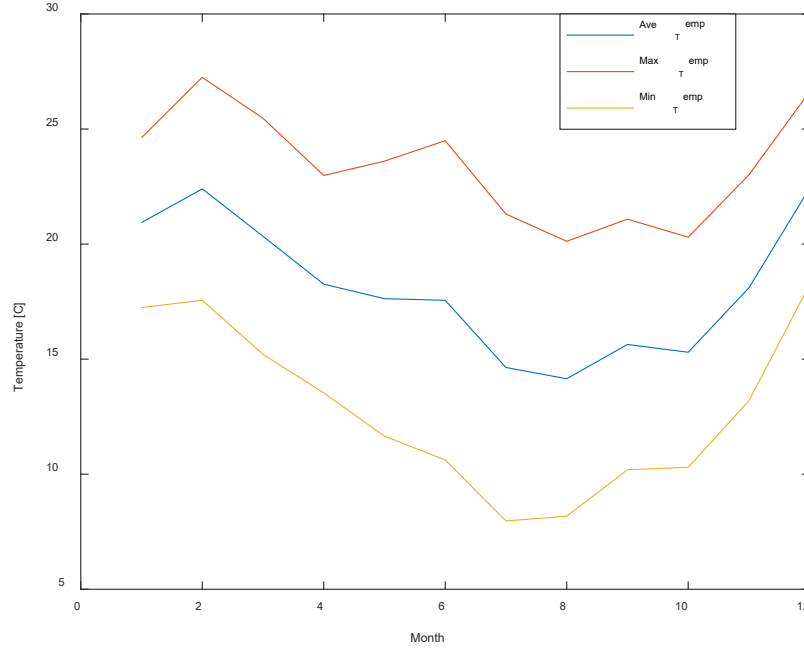


Figure 3.42: Monthly average ambient temperature for the year 2020 at Gqeberha

3.8.3 Lifecycle cost analysis

A projected lifetime of 20 years is a reasonable starting point for the lifecycle cost analysis of the proposed power dispatch optimal energy system for an EVCS with battery storage and a P2P-sharing scheme. This duration aligns with the typical lifespan of an EVCS and allows for a comprehensive assessment of the system's feasibility and cost effectiveness over its operational lifetime. By considering a 20-year project lifetime, one can capture the long-term benefits and costs associated with the proposed system. It allows for the evaluation of factors such as initial capital expenditure, ongoing operating and maintenance costs, energy consumption, and potential revenue generation through the P2P-sharing scheme.

Additionally, a longer project lifetime provides a more accurate assessment of the system's financial viability and ROI. It allows for a better understanding of the system's performance, potential savings, and the payback period. Equation 3.31 calculates the total lifecycle cost of the system, the projected operating and maintenance costs, as well as the expected energy consumption and energy prices over the 20-year project lifecycle.

$$LCC = C_{initial} + C_{OM} + C_{EC} \quad (3.31)$$

Where:

- $C_{initial}$ represents the initial cost of implementing the proposed system. It includes the capital expenditure required to set up the system, such as the cost of equipment, installation, and any necessary infrastructure.
- C_{OM} refers to the operating and maintenance costs incurred over the project's lifetime. It includes expenses associated with routine maintenance, repairs, and any ongoing operational costs.
- C_{EC} represents the energy cost component, which includes the cost of energy consumed by the system over the project's lifetime.

Table 3.2 provides information on the initial implementation costs of the hybrid PV and wind system for the grid-tied hybrid EVCS. The components included in the cost estimation are as follows:

3.8.3.1 PV system

The PV system consists of 55 solar panels, each with a power rating of 535 Wp. The cost includes the panels themselves and mounting equipment such as rails, brackets, stands, and concrete foundations.

3.8.3.2 Wind turbine

The hybrid system incorporates a 10 kW wind turbine. The initial implementation cost covers the turbine itself, along with any necessary infrastructure and installation expenses.

3.8.3.3 BESS

The BESS comprises multiple LiFePO₄ battery banks with a total capacity of 100 kWh. The cost associated with the battery bank includes the batteries, cabling, and data-monitoring hardware and software for logging purposes.

3.8.3.4 Hybrid inverter

The hybrid system incorporates a 100 kW inverter. The initial implementation cost covers the inverter with smart-charge capability, along with any necessary infrastructure and installation expenses.

Table 3.2: Investment costs of an open-loop system

Components	Costs
PV system	US\$9 625.82
Wind system	US\$4 281.48
Hybrid inverter	US\$5 935.25
LifePO4 battery bank	US\$37 409.28
Total	US\$57 241.83

Table 3.2 presents the energy costs incurred for each system in 2020, which served as the baseline for evaluating potential cost savings and revenue generation over the 20-year project lifespan. The previously discussed costs were utilised for this analysis. To account for future changes in electricity prices, a 10% increase in the electricity price per year was assumed throughout the project's lifetime. This assumption helped to estimate the potential cost savings that the hybrid system can provide compared to conventional energy sources. Additionally, annual operation and maintenance costs were considered, which amounted to 1% of the initial investment cost. This cost is subject to an average increase in the inflation rate, which is stated to be 5.3% annually [125]. The financial analysis incorporated cash flow projections, net present value, and payback-period calculations. These metrics were used to assess the feasibility of the hybrid system and to estimate the time required to recoup the initial implementation costs. By considering the energy costs, future electricity price increases, and operation and maintenance expenses, the financial analysis provides insight into the economic viability of the hybrid system. The net present value calculation helped with determining the net value of the investment over its lifespan, while the payback period indicated how long it would take to recover the initial implementation costs. By following the abovementioned analysis steps and conducting a comprehensive financial analysis, the operational costs and financial viability of the hybrid system over its 20-year project lifetime can be evaluated.

Table 3.3: Total energy cost comparison between the baseline and open-loop models with optimal-control system

Model	Costs
Baseline	US\$1 291 247.39
Proposed model with optimal control	US\$940 236.52
Savings (proposed model with optimal control)	US\$351 010.87

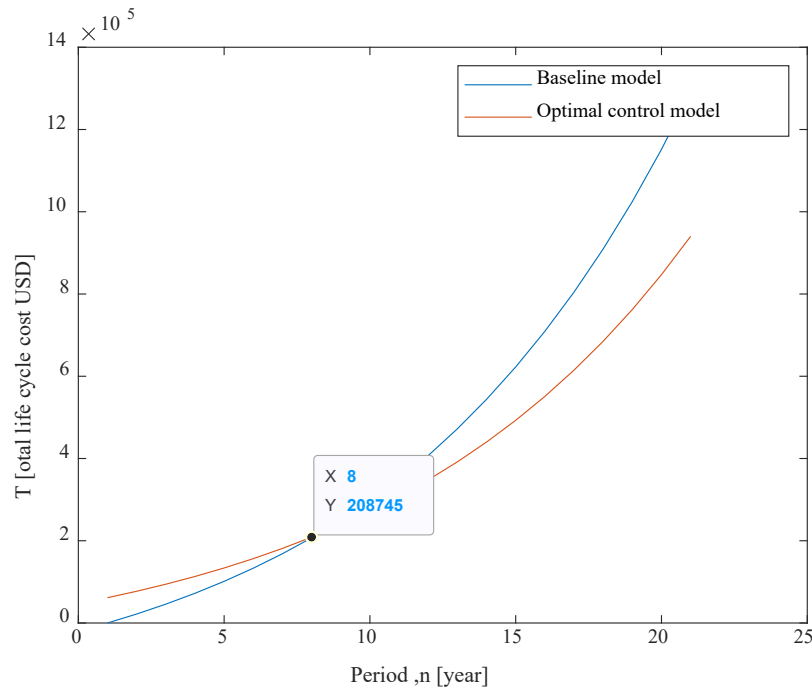


Figure 3.43: Breakeven point analysis between the baseline and the open-loop optimal-control models

Figure 3.43 displays the breakeven point analysis between the baseline system and the proposed system with optimal control. The predicted breakeven point for the proposed system is eight years. This indicates that after eight years of operation, the cost savings or revenue generated by the proposed system would be sufficient to offset the initial implementation costs. The total cost associated with the proposed system was stated as US\$208 745. This figure represents the cumulative expenses incurred throughout the eight-year period until the breakeven point is reached. Beyond this point, the system is expected to generate savings or revenue that exceeds the initial investment, resulting in a net positive financial impact.

3.9 CONCLUSION

The proposed system is a grid-integrated PV-wind energy system with P2P energy sharing and a CBB for energy storage and reserve capacity. The main objectives are to minimise grid utilisation, promote the use of renewable energy, mitigate high energy costs during peak hours, and promote P2P sharing among prosumers. To ensure optimal power dispatch, the system implements constraints such as a hierarchy-charging scheme. This scheme likely prioritises charging based on factors such as available renewable energy generation, battery SoC, and user demand; among others. The simulation of the hybrid energy system considered daily varying weather and load conditions, which provided an accurate representation of real-world scenarios and minimised uncertainties. This comprehensive approach allowed for a more realistic analysis of the system's performance and economic feasibility. The model incorporated an optimal-control algorithm, which optimised the operation and utilisation of the system's components. The algorithm aimed to minimise grid utilisation, optimise the utilisation of RES, protect the energy storage utilisation, and promote P2P sharing with dynamic pricing. The simulation results demonstrated that the proposed system with optimal control significantly reduces energy costs compared to a system without optimal control. A lifecycle cost analysis revealed that the breakeven point for the project would be reached in eight years. Over the 20-year project lifetime, projected savings of US\$351 010.87 are expected, which are equivalent to a 27.18% reduction in costs. These results highlight the economic feasibility of implementing the proposed system and showcase the potential for significant cost savings. The integration of renewable energy systems, energy storage, and optimal-control strategies not only reduces energy consumption and costs but also contributes to a decrease in the overall carbon footprint. Additionally, the implementation of such systems can promote profitability through P2P energy sharing, decrease total operating costs, and ensure sustainable energy management. Overall, the model and simulation outcomes provide valuable insight into the benefits of integrating renewable energy, energy storage, and optimal-control strategies in the context of an EVCS. The results emphasise the potential for cost savings, reduced energy consumption, improved sustainability, and increased profitability.

CHAPTER IV: MODEL PREDICTIVE CONTROL (MPC) OPTIMISATION OF A HYBRID SMART GRID WITH PV-WIND-BATTERY STORAGE INCORPORATING DEMAND-SIDE MANAGEMENT

4.1 INTRODUCTION

The use of renewable energy technologies has become a global trend. The benefits associated with using these resources make their implementation in many electric engineering power systems a worthwhile decision. However, the variability of these resources presents challenges in their integration, which necessitates the use of a controller to optimise the system. The optimal sizing of EVCSs has relied on assumptions about the charging patterns of EV owners; however, this approach proved to be biased and inadequate due to the absence of provisions for random charging. To address this limitation, a more sophisticated characterisation of consumer characteristics has emerged, which incorporates activity-based charging models and accommodates random-based charging. This robust energy management strategy, known as smart charging, utilises real-time randomised algorithms to ensure grid stability in an efficient and cost-effective manner. While this strategy is effective in stable grids, it faces challenges in power-constrained environments with frequent load shedding. The occurrence and severity of load shedding vary, which makes it difficult to accurately assume system operations that are reliant on the grid. The development of adaptive and resilient smart-charging strategies thus becomes essential. These strategies must dynamically respond to load-shedding events, optimise the charging process, and maintain grid stability. Over the years, various control strategies have been developed and implemented to optimise the performance and operation of renewable energy systems with different resource combinations. These control strategies are tailored to suit various renewable energy systems with a vast combination of resources for optimal performance and operation.

This chapter aims to discuss and investigate an advanced control strategy that is able to adequately control and maintain an EVCS's daily activities while satisfying the predefined set of constraints, and

to develop a mathematical model of this framework. Understanding the actual control strategy is crucial for achieving the aforementioned objectives. Several advanced control methods are available that can be employed to ensure stable and reliable EVCS operation. The choice of controller depends on the specific control requirements, system characteristics, and desired performance objectives. The list includes adaptive control, advanced optimisation techniques, MPC, reinforced learning, and fuzzy logic controls. These controllers work together to optimise the charging process, ensure grid integration, and manage power resources efficiently in an EVCS. The specific combination and functionality of controllers may vary depending on the charging infrastructure, the scale of the EVCS, and the desired charging capabilities [154–158].

Each of the control strategies offers distinct advantages for EVCSs. Adaptive control strategies in EVCSs are known to respond to changes in the charging environment, user demands, and system conditions. From the literature it can be deduced that the employment of various metaheuristic optimisation strategies enables the systems to adapt, optimise performance, and make intelligent decisions based on real-time conditions, constraints, and objectives [159–163].

Advanced optimisation techniques in the station are exceptional in ensuring overall performance of a system with various power resources through the consideration of operational constraints and user requirements. In this section, advanced optimisation techniques were utilised to tackle specific challenges in the management, control, and optimisation of EVCSs. These techniques enable real-time energy and reserve management, centralised and decentralised control strategies, and the optimisation of EV charging schedules, power dispatch, and profit maximisation [164–168].

MPC, on the other hand, was used to provide a systematic approach to optimising the charging process while considering operational constraints and objectives. It was also used to address uncertainties, balancing the DC bus, scheduling EV charging with RES, optimising real-time power management, and decentralised voltage control. It enabled effective control, optimisation, and coordination in different aspects of an EVCS and their integration with RES and grid systems [169–173].

Reinforcement learning enabled adaptive decision making, optimisation, and control in various aspects of EV charging, routing, power management, and system operations. It also allowed

responsive and efficient solutions, considering the dynamic and stochastic nature of the problems, learning from feedback and rewards, and adapting to changing conditions [174–178].

Fuzzy logic control was utilised to achieve fairness among EVs, optimise charging/discharging operations, manage charging and discharging in parking lots, enhance the efficiency and performance of EVCSs, and determine optimal sizing solutions for fast-charging stations. Fuzzy logic control allowed for rule-based decision making, considering various factors and objectives, to improve the overall operation and management of EVCSs [179–183].

However, when considering a renewable energy resource and its storage components in an EVCS, advanced optimisation techniques and MPC take precedence due to their optimisation capacity and capability [169,171,184–185]. The selection of one over the other comes down to performance requirements, the desired level of real-time control, and the sets of constraints. Among the two types, MPC controllers are usually selected due to the fact that they offer significant advantages, such as the utilisation of a mathematical model of a system being controlled, which captures the system's behaviour and dynamics and enabling it to make predictions on how the system will respond when subjected to different control inputs. Its ability to predict enables the MPC controller to optimise control actions over a specific horizon.

However, they also come with challenges such as computational complexity, model mismatch, and complexity in system identification. By acknowledging and addressing these challenges with technological advancements, they are increasingly being integrated into common controllers for their ability to optimise control strategies, adapt to dynamic conditions, and improve the overall efficiency and performance of power systems.

This chapter aims to compare the open-loop optimal-control model from a previous chapter with a proposed closed-loop MPC model. The focus is on a PV-wind-grid system integrated with P2P and energy storage and considering a random charging pattern under a ToU tariff. The objective is to minimise grid energy costs while considering constraints on energy transfer from the utility grid. The proposed closed-loop MPC model improves on the open-loop optimal control by utilising a feedback system and accommodating variable demand patterns and external disturbances such as grid outages and climatic conditions. The modelling of the microgrid-connected PV-wind-grid system with P2P and energy storage is done using a linear programming framework. The open-loop model is cost

effective and suitable for customers and prosumers with steady demand patterns, while the closed-loop MPC model is more robust against demand pattern changes and external disturbances.

The chapter primarily focuses on developing and comparing control strategies to optimise the operation of an EVCS in a PV-wind-grid-integrated system. The objective is to minimise costs while meeting load demands and considering energy transfer constraints. This study distinguishes itself from others by simultaneously minimising grid energy costs and battery utilisation, while also incorporating constraints between controllable variables and battery SoC under demand-side management. Specifically, the chapter explores the ToU tariff as a form of demand-side management. The proposed closed-loop online strategy builds upon the optimal-control scheme that is based on the open-loop mechanism. It applies the MPC strategy to a hybrid smart grid with PV-wind-battery storage, incorporating demand-side management, prosumers, and EVCS profitability under the Eskom ToU tariff at NMU in Gqeberha.

Unlike the open-loop control strategy, the closed-loop approach incorporates feedback on the main battery's SoC. The chapter suggests that the optimisation management strategy for the hybrid smart grid, with a PV-wind BSS and P2P charging strategy, can be modelled as a control problem, and solved using the MPC approach to benefit from feedback and prediction at the tertiary level. MPC schemes are currently favoured in power systems due to their advantages, including robustness, prediction of future system behaviours, fast response, consideration of non-linearity and constraints, handling of multi-input multi-output systems, and other benefits. Economic MPC is suitable for online optimisation control and offers high-precision receding horizon optimisation [184–187].

The chapter is organised as follows: Section 4.2 presents the mathematical model of various components within the hybrid smart grid with PV-wind battery storage and P2P energy sharing, Section 4.3 presents the demand-side management model, Section 4.4 presents the MPC optimisation problem, Section 4.5 presents the mathematical model formulation for the proposed system, Section 4.6 presents a case study, Section 4.7 discusses the simulation results, and Section 4.8 concludes the chapter.

4.2 MATHEMATICAL MODEL OF A HYBRID SMART GRID WITH PV-WIND-BATTERY STORAGE AND P2P ENERGY SHARING

4.2.1 Schematic model layout

The proposed microgrid-connected system, as depicted in Figure 4.1, is designed to integrate various RES and storage systems to efficiently meet the load requirements. The system consists of PV and wind sources, a battery bank with a P2P scheme generator, and both AC and DC loads. The system is connected to the utility grid through a point of common coupling. The system's priority is to utilise the energy generated from the PV and wind sources to supply the loads. However, when the renewable energy system cannot meet the load requirements, the system employs a hierarchical order to supplement the load. The prosumers, grid, and battery bank are used in a sequential manner to meet the additional energy demand.

The PV and wind systems generate power that is utilised to charge EVs and the BSS. The BSS acts as a storage system for excess energy generated by the RES. It can also act as a supplementary energy source during periods when the load requirements exceed the available generated energy. When there is minimal activity at the EVCS and the BSS is fully charged, any excess power from the RER can be sold back to the utility grid. This allows for the efficient utilisation of the generated energy and the possibility of earning revenue from the excess power. During peak periods when the RER and the BSS cannot meet the load requirements, the system promotes P2P EV charging. The EMS plays a crucial role in managing this P2P energy-sharing mode. It constantly communicates with the EVs and makes decisions based on the SoC of each vehicle.

