Integration of Vehicle-to-Grid Technologies in Packetized Energy Microgrids: A Co-Simulation Study

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Abstract

Packetized Energy (PE) schemes, inspired by communications technology, have gained attention as a potential solution for power management which can effectively control demand in real-time to match power availability. This thesis presents the development of a co-simulation platform, based on PEMT-CoSim, to investigate the integration of Vehicle-to-Grid (V2G) technology with Packetized Energy Trading (PET) in microgrid scenarios. The platform employs an iterative double auction mechanism to match orders, facilitating the interaction between electric vehicles as mobile energy storage units and other microgrid prosumers, with a focus on electric air conditioning units as responsive loads that can be switched on or off according to availability, and solar photovoltaics as intermittently available distributed energy resources.

Using the developed co-simulation, this study evaluates how V2G-capable electric vehicles can enhance the stability and efficiency of PET-based microgrids. The results demonstrate the capability of V2G electric vehicles to act as an energy reservoir, effectively managing demand-side load, thus mitigating its fluctuation from available supply while maintaining quality of service.

These results have significance in the broader context of facilitating the Energy Transition and mitigating climate change. By demonstrating the utility of the integration of PET and V2G technologies for load-shifting, and providing a simulation platform to further investigate their interactions, this research can encourage higher penetration of renewable energy sources. This is crucial for reducing reliance on fossil fuels and supporting the transition to a more sustainable and resilient energy system.

Contents

1 Introduction **1**

2 Background and Related Work **2**
2.1 Background . . . 2
2.2 Packetized Energy Management (PEM) . . . 2
2.3 Packetized Energy Trading (PET) . . . 3
2.4 Vehicle-to-Grid (V2G) Technology . . . 3
2.5 PEMT-CoSim . . . 4
2.5.1 PEMT-CoSim Federates . . . 4

3 Aims and Objectives **6**

4 Methodology **7**
4.1 Experimental Design . . . 7
4.1.1 Houses . . . 8
4.1.2 Grid Supply . . . 8
4.1.3 Market . . . 9
4.1.4 Bid Formulation . . . 9
4.2 Cosimulation Development . . . 10
4.2.1 Cosimulation . . . 10
4.2.2 EV Federate . . . 11
4.2.3 PET Market . . . 14
4.2.4 Codebase Improvements . . . 14
4.3 Evaluation Metrics . . . 14
4.4 Data Collection . . . 15

5 Results **16**
5.1 Scenario 1 . . . 16
5.2 Scenario 2 . . . 18
5.3 Scenario 3 . . . 19
5.4 Scenario 4 . . . 21
5.5 Scenario 5 . . . 23

6 Conclusion **26**
6.1 Future Work . . . 26

A Order Matching Algorithm **31**

B EV Load Range Algorithm **32**

C EV Bid Formulation Algorithm **33**

D Software Used **34**

Nomenclature

n_{houses} Number of houses in a simulation scenario

n_{EV} Number of electric vehicles attached to houses in a simulation scenario

n_{PV} Number of solar PV arrays attached to houses in a simulation scenario

t_{market} Market period of the PET scheme

$P^{\text{grid}}_{\text{capacity}}$ The fixed grid load cap for a scenario

$T^2_{\text{excess}}(t)$ The squared excess temperature of a particular house at time t

$\overline{T^2_{\text{excess}}}(t)$ The mean T^2_{excess} of all houses at time t

$\overline{T^2_{\text{excess}}}$ The mean $\overline{T^2_{\text{excess}}}(t)$ over a time period

$\overline{P_{\text{target}}}$ The average of $P_{\text{target}}(t)$ over time

$P_{\text{target}}(t)$ The total power needed by all houses to meet their requirements

1. Introduction

Energy sustainability and climate change mitigation have ascended to the forefront of global policy concern, pushing the search for effective solutions into overdrive. Central to these efforts is the need for improved approaches to energy generation, distribution, and consumption. A key strategy has been the integration of renewable energy sources into the power grid, which not only curbs our reliance on fossil fuels but also paves the way for a more resilient and flexible energy infrastructure. However, this transition brings new challenges, including generation capacity fluctuation, which poses substantial difficulties for grid operators who must ensure that consumers' power needs are met. This thesis focuses on one of the transformative solutions aimed at addressing these challenges: Packetized Energy (PE). In particular, I will investigate the utility of Vehicle-to-Grid (V2G) electric vehicles in addressing grid load variability within a microgrid PE scheme.

My research centers on the idea that V2G electric vehicles, acting as mobile energy storage units, can have a profound impact on the overall stability and efficiency of PE microgrids. While previous studies have explored V2G technology and Packetized Energy Management (PEM) systems (mostly separately), the novelty of this research lies in the study of the interaction between these two systems facilitated through co-simulation.

The primary objective of this research is to develop a cosimulation platform which can demonstrate the capability of V2G EVs, as participants in a Packetized Energy Trading (PET) scheme, to improve power supply continuity when generation capacity is variable. To achieve this, I have built upon the basic structure of PEMT-CoSim, a recently developed platform for PET cosimulation. Extending PEMT-CoSim to incorporate modeling of EV behaviour, as well as a new market mechanism and improved house control behaviors, has been the principal undertaking of my work.

The structure of this thesis is as follows: after this introductory section, in Section 2 a literature review is presented, exploring the most relevant current research in PEM and V2G technology. Section 3 provides a specification of the aims and objectives of the project. Following this, in Section 4 the methodology used to develop and test the cosimulation platform is described, detailing the scenarios that will be investigated, the modifications to the PEMT-CoSim platform needed to facilitate their simulation, and defining quantitative metrics by which I will evaluate my results. Section 5 presents my results and analyses, highlighting my findings from comparison of the various simulation scenarios. Finally, in the Conclusion (Section 6) I will summarize the key insights from my simulation experiments and their significance, and discuss them in relation to practical applications and opportunities for future research. The reference list and appendices with additional data are provided at the end of the thesis.

2. Background and Related Work

In this section I provide a summary of the research relevant to this project in the fields of packetized energy (PE), peer-to-peer (P2P) energy trading and vehicle-to-grid (V2G) technology, followed by a more detailed description of PEMT-CoSim, which is the most important piece of literature for this project.

2.1 Background

The global energy landscape is experiencing a significant transformation driven by increasing awareness of climate change, commitments to reducing carbon emissions, and rapid technological advancements in renewable energy and energy storage solutions. The urgency of mitigating climate change has led to a shift towards the electrification of transport, heating, and other sectors in a bid to decarbonize. This Energy Transition (ET) is expected to result in soaring electricity demand [36, 30], and must be accompanied by a transition to renewable power generation.

Traditional grid systems, often reliant on stable but environmentally harmful sources such as coal and nuclear, are not well-equipped to handle the variability and uncertainty associated with renewable energy sources. Many attempts to integrate intermittent renewable sources such as wind and solar with these inflexible distribution systems have resulted in severe underutilitization and power abandonment - in the UK a million homes could be powered by wind power wasted each year due to lack of storage capacity [37, 41] - and this incurs significant cost, both financial and environmental. Further, the traditional approach of ensuring electric grid reliability through fast-ramping generators is becoming outdated [20]. Therefore, novel management strategies and technologies are essential for integrating intermittent renewable sources effectively into the grid.

Three important topics from this discussion are the focus of this project: Packetized Energy Management (PEM), Packetized Energy Trading (PET), and Vehicle-to-Grid (V2G) technology.

2.2 Packetized Energy Management (PEM)

Packetized Energy Management (PEM) is one approach to demand-side load control that has gained attention in recent years, often considered under the umbrella of "smart grid" technology. Initially introduced by Toyoda and Saitoh in 1998, PEM represents energy in discrete time- and load-bounded packets [2] which are requested from a controller. These requests can be rejected if the controller determines that there is insufficient power supply or demand to meet them. This representation allows for more granular control over energy distribution and utilization. Figure 1 provides a simplified illustration of this concept: the first graph shows a peak in demand overloading a traditional grid supply, the second shows the same load "packetized", and the third shows the same quantity of power packets with excess demand shifted to times of higher supply availability.

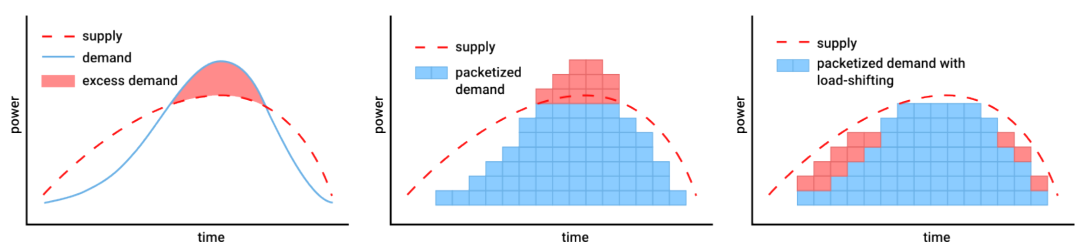

Figure 1: An illustration of the Packetized Energy concept for shifting demand to fit supply

The transition towards renewable energy sources and their integration into the grid can be facilitated by PEM. [20] shows the potential utility of PEM in ensuring electric grid reliability using flexible and controllable distributed energy resources (DERs), presenting a macro-model of aggregate behavior of packetized DERs and demonstrating that PEM can improve coordination between supply and demand. [31] shows that PEM provides load balancing and ramping services for the grid through large-scale coordination of DERs. [38] proposes a virtual battery model of PEM and a model predictive control framework that improves load tracking of a control signal. [15] describes a new PEM operating framework, Packetized Direct Load Control, and emphasize trade-offs between controllability and consumer choice. They highlight that systems allowing consumers to independently decide energy preferences based on price signals often result in unpredictable energy behavior, thus reinforcing the importance of load control systems ensuring QoS. [36] explains how real-time coordination of demand through PEM can be an alternative to scaling up grid infrastructure electricity demand increases through the ET.

The PEM concept has evolved over time and found particular utility in managing variable demand-side loads such as Heating, Ventilation, and Air Conditioning (HVAC). It is estimated that space cooling makes up approximately 16% of all residential electrical power consumption in the US [23], making it an important target for optimisation. [17] and [18] investigate the use of PEM in the specific context of Thermostatically Controlled Loads (TCLs) such as HVAC. Emphasizing the importance of managing TCLs in a manner that preserves the quality of service (QoS) to consumers, their studies depict how a packetized, probabilistic approach to energy delivery can allow load to closely track a time-varying reference signal without significant degradation of QoS, as shown in a simulation of 1000 water heaters.

PEM is related to the concept of the "Energy Internet" (EI), first proposed in 2004 and foregrounded by the US National Science Foundation in 2011 [6] as an evolved, decentralized energy sharing network with increased flexibility and efficiency contrasted with traditional power distribution infrastructure. The EI concept has received increasing attention since then [29, 35], and [25] explores the practicalities of a PEM-based Energy Internet, suggesting that the concept is scalable to multiple connected microgrids and could be made possible using 5G-and-beyond technology for communications.

2.3 Packetized Energy Trading (PET)

PET refers to the application of packetization to the energy market. Energy supply purchased both from the Utility Grid (UG) and from geographically-proximal Distributed Energy Resources (DERs) is packetised, with individual packets being bought and sold on a market which may be centralised or decentralised.

[27] describes the P2P energy packet trading problem in microgrid scenarios, where consumers can buy power from DERs or the UG. They present an iterative auction mechanism for power packets and show, through simulation, that PET can lower the average unit price for energy. Another study [16] introduces a bidding system for microgrid P2P energy trading and demonstrates how it can balance supply and demand and facilitate the integration of renewable energy sources.

[24] offers significant insights into the valuation of TE systems by developing a comprehensive simulation-based method using FNCS [13], a cosimulation system. Their open-source simulation platform is similar to PEMT-CoSim, described below.

2.4 Vehicle-to-Grid (V2G) Technology

V2G technology was first described by Kempton and Letendre in 1997 as the capability of EVs to serve as a power source for electric utilities [1]. [12] discusses the opportunities of grid-connected EVs in the context of V2G.