The SoC serves as an indicator of whether a vehicle needs to be recharged or if it can participate in energy trading. The proposed microgrid system aims to optimise the utilisation of RER, storage systems, and P2P energy sharing to efficiently meet the load requirements. The EMS plays a vital role in coordinating the various components and ensuring that the overall system operation is optimised.

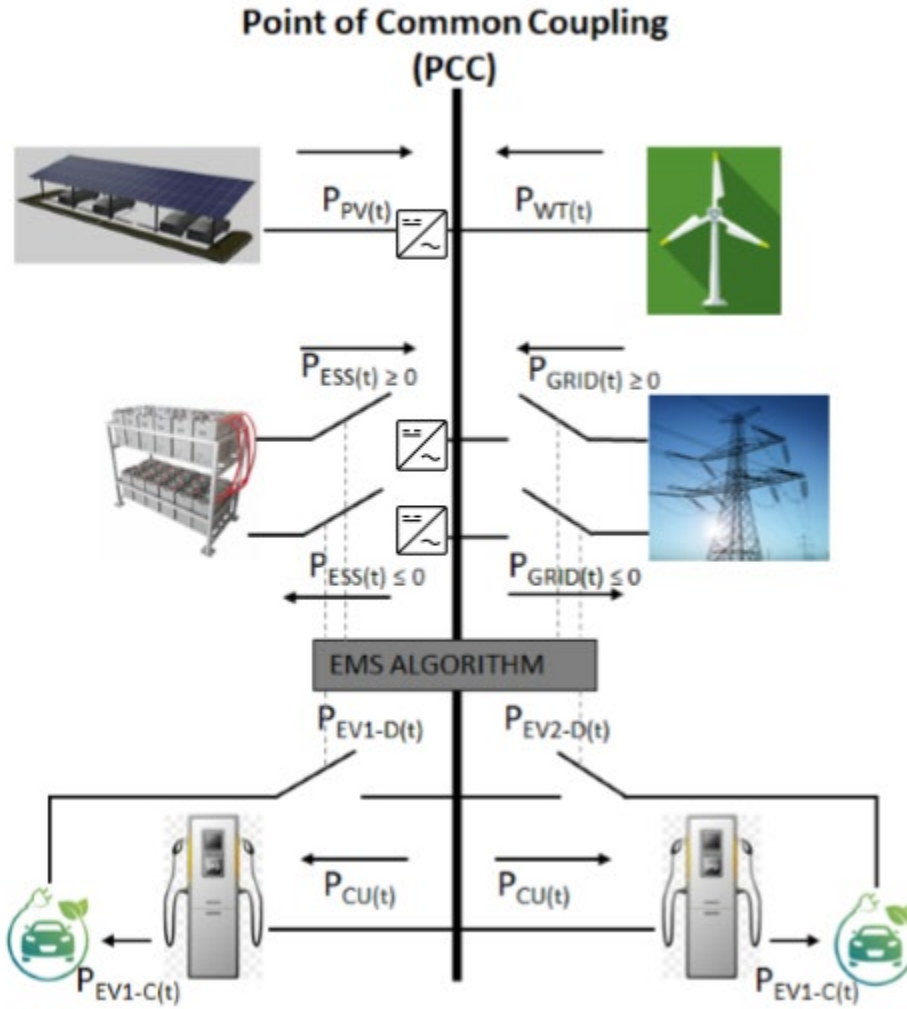


Figure 4.1: Schematic of a grid-integrated PV-wind system with battery storage and a P2P energy-sharing scheme

4.2.1.1 Grid power

The hierarchy-charging scheme is still prevalent in this chapter, where priority is given to the RER, seconded by the battery utilisation backed by P2P sharing and conditional acceptance of the grid utilisation. The grid is to be prioritised when the RER are not able to meet the load demand and the battery has reached its set constraint for discharging. Furthermore, the grid should be used mainly during off-peak hours to increase profitability and to lessen grid dependability. During off-peak hours, batteries are allowed to charge from the grid. This set of boundaries imposed on the grid can be represented as follows [188]:

$$-P_{min(t)} \leq P_{Grid(t)} \leq +P_{max(t)} \quad (4.1)$$

When load shedding is factored in, the power from the grid can be represented by the following equation [188], which states the actual power that is available from the grid during different conditions:

$$P_{Grid(t)} = \alpha_G P_{Grid(t)} \quad (4.2)$$

Where:

- ∞ represents the uncapped scenario of no limitation on the amount of energy when the grid is permitted to act as a mode of supply;
- $P_{Grid(t)}$ represents the power from the grid at any interval in accordance with the permissible hierarchy; and
- α_G represents the grid availability parameter where a positive one represents normal operation and negative one representing power outage periods.

PV, wind, and P2P were already discussed in detail in the previous chapter; the mathematical formulation of each is therefore applicable in this chapter as well.

4.2.1.2 Battery power

The dynamic energy storage plays a critical part in the correct deployment of the resource and facilitates the charge and discharge practicality. Below is the mathematical representation of that relationship in terms of the SoC [142]:

$$SoC(j+1) = SOC(j) - \frac{1}{E_n \eta_{ch/dsch}} \int_0^N P_B(j) dj \quad (4.3)$$

Where:

- $SoC(j)$ is the initial state of charge of the battery at the start of every sampling time;

- En is simply the nominal capacity of the energy storage;
- P_B is the power flowing from/to the battery; and
- η_{ch} and η_{dsch} represent the charging and discharging efficiency respectively.

The power flow into the battery storage of the hybrid system during charging and discharging processes can be described by Equations 4.4 and 4.5 [143]:

For charging:

$$P_{ch}(j+1) = P_{ch}(j)(1 - \sigma) + (P_G(j) + P_{PV}(j) + P_W(j) - P_D(j)/\eta_{inv})\eta_{ch} \quad (4.4)$$

For discharging:

$$P_{dsch}(j+1) = P_{ch}(j)(1 - \sigma) + P_D(j)/\eta_{inv} - (P_G(j) - \mp P_{PV}(j) - \mp P_W(j))/\eta_{inv} \quad (4.5)$$

Where:

- P_{ch} represents the charging power;
- P_{dsch} is the discharging power;
- P_D is the power demand;
- σ is the hourly self-discharge rate; and
- η_{inv} is the efficiency of the inverter.

The SoC of the battery should then be based on the same concept as in Equation 3.11, which can be expressed as follows for the current optimisation:

$$SoC_{min} \leq SoC(k) \leq SoC_{max} \quad (4.6)$$

4.3 DEMAND-SIDE MANAGEMENT MODEL

The hybrid smart grid, with PV-wind-BSS and P2P-charging strategy, closed-loop model aims to minimise the operating cost within the framework of demand-side management under Eskom's ToU tariff structure for a large business using medium voltage. The structure forms a huge part of the modelling due to its direct cost implications. The pricing for the two scenarios under scrutiny is

presented Figure 4.2 for a day with and without cloud cover from the available data at the EVCS in Uyilo, NMU at Gqeberha in the Eastern Cape province of South Africa.

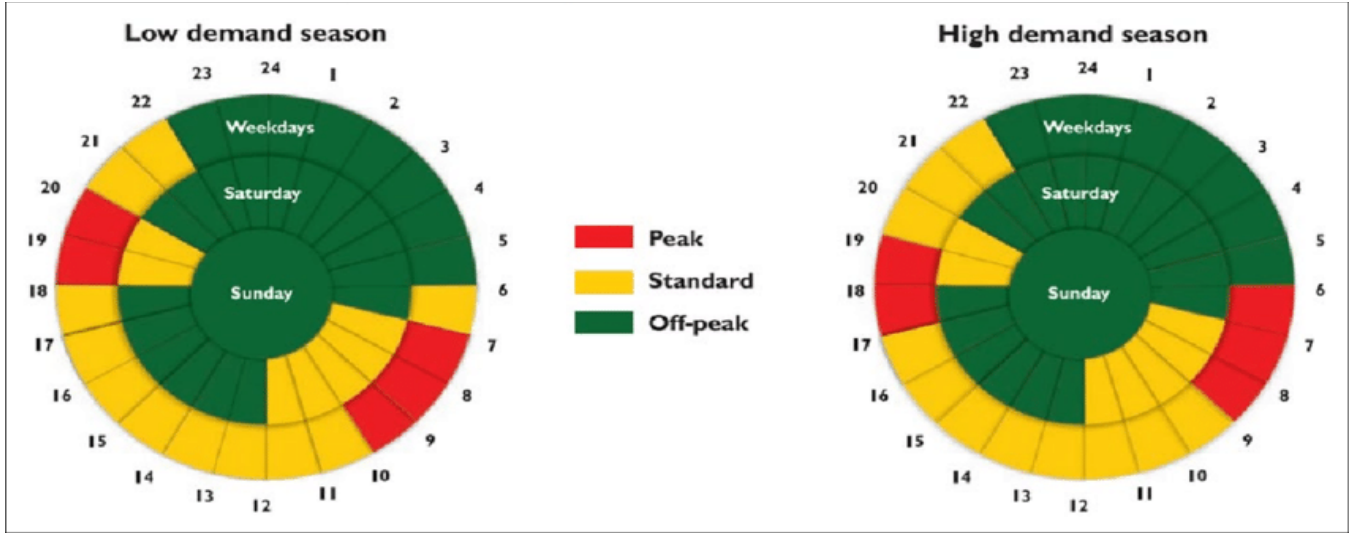


Figure 4.2: ToU for low and high demand seasons for 2020/2021 at Gqeberha [189]

4.3.1 Optimisation problem

4.3.1.1 Objective function

The main objective of this chapter is minimising the grid cost, limiting the battery utilisation, and promoting the use of renewable energy and a P2P-sharing scheme for profitability, sustainability, and reliability of the system. Both present and future variables were considered in the objective function at each sampling time k . The mathematical representation of the objective function is as follows [189, 190]:

$$f_1 = \min(\sum_{j=k}^{k+N_c-1} \rho_j (P_{G-B}(j/k) + P_{G-L}(j/k)) \Delta t_s - \sum_{j=k}^{k+N_c-1} (P_{PV-G}(j/k) - P_{PV-loss factor} * P_{PV-L}(j/k) + (P_{W-G}(j/k) - P_{W-loss factor} * P_{W-L}(j/k)) \Delta t_s - \sum_{j=k}^{k+N_c-1} (\rho_p P_{B-G}(j/k)) \Delta t_s \quad (4.7)$$

Where:

- $(P_{G-B}(j/k))$ represents the grid power to BSS;
- $(P_{G-L}(j/k))$ represents the grid power to the load;
- $(P_{PV-G}(j/k))$ represents the power generated from the PV supplied to the grid;
- $(P_{W-G}(j/k))$ represents the power generated from the wind supplied to the grid;

- N_c represents the control horizon; and
- t_s is the sampling time.

4.3.2 Variable constraints

The hybrid smart grid, with PV-wind-BSS and a P2P charging strategy, was modelled as a linear programming multi-criteria optimisation problem. Due to the randomised nature of recharging at the EVCS, a period was selected to depict a possible scenario for simulation purpose, even though time and load requirements may differ in an actual station. With this in mind, the load demand balance in the EVCS can be expressed as follows [188]:

$$P_L(j) = P_{G-L} \left(\frac{j}{k} \right) + (P_{PV-L}(j) - P_{PV-loss \text{ factor}} * P_{PV-L}(j)) + (P_{PV-L}(j) - P_{PV-loss \text{ factor}} * P_{PV-L}(j)) + P_{B-L} \left(\frac{j}{k} \right), j = k, \dots k + N_c - 1 \quad (4.8)$$

Where:

- $(P_{G-L} (j/k))$ represents the predicted power from the grid to the load at jth sampling time in line with the measured information at instant k ;
- $P_{B-L} (j/k)$ represents the predicted power from the battery to the load at jth sampling time in line with the measured information at instant k ;
- $P_{PV-L}(j)$ represents the PV power to the load; and
- $P_{W-L}(j)$ represents wind power to the load.

The hierarchy still stands where P_{PV} and P_w are the prioritised resources for charging at the station, whereby the surplus is used to first charge the battery. Once the battery is fully charged, the surplus is sold to the grid with the provision that no load is neglected during that process. Battery storage health is preserved by limiting its utilisation in the station and it is only used to supply the load when the primary resources are not able to, as well as during peak periods or load shedding.

The restriction of the battery power limit is represented as follows [188]:

$$0 \leq P_B \left(\frac{j}{k} \right) \leq P_{nB} \quad (4.9)$$

Similarly, the bounds imposed on the grid are in accordance with the previously imposed hierarchy, which prioritised renewable energy supply, followed by P2P. These bounds can be represented as follows [188]:

$$-\infty \leq P_{Grid(j/k)} \leq +\infty \quad (4.10)$$

4.4 MPC ALGORITHM

This work employed a deterministic linear optimisation approach to solve the power-dispatch problem and to minimise the energy costs associated with operating the system. The open-loop model introduces an optimal power dispatch for the EVCS and utilises a hierarchical optimisation scheme to enhance efficiency and cost effectiveness. Additionally, an adaptive control model, the MPC technique, incorporating multiple estimation models and a class of MIMO frameworks, is introduced to further improve savings and profitability without compromising system integrity. MPC, known for its fast, transient response and flexibility in accommodating different constraints, plays a crucial role in system optimisation. The controller utilises current plant measurements, dynamic states, and process variable targets to calculate future events and employs predefined cost functions to determine optimal values for future control inputs. The system constraints are modelled based on practical limitations and are expressed concisely [191–194].

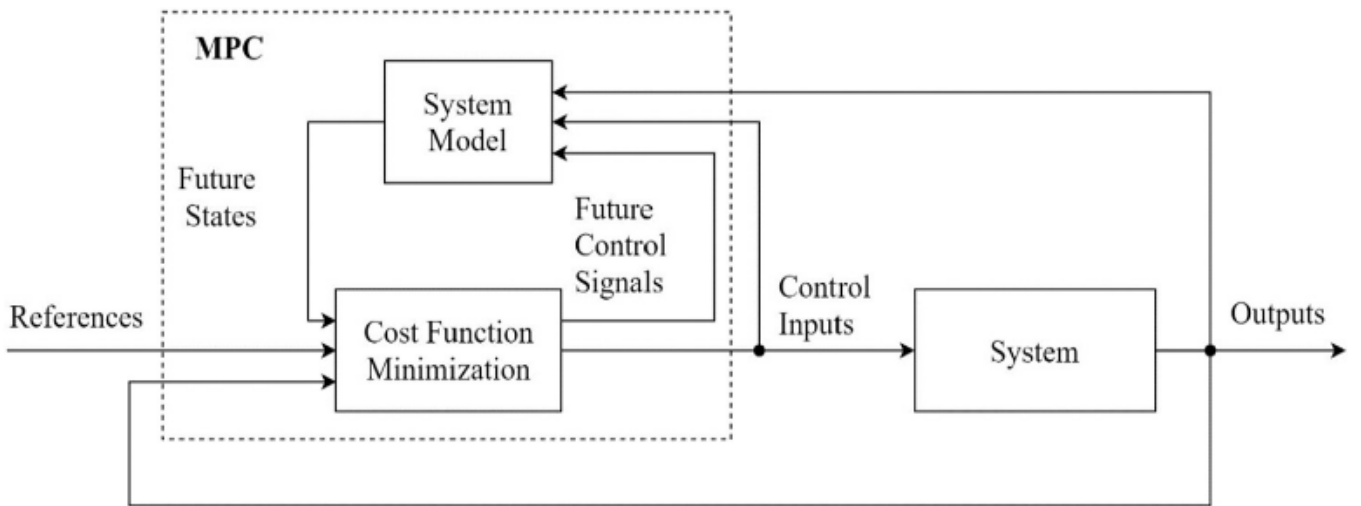


Figure 4.3: Structure of an MPC-based control approach [195]

The optimisation strategy involves minimising a defined objective function while considering the constraints. The dynamic optimiser represents the chosen solver for optimisation at each sampling time, with only the first optimal control of each input applied. The design of the optimal control based on MPC includes forecasting the daily power demand and PV and wind power output. Deviations from the forecasted values are considered as disturbances in microgrid systems. The control vector, denoted as X , contains all control variables, and a linear state space control is derived from the microgrid-connected PV-wind with a battery bank system and can be expressed as follows [188]:

$$X(k) = [P_G(k/k) \dots P_G(k + N_C - 1/k), P_B(k/k) \dots P_B(k + N_C + 1/k)]. \quad (4.11)$$

The controller evaluates the time step k and determines the control horizon N_C . It then solves an open-loop optimisation problem over this horizon N_C to find the optimal solution. In this solution, only the initial values of the control variables, specifically P_G (power from the grid) and P_B , are applied in the microgrid.

The MPC approach solves an open-loop optimisation problem with an operating horizon to obtain an optimal solution, with only the first control variables implemented in the microgrid. The microgrid-connected PV-wind system with battery backup and P2P-sharing mode is modelled as a MIMO system. The key advantage of MPC is its ability to optimise multiple variables while considering constraints and forecasting future system behaviours.

The optimisation problem in MPC includes both control and predicting horizons. In MPC, the optimisation problem involves two key horizons: the control N_C and the N_p . The control horizon determines the number of future time steps considered for optimising control decisions, such as adjusting system inputs. Beyond the control horizon, the controller assumes constant actions or follows a predetermined policy until the end of the N_p . The control horizon is given by [196]:

$$N_C = N - k + 1 \quad (4.12)$$

Where N is the total number of samples in the operating horizon of 24 hours.

The MPC approach solves the optimisation problem as follows [196]:

- 1) The control horizon is determined for each sampling time, $N_c(k)$, using Equation 4.12.
- 2) The optimum solution is obtained within that horizon by minimising the cost function and subject to constraints (Equation 4.7).
- 3) The first switching control is then executed in the microgrid energy system based on the optimal solution $[P_G(1/k), P_B(1/k)]$.
- 4) Measure the state variable, which is the CBB's SoC.
- 5) Set $k = k + 1$, and update system states, inputs, and output.
- 6) This process is repeated until a predefined value is reached.

The optimisation problem is solved using linear programming in the OPTI Toolbox, which is a free MATLAB toolbox for solving linear optimisation problems. Linear programming offers a reliable and efficient solution for optimising the system in an easy and fast manner.

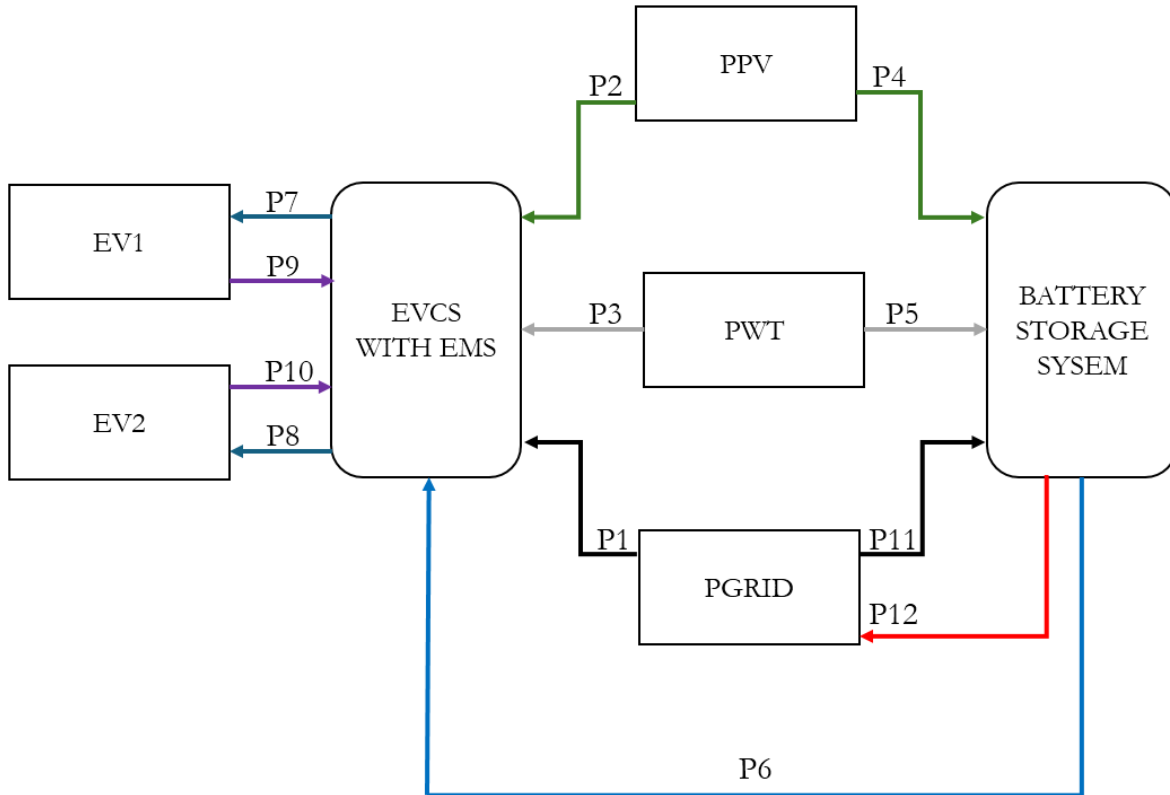


Figure 4.4: Closed-loop model for a smart grid PV-wind hybrid system

4.5 MATHEMATICAL MODEL FORMULATION

4.5.1 Objective function

The objective is to develop an optimum algorithm design problem to maximise the use of a hybrid renewable energy system and to minimise the grid and storage component's utilisation [188].

$$\min f(x) \text{ subjected to } \begin{cases} A_{eq}x = b_{eq} \\ Ax = b \\ l_b \leq x \leq U_b \end{cases} \quad (4.13)$$

The objective function $f^T X$ aims for minimisation and is linear in nature, with vector X containing all the control variables relevant to the optimisation challenge. The coefficients A_{eq} and b_{eq} correspond to the equality constraints, whereas l_b and U_b define the lower and upper bounds for the variables respectively.

$$f^T = [\omega t_s \rho(j) \dots \omega t_s \rho(N_c), \omega t_s(j) \rho \eta_{ch}, \dots, \omega t_s(N_c) \rho \eta_{ch}, \omega t_s(j) \rho \eta_{dch} \dots \omega t_s(N_c) \rho \eta_{dch}, 0 \dots 0_{N_c}, \dots, t_s \rho(j) \dots t_s \rho(N_c), 0 \dots 0_{N_c}]_{1 \times 12N_c} \quad (4.14)$$

$$X = [P_1(j), \dots, P_1(N_c), P_2(j), \dots, P_2(N_c), P_{12}(j), \dots, P_{12}(N_c)]_{1 \times 12N_c} \quad (4.15)$$

Where:

- t_s is the time step; and
- η_{ch} is the charging efficiency of the battery

4.5.2 Equality constraints

From the power-balance equality constraints in Equation 1.7, matrix A_{eq} is expressed as:

$$A_{eq1} = \left[\begin{array}{c|c|c|c|c|c} \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} & \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} & \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} & \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} & \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} & \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} & \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} \\ \hline \end{array} \right]_{N_c \times 3N_c} \dots \left[\begin{array}{c|c|c|c|c|c} \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} & \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} & \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} & \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} & \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} & \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} \\ \hline \end{array} \right]_{N_c \times 12N_c} \quad (4.16)$$

and

$$A_{eq2} = [0 \ 0 \ \dots \ 0 | \dots | 0 \ 0 \ \dots \ 0]_{1 \times 3N_c} [1 \ 1 \ \dots \ 1 | 1 \ 1 \ \dots \ 1 | -1 \ -1 \ \dots \ -1 | 0 \ 0 \ \dots \ 0 | \dots | 0 \ 0 \ \dots \ 0]_{1 \times 12N_c} \quad (4.17)$$

$$A_{eq} = \begin{bmatrix} A_{eq1} \\ A_{eq2} \end{bmatrix} \quad (4.18)$$

4.5.2.1 Constraints equations

The first row of the matrix contains the coefficients for the constraint equation:

- The first element is -1, which corresponds to the load power (PL).
- The next four elements are 1, which correspond to the grid power (PG), PV power (PPV), wind power (PW), and battery power (PB) respectively.
- These coefficients indicate that the load power should be equal to the sum of the grid, PV, wind, and battery power.

4.5.2.2 Sub-matrices

The matrix is divided into several sub-matrices, each separated by a vertical bar (|):

- The first sub-matrix (before the first |) contains the coefficients for the load power and the main power sources (grid, PV, wind, and battery).
- The subsequent sub-matrices (between the | symbols) represents constraints between the grid and battery power sources.

(a) The battery power (P_B) column

The use of a -1 coefficient reflects the fact that the battery was being discharged to provide supplemental power during high demand periods, rather than being charged from the grid. This allowed the battery to offset a portion of the peak load requirements to improve the overall efficiency and load balancing of the energy system.

(b) The grid power (P_G) column

The use of a coefficient of 1 reflects the fact that during low demand periods the grid was used to charge the BSS, rather than the battery discharging to meet the load. This allowed the grid power to

supplement the overall electricity supply, ensuring that the battery could be fully recharged and ready to support peak load periods.

(c) *Constraints column (-marked columns)*

These columns represent constraints between the grid and battery power sources, at different ToUs.

The BESS is used during peak demand times to supplement the RER in order to meet the overall electricity load. Meanwhile, the main power grid is utilised during off-peak periods to charge the battery storage.

The vector b_{eq} is given by:

$$b_{eq} = \begin{bmatrix} b_{eq1} \\ b_{eq2} \end{bmatrix} \quad (4.19)$$

such that

$$b_{eq1} = P_L(j) \dots P_L(N_c)]_{N_c}^T \quad (4.20)$$

$$b_{eq2} = 0$$

Equation 4.25 represents the difference between the load power and the sum of the PV, wind, grid, and battery power for each component, which is the right-hand side of the constraint equation represented by the matrix A_{eq} .

Similarly, the inequality constraints can be derived from Equation 4.21:

$$\begin{cases} SoC_{min} \leq SoC(k) \Rightarrow -SoC(k) \leq -SoC_{min} \\ SoC(k) \leq SoC_{max} \end{cases} \quad (4.21)$$

These two inequalities together represent the constraint on the SoC of the battery, which ensures that it remains within the acceptable range defined by SoC_{min} and SoC_{max} .

The solution X must satisfy all sets (15 for the proposed system) of inequalities simultaneously in order to be a feasible solution to the overall system of linear inequalities.

$$N_c \times 12N_c$$

(4.22)

(4.23)

(4.24)

(4.25)

(4.26)

(4.27)

(4.28)

(4.29)

(4.30)

(4.31)

$$0^{11}]_{N_c \times 12 N_c}$$

(4.32)

(4.33)

(4.34)

(4.35)

$$A_{15} = \left[\begin{array}{cccc|cccc|cccc|cccc|cccc} 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 1 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 1 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 1 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \end{array} \right]_{N_c \times 7N_c} \left[\begin{array}{cccc|cccc|cccc|cccc|cccc} 1 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \end{array} \right]_{N_c \times 12N_c} \quad (4.36)$$

A₁ to A₃: These matrices represent the limits on the power output from the PV, wind, grid, and battery respectively. The coefficients in these matrices will depend on the specific power limits for each component.

A₄ to A₇: These matrices represent the SoC constraints for the main battery, to ensure that the battery SoC remains within its acceptable range.

A₈ to A₁₁: These matrices represent the SoC₁ constraints for EV1 battery, to ensure that battery SOC₁ remains within its acceptable range (the battery's SoC must be maintained within the range of 30% to 100%. Additionally, during P2P energy sharing, the depth of discharge should be limited to a maximum of 30%).

A₁₂ to A₁₅: These matrices represent the SoC₂ constraints for EV2 battery, to ensure that battery SOC₂ remains within its acceptable range (the battery's SoC must be maintained within the range of 30% to 100%. Additionally, during P2P energy sharing, the depth of discharge should be limited to a maximum of 30%).

$$b_i = [SoC(0) - SoC_{min} \dots SoC(0) - SoC_{min}]_{1 \times N_c}^T \quad (4.37)$$

This vector represents the difference between the initial battery SoC and the minimum allowed SoC, repeated N_c times. The initial battery SoC must be greater than or equal to the minimum allowed SoC.

The linear inequality in canonical form in Equation 4.13 can then be expressed as:

$$\begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_{15} \end{bmatrix} X \leq \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_{15} \end{bmatrix} \quad (4.38)$$

The control variables have limits that are determined by lower bounds (Lb) and upper bounds (Ub). In a system without PV and wind power, the lower bound for the grid utility is set to zero to prevent the battery power from being sold to the grid. However, when PV and wind power are available, the lower bound is set to negative infinity to allow the excess PV and wind power to be sold to the grid. This condition is implemented in the eMPC algorithm using an if-else loop. The Lb and Ub can therefore be expressed as follows:

$$L_b = [0 \cdots 0_{N_c}, 0 \cdots 0_{N_c}, \dots, 0 \cdots 0_{N_c}]_{1 \times 12N_c}^T \quad (4.39)$$

and

$$U_b = [1000 \cdots 1000_{N_c}, 1000 \cdots 1000_{N_c}, \dots, 1000 \cdots 1000_{N_c}]_{1 \times 12N_c}^T \quad (4.40)$$

4.6 CASE STUDY

The recorded dataset from Uyilo's EVCS at NMU in Gqeberha provided information for the two specific days under scrutiny. The station is equipped with a smart grid facility comprising of PV, ESS (storage through second-life EV battery packs), and V2G capability. The selection focused on the online availability of SAURAN, considering irradiation and ambient temperature. The station's EMS contains comprehensive records of the PV and energy storage data, including days with and without overcast conditions. The analysis revealed that July and September 2020 showed promising results for model validation. The load profile was analysed in Section 3.6.2 and from the typical load in Figure 3.19 the data were graphically represented to suit normal working hours in South Africa, with the exception of a few overtimes factored into Figure 3.12. Resource availability was discussed in Section 3.6.2, which included the climatic conditions and the available resources for the selected days under scrutiny. The parameters presented in Table 3.1 are used in this chapter to analyse the effectiveness of the MPC strategy.

4.7 RESULTS AND DISCUSSION

It is worth noting that the results obtained from the MPC algorithm in this study exhibited a concentration in a single quadrant, which aligned with the specific characteristics of the proposed approach. The direction and quadrant of power flow were influenced by the control strategy and optimisation objective of the MPC algorithm. In this case, the algorithm aimed to minimise grid power consumption and encouraged power flows from the grid to the EVCS during off-peak periods, as dictated by the ToU tariffs in South Africa.

Consequently, all power flows, including those from the grid, RER, and the battery, are concentrated in the quadrant where power is received from the grid. The decision to represent the results in a single quadrant was based on the fact that it aligned with the intended control strategy and fulfilled the operational goals of the system. Even though it is not a popular representation, having power flows concentrated in one quadrant is acceptable and deemed a valid outcome of the MPC optimisation process [197–202].

The energy generation of both the wind and PV is the same as discussed in the previous scenario in Section 3.7.1 and is thus not duplicated in this section. The amount of wind to the BESS has significantly changed since P2P took first priority for satisfying the load. The power stored from the wind is noticeably being stored for longer periods than presented in Section 3.7.1, as is evident in Figure 4.8.

4.7.1 Scenario 1 (uninterrupted power from the grid)

The results depicted in this chapter are for the selected spring day, while the results for the winter day are depicted in the appendix.

The MPC model was analysed in a scenario when there are no power interruptions from the grid. During this period, from 00:00 until 24:00, the grid is available at the EVCS; however, hierarchy-power utilisation still takes effect. Grid power is still subject to utilisation when the energy price is cheaper, as presented in Figure 4.5, and the RER have not generated enough to meet the load requirements. Similarly, the CBB only charges during off-peak hours as a measure to save grid costs. The excess power generated from the RER is sold back to the electrical grid once the BESS is fully charged. This transfer of the surplus renewable power from the charged battery to the grid is

represented by the turquoise colour coding in Figure 4.5, which is consistent with the depiction in Figure 4.6, which is explained in detail towards the end of Scenario 1 in this section.

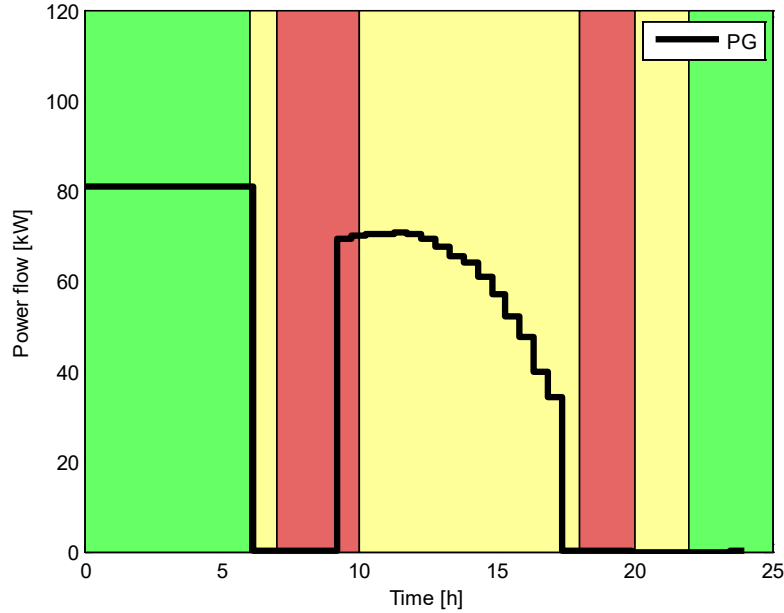


Figure 4.5: Grid power from the MPC: Simulated results for the selected spring day

4.7.1.1 Analysis of the power flow during off-peak ToU intervals (00:00 to 06:00)

During the first off-peak ToU period, which takes place between 00:00 and 06:00, the tariff structures are at their lowest. This is the time that is more suitable for the battery to be charged by the utility grid and to be stored for later usage when the grid is under pressure or at a higher tariff structure to maintain lower energy costs and profitability at the EVCS. Since the charging activities have not yet been initiated at the station, the wind power, whose availability is not time dependent like the PV power, is also stored in the battery in conjunction with grid power, as shown in Figures 4.6 to 4.8.