[11] provides a review of the benefits and challenges of V2G technology, enumerating services that V2G-capable vehicles can provide: "reactive power support, active power regulation, tracking of variable renewable energy sources, load balancing, and current harmonic filtering". Several studies [4, 8, 5] have explored frameworks and strategies to optimize the charging and discharging patterns of V2G EVs. While [11] suggests battery degradation due to repeated charge/discharge cycling as a potential barrier to adoption of V2G technology, [33] evaluates V2G economics and finds that "EV

battery cost and thus degradation due to cycling have little effect" on V2G financial viability. [43] quantifies the global EV battery capacity available for grid storage and suggests that EV batteries alone could satisfy short-term grid storage demand by 2030.

In recent years a few studies have investigated the potential combination of V2G and smart grid technologies. Numerous authors [9, 10, 7] have explored different strategies for optimal EV charge scheduling in smart grid scenarios, and [14] develops upon these investigations to describe a decentralized and packetized approach to EV charge management, comparing the performance of the packetized approach to both a centralized optimization method and a simple "first-come, first-served charging scheme" in a simulated test case, and showing substantial advantages for the packetized approach. [28] suggests approaches to charge scheduling using PEM while meeting certain quality of service constraints, in tandem with an investigation into optimal placement and sizing of EV charging stations.

2.5 PEMT-CoSim

PEMT-CoSim, a co-simulation environment for PE systems, has been proposed [40] as an extensible modeling framework capable of integrating a variety of distinct, separately-simulated agents participating in a PE/PET scheme. It is built upon the Transactive Energy Simulation Platform (TESP) presented in [24]. The platform coordinates a collection of sub-simulation "federates", each of which simulates a different aspect of the overall scenario: GridLAB-D for microgrid power flow, PyPower for grid supply and market pricing, EnergyPlus for large building loads, a weather federate, and a PE/PET substation federate which, besides the cosimulation architecture, is the major novel contribution. The behaviour of the substation federate is examined in detail below alongside a summary treatment of the other federates. These federates share values with other and maintain simulation-time synchronisation using the HELICS synchronisation broker presented in [19].

PEMT-CoSim provides the groundwork for the implementation work I have done in this project.

2.5.1 PEMT-CoSim Federates

HELICS Broker

HELICS is a co-simulation framework that enables synchronized communication between separate domain-specific simulation federates. It is primarily employed for examining interactions between models and understanding the behavior of complex systems. The core of HELICS is a **broker**, which orchestrates the exchange of value messages between federates and manages time synchronization.

Federates define *publications* (variables published for others) and *subscriptions* (variables received from others). In each simulation loop, a federate requests a simulation time, $t_{requested}$, greater than the current time, $t_{current}$, from the HELICS broker. The broker grants a time, $t_{granted}$, within this range. The federate then retrieves values from its subscriptions (updated until $t_{granted}$), and conducts its independent simulation for the time frame $t_{current}$ to $t_{granted}$. Upon reaching $t_{granted}$, it updates its publications and requests a new time slot, repeating the process.

This mechanism ensures concurrent execution of federates with synchronized simulation times, facilitating the timely exchange of relevant data. The following sections include tables detailing the publications and subscriptions of each federate in my co-simulation setup each federate in my cosimulation setup are tabulated at the end of the following sections.

Substation

The substation federate is where the main business logic for the PET simulation is held. Its functionality has two main components: prosumer control and market simulation.

Prosumer Control Each market round, the substation federate assigns each prosumer (house) a market role - buyer, seller, or non-participant - based on predicted load and solar PV supply. Bids to buy or sell power in multiples of a defined packet quantity are formulated according to some simple rules, and submitted to the market.

After market clearing via double auction as described below, the substation federate implements a post-market control routine for each house. This involves toggling HVAC systems and adjusting battery and solar PV outputs according to the outcome of the house's market bid.

Market Simulation PEMT-CoSim employs a double auction mechanism in its market system. In this system, each bid submitted specifies whether it is from a buyer or a seller, the quantity of energy involved (in packets), the price at which the participant is willing to buy or sell, and whether the bid is unresponsive (part of the "base load") or responsive. The market then determines a single clearing price, which is the lowest price at which the sum of the quantities that sellers are willing to sell exceeds the sum of the quantities that buyers are willing to purchase. At this clearing price, all buyers make their purchases and all sellers make their sales. For bids that are marked as "unresponsive", indicating that they cannot be rejected and form part of the base load, the market assigns them the maximum price, ensuring that they are always accepted.

GridLAB-D

The GridLAB-D federate is responsible for modelling the houses, the loads that they produce, and the power flow of the microgrid. It is an integration of GridLAB-D, an existing open-source power distribution simulation software [3].

Besides power flow solving and measurement, the key GridLAB-D feature used by PEMT-CoSim is the HVAC simulation, which models the change in air temperature over time of each house, taking into account external air temperature (provided by the weather federate) and the state of the HVAC system in that house. Physical factors such as number of doors, thermal transmittance of surfaces, rate of air change etc. are also used in these calculations, and their fixed values for each house are taken from the examples provided in TESP [24]. Internally, GridLAB-D uses systems of differential equations to solve for the changes in its variables over time, the details of which are out of the scope of this project.

PyPower

The pertinent feature of the PyPower federate is that it provides the Local Marginal Price (LMP) of the grid power supply to the other federates. The LMP represents the marginal cost of supplying the next increment of electric load at a specific location (in this case at the connection point between the microgrid and the wider grid distribution network). The PyPower federate is built around the PyPower Python library, a port of the MATPOWER power flow and Optimal Power Flow (OPF) solver to Python [26]

Weather

The weather federate provides temperature, humidity, solar irradiance and wind speed data, which are loaded from a dataset provided as part of TESP [24].

EnergyPlus

The EnergyPlus federate is capable of simulating the electrical load of a large building such as a school or shopping centre. This capability is not used in my investigation, which focuses on residential scenarios.

3. Aims and Objectives

The primary aim of this research is to explore the potential of PET schemes as a medium for the integration of electric vehicles and renewable energy sources in microgrids, and to assess the impact on grid stability and energy optimization. To this end, the study endeavors to produce a collection of simulations modeling the interaction between household loads, electric vehicles, renewable energy sources and main grid supply, as they trade energy packets on a continuous energy market.

To achieve these aims, I set out the following objectives:

1. To develop a co-simulation platform capable of incorporating a realistic representation of electric vehicles, renewable energy sources, and market mechanisms within a microgrid PET scheme.
2. To establish quantitative metrics to objectively evaluate the results of the simulations in terms of energy optimization, grid stability, and integration efficiency.
3. To design and execute simulation scenarios reflecting various conditions and parameters to analyze the resulting performance and behavior of the PET scheme.
4. To collect and analyze data from the simulations and derive insights into the interactions and dynamics of the PET scheme
5. To propose recommendations for improving the design and operation of PET microgrids for better integration of electric vehicles and renewable energy sources, and identify areas for further research.

The outcomes of this study hold promise for the ongoing advancement of Packetized Energy (PET) research technology. Through a comprehensive analysis of power trading dynamics and the seamless integration of electric vehicles and renewable sources, I aim to provide valuable insights and recommendations that can inform future development and research. My hope is that both the findings and the developed platform offer a stepping stone towards the realization of intelligent power management strategies, empowering the transition to a greener and more sustainable energy future.

4. Methodology

In this section, I will present a detailed exposition of the work undertaken to obtain my results.

First, the Experimental Design section 4.1 will discuss the various simulation scenarios devised to analyze the performance of the PET system under different conditions.

With this context in mind, section 4.2 will detail the customizations and refinements made to the PEMT-CoSim platform to make the designed experiments achievable. In particular, it sheds light on the integration of the EV Federate, which simulates the dynamics of electric vehicles, and the redesign of the market mechanism. I will also describe in Section 4.2.4 the extensive enhancements made to the codebase to modernize, improve clarity and hopefully foster open-source collaboration.

The definition of quantitative metrics to evaluate the simulation results will be presented in 4.3, followed by a brief discussion of how data is collected and aggregated from the simulations as the progress in 4.4.

4.1 Experimental Design

In this chapter, I describe the PET scenario which I have investigated and the components and interactions which it comprises.

The scenario simulated for this project is illustrated in figure 2 and consists of a collection of n_{houses} houses, as described in 4.1.1, connected together in a microgrid. Every house is able to buy and sell power in fixed-length packets by submitting bids to the microgrid power market, which operates as described in section 4.1.3. Additionally, the microgrid is connected to a wider grid power supply, detailed in 4.1.2.

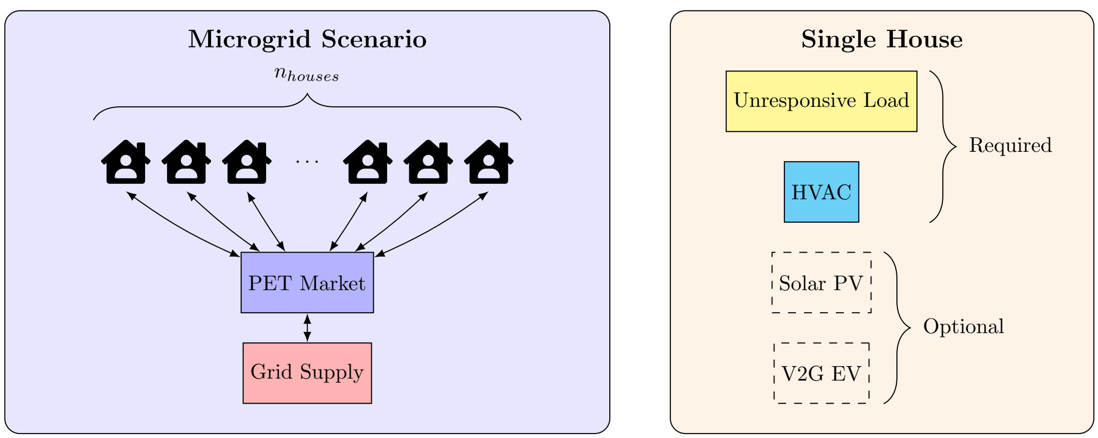

Figure 2: Simulation Scenario

The critical characteristic of the simulated scenario is that all power consumed or supplied by any agent connected to the microgrid must be accounted for by a transaction or transactions on the packetised market. This criterion enables the market to act as a power load regulator, since agents who wish to place a load onto the microgrid must first place a buy order and have it fulfilled. If there is insufficient supply to meet the load, the bid will be rejected and the load must not be connected.

To assess the utility of the PET scheme and the contribution that EVs can make to flattening the grid load and minimising excess demand, I will compare several variations of the described scenario. The parameters for these variations are detailed in 4.1. Each simulation will be run for 8 days of simulation time, and the first four days of results will be discarded so that the results give an accurate indication of the steady-state behaviour of the system.

Scenario Number	Grid Capacity / kW	Houses	EVs	PVs
1	unlimited	30	0	0
2	100	30	0	0
3	100	30	0	30
4	100	30	30	0
5	100	30	30	30

Table 4.1: Simulation Scenario Variations

4.1.1 Houses

The house is the typical participant in the PET system. Every house has a collection of standard electrical appliances and an HVAC air conditioning system, which is only capable of cooling (not heating). Of the n_{houses} total houses, n_{EV} have a V2G EV and n_{PV} have a solar photovoltaic array for power generation (detailed below). The loads and supplies produced by these various devices within the house can be split into two categories: "responsive" and "unresponsive".

Unresponsive loads are those which are **inflexible** - sufficient power must be provided to meet them, and inadequate supply for the unresponsive loads is considered a failure case of the simulation. The GridLAB-D federate simulates several unresponsive appliance loads (microwaves, refrigerators, dryers, lights etc) for each house using simple preset load schedule files.

Responsive loads are **flexible**, and can be switched on or off according to some control signal from the house substation PE controller. In my simulation scenario, the HVAC systems behave as responsive loads, and the solar PV arrays are responsive supplies. The V2G EVs can operate either as responsive loads or supplies, either discharging (creating a supply) or charging (creating a load) according to control signals from the PET controller.

EVs

The EVs in the scenarios investigated are capable of bidirectional charging/discharging at defined maximum rates when at their home charging station, which is the only place they do so. This charging and discharging has realistic efficiencies applied, so the charge rate of the battery is slightly lower than the load on the microgrid, and the discharge rate is slightly higher than the supply provided to the microgrid.

EVs travel according to defined mobility patterns (explained in 4.2.2), consuming energy from their batteries during driving. These mobility patterns affect their availability as power resources for the microgrid, since when they are not at home they are unavailable. When at home, they act as traders in the PET scheme, following the bid formulation procedure described in 4.1.4.

Solar PV Arrays

In the simulation, each solar photovoltaic (PV) array is initially assigned a varying number of panels, ranging from 8 to 20, which is determined randomly. Every individual panel within these arrays has the capacity to produce up to 480 watts of power. The selection of these values is based on representative data taken from TESP for PEMT-CoSim [24].

4.1.2 Grid Supply

The grid power supply is a constant-capacity dispatchable power generation resource, which submits a fixed-quantity sell bid to the market every market round. The power supplied by the grid to the microgrid is adjusted based on the proportion of this bid which is fulfilled.

The grid supply prices its sell orders at the Local Marginal Price (LMP) determined by a grid power flow simulation. The LMP is the cost of producing and supplying an additional unit of electricity at a particular node or location on the power grid. The LMP increases with the demand to supply ratio, although the specific mechanics that govern LMP determination are outside of the scope of this project.

4.1.3 Market

The PET market operates as a price-first continuous double auction, where sell orders are treated as divisible (i.e. they may be partially fulfilled, requiring the seller to produce some fraction of the power they advertised for sale) and buy orders as indivisible (they must be either accepted or rejected in full). Note that this mechanic also allows for multiple sellers to fulfill a single buy order provided that their total sale quantity is at least the buy order quantity.

Each market period t_{market}, the auction system aggregates bids from all traders, and then matches successively matches order orders with the aim of minimising the amount spent while fulfilling all buy orders possible.

In this investigation, I have used $t_{\text{market}} = 300s$, which is the market period chosen by PEMT-CoSim [40, p. 6] and provides a good balance of not being so short that the frequency of bid formulation and market clearing slows down the simulation (and demanding high bandwidth in real-life), but short enough that traders can reasonably commit to fulfill buy/sell orders for that length of time.

4.1.4 Bid Formulation

At the beginning of each market period, house units are required to submit bids to the market, indicating the quantities of power they aim to buy or sell in the subsequent market period. The bid formulation process for any given load or supply encompasses two critical components: **power prediction** and **price determination**.

Accurate power predictions are imperative as each house's load is constrained by the sum of their successfully matched orders. An underestimation of power requirements can lead to a power shortfall, whereas an overestimation could result in unnecessary expenses and potential grid imbalances due to the discrepancy between the actual load and the supply generated to match the sell orders.

The pricing policies are designed with the dual objectives of minimizing energy costs while ensuring sufficient power availability for each household. Different types of agents involved in power trading within this simulation employ specific bid formulation strategies, which are elaborated upon in detail below. I found that interactions between these pricing strategies were difficult to predict, especially when combined with the dynamics of variable power supply. These interactions hold considerable influence in shaping the electricity consumption and production patterns of all entities within the microgrid. Refining the pricing strategies to find a balanced market equilibrium that serves the function of reducing grid overload while meeting power needs took some fine-tuning.

Grid Supply

The grid supply offers a fixed quantity of power in each market period, which is determined by a predetermined grid cap associated with each scenario. The bidding strategy for the grid supply's bids is straightforward; the price is always set at the LMP provided by the PyPower federate, and the bid quantity is always equal to the fixed grid load cap $P^{\text{grid}}_{\text{capacity}}$.

House HVAC Load

The HVAC load is predicted using a simple rule - it is set to 4kW if the HVAC needs power due to deviation from the setpoint, or 0 if not. This approximation is used as 4kW is close to the average load when cooling is required, and a more precise predicted was not found to be necessary (although could be an area for improvement). Buy bids for HVAC loads are submitted with a high fixed price, designed to be higher than other trader prices but lower than unresponsive load bids. This ensures that HVAC power demand is met when possible but with lower priority than the unresponsive load.

House Unresponsive Load

The unresponsive load for each house is calculated as the predicted total house load minus the predicted HVAC load. Buy bids for the unresponsive load have a high price attached, ensuring that they are always fulfilled if there is enough power. This approach is crucial as unresponsive loads cannot be switched off. There is no special algorithm for bid formulation - the unresponsive load is predicted by measurement, and a fixed high-price bid is created.

EV Load and Supply

Electric Vehicles (EVs) can act as either a load or a supply. They receive load_{min} and load_{max} publications from the EV federate. A positive value of these variables indicates capacity for **charging** load, whereas a negative value indicates capacity for **discharging** power.

At each market period, the EV first determines its load range $[\text{load}_{\text{min}}, \text{load}_{\text{max}}]$ according to the procedure in Listing B, which is designed to ensure that the SoC of the battery always stays within an acceptable range that will allow the owner to drive it. Next, the EV determines its market bids. If $\text{load}_{\text{min}} > 0$ (i.e. the EV must charge), it submits only a buy bid for load_{min} with a very high price. If $\text{load}_{\text{max}} < 0$ (the EV must discharge), it submits only a sell bid for load_{max} with a very low price. If the EV can either charge or discharge, it submits two bids: a buy order for load_{max} and a sell order for $-\text{load}_{\text{min}}$.

In the two-bid case, prices are determined according to the the algorithm in Listing C, which is dependent on averages of the recent LMP history of the market. This pricing algorithm is simple but has a couple of important features:

- The sell price is always at least slightly above the buy price, which prevents the EV from pointlessly purchasing its own sell bids.
- The buy price tracks the 24hr mean of the LMP, so the EV will buy when the price is relatively low and sell when it is relatively high.

PV Supply

PV installations always aim to generate at their maximum capacity and sell all of their generated power, as any time spent generating below max capacity represents a missed opportunity for renewable power generation. PV power output is predicted by multiplying the voltage and current values for the PV array published from GridLAB-D, yielding wattage. The PV sell price is fixed at a value that creates a good market equilibrium where PV power wastage is minimised; in this study I have used 0.0148$/kWh.

4.2 Cosimulation Development

In this section, I will briefly outline the general architecture of HELICS cosimulation systems and the role that the federates and broker play. I will then detail the work done to extend the PEMT-CoSim platform and develop the simulations in this project. It is vital to acknowledge that the core architecture and initial codebase of PEMT-CoSim provided an invaluable foundation for my work. The basic implementations of PE management and trading systems, and the integration of GridLAB-D, pypower, substation, weather, and EnergyPlus federates synchronized through the HELICS broker were an excellent starting point from which to proceed with the development of a system tailored for V2G EV simulations. The principal changes made to PEMT-CoSim for this work are the development of the EV federate and the change in market mechanism, which are explained in sections 4.2.2 and 4.1.3.

4.2.1 Cosimulation

Cosimulation is a technique for simulation of multiple interconnected components in a synchronized manner. It facilitates the integration of different simulation models, often from different domains, to create a cohesive virtual environment for studying complex systems. By simulating these systems together, cosimulation allows for the examination and measurement of their mutual influence, feedback loops, and overall system performance.

The cosimulation architecture used for this project is based on PEMT-CoSim, the PET cosimulation platform described in Section 2.5 of my literature review. While I have used the PEMT-CoSim architecture as a base, I have extensively modified the platform by:

- Developing and integrating the novel EV federate as described in 4.2.2
- Developing and integrating the continuous double auction market as described in 4.2.3. This replaces an incomplete non-continuous double auction with that existed in PEMT-CoSim.
- Redesigning the energy trading system such that all energy consumed must be traded on the market, and packets are defined by time rather than power
- Comprehensively modernising and rewriting the codebase and upgrading its dependencies to build a platform that is substantially more legible, efficient and extensible for future simulation development

The key contributions of this work are the development and integration of the EV federate and of the new market mechanism. The federated structure of the project cosimulation and the values published to and subscribed from each federate are illustrated in Figure 3. Federates which already existed in PEMT-CoSim are coloured in blue if they were used in this project, and the unused EnergyPlus federate is coloured in red. The novel EV federate is colored in green.

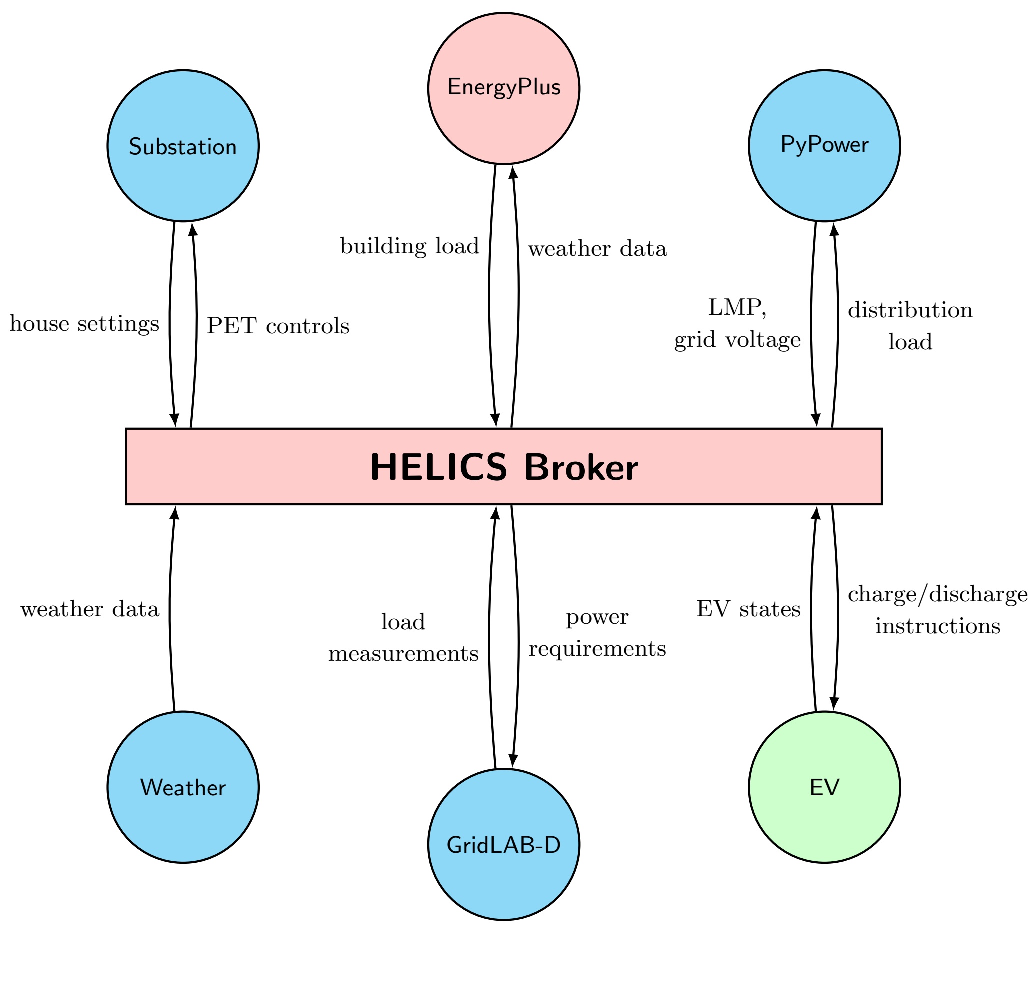

Figure 3: Cosimulation Architecture

4.2.2 EV Federate

The function of the EV Federate is to incorporate EV mobility data and the resulting availability of each EV to the microgrid for charging or discharging into the simulation. The mobility pattern of each EV is generated using the emobpy Python library [32] before the simulation runs. This library was selected as the data source as it is capable of generating realistic time-series mobility patterns based on recent documented vehicle mobility statistics and physical properties of battery-electric vehicles. The generated data includes the location, state (driving or stationary), and distance driven of each EV over time and the corresponding battery load due to driving. A sample of four days of EV mobility data for 30 EVs is illustrated in Figure 4.