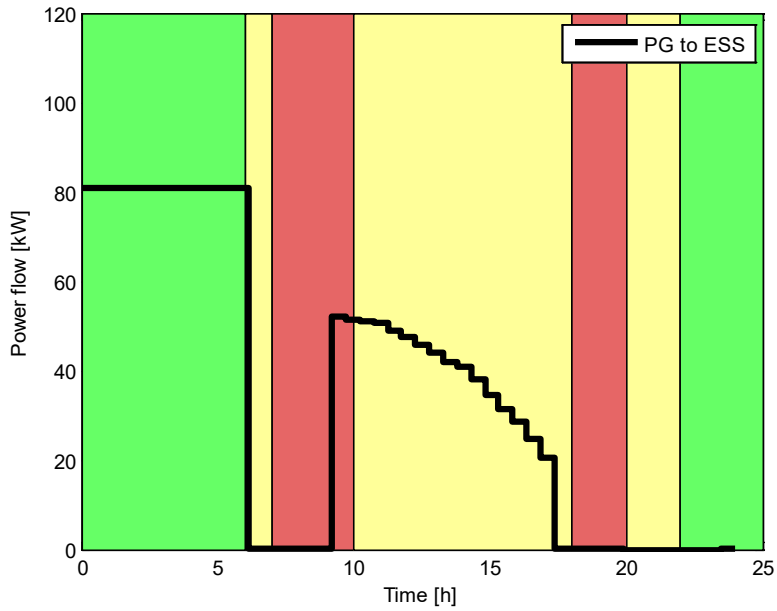


Figure 4.6: Power supplied by the grid to battery storage from the MPC: Simulated results for the selected spring day

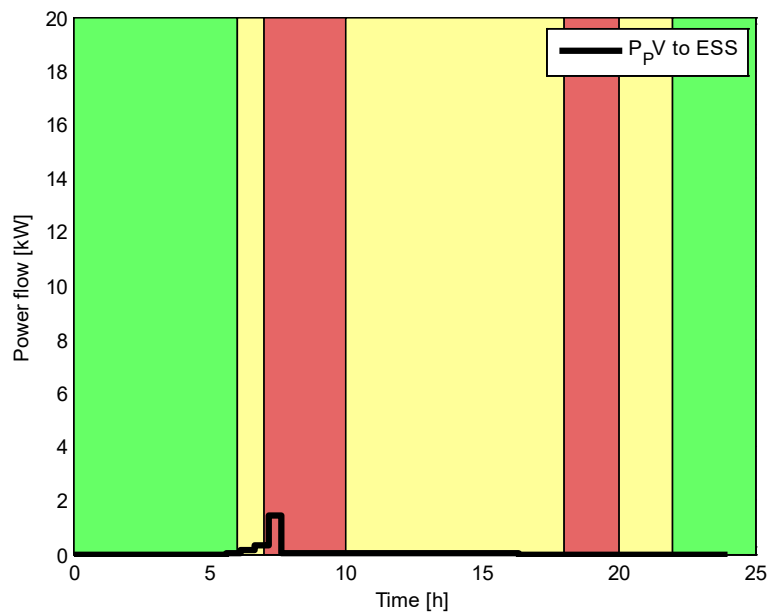


Figure 4.7: PV power to battery storage from the MPC: Simulated results for the selected spring day

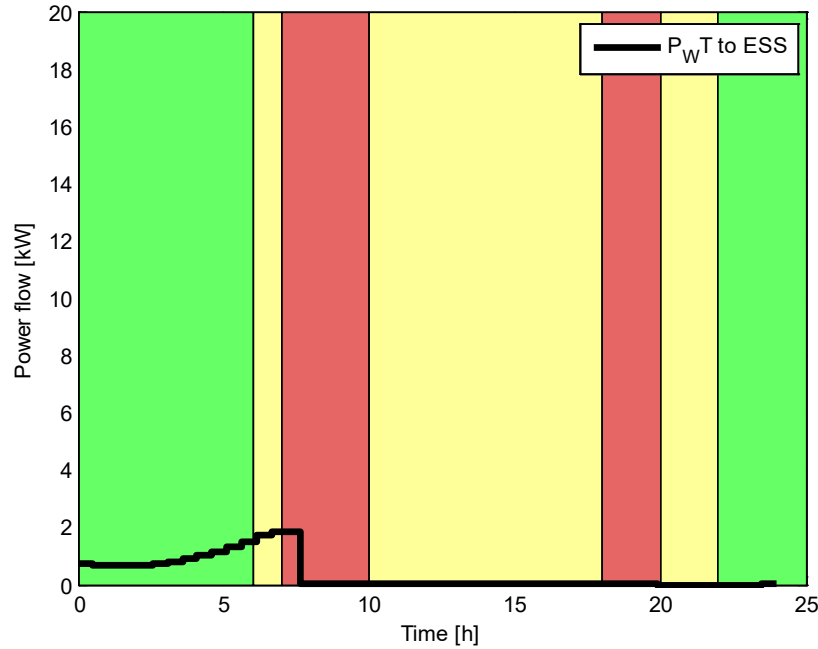


Figure 4.8: Wind power to battery storage from the MPC: Simulated results for the selected spring day

4.7.1.2 Analysis of the power flow during standard ToU intervals (06:00 to 07:00)

The period from 06:00 to 07:00 is the first standard time of the day, whereby the storage is still supplied by the grid, since the costs are still reasonable at this time as compared to the peak tariff structure. Wind power is still exhibiting satisfactory generation capabilities, which yields more storage power during this period due to the absence of the load as a result of no charging activity at the EVCS during that period. The boundaries that have been set ensure that grid utilisation for battery charging is eliminated. It is important to note that the utilisation of standard tariffs is reserved for emergencies, and it is only used to charge EVs when the solar PV and wind systems are generating enough energy to satisfy the demand. It is worth mentioning that during this period, the energy generated by the wind system may start to depreciate as the temperature rises, which results in a decrease in humidity. These factors can impact the wind system's efficiency and output, which can potentially affect the amount of power available for battery charging. By considering these factors and utilising the available wind power during this time, the EVCS optimises the use of RER and ensures that the battery is charged efficiently.

4.7.1.3 Analysis of the power flow during peak ToU intervals (07:00 to 10:00)

During the first peak period of the day, the solar PV system begins its production and starts to generate its minimal capacity of power, with an increase in production every hour due to the peak in resource availability. This indicates that the solar panels are operating efficiently and contributing significantly to the overall electricity supply. On the other hand, the wind system experiences a decrease in production during this time. Despite the decline in wind power generation, renewable energies, together with battery storage, are still utilised as the primary source of power to meet the load requirements of the EVCS. The grid utilisation is disabled due to the higher electricity prices structured during the peak period. The higher electricity prices during the peak period can act as a deterrent for relying solely on grid power. As a result, the charging station aims to minimise its reliance on grid electricity and to optimise the utilisation of RES, such as the PV and wind. During this time, the power transferred from the battery to the load (referred to as P₆) remains at zero. This is because the SoC of the battery has not yet sufficiently recovered to a level where it can actively supply power to the load, as shown in Figure 3.21. The prioritisation of power sources and the avoidance of grid usage during this period align with the goal of maximising the utilisation of RER while minimising costs associated with grid electricity. By optimising the utilisation of wind and solar power, the EVCS aims to maintain a reliable power supply and to ensure that the battery's SoC is gradually restored for future use. At this stage, the storage capacity is getting a little power from the PV system, which persists until the start of the next ToU, as indicated by Figure 4.7.

4.7.1.4 Analysis of the power flow during standard ToU intervals (10:00 to 18:00)

During the second occurrence of the standard period, the EVCS utilises a mix of power generation to cater for the load requirements. The grid utilisation drastically increases since the cost associated with the standard tariffs is not as steep as for the previous condition of peak. The PV power peaks production and is used in conjunction with the grid. Cost reductions are still applicable. As the day progresses, the wind resource picks up and results in the reduction of grid utilisation.

Midday precipitation from 12:30 to 13:30 brings about a decrease in PV energy generation, while the wind system begins to pick up energy generation from 13:00, with a gradual increase every 30 minutes. During this time, a hierarchy-charging strategy is implemented at the station. This strategy

primarily involves utilising RER ($P_2 + P_3$), BESS (P_6), and EV prosumers (P_7 and P_8) to meet the load demand. The grid utilisation is reduced while the storage system in conjunction with the renewable energy resource satisfies the load, as depicted in Figure 4.9. In both Figure 4.9 and Figure 3.28, it is evident that the resources at the charging station are modelled to meet the load requirement, but there is a significant difference in the utilization of the grid between the two figures. While the amount supplied to the load remains the same regardless, the grid utilization is notably reduced compared to Figures 3.25 and 4.6. This observation clearly demonstrates the effectiveness of the MPC strategy when the model is exposed to an equivalent duration of power outage, as depicted in Figures 3.37 and 4.15, respectively.

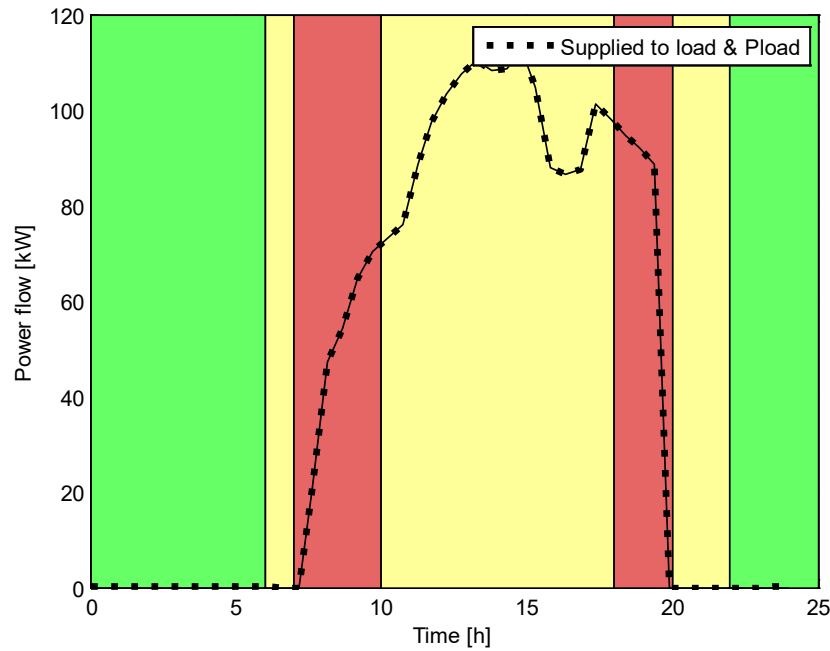


Figure 4.9: Load supplied by all the resources from the MPC: Simulated results for the selected spring day

4.7.1.5 Analysis of the power flow during peak ToU intervals (18:00 to 20:00)

During the ultimate peak period of the day, the PV system reaches its maximum generation capacity as the sun approaches its setting phase. This places significant demand on the grid, the wind system (P_3), BESS (P_6), and EV prosumers (P_7 and P_8), who become the primary suppliers of power for the remaining duration while still meeting the load requirements. Despite this, priority is maintained

for the primary resources. The battery continues to discharge, supplying power to the load, as illustrated in Figures 4.10 (BESS) and 4.11 (battery SoC).

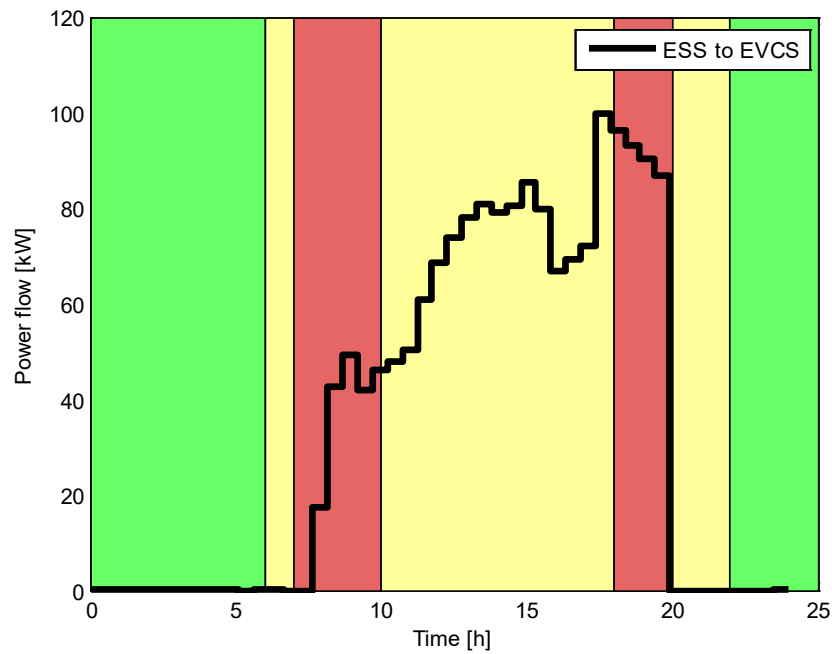


Figure 4.10: Power supplied by the battery storage to the EVCS from the MPC: Simulated results for the selected spring day

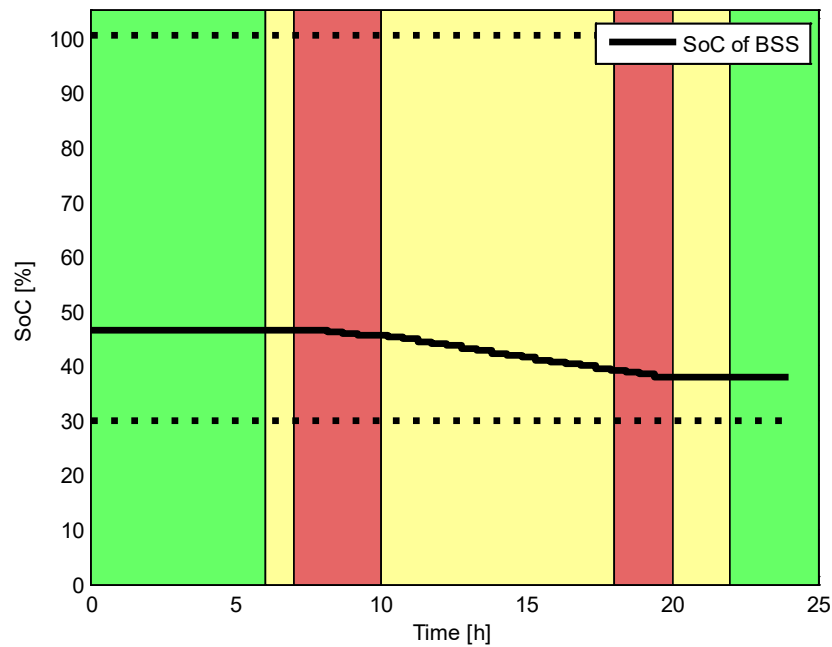


Figure 4.11: Battery storage from the MPC: Simulated results for the selected spring day

4.7.1.6 Analysis of the power flow during standard ToU intervals (20:00 to 22:00)

During the final standard period of the day, the grid ceases to supply energy to the EVCS due to the absence of load or further charging activity. Instead, the surplus wind power generated is redirected to charge the ESS at the station. This efficient utilisation of wind energy ensures that the excess power is effectively stored for future use. The ESS plays a pivotal role in storing renewable energy, enabling its deployment when primary sources like the wind system are insufficient or when demand surpasses immediate supply. By charging the ESS with wind power and bolstering its SoC, the EVCS optimises the utilisation of RER and prepares for potential future demands or unforeseen events. Notably, no additional charging activities are documented beyond this juncture, which indicates the completion of daily charging operations at the station.

4.7.1.7 Analysis of the power flow during standard ToU intervals (22:00 to 24:00)

As the day progresses into its final standard period, a notable shift occurs at the EVCS: the grid energy, previously supplying power, ceases to do so. This transition is spurred by the absence of any load presence or further charging activity beyond this point. Instead, a strategic redirection of resources takes place, where the surplus wind power generated steps in to fulfil the role of energising the charging station. Specifically, this surplus wind energy is harnessed to charge the ESS stationed at the facility.

This decision to channel wind power towards charging the ESS is testament to the MPC model's commitment to sustainability and resource optimisation. By effectively storing the excess wind energy in the ESS, the EVCS ensures the preservation and utilisation of RER for future needs. The ESS acts as a crucial reservoir by safeguarding renewable energy for times when primary power sources, such as the wind system, may face limitations or when demand surpasses immediate supply capacity. Furthermore, the absence of further charging activity after this transition signifies the completion of daily charging operations at the station. This observation underscores the station's adherence to a structured charging schedule, which ensures optimal resource utilisation while aligning with broader energy management objectives, as depicted by Figure 4.12.

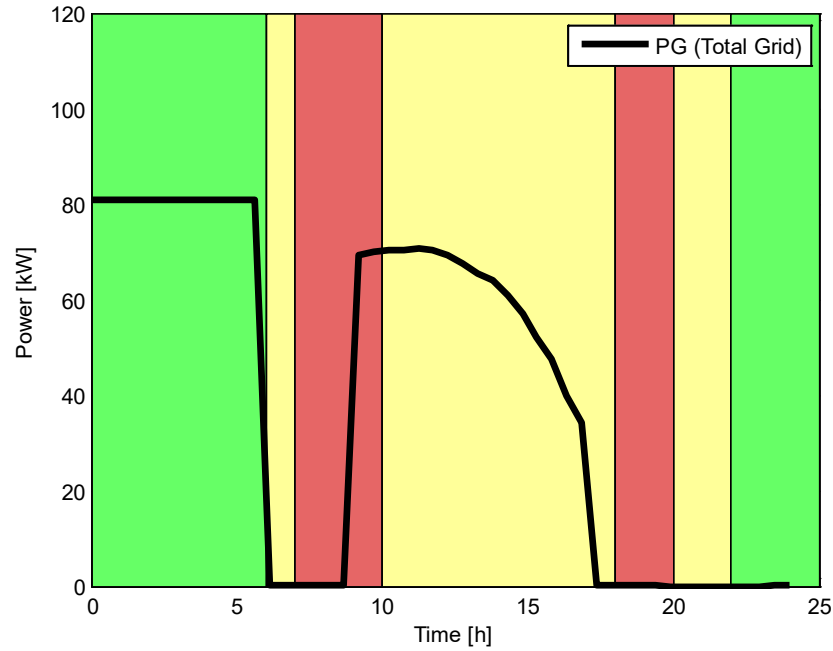


Figure 4.12: Total power supplied by the grid from the MPC: Simulated results for the selected spring day

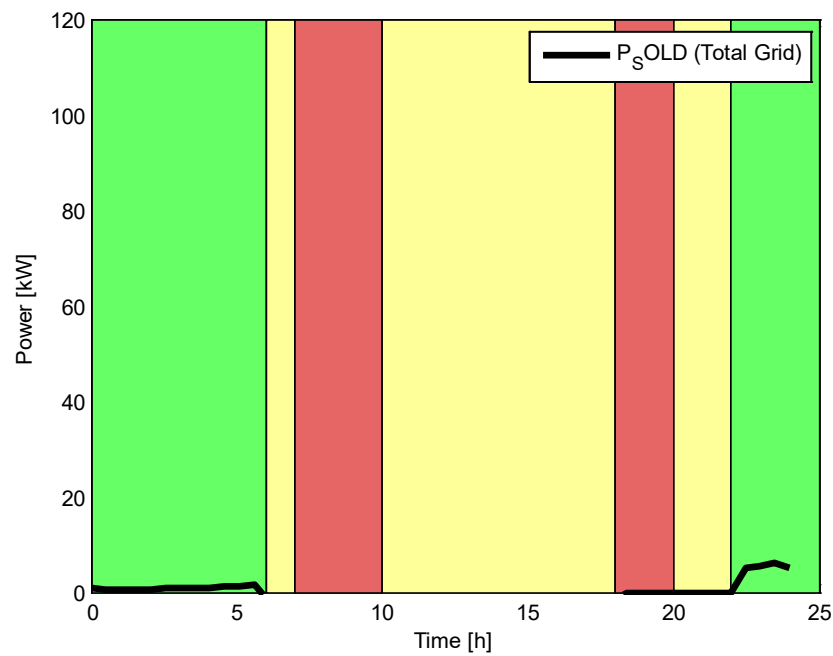


Figure 4.13: Total power sold to the grid from the MPC: Simulated results for the selected spring day

The total power sold to the grid, as depicted in Figure 4.13, represents the cumulative amount of surplus energy that has been supplied by the fully charged BESS back to the main electricity grid during this period of inactivity or low demand at the local station or facility. This flow of excess power from the battery to the grid showcases the potential for the integrated BESS to actively contribute to and support the broader power grid. By enabling this two-way exchange of energy, the system can participate in energy trading and load-balancing activities, which will help to ensure optimal utilisation of the available RER. Furthermore, this capability fosters the development of a more sustainable and efficient energy ecosystem. Instead of renewable energy generation being wasted or underutilised during periods of low local demand, the battery storage allows that excess clean power to be captured and channelled back into the grid. This improves the overall integration of variable renewable sources and enhances the resilience and reliability of the entire power system.

4.7.2 Scenario 1 (power outages / load shedding)

The scenario below speaks to the highest stage of load shedding that could be imposed on customers at the EVCS. During this period, as indicated by Figure 4.14, the supply from the grid is zero, and the load requirements are left to the RER and the battery storage to supplement. As a result, the energy supplied by the renewable energies is not sufficient to meet the load demand and the storage is unable to charge up during off-peak hours since this scenario is imposed for a full day, as depicted by Figure 4.15. With the absence of the storage component and grid during this period, other options are necessary to ensure stability at the station. The P2P energy-sharing option is promoted at the station under dynamic pricing as a tool to combat charging inadequacies. To ensure profitability and just services at the station, several constraints were imposed on the system as a means to maintain the battery's state of health for prosumers and to ensure fair trade prices. Prosumers are allowed to trade only if they meet predefined constraints such as SoC limits, energy exchange limit, and compliance with the station's regulations.

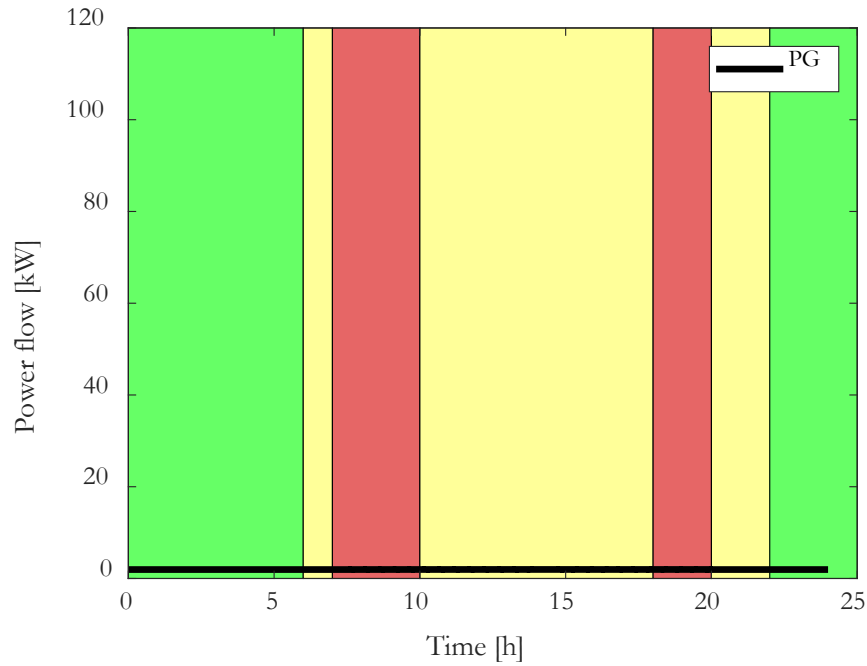


Figure 4.14: Simulated results of the MPC grid power during load shedding for the chosen spring day

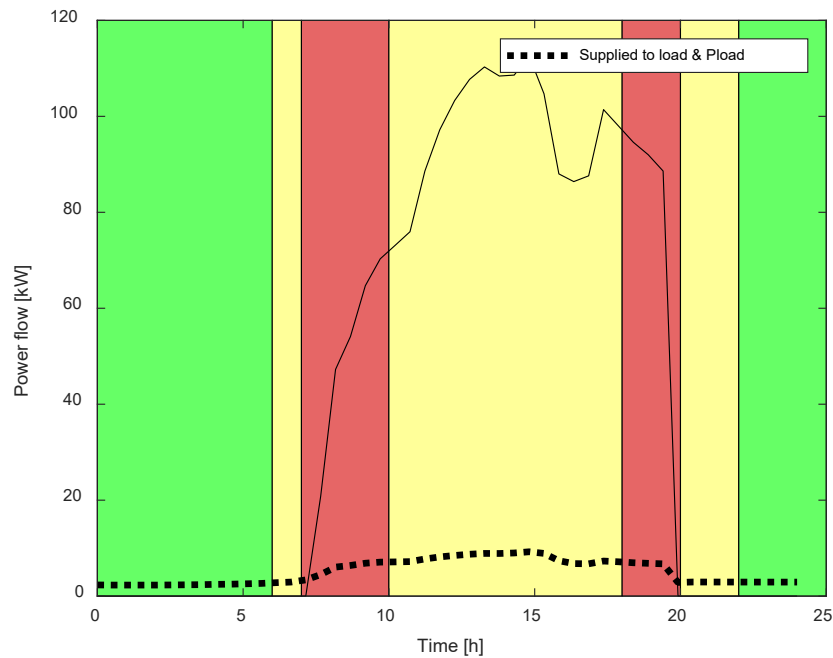


Figure 4.15: Simulated results of the MPC power supplied to the load during load shedding for the chosen spring day

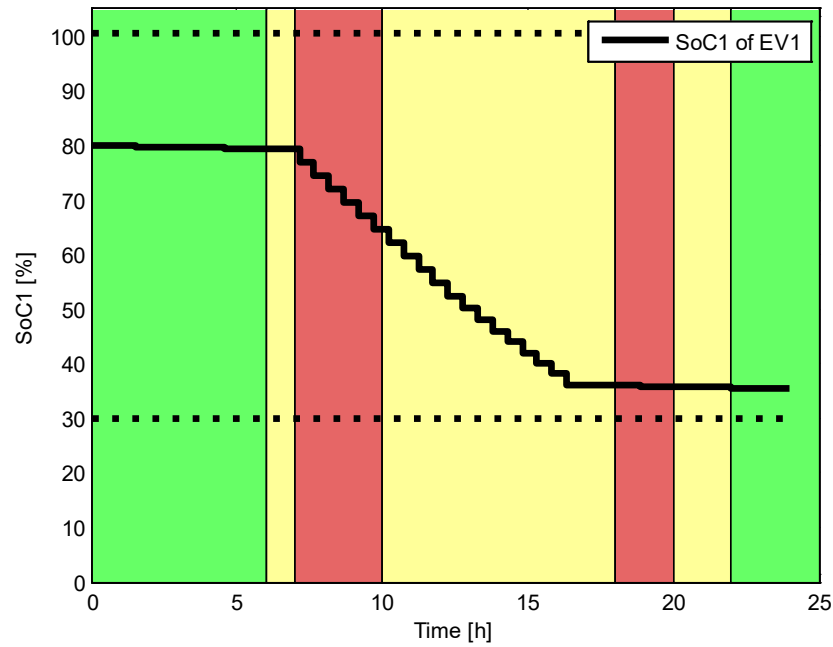


Figure 4.16: Simulated results of the MPC P2P sharing to supplement the load during load shedding for the chosen spring day (seller's battery SoC)

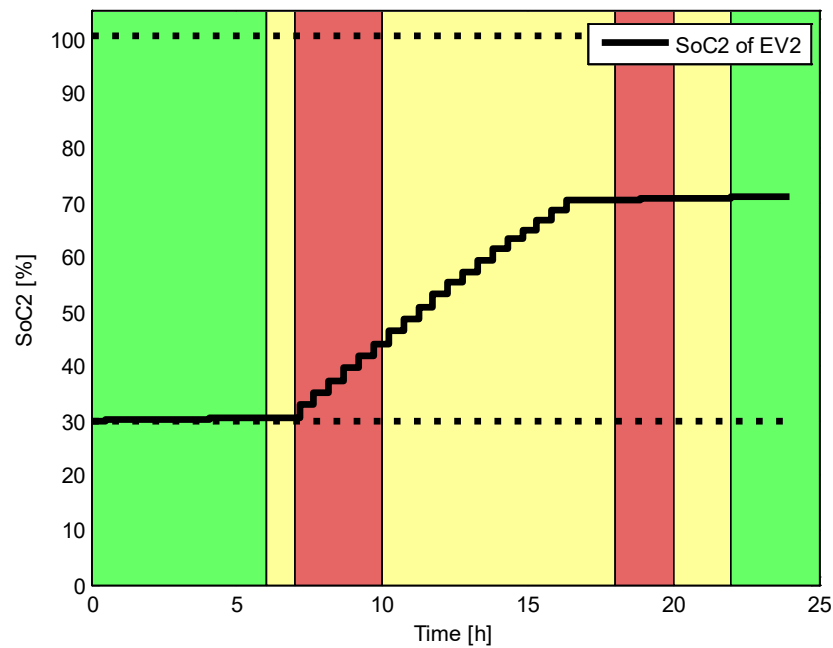


Figure 4.17: Simulated results of the MPC P2P sharing to supplement the load during load shedding for the chosen spring day (buyer's battery SoC)

Prosumers are allowed to trade up to 70% of their power subject to the condition that their battery SoC does not discharge to below 30%. The regulations of the EVCS should be met, keeping in mind that the station facilitates this trades at a reasonable fee since it is a business entity. The trade among prosumers was depicted by Figure 4.16 and 4.17 respectively.

4.7.3 Economics analysis of the system

4.7.3.1 Lifecycle cost analysis

The profitability aspect of the EVCS is quite important in this study as it speaks to the investment aspect of the case study. For any project the ROI is always a factor that needs to be achieved within measurable time frames, which is why the lifecycle cost analysis is employed in this section to address the ROI factor. The lifecycle cost analysis was utilised in this study to reduce the net energy cost through the effective management of the power flow between the grid, ESS, and RES such as PV and wind.

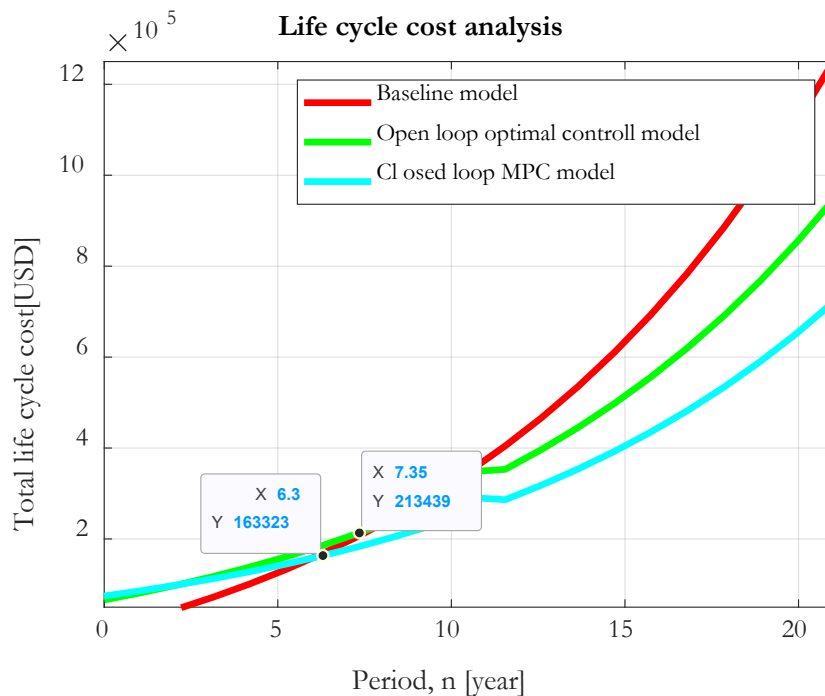


Figure 4.18: Breakeven point analysis between the baseline, open-loop optimal control, and closed-loop MPC optimal-control models

The economic analysis conducted for the worst-case scenario day aimed to compare the potential energy savings with the baseline system, open-loop optimal control, and the closed-loop MPC optimal control. This analysis involved evaluating the cumulative energy costs of each system listed above. Figure 4.18 illustrates the cumulative costs of the three systems and depicts how they evolve from the start of the day at 00:00 to the end at 24:00. The graph demonstrates a noticeable divergence in cumulative costs between the three systems, with MPC optimal control exhibiting the highest cost savings as compared to the optimally controlled system and the baseline system.

The MPC optimal control further increases savings at the EVCS due to its future prediction capability and its ability to use constraints and constant checking to eliminate disturbances that could deter the optimisation of the system. These findings provide valuable insight into the potential financial advantages of implementing the proposed system compared to the baseline system. The boundaries imposed on the systems enabled the MPC optimisation to use a future horizon to anticipate disturbances and implement measures to address them for the next horizon's prediction. For a clear depiction of the cost saving, the annual operating cost of each model was analysed for both the open-loop and closed-loop model to assess the potential savings.

The lifecycle cost analysis was then assessed for both models. It can be observed that the MPC model further increased the savings by 18.04% on top of the already established savings achieved with the open-loop optimal control. The reduction in cost is due to the reduced number of years brought about by the closed-loop MPC optimal control, as can be seen in Figure 4.18. This indicates the impact of having an MPC controller and the added advantages associated with its future prediction and ability to assess and address disturbances foreseen by the presiding horizon formulation of this tool. The breakeven point was improved through the enhancement of the control. With open-loop control, the breakeven point was 8.3 years, which was reduced to 6.3 years with the employment of closed-loop MPC.

Table 4.1 provides information on the initial implementation cost of the hybrid PV and wind system with battery backup and EMS, as well as the inverter for a smart grid-tied hybrid EVCS.

The components included in the cost estimation were as follows:

Table 4.1: Investment costs of a closed-loop system

Components	Costs
PV system	US\$9 625.82
Wind system	US\$4 281.48
Hybrid inverter	US\$5 935.25
LifePO4 battery bank	US\$37 409.28
EMS	US\$8 657.00
Total	US\$65 898.83

Table 4.2 displays the results of the baseline, open-loop with optimal control, as well as the closed-loop MPC optimal control. From these two tables a clear analysis can be achieved, as discussed above. The cost was compared to the baseline for both the optimal control from Chapter 3 and the MPC control in this chapter.

Table 4.2: Total energy costs comparison between the baseline, open-loop, and closed-loop systems

Model	Costs
Baseline	US\$1 250 231.91
Proposed model with optimal control	US\$934 493.68
Proposed model with MPC control	US\$709 053.74
Savings (proposed model with optimal control)	US\$315 738.23
Savings (proposed model with MPC optimal control)	US\$541 557.17

4.8 CONCLUSION

This chapter developed a closed-loop optimal MPC control for a hybrid smart grid EVCS. The open-loop system and the MPC closed-loop control were simulated and compared to evaluate the cost savings under the Eskom tariff structure and demand side. The simulated model of the EVCS in a closed-loop environment consisted of PV-wind and a battery backup system with P2P-sharing strategies, which were subjected to constraints between the controllable variables under Eskom's ToU tariff structure. In the formulated optimisation problem, the control variables were the grid power and the battery backup power. The variables under scrutiny between the open- and closed-loop system differed due to the complexity and dynamics of the two systems since the open-loop system

is simpler in structure and variables. The robustness and adaptability of the closed-loop system also played a role in these differences, as the open-loop system lacked adaptability and robustness as it does not incorporate feedback, and has multiple control objectives and constraints.

The RER in the proposed model were not seen as decision variables due to their imminent nature. The decision variables were left to the discretion of the grid and battery backup respectively. The proper implementation of the model grid cost, as well as the reduction of battery utilisation during off-peak periods, improved the energy efficiency and maximised the profits of the EVCS through selling surplus energy from the PV and wind sources to the grid and charging with the RER during peak hours. During the peak price tariff, RES' power is prioritised to cover the load demand. The simulations demonstrated that the proposed MPC strategy presents superior performance in terms of operational and energy efficiency while considering the constraint tied between the grid utility and the battery storage cost.

The MPC also considered the constraints related to the battery SoC and presented advantages of robustly dealing with uncertainties and disturbances, which were handled before the next control period, and the control variables were corrected accordingly for the next period by applying the receding horizon. Furthermore, the suitable range of the weighting factor was determined in order to significantly lower the operation cost of the grid-PV-wind with battery bank and P2P charging connected systems. It was observed that the BESS played a crucial role in supplementing the renewable energy system during a blackout or to address power quality problems from the grid utility. The simulation findings revealed that employing MPC control outperformed the open-loop system by minimising energy costs. A comprehensive lifecycle cost analysis suggests that the project would break even in 6.3 years, with projected savings of US\$529 557.17 over a 20-year span. A 42.37% decrease in costs from the initial savings of 25.25% from the optimised control of an open-loop model is also seen, which translates to an added 18.04%, as well as reaching the breakeven point two years earlier than with the optimal control of an open-loop model. These results underscore the economic viability of the proposed system and its capacity for substantial savings.

CHAPTER V: CONCLUSION

5.1 SUMMARY AND CONCLUSION

To foster sustainability, reliability, and profitability at EVCSs and the widespread adoption of EVs in South Africa, a number of tailored solutions should be considered to lower the grid cost and offer uninterrupted power supply at EVCSs irrespective of climatic, imposed, or unintended conditions such as load shedding / power cuts / power failure. This tailored solution includes, but is not limited to, the introduction of an EMS, optimal-control strategies, the inclusion of more energy mixes, and incentive-based charging for prosumers. The implementation of an EMS and AI-based controllers was prioritised in this study to reach the set goals. Two models were developed to address the challenges highlighted in Section 1.3. The aim of the work was to develop an optimal power dispatch scheme of an EVCS microgrid comprising PV-wind-grid-integrated energy with a CBB and P2P EV charging strategies. The aim of the models was to optimise the system for reliability and profitability while minimising operational costs. By considering factors such as energy demand, grid stability, battery health, and charging costs, the models aimed to find the most efficient utilisation of resources. To demonstrate the practicality of the system, NMU's EVCS was used as a base model. The study conducted a comprehensive techno-economic evaluation of the EVCS across two decades. It scrutinised the economic feasibility and advantages of the proposed models. Compared to a conventional baseline model lacking wind and P2P-sharing strategies for fulfilling the same energy requirements, the findings showed significant grid and energy storage cost savings for the EVCS, which underscored the financial benefits of the optimisation strategy. The proposed system achieved notable reductions in energy demand costs of 38.14% by taking advantage of ToU tariffs. Furthermore, through optimal control, it managed to lower peak demand, achieving cost savings of 30.5%. A lifecycle cost analysis indicated that the project would reach its breakeven point within eight years, with expected savings of US\$333 355.81 over the 20-year lifespan of the project, which translates to a 30.464% decrease in costs.