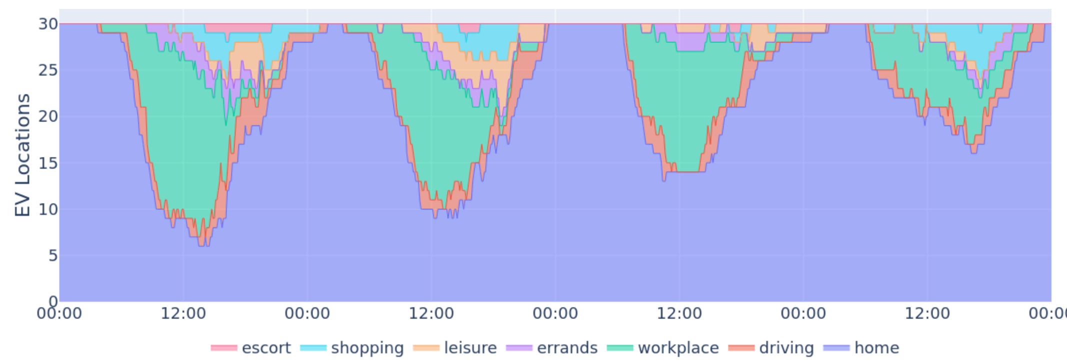

Figure 4: Locations of 30 EVs over a sample four day period

In addition to mobility patterns, the emobpy library also provides essential parameters related to different car models, such as battery capacity, motor efficiency and maximum charging and discharging rates. These parameters are used to model the the battery discharge from driving over time. A sample of four days of total driving battery load data for 30 EVs and the resulting total cumulative energy usage is provided in Figure 5.

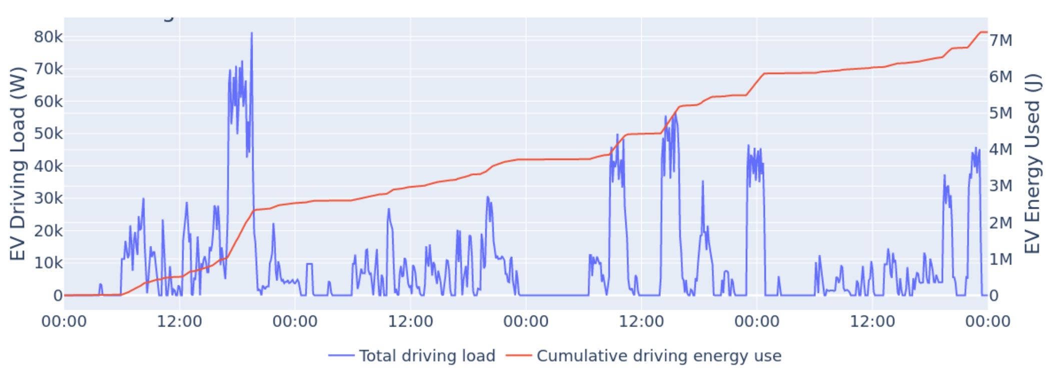

Figure 5: Battery discharging due to driving for 30 EVs over a sample four day period

Two per-vehicle variations in physical and mobility parameters contribute to a more diversified and realistic simulation:

1. **Car Model**
   I opted to incorporate two electric vehicle models available in emobpy: the Tesla Model Y Long Range AWD and the Volkswagen ID.3. These models were chosen based on their global popularity, being among the highest-selling EVs in the world [42], making them suitable to reflect the typical characteristics of electric vehicles on the market today. The selection of each EV's model within the simulation adheres to a ratio of 60:40 in favor of the Tesla Model 3 Long Range AWD. Models are randomly assigned while maintaining this proportion.

2. **Mobility Rules**
   emobpy allows for the specification of rule sets which, alongside the statistical distributions, govern the mobility profiles generated. I have used a mixture of their standard "full-time worker" and "unemployed" rule sets in an 80:20 ratio in this project.

Publications and Subscriptions

The HELICS publications and subscriptions of the EV federate are enumerated in Tables 4.2 and 4.3, and Figure 4.2.2 shows the sequence of communications between federates that happens at each market round. This sequence allows each federate to update the values it needs from others, perform the necessary processing and broadcast its own updates to others. Note that a full round-trip is needed at each market round between the EV and PET federates, as the PET federate must learn the new load ranges of the EVs for it to determine bids to submit to the market, and in turn broadcast its desired loads back to the EV federate.

Name	Count	Type	Unit	From	Note
Desired Charge Rate	n_{EV}	float	W	PET	

Table 4.2: EV Federate Subscriptions

Name	Count	Type	Unit	Recipients	Note
$\mathrm{load}_{\mathrm{min}}$	n_{EV}	string	N	PET	Minimum Load
$\mathrm{load}_{\mathrm{max}}$	n_{EV}	string	N	PET	Maximum Load
Charging Load	n_{EV}	float	W	GridLAB-D	Current load on home charge

Table 4.3: EV Federate Publications

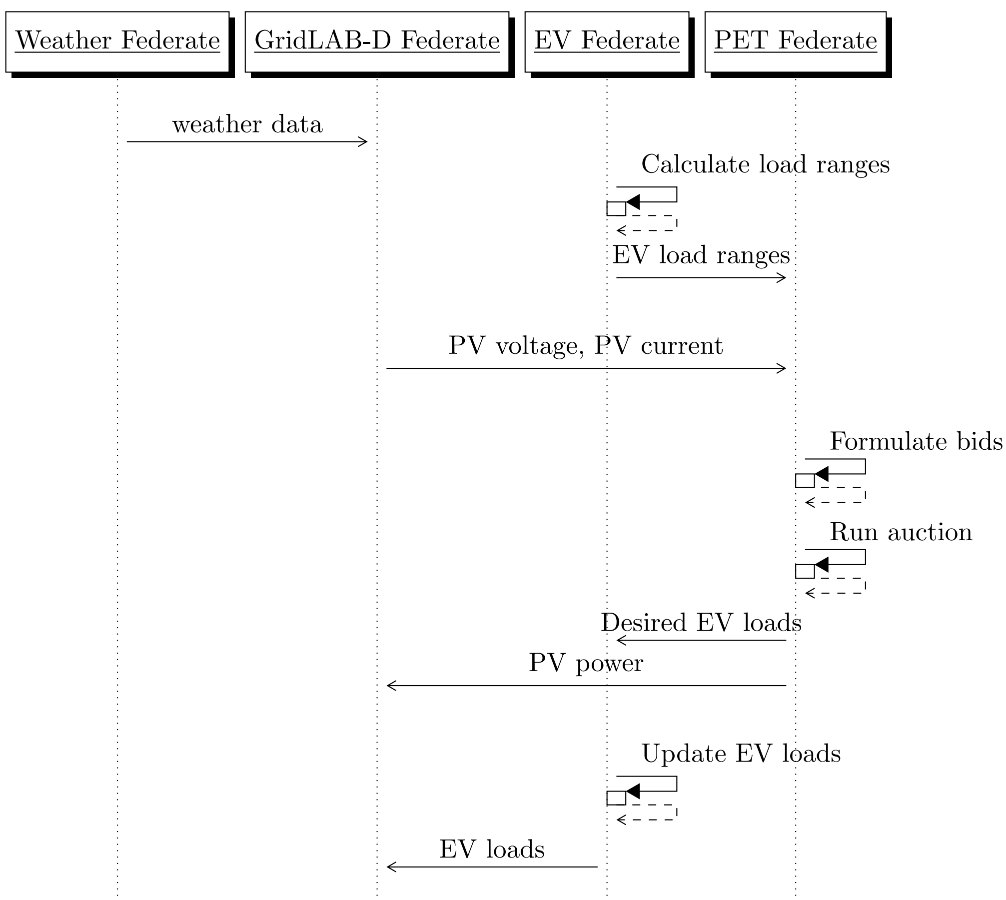

Figure 6: Sequence of messages exchanged for each market round

4.2.3 PET Market

A key development upon PEMT-CoSim from this work is the significant enhancement made to the market mechanism. The PET market in PEMT-CoSim utilized a Double Auction mechanism with a single clearing price. This approach, while simple, often led to a limited number of orders being matched in each market round. The rigidity of a single clearing price could hinder the efficiency of the market, especially in scenarios where a diverse range of bid and ask prices are present.

To address these limitations, the market component of the substation federate was replaced with an implementation of Continuous Double Auction (CDA). Unlike its predecessor, the CDA strives to match as many orders as possible and permits transactions to take place at varying prices within the same round. This feature is highly advantageous in a peer-to-peer PET trading scenario where the availability of resources is time-bounded. For instance, if a solar PV installation fails to fulfill its sell orders within a certain time frame due to the single clearing price constraint, the renewable power generation opportunity is irreversibly lost. The Continuous Double Auction, by enabling more flexible pricing, optimizes the matching of buy and sell orders, ensuring that resources such as renewable energy are utilized efficiently when available. The algorithm employed for this new market order matching is depicted in Listing A.

4.2.4 Codebase Improvements

During the course of this research project, I made significant improvements to the PEMT-CoSim codebase. It is my hope that the more well-structured, up-to-date and readable codebase will be more accessible and inviting to other researchers and developers, and will encourage them to understand, use, and contribute to the codebase. Hopefully this will facilitate further development and extensions of PEMT-CoSim and contribute to the evolution and sustainability of the project in the open-source community. The key improvements made to the codebase are outlined below, and a list of softwares and libraries used during the project is provided in D. I plan to submit the work done on PEMT-CoSim to be merged into its public GitHub repository after a bit more polishing.

Code Refactoring
Python code was extensively refactored, tidied, and rationalized. This effort aimed at enhancing code quality, improving readability, structure, and maintainability. The primary area of focus was the substation federate, but improvements were applied throughout the rest of the codebase.

Dependency Updating
Several dependencies, including most significantly HELICS [19] and GridLAB-D [3] as well as numerous Python library dependencies, were updated to their latest versions. This required some Python code modifications to fit the updated APIs of these dependencies. The project was updated to use the Anaconda package management system [21] and version numbers fixed to ensure a repeatable configuration. Some unneeded dependencies were removed.

Docker Containment
The Docker container engine is used to host the simulation and its dependencies in a platform-independent environment. I rebuilt the Docker setup for the cosimulation in the process of bringing the dependencies up to date, also upgrading the container operating system used (to the latest LTS Ubuntu). The new Docker setup also allows for single-run simulation containers to be created, allowing numerous concurrent simulations to be quickly spun up on a high-CPU host. This function was invaluable during debugging of the simulation and refinement of the scenario parameters, which required many runs with small adjustments.

4.3 Evaluation Metrics

Key metrics that will be used to appraise the performance of the PET scheme in each scenario are defined in this section. Let's first

Quality of Service

Quality of service is probably the most important factor in evaluating the fitness of an energy trading system. This study focuses on house air temperature as an indicator of quality of service for flexible loads, and by extension as a proxy for power sufficiency. If an HVAC system does not receive an adequate power supply, the air temperature in the house may deviate from the desired range specified in the house configuration. This deviation can therefore be used as an indicator of power shortfall. At any given time t, we can quantify HVAC operating deficiency of a house as the squared house excess temperature $\max(T_{\text{air}} - T_{\text{setpoint}}, 0)^2$, which we will call $T^2_{\text{excess}}(t)$. The excess temperature is squared to more heavily penalise larger deviations from the setpoint. A $T^2_{\text{excess}}(t)$ value close to 0 indicates a high degree of power sufficiency.

The mean T^2_{excess} of all houses at time t is denoted by $\overline{T^2_{\text{excess}}}(t)$, and the mean of this value over time by $\overline{T^2_{\text{excess}}}$. $\overline{T^2_{\text{excess}}}$ is the principal comparative metric of power sufficiency.

Supply Utilisation

In scenarios where renewable power is available from Distributed Energy Resources (DERs) such as solar PV installations, it is essential that the PET system maximizes the usage of these resources to minimize the grid dependency. DERs should ideally operate at their maximum output capacity at all times. The underutilization of renewable sources is a missed opportunity and can be quantified at a given time t by calculating the difference between the maximum output capacity and the actual output consumed, denoted as $P^{\text{resource}}_{\text{surplus}}(t)$. As with power sufficiency, this metric is averaged over time to find $\overline{P^{\text{resource}}_{\text{surplus}}}$. This measure should be limited by $\overline{P_{\text{target}}}$, the average total power needed by houses to meet their requirements, because power left unused once all needs are met is not considered underutilisation.

Energy Cost

Minimizing the total cost incurred by the consumers in meeting their energy requirements is one of the main objectives of the power trading system. This cost is computed by summing the costs of the consumer's accepted buy orders and subtracting the revenue from their accepted sell orders. The energy cost is an indicator of the economic efficiency of the trading system and is measured in the local currency (USD/day). In this study, Volume-Weighted Average Price (VWAP) is used as a metric to compare the cost-to-consumer of each scenario. VWAP is the average price of energy transactions over a given period of time, weighted by transaction quantity.

4.4 Data Collection

Throughout all simulation runs, data representing the state of each federate was collected and recorded every time step. The variables collected include, for example, power demand at various junctions, air temperatures, bid prices, market matched transactions, grid load, and for EVs the location, state of charge and charging and discharging rates due to being plugged-in or driving.

Data was serialized and stored at regular intervals using Python's `pickle` module. Additionally, for structured data, such as time-series data or tabular data, the Pandas [22] library was employed to organise data into `DataFrame`s, which offer various useful data manipulation capabilities, which were then saved to disk using `pickle`.

Saving the time-series data of nearly all variables from each simulation run in these structured serialized files streamlined the process of producing graphical representations to visualize trends and relationships between different variables, which were generated using the Plotly [34] Python library separately after simulation completed.

5. Results

In this section I will detail the simulation results for each of the scenarios defined in Section 4.1, scrutinize and explain the behaviour observed, and compare the outcomes using the metrics laid out in Section 4.3 to assess the extent to which the designed PET scheme optimizes energy resource usage in each scenario.

5.1 Scenario 1

Houses	EVs	PVs	Grid Supply Cap
30	0	0	uncapped

$$\overline{T^2_{\text{excess}}} = 0.2724, \quad \overline{\text{VWAP}} = 0.01746$$
$$\overline{P_{\text{supplied}}} = \overline{P_{\text{target}}} = 80.0\text{kW}$$

Scenario 1 is effectively a control case for the experiment: a microgrid with 30 houses, no EVs, and no PV installations, where the only source of power is the main grid, which provides unlimited power at the LMP. Since there are no constraints on the grid supply, the behavior of the loads is essentially as it would be in a traditional, non-PET power supply system. Analyzing this scenario allows us to understand the baseline characteristics of the unresponsive and HVAC loads in the microgrid. We can observe the total power needed by the houses to meet their requirements at each time t, which we will call $P_{\text{target}}(t)$. We will find the average of this value over time, called $\overline{P_{\text{target}}}$. $\overline{P_{\text{target}}}$ serves as an important reference point when evaluating the behaviour of the more dynamic multi-agent scenarios. In the absence of any changes to external factors or system efficiency, the average power entering the system over time $\overline{P_{\text{supplied}}}$ must be at least $\overline{P_{\text{target}}}$, or the supply system is necessarily deficient. This metric becomes useful when complex time-variable supply dynamics make it difficult to see whether a shifting of supply to different times (e.g. using EVs as as a reservoir) could fix a shortfall.

Below, three plots are presented, showing the time-series behavior of Scenario 1 over an average day. The values for each time are calculated as the average value at that time over four simulation days.

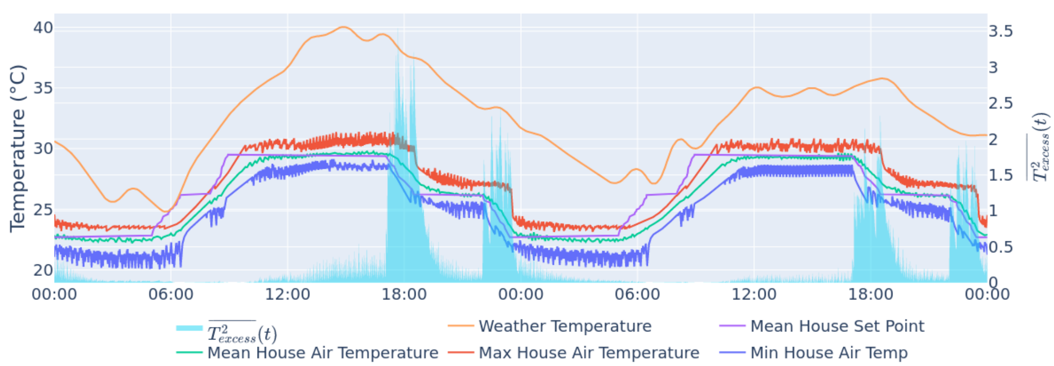

Figure 7: Scenario 1 HVAC Performance

Figure 7 illustrates the HVAC behaviour of Scenario 1: the mean HVAC setpoint, the minimum, maximum and mean house air temperature, the outdoor weather temperature, and the calculated value of $\overline{T_{\text{excess}}}^2(t)$

As the grid supply is unlimited, the HVAC systems are able to operate at all times as much as is necessary to keep the house air temperature within the acceptable range, so the air temperature closely tracks the setpoint. The only noticeable deviation is observed in the morning when the setpoint is increasing. Due to the absence of active heating equipment, the air temperature in the house rises only at the natural rate (with HVAC off) and cannot keep up with the rate at which the setpoint increases. This is a common feature of all simulation scenarios. As outlined in the metrics section, we quantify **positive** deviation from the setpoint with $\overline{T^2_{\text{excess}}}(t)$. Since the only significant deviation in Scenario 1 is negative, it does not affect the value of $\overline{T^2_{\text{excess}}}(t)$, which is consistently low. The $\overline{T^2_{\text{excess}}}$ value for Scenario 1 will be a point of comparison for the subsequent scenarios.

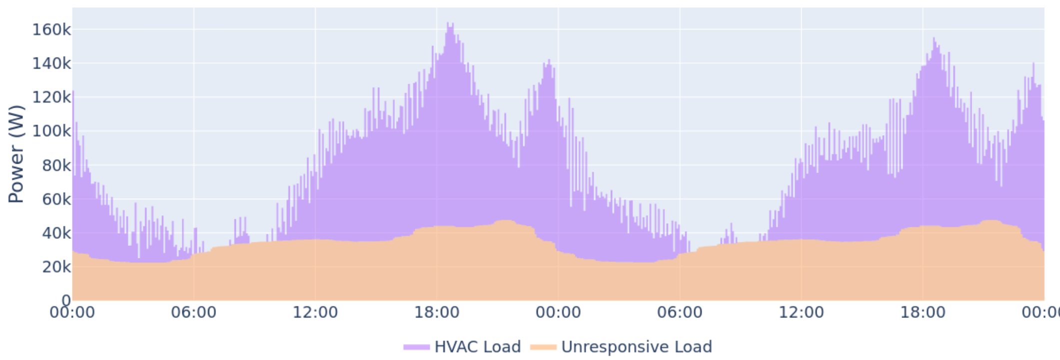

Figure 8: Scenario 1 Load Breakdown

Figure 8 presents the load that the microgrid exerts on the grid supply. It is depicted as a stacked graph, which shows the proportion of the total load contributed by HVAC and unresponsive loads. The graph reveals that the load fluctuates significantly throughout the day. The load peaks are not at the points of highest temperature, but instead at the times when the HVAC set points decrease, increasing the power needed to push the temperature down toward them. The highest of these peaks is around 18:30pm, and a second lower peak is observed at around 23:30pm. The minimum load is around 6am, which can be attributed to low unresponsive loads (as fewer appliances are in use) and the lowest weather temperature, which occurs just before sunrise.

To calculate the average power consumed by the microgrid, the curves of unresponsive load $P_{\text{unresponsive}}(t)$ and HVAC load $P_{\text{HVAC}}(t)$ were integrated using the trapezoidal rule, and divided by the length of simulated time. The results of these integrations and their sum are as follows:

$$\overline{P_{\text{unresponsive}}} = 34.5\text{kW}$$
$$\overline{P_{\text{HVAC}}} = 45.5\text{kW}$$
$$\overline{P_{\text{target}}} = P_{\text{unresponsive}} + P_{\text{HVAC}} = 80.0\text{kW}$$

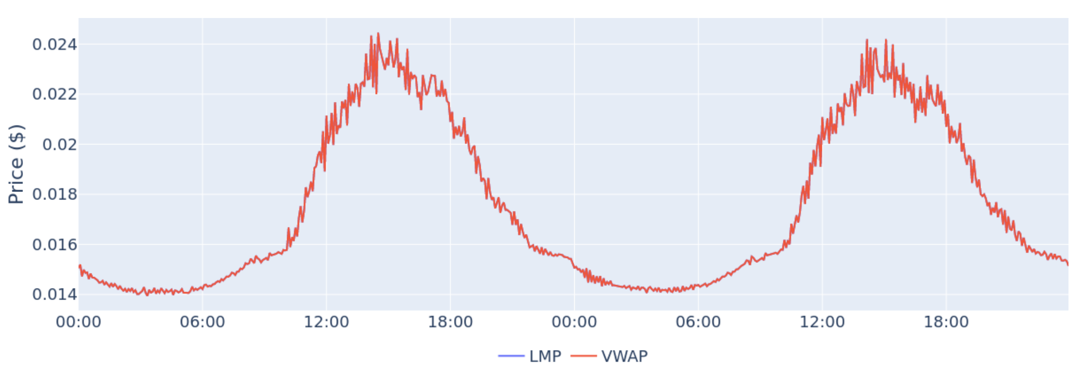

Figure 9: Scenario 1 Price

Figure 9 displays the average price paid for power over time. In Scenario 1, this price is always equal to the Locational Marginal Price (LMP) as the grid is the only power supplier and it sells at the LMP. This will be important to remember when contrasting the cost implications in the scenarios that EVs as power reservoirs.

In summary, Scenario 1 provides valuable baseline data for understanding the dynamics of a microgrid with unrestricted grid supply. The insights gained from this control case will be instrumental for comparative analysis with the subsequent scenarios involving EVs and PV installations.

5.2 Scenario 2

Houses	**EVs**	**PVs**	**Grid Supply Cap**
30	0	0	100kW

$$\overline{T^2_{\text{excess}}} = 3.335, \quad \overline{\text{VWAP}} = 0.01726 \text{ USD/kWh}$$

The purpose of Scenario 2 is to illustrate plainly the effect of insufficient power supply on the indoor air temperature within the houses in a simple setting, so that it can be understood before proceeding to the more complex scenarios with dynamic interactions between agents.