Chapter IV presented MPC optimisation of a hybrid smart grid with PV-wind and a CBB incorporating demand-side management, a P2P charging scheme, as well as EVCS profitability. The objective of this model was to enhance the first model's open-loop optimal-control strategy by

lowering operational costs. This was achieved through minimising the charges associated with peak demand from the grid, while also considering the constraints imposed by the tariff structure. The model skilfully managed the charging and discharging of the BESS, as well as the power distribution from the grid, to ensure that these operations remained within viable limits. It focused on maximising the satisfaction of EV users by meeting all the EVCS's requirements and providing a cost-effective charging solution, including a P2P energy-sharing scheme. This optimal power scheduling was framed as a control problem to leverage the benefits of feedback and predictive capabilities. The MPC framework was linearised to efficiently handle two distinct scenarios: one considering the presence of power cuts and the other assuming uninterrupted power supply.

5.2 SUGGESTIONS FOR FURTHER RESEARCH

For further research, the following aspects can be considered:

5.2.1 Globally

The lack of research availability on a mix of grid integration, smart charging, energy storage integration, prosumer aspects, and dynamic pricing while mitigating cyber threats and the security of prosumers should be further investigated.

Existing research tends to focus on individual aspects or combinations of two or three elements related to EV charging infrastructure. A comprehensive approach is essential for a holistic understanding and effective implementation of advanced charging systems as a sustainable business model.

5.2.2 Locally

The consideration of load spectrum and its impact on the utility grid is lacking in most of the charging infrastructure in the country, especially in grid-based locations such as car dealerships and malls. The few EVCSs that have integrated renewable energies, such as those found in research facilities (either universities or state-owned entities) or companies promoting green solutions, often prioritise research or environmental goals over profitability.

A comprehensive approach that involves various stakeholders, including government bodies, utility companies, and charging infrastructure providers, to collaborate and develop guidelines or

standards that ensure the consideration of load spectrum in the planning and implementation of EV charging infrastructure, can be explored.

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APPENDIX

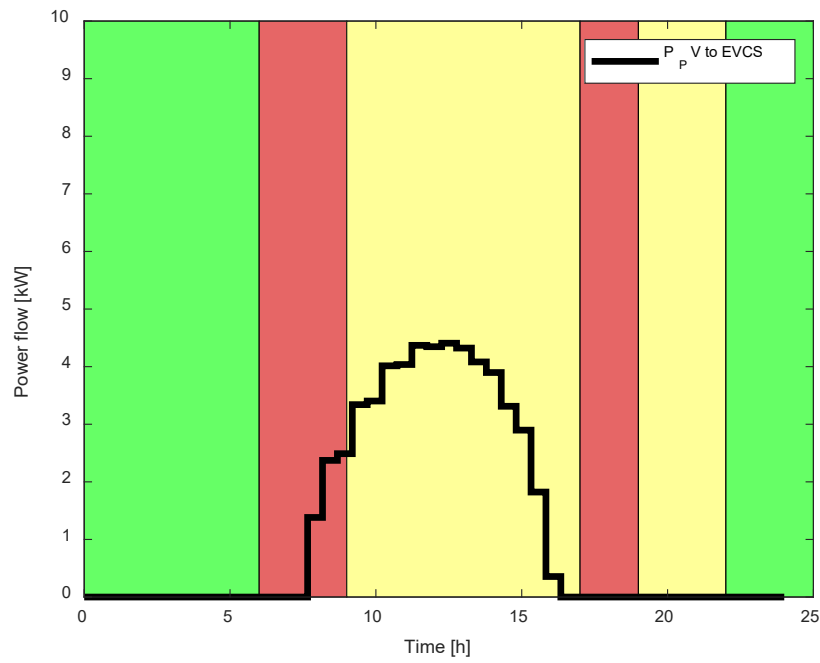


Figure A1: PV energy generation: Simulated results for the selected winter day

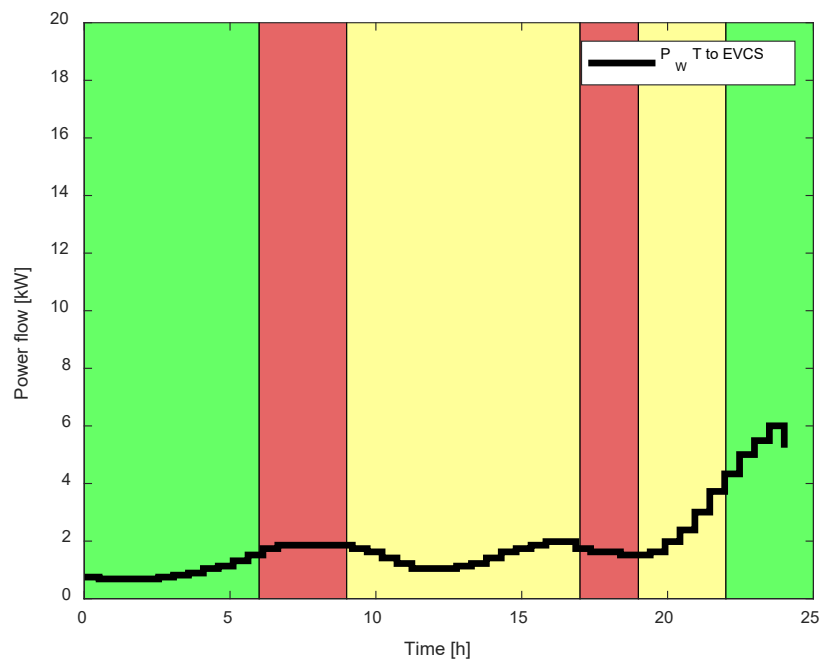


Figure A2: Wind energy generation: Simulated results for the selected winter day

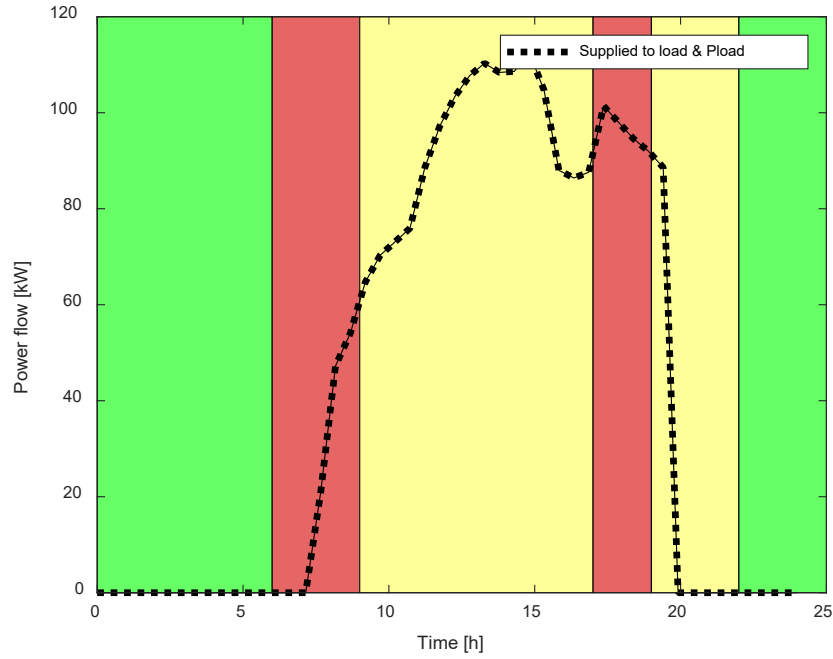


Figure A3: Power supplied to the load from all the resources at the station for the selected winter day

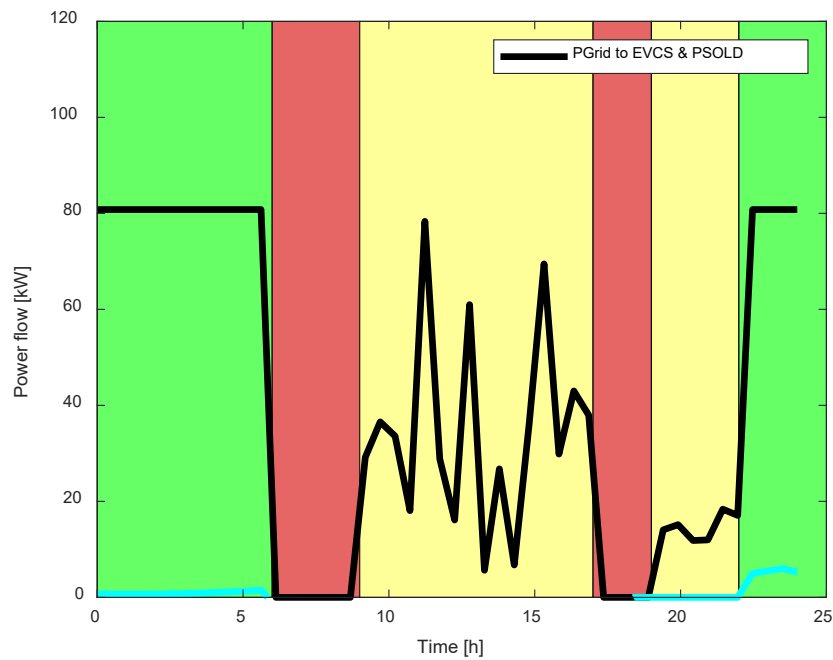


Figure A4: Grid power subjected to the proposed constraints: Simulated results for the selected winter day