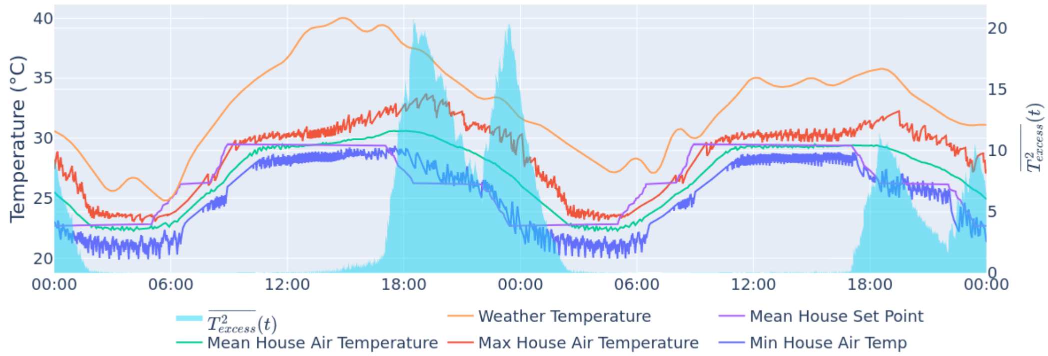

Figure 10: Scenario 2 HVAC Performance

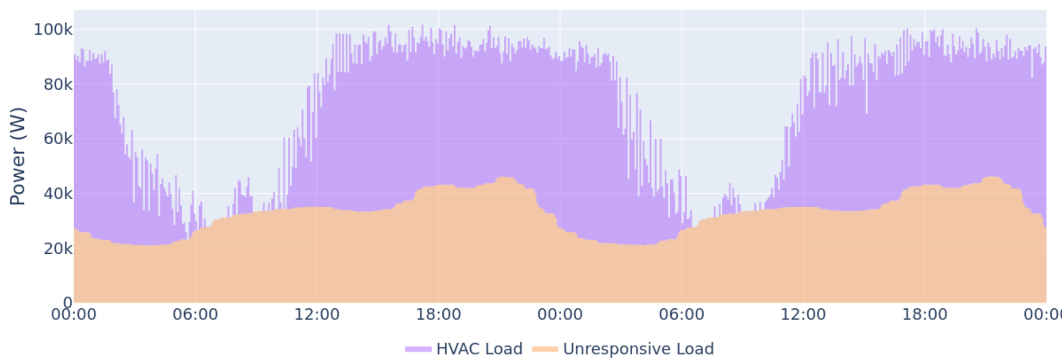

Figure 11: Scenario 2 Load Breakdown

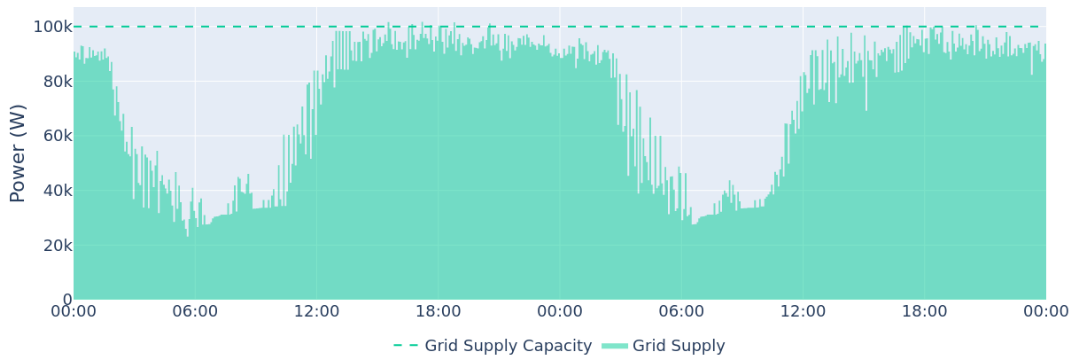

Figure 12: Scenario 2 Grid Supply and Grid Capacity

When the sum of the unresponsive load and the desired HVAC load exceeds the grid supply, house HVAC units shut down. The load is effectively "clipped" at the grid cap $P^{\text{grid}}_{\text{capacity}}$, as seen in Figure 12, although the actual maximum load often falls slightly below the supply cap due to the indivisibility of the load buy orders. This load shedding behaviour is most pronounced in the late afternoon and evening. As observed in Scenario 1, this period corresponds with the time when the HVAC load needed to maintain the setpoint reaches its highest levels.

Consequently, the indoor air temperature deviates above the set point due to the lack of sufficient HVAC operation. This deviation is clearly visible between approximately 17:00pm and 02:00am in Figure 10, illustrating the tangible impact of power supply inadequacy on quality of service. For this scenario, $\overline{T^2_{\text{excess}}}$ is much higher than the ideal value seen in Scenario 1.

In price terms, Scenario 2 is identical to Scenario 1, as it has the same single grid supply priced at LMP.

5.3 Scenario 3

Houses	EVs	PVs	Grid Supply Cap
30	0	30	100kW

$$\overline{T^2_{\text{excess}}} = 1.737, \quad \overline{P^{\text{PV}}_{\text{surplus}}} = 5.275\text{kW}, \quad \overline{\text{VWAP}} = 0.01556\text{USD/kWh}$$

In Scenario 3, all 30 houses have solar PV installations, none have EVs, and the grid supply cap remains at 100kW. This scenario is an example of a case where $\overline{P_{\text{capacity}}}$, the average power available to enter the system over the course of a day, exceeds $\overline{P_{\text{target}}}$, but due to the mismatch in the timing of PV generation and power demand, there is still notable excess temperature.

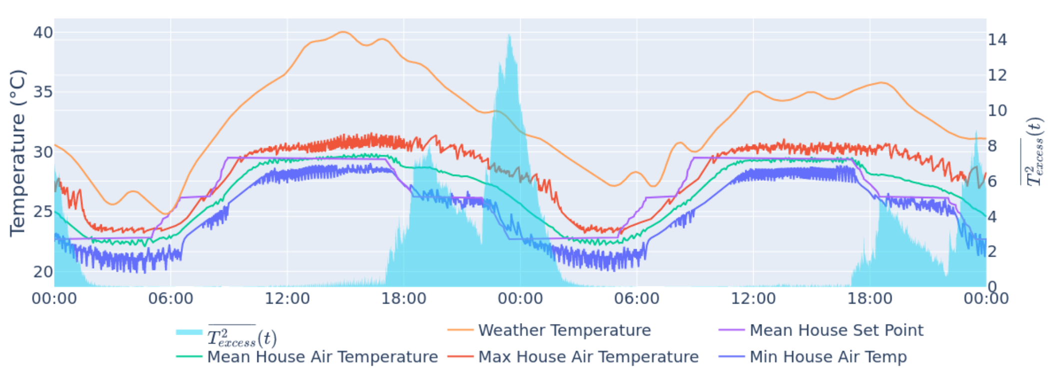

Figure 13: Scenario 3 HVAC Performance

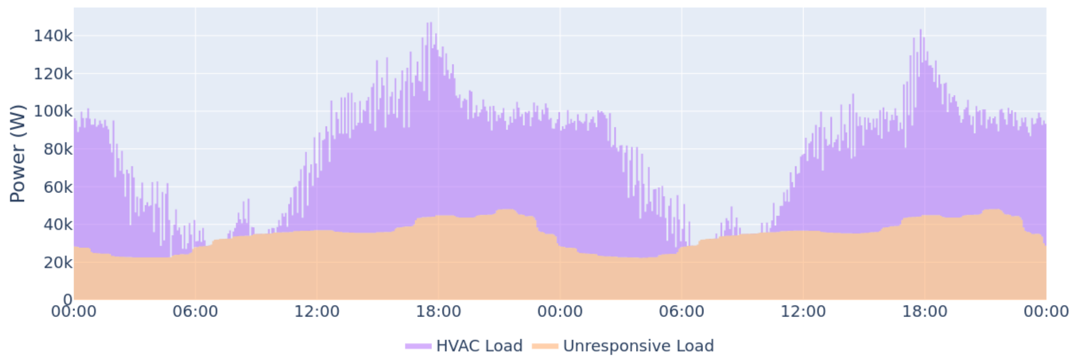

Figure 14: Scenario 3 Load Breakdown

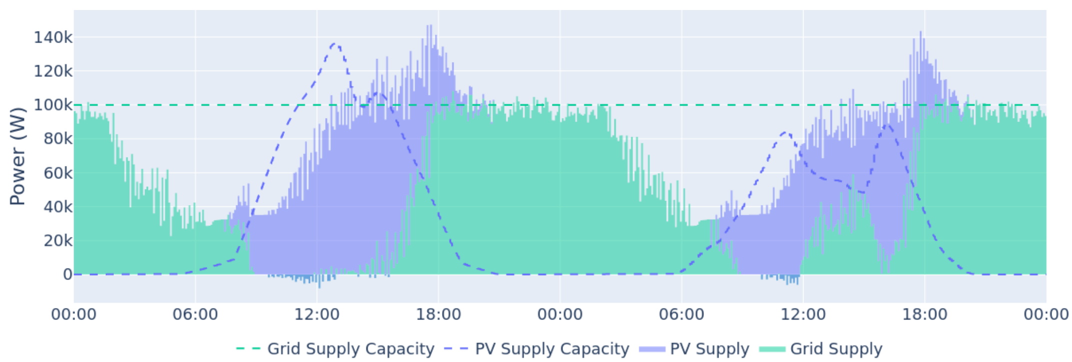

Figure 15: Scenario 3 Supply Breakdown

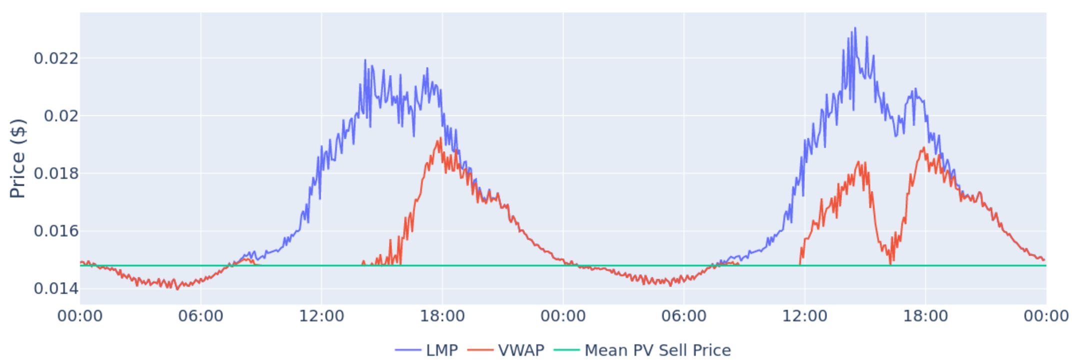

Figure 16: Scenario 3 Price

We can calculate P_{capacity} in this case as the sum of the averages over time of the grid and PV capacity curves, which are shown as dashed lines in Figure 15. These values and their sum are as follows:

$$\overline{P^{\text{PV}}_{\text{capacity}}} = 32.2\text{kW}$$
$$\overline{P^{\text{grid}}_{\text{capacity}}} = 100\text{kW}$$
$$\overline{P_{\text{capacity}}} = \overline{P_{\text{capacity}^{\text{PV}}}} + \overline{P^{\text{grid}}_{\text{capacity}}} = 132.2\text{kW}$$

These figures clearly show that **on average** the power capacity produced by the grid and PV supplies would be more than adequate to meet the needs of the houses over time.

Figure 15 shows the breakdown of power supply sources over time in Scenario 2. PV installations can produce power from around 07:00am and reach their peak power capacity around 12:00pm, but their capacity diminishes through the afternoon and becomes negligible by 21:00pm. On the other hand, the demand for power P_{target} peaks at 18:30pm and surpasses the grid cap from 13:00pm right through to 02:00am. Consequently, despite the average power available being above the target, there is under-utilisation of the PV power resource ($\overline{P_{\text{surplus}}(\text{PV})} = 5.275\text{kW}$).

This under-utilisation results in excess temperature in the evening and night time, with a high $\overline{T^2_{\text{excess}}}$ value of 1.73704. This value is lower than that observed in Scenario 2, indicating some mitigating effect from the PV installations (evident in the reduction of the first $\overline{T^2_{\text{excess}}}(t)$ peak around 18:30pm, and corresponding total power supply above the grid cap). However, it remains relatively high due to the timing mismatch between solar generation and power demand.

The plot of price over time in this scenario (Figure 16) reveals that during bright sunlight hours, the VWAP paid for power drops below the LMP. This is because the PV sell orders, which are priced below the LMP, fulfill some buy orders, effectively reducing the average price paid for power during these hours. The overall average VWAP is therefore lower than that in Scenarios 1 and 2.

5.4 Scenario 4

Houses	EVs	PVs	Grid Supply Cap
30	30	0	100kW

$$\overline{T^2_{\text{excess}}} = 0.2713, \quad \overline{\text{VWAP}} = 0.01739\text{USD/kWh}$$

The microgrid in Scenario 4 incorporates 30 EVs and no PV installations, and maintains the grid supply cap at 100kW. The focus in this scenario is on understanding the role of the EVs in flattening the load curve to match grid capacity and effectively utilizing the available power supply from the grid.

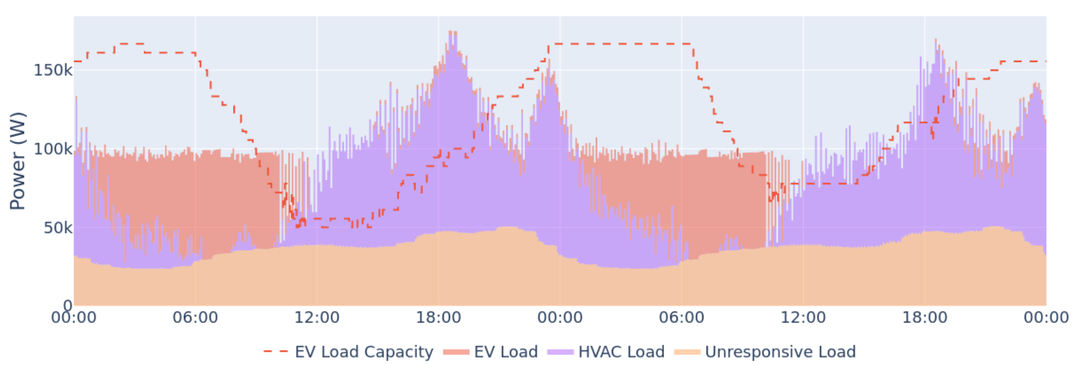

Figure 17: Scenario 4 Load Breakdown

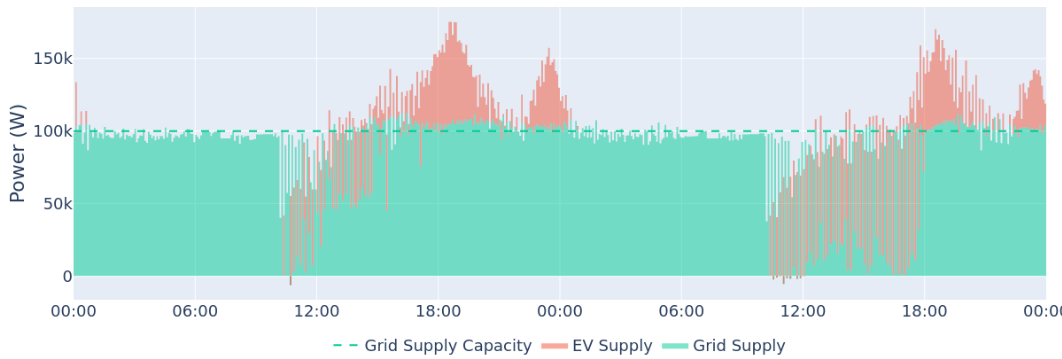

Figure 18: Scenario 4 Supply Breakdown

The load (Figure 17) and supply (Figure 18) plots for Scenario 4 clearly show the efficacy with which the EVs match the supply curve to correspond to the required load. The EVs charge predominantly between 01:00am and 10:00am, when the LMP is low and most EVs are at home, and discharge during times when the power demand surpasses the grid capacity. Discharge peaks around 19:00pm. The load curve is substantially flattened, reflecting the effective load management facilitated by the EVs.

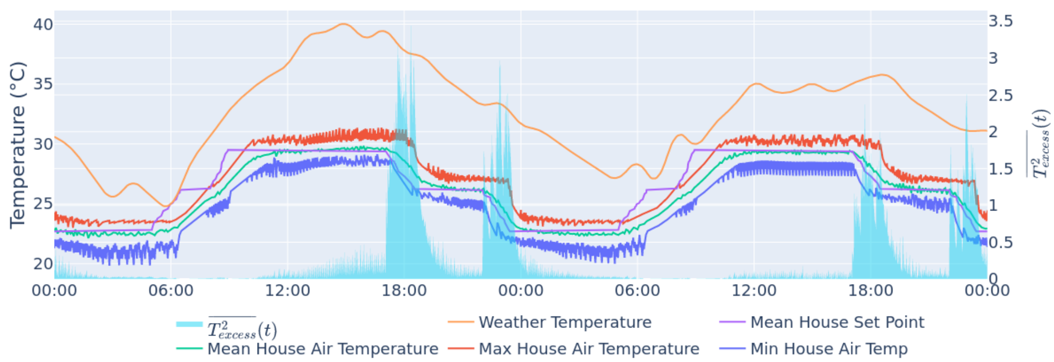

Figure 19: Scenario 4 HVAC Performance

In Scenario 4 the mean house air temperature closely adheres to the mean setpoint throughout the entire day. The excess temperatures observed in Scenarios 2 and 3 during the early afternoon and evening are significantly mitigated - peaks occur at similar times but much lower values, similar to Scenario 1. $\overline{T^2_{\text{excess}}}$ in this scenario is reduced to 0.2713, a dramatic improvement compared to Scenarios 2 and 3. This figure is close to the ideal value observed in Scenario 1. This indicates that the integration of EVs substantially improves the system's ability to maintain desired temperature settings.

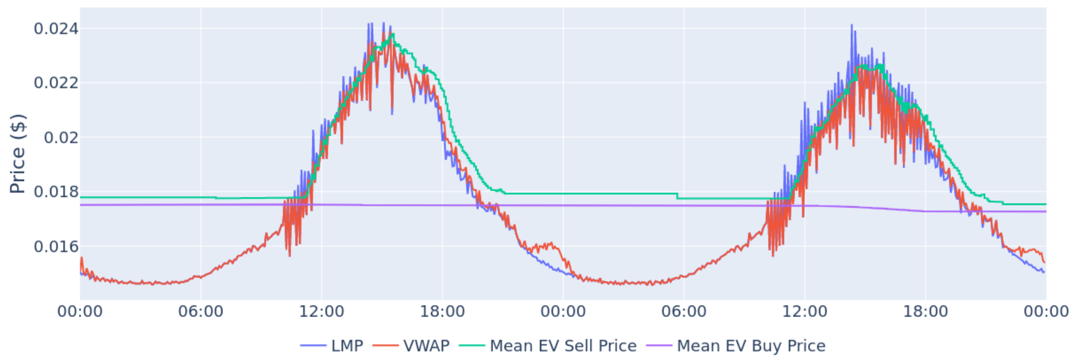

Figure 20: Scenario 4 Price

The price plot (Figure 20) shows that the VWAP stays in close proximity to the LMP. This behavior is anticipated as all power entering the system is procured at the LMP. The integration of EVs does not therefore significantly alter the price paid, but their role in load-shifting enables better meeting of house power requirements at the same price point as Scenario 1.

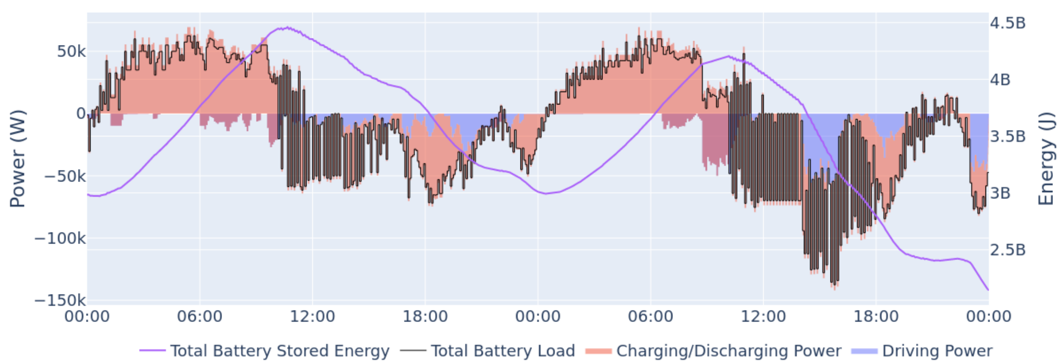

Figure 21: Scenario 4 EV Battery and Power State

Figure 21 shows the total energy stored in the EV batteries over time, as well as the change in this total energy as a stacked graph of the components attributable to charging/discharging and driving. The most prominent peaks in driving load occur around 09:45am and 18:00pm.

5.5 Scenario 5

Houses	EVs	PVs	Grid Supply Cap
30	30	30	100kW

$$\overline{T^2_{\text{excess}}} = 0.2616, \quad \overline{P^{\text{PV}}_{\text{surplus}}} = 2526\text{kW}, \quad \overline{\text{VWAP}} = 0.01565\text{USD/kWh}$$

In Scenario 5, every house is equipped with a PV installation and an EV. This scenario demonstrates the potential of combining EVs with intermittent sources such as solar PV in the PET scheme, illustrating the ability of their collaborative behaviour to meet electricity demand.

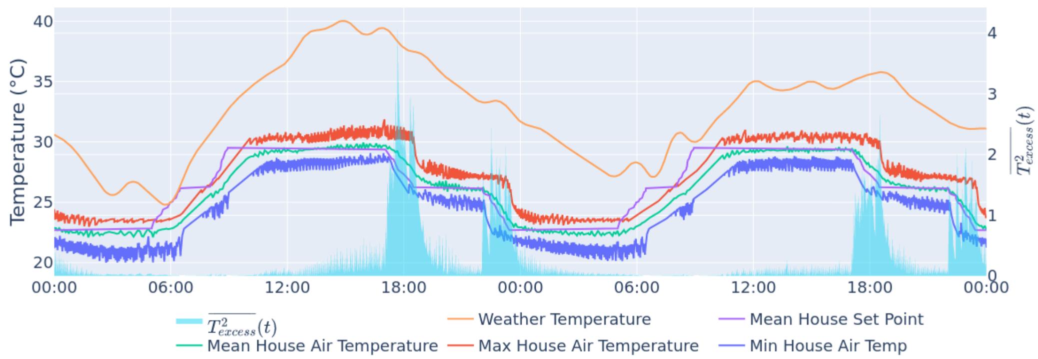

Figure 22: Scenario 5 HVAC Performance

Figure 22 shows that the mean air temperature in the houses closely follows the mean set point throughout the simulation - the HVAC system is effectively maintaining the desired temperature, resulting in a very low value for $\overline{T^2_{\text{excess}}}$, similar to that of the uncapped Scenario 1.