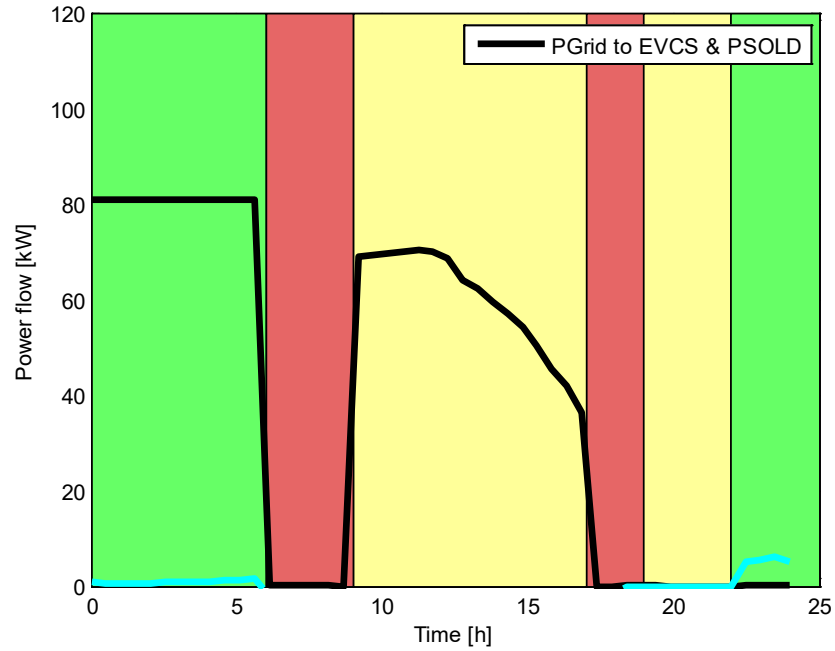


Figure A5: Grid power: MPC simulated results for the selected winter day

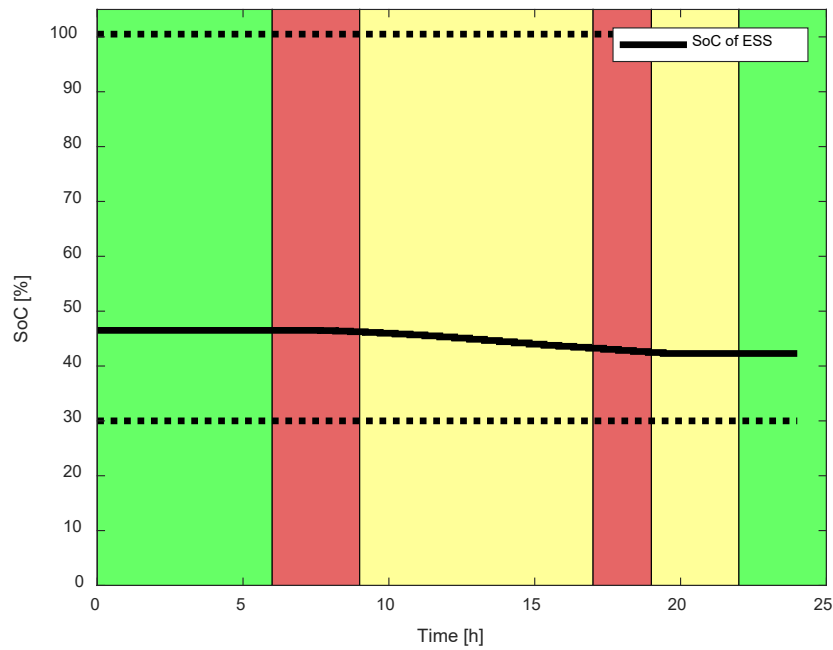


Figure A6: SoC for energy storage: Simulated results for the selected winter day

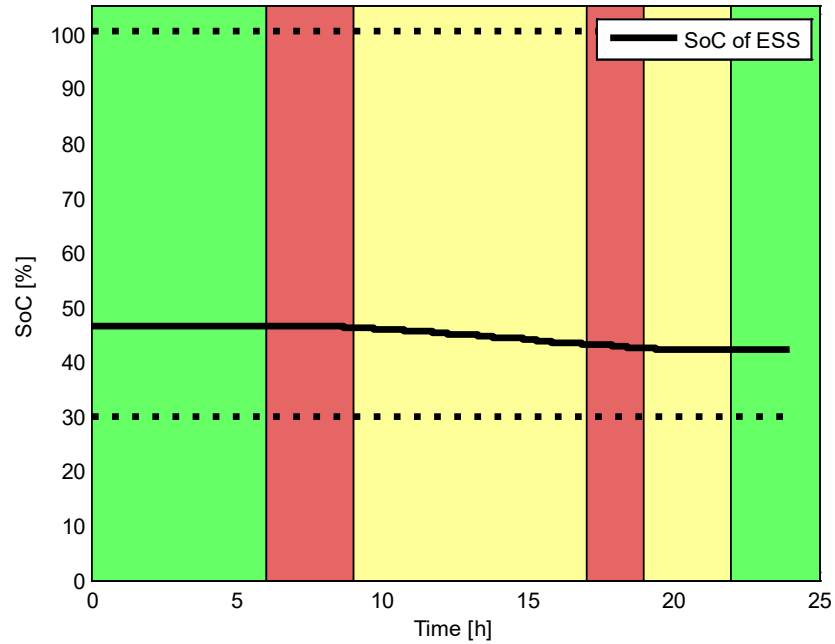


Figure A7: Battery storage: MPC simulated results for the selected winter day

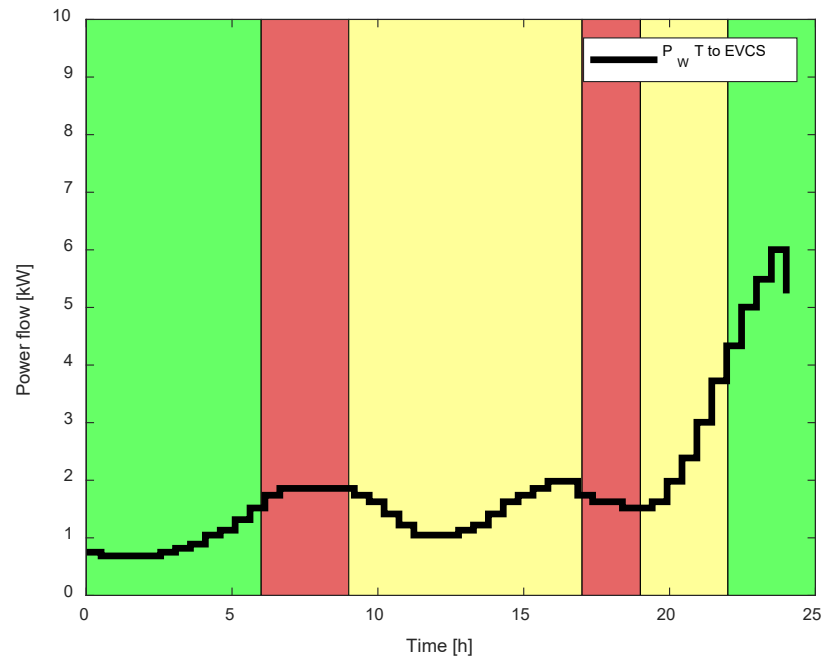


Figure A8: Wind power to the EVCS: Simulated results for the selected winter day

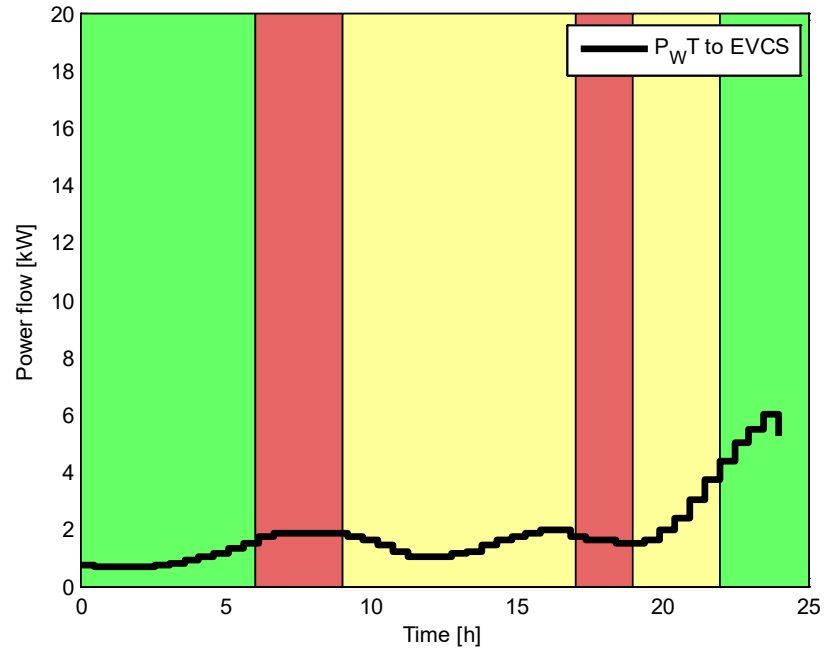


Figure A9: Wind power to EVCS: MPC simulated results for the selected winter day

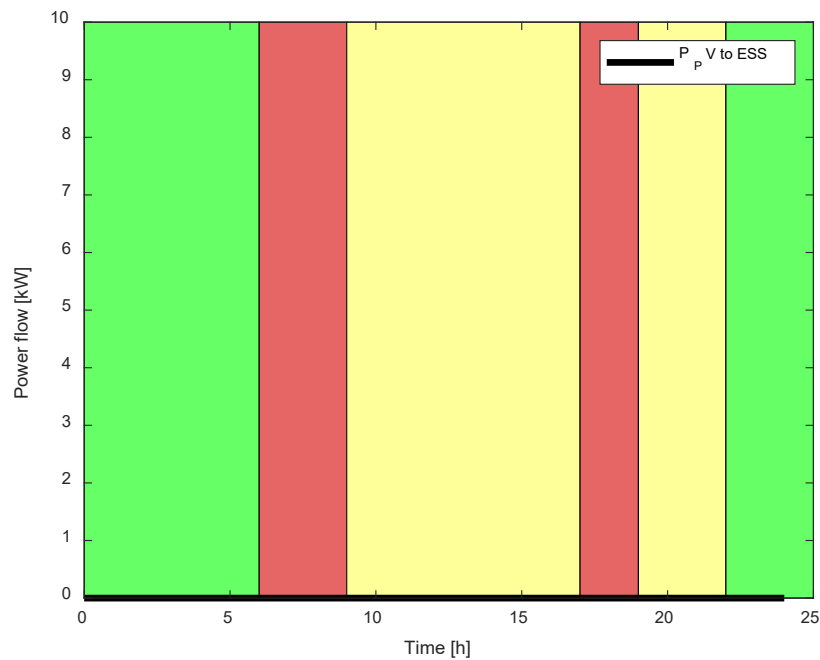


Figure A10: PV power to the ESS: Simulated results for the selected winter day

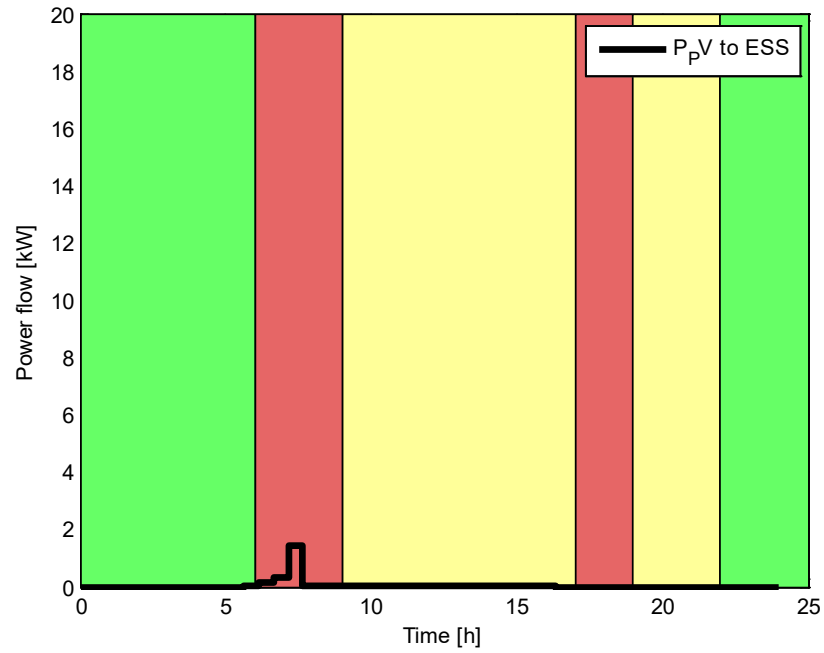


Figure A11: PV power to the ESS: MPC simulated results for the selected winter day

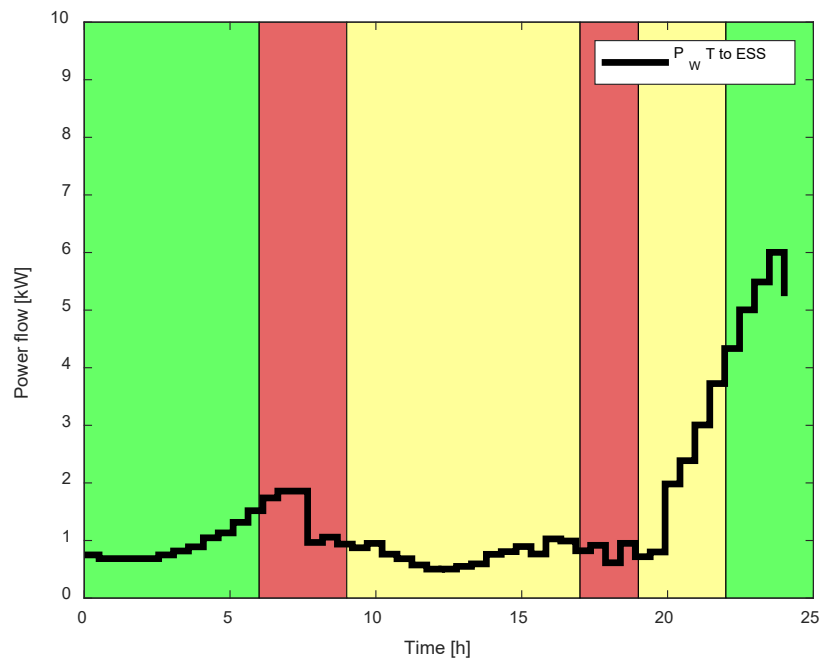


Figure A12: Wind power to the ESS: Simulated results for the selected winter day

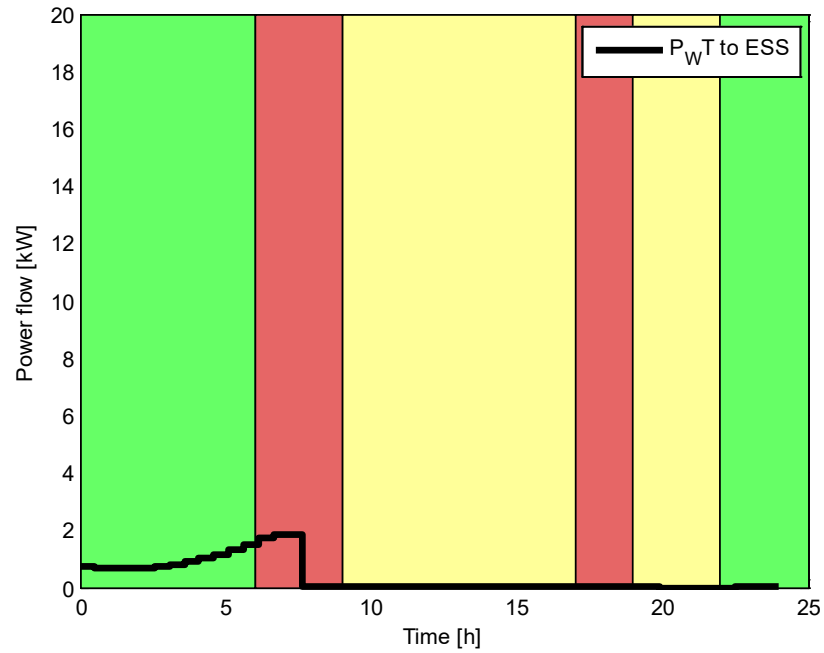


Figure A13: Wind power to the ESS: MPC simulated results for the selected winter day

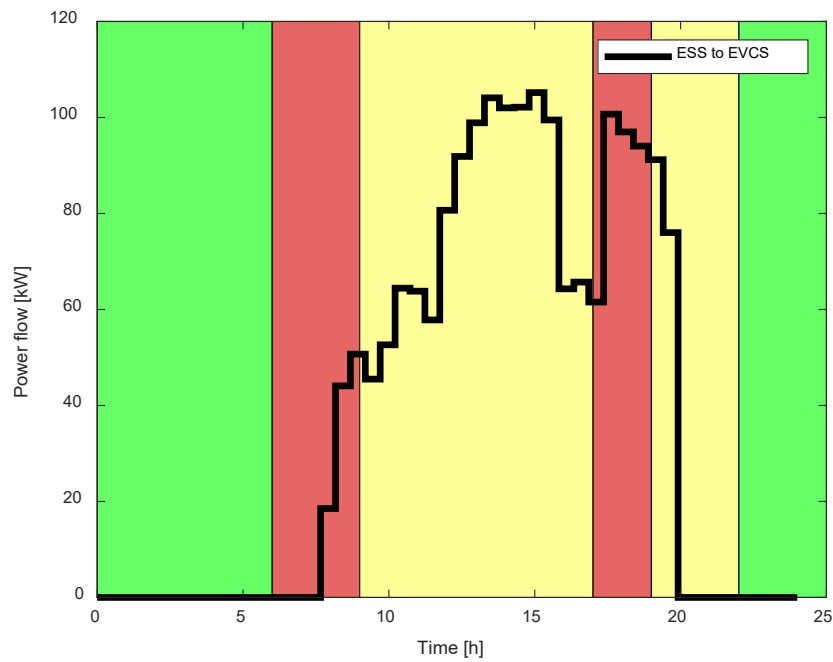


Figure A14: Power supplied by the battery storage to the EVCS: Simulated results for the selected winter day

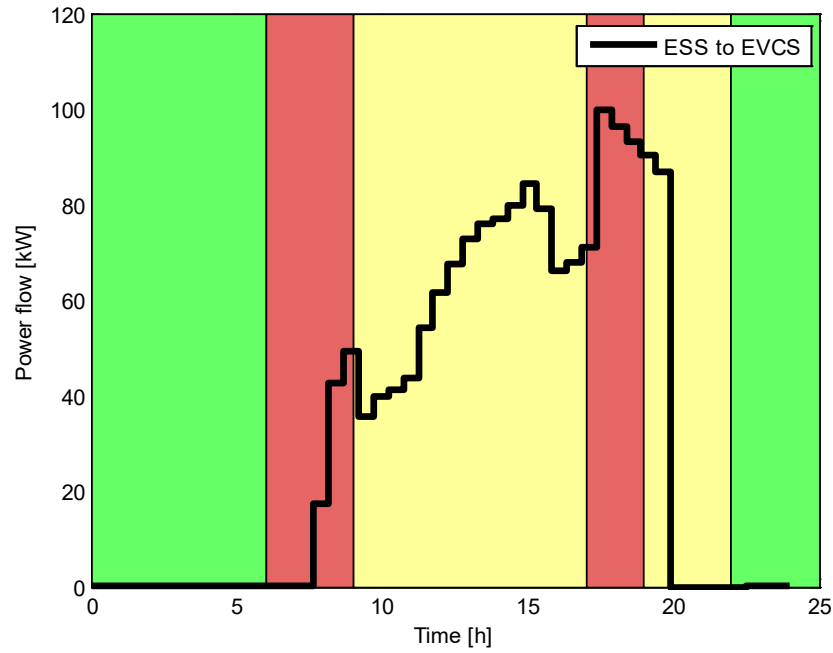


Figure A15: Power supplied by the battery storage to the EVCS: MPC simulated results for the selected winter day

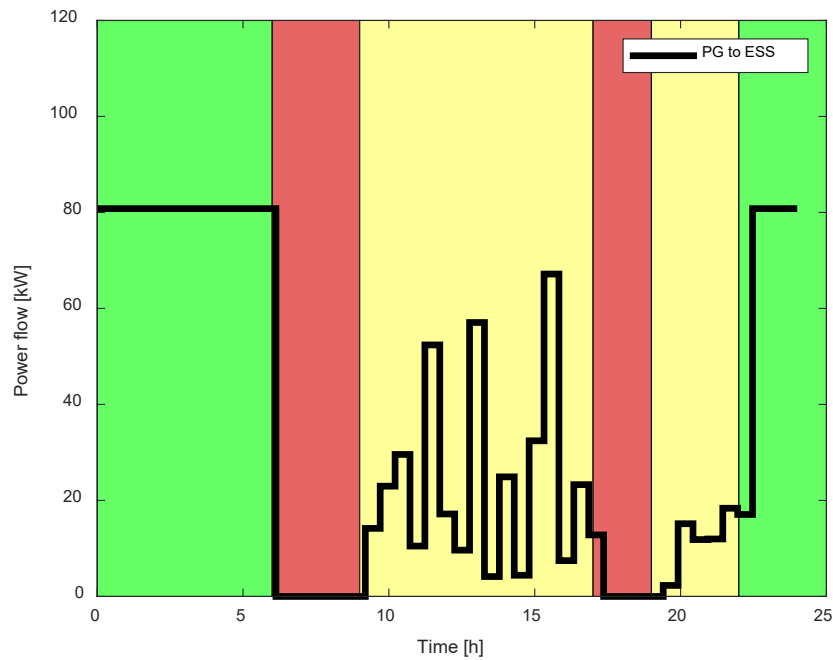


Figure A16: Power supplied by the battery storage to the EVCS: Simulated results for the selected winter day

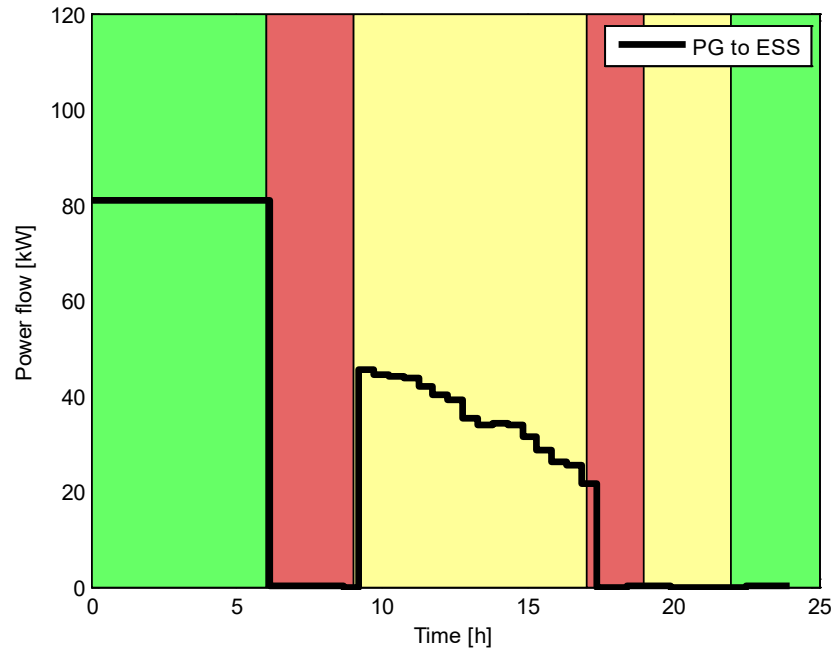


Figure A17: Power supplied by the battery storage to the EVCS: MPC simulated results for the selected winter day

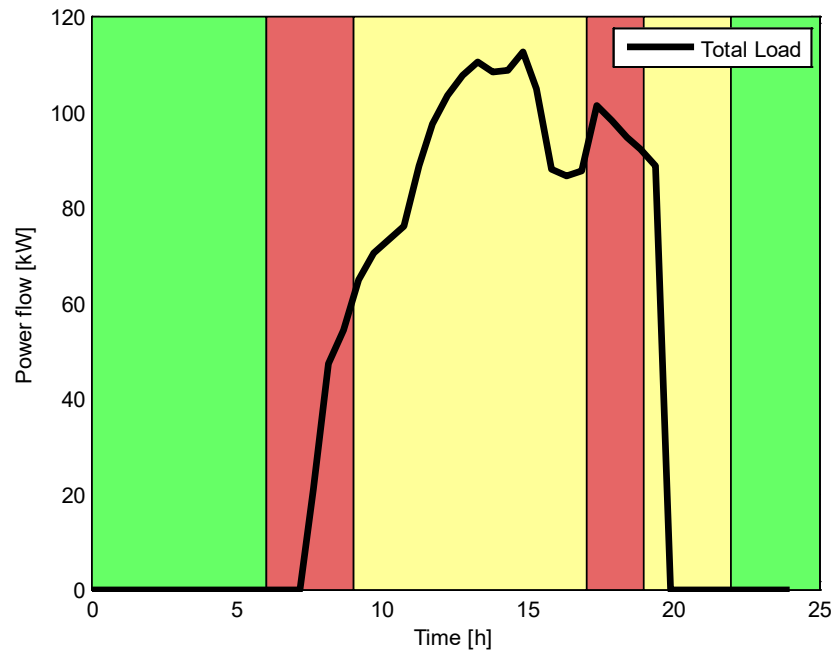


Figure A18: Load requirements at the EVCS for the selected winter day

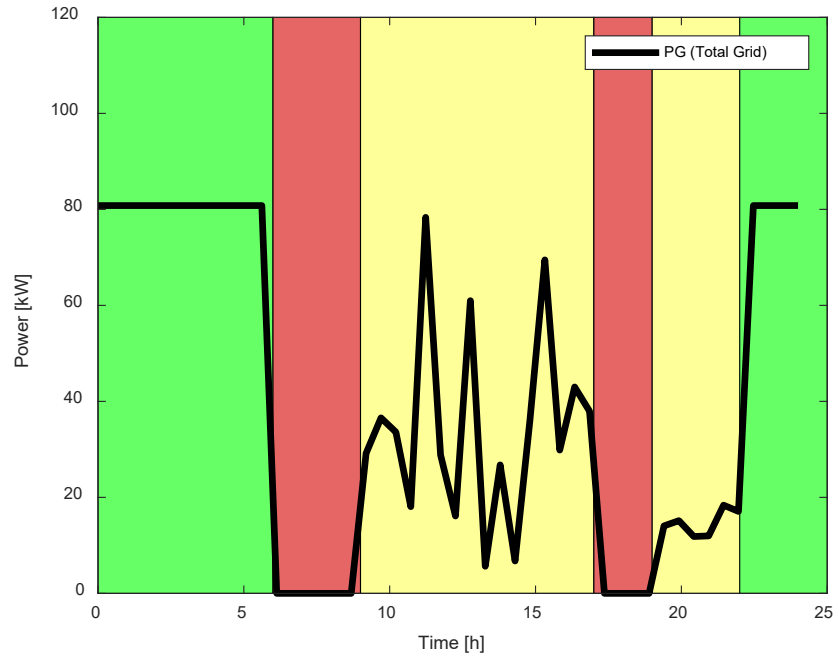


Figure A19: Total power utilised from the grid subjected to the constraints for the selected winter day