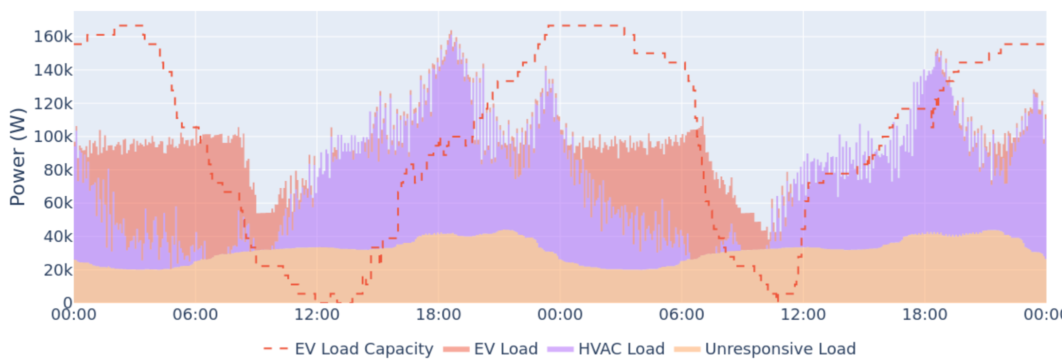

Figure 23: Scenario 5 Load Breakdown

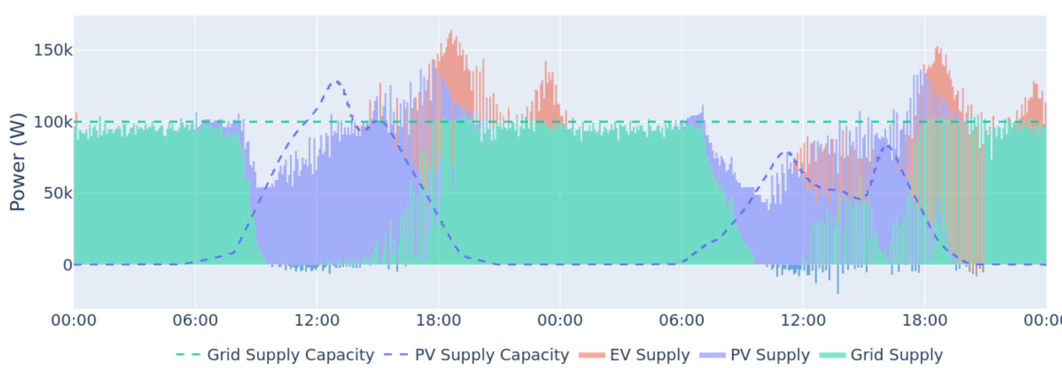

Figure 24: Scenario 5 Supply Breakdown

Figures 23 and 24 show the load and supply curves of Scenario 5. These figures illustrate that by acting as a reservoir for electrical energy, the EVs ensure that the unused PV capacity $\overline{P_{\text{surplus}}(\text{PV})}$ is kept to a minimum. This is particularly evident during the morning hours from around 6am onwards, when the supply of PV power is high, but HVAC demand is relatively low as the mean setpoint is increasing. During this period, the EVs buy a substantial amount of power generated by the PV arrays. This results in the amount of power generated by the PV installations staying close to their maximum capacity, where without the EVs (as in Scenario 3) it would fall short.

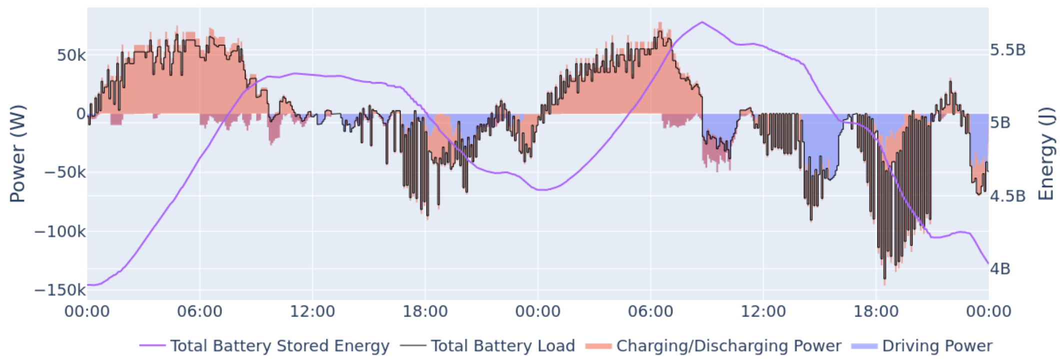

Figure 25: Scenario 5 EV Battery and Power State

In Scenario 5 EVs sell power mostly in the evening, starting around 6pm, when HVAC load is high due to falling temperature set points, PV supply is low, and the grid supply is at capacity. By selling the stored power back to the microgrid at these times, the EVs play a crucial role in meeting energy demand.

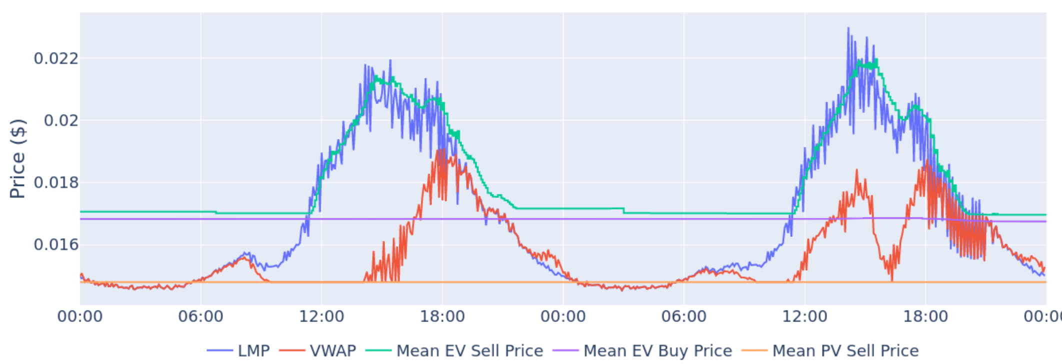

Figure 26: Scenario 5 Price

The average power price $\overline{\text{VWAP}}$ is also lower than that of all other scenarios, with the exception of Scenario 3, which achieves a low $\overline{\text{VWAP}}$ but does not adequately meet the energy demands of the microgrid.

In summary, Scenario 5 clearly shows that the interaction, facilitated by PET, between the grid, PVs and EVs is capable of meeting energy requirements while maintaining quality of service under a grid capacity constraint.

6. Conclusion

In this research, the primary objective was to create and assess a cosimulation platform, based on PEMT-CoSim, that could effectively demonstrate the utility of V2G EVs in microgrid PET schemes, particularly when power generation fluctuates. In simple terms, the study aimed to investigate how electric vehicles could actively contribute to the stability of a microgrid PET network by both consuming and providing electricity in a smart and coordinated way.

The cosimulation platform was successfully developed, and the outcomes from various simulations have indeed demonstrated that electric vehicles, as part of a PET scheme, have the capacity to significantly contribute to the smooth and continuous supply of electricity.

The simulated PET scheme enables the utilization of a collection of EVs as a power reservoir. While the availability of these vehicles to the microgrid is not constant due to their travel schedules, the PET system manages this availability responsively. Coordinated EV charging and discharging allows for substantial reduction of PV power underutilisation while maintaining quality of service for and optimising price paid by consumers.

These findings are significant in the broader context of promoting the Energy Transition and tackling climate change. By ensuring a more reliable and efficient power supply and improving renewable resource utilisation, the integration of V2G EVs and PET can contribute to making renewable energy sources more viable and attractive.

A substantial portion of this research was dedicated to refining and expanding PEMT-CoSim. In addition to the modifications made to permit the specific investigation in this thesis, the codebase was extensively rewritten to modernise it and make it more legible. My hope is that this will invite further open-source development.

6.1 Future Work

There are many opportunities for further investigation in this area, and further development of this cosimulation system. I hope that the enhancements made to the legibility of the PEMT-CoSim codebase during this research will make subsequent advancements and modifications easier. Outlined below are a few key opportunity areas for future research.

EVs as Power Packets
In this study, each EV can only charge at its home station, but future investigation could eplore the use of EVs as mobile energy carriers, where an EV can charge in one location and transport this energy to another location where it discharges. This could occur within a single microgrid or between separate microgrids. The cosimulation system and EV federate developed in this study is well-suited for extension to model and analyze such scenarios.

Bid Formulation System
The current bid formulation mechanism within the cosimulation is essentially a proof-of-concept to demonstrate the potential of V2G EVs as a power reservoir. A potential avenue for future work lies in refining this mechanism to establish more stable, reliable, and cost-effective market equilibrium properties under diverse conditions. This could involve integrating advanced algorithms or machine learning techniques (such as for demand prediction) to optimize bid pricing and adapting dynamically to grid conditions and market demands.

EV Modeling
The current model could benefit from a more detailed and accurate representation of EV features and behavior. Investigating how various charging and discharging cycles impact battery life through battery degradation, and integrating these effects into the model, would provide a more realistic assessment of long-term system performance and costs. Simulating a more diverse range of EV mobility patterns

(daily commuting patterns, fleet operations, sporadic usage etc.) would allow assessment of how these variations impact the efficacy of the system and improve its adaptability.

Resiliency to Supply Disturbances
Assessing and enhancing the resiliency of the PET system to supply disturbances is critical. This includes studying how the system reacts to events such as blackouts/equipment failures, extreme weather conditions, or sudden changes in demand, and adjusting system policies to improve its response.

Scalability and Large-Scale Simulations
Investigating and improving the scalability of the PEMT-CoSim model would be vital for it to be applicable to real-world scenarios. Future work could involve testing the model in larger microgrid settings, or in environments with multiple interconnected microgrids (a setting which presents a range of options for inter-microgrid trading systems). Evaluating how the model behaves under the increased complexity and diversity of larger systems could help to fine-tune its accuracy, performance and robustness.

Communication Protocols
The effective coordination of the PET system requires robust and secure communication protocols. Future work could explore the suitability of various communication technologies, for example blockchain-based systems, to ensure reliable, low-cost and secure data transfer for traders.

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A. Order Matching Algorithm

Algorithm 1 Market Order Matching

```
procedure MatchOrders(bids)
    buyers ← Buyers from bids, sorted by price descending
    sellers ← sellers from bids, sorted by price ascending
    transactions ← ∅
    while buyers is not empty do
        buyer ← buyers[0]
        matched ← first subset of sellers with total quantity ≥ buyer.quantity
        if matched = ∅ then
            buyers.remove(buyer)
        else
            for seller in matched do
                transaction_quantity ← min(seller.quantity, buyer.quantity)
                if transaction_quantity > 0 then
                    Subtract transaction_quantity from buyer and seller quantities
                    Append transaction details to transactions
                    if seller.quantity = 0 then
                        Remove seller from sellers
                    end if
                end if
            end for
            if buyer.quantity = 0 then
                Remove buyer from buyers
            end if
        end if
    end while
    return transactions
end procedure
```

B. EV Load Range Algorithm

Algorithm 2 Market Order Matching

```
procedure GetEVLoadRange
    soc ← Current battery SoC
    location ← Current EV location
    time_to_next_loc ← Time until EV next changes location
    next_loc ← Next location EV will change to
    max_discharge ← EV maximum discharge rate
    max_charge ← EV maximum charge rate
    if location ≠ "home" then
        return 0, 0
    else if next_loc ≠ "home" & time_to_next_loc < t_market then
        return [0, 0]
    else if 0.9 < soc then
        return [−max_discharge, 0]
    else if 0.3 < soc < 0.9 then
        return [−max_discharge, max_charge]
    else if 0.2 < soc < 0.3 then
        return [0, max_charge]
    else
        return [max_charge, max_charge]
    end if
end procedure
```

C. EV Bid Formulation Algorithm

Algorithm 3 EV Bid Formulation Procedure

procedure FormulateEVBids
    ma_long ← Mean LMP over last 24 hours
    ma_short ← Mean LMP over last 30 minutes
    iqr_long ← IQR of LMP of last 24 hours
    ev_buy_price ← ma_long
    ev_sell_price ← $\max(\texttt{ev\_buy\_price} + \texttt{iqr\_long} * 0.05, \texttt{ma\_short} + \texttt{iqr\_long} * 0.1)$
end procedure

D. Software Used

Table D.1: Software Used in the Study

Name	**Version**	**URL**	**Usage Summary**
`emobpy`	0.6.2	`https://pypi.org/project/emobpy`	Generating EV mobility and driving consumption patterns
`glm`	0.4.4	`https://pypi.org/project/glm`	Inspecting and manipulating GridLAB-D .glm files
`helics`	3.4.0	`https://pypi.org/project/helics`	Interacting with the HELICS cosimulation from Python
`pandas`	1.5.3	`https://pypi.org/project/pandas`	General data manipulation
`numpy`	1.24.3	`https://pypi.org/project/numpy`	General mathematical operations
`plotly`	5.14.1	`https://pypi.org/project/plotly`	Creating graphs and figures
`PYPOWER`	5.1.16	`https://pypi.org/project/PYPOWER`	Part of TESP for grid power flow
`scipy`	1.10.1	`https://pypi.org/project/scipy`	Calculating integrals (used for metrics)
HELICS	3.4.0	`https://helics.org`	Coordinating interaction between various simulation tools
GridLAB-D	5.1.0	`https://www.gridlabd.org`	Power flow simulation as part of the GridLAB-D federate
Docker	24.0.2	`https://www.docker.com/`	Containerizing the cosimulation for cross-platform compatibility and concurrent runs