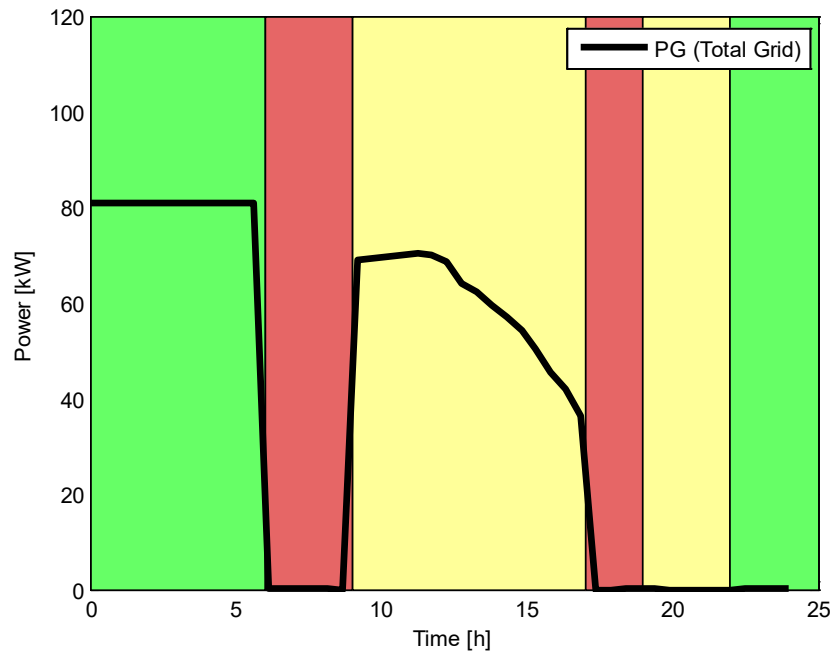


Figure A20: Total power utilised from the grid subjected the constraints for the MPC for the selected winter day

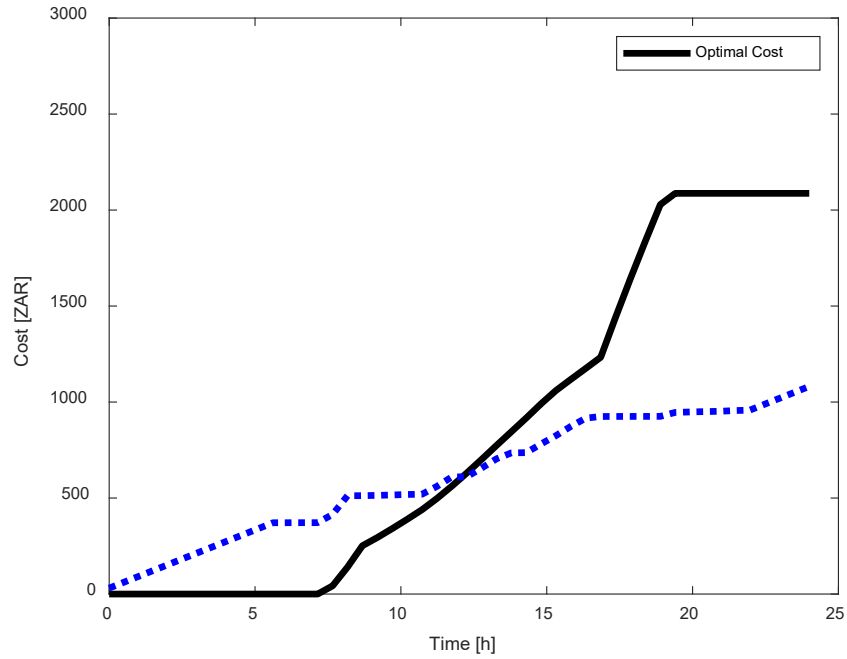


Figure A21: Optimal savings for the selected winter day

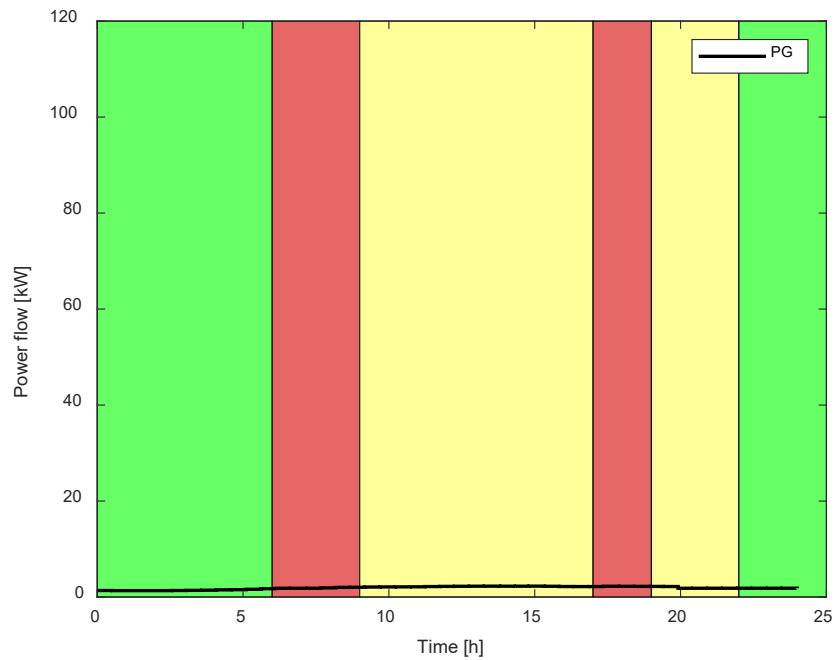


Figure A22: Total power from the grid: Simulated results for the selected winter day during a load-shedding scenario

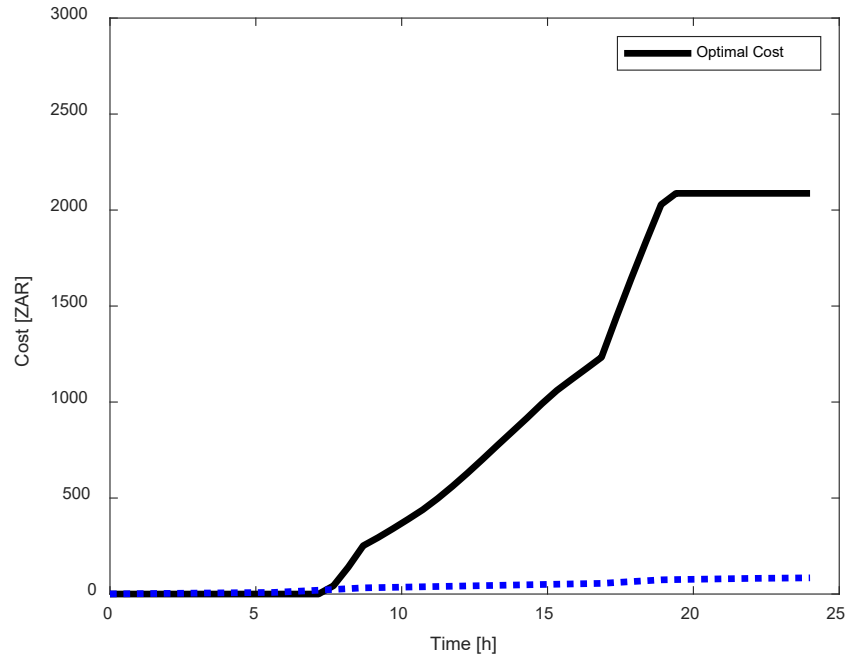


Figure A23: Optimal savings for the selected winter day during a load-shedding scenario

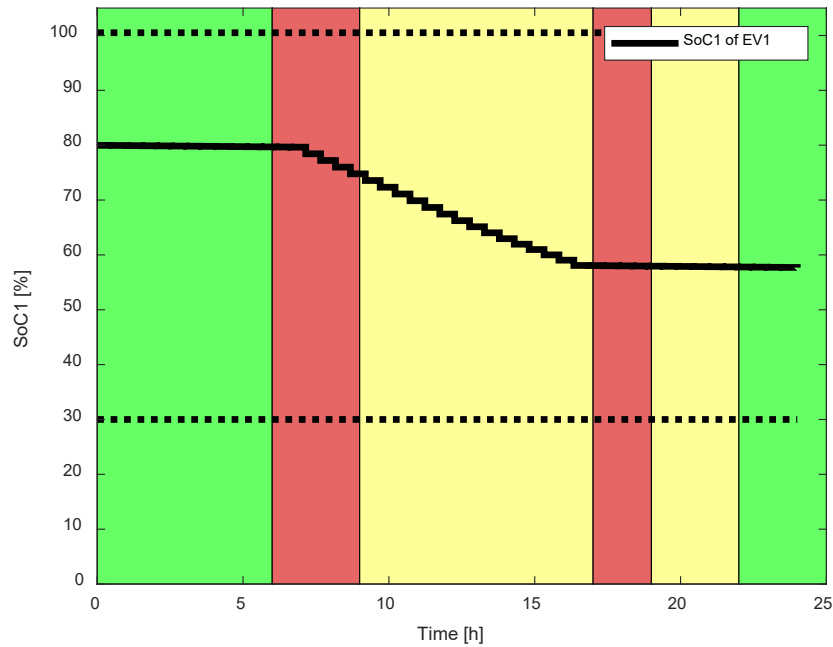


Figure A24: Simulated results of P2P sharing to supplement the load during load shedding for the chosen winter day (seller's battery SoC)

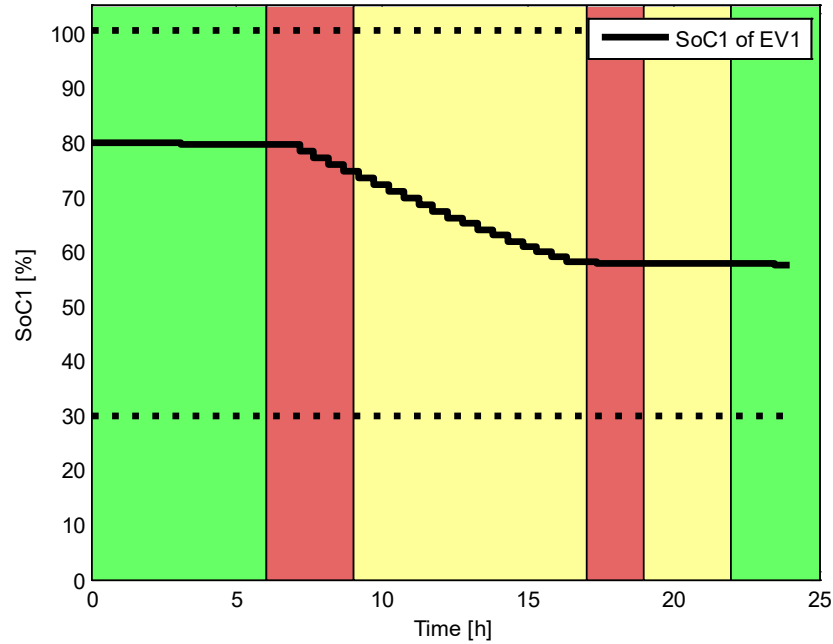


Figure A25: Simulated results of the MPC P2P sharing to supplement the load during load shedding for the chosen winter day (seller's battery SoC)

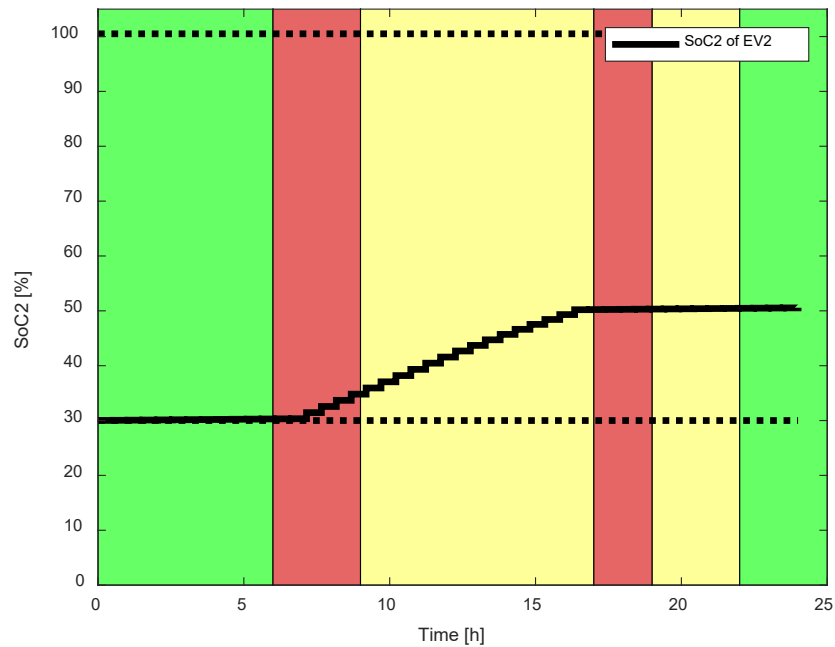


Figure A26: Simulated results of P2P sharing to supplement the load during load shedding for the chosen winter day (buyer's battery SoC)

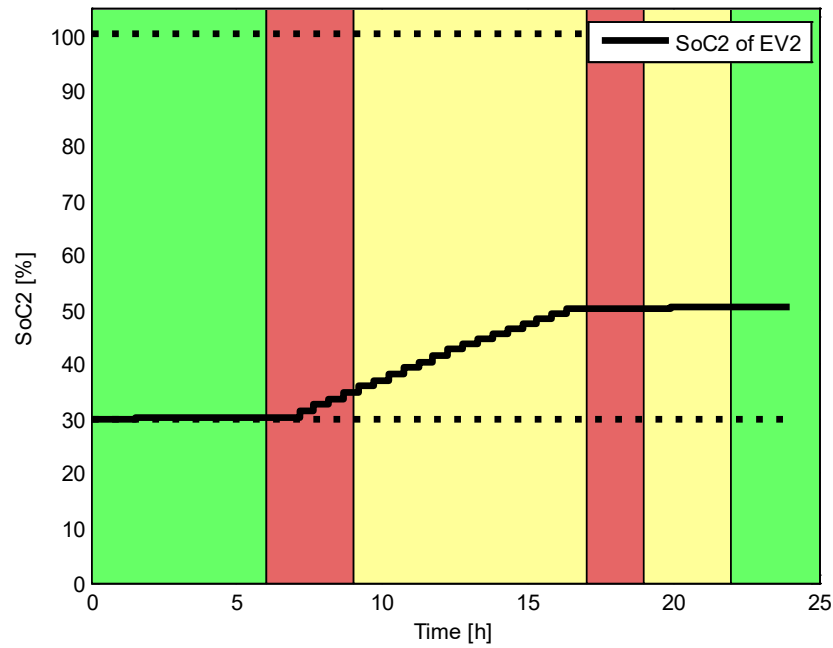


Figure A27: Simulated results of the MPC P2P sharing to supplement the load during load shedding for the chosen winter day (buyer's battery SoC)

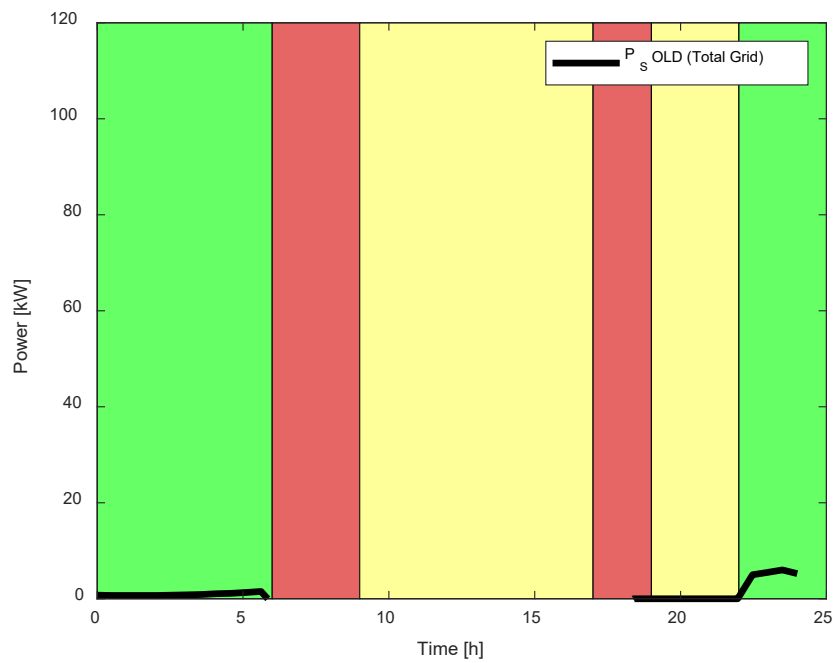


Figure A28: Total power sold to the grid: Simulated results for the selected winter day

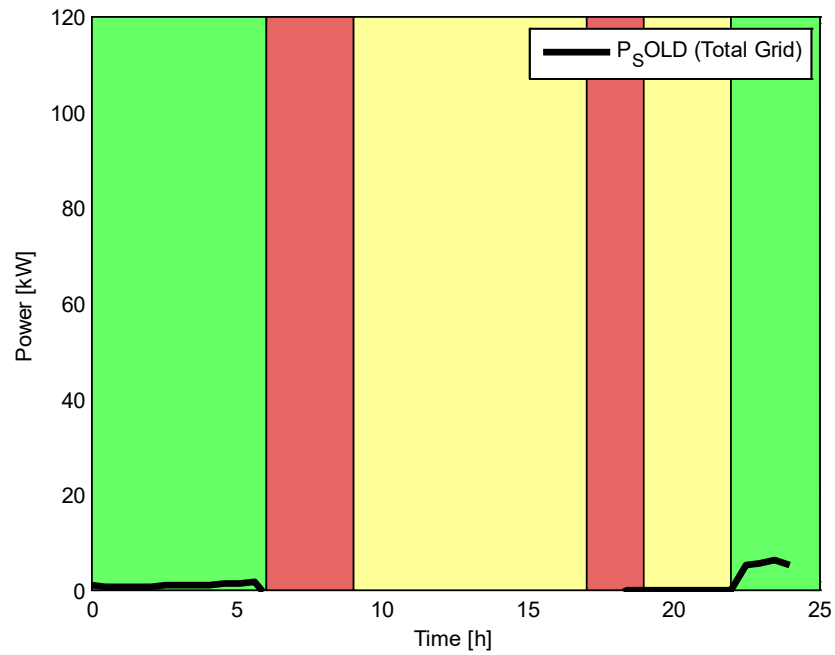


Figure A29: Total power sold to the grid: MPC simulated results for the selected winter day