

TECHNICAL UNIVERSITY OF CRETE DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

Diploma Dissertation

Optimal Power Management of Residential Microgrids with integrated Renewable Energy Sources and Plug-In Electric Vehicles

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Chania, August 2020

Acknowledgement

I would like to thank my supervisor, Prof. Kanellos Fotios for his assistance, support and much needed guidance throughout this whole project that was incredibly engaging and interesting to me. I am also grateful to Prof. Koutroulis Eftychios and Prof. Stavrakakis Georgios for serving on my thesis committee.

Finally, I would like to thank my family and friends for their love and support, and a special thanks to my parents for the inspiration to study electrical engineering.

Abstract

The rapid development and diffusion of microgrids throughout the main grid has paved the way for new power management strategies to develop. The traditional structure of centralized power generation is being replaced with Distributed Energy Resources (DERs), while demand response strategies are introducing better load flexibility. Additionally, Electric Vehicles (EVs) are similarly increasing in popularity, therefore presenting new opportunities and challenges to the grid.

Considering the above, the aim of this dissertation is to develop an algorithm that accomplishes optimal operation of a residential household microgrid with a grid-connected EV and rooftop solar panels as the renewable energy source (RES). The algorithm focuses on minimizing the main cost equation through the fmincon function of Matlab, while simultaneously adhering to all the constraints inherent to the above power system. Additionally, multiple different scenarios regarding season, house occupancy and cost of power model are simulated, in order to showcase the effectiveness of the algorithm in a wide variety of environments. The significance of this dissertation is that it clearly illustrates the cost savings that can be achieved through the proper management of EVs and loads in a residential microgrid.

Περίληψη

Η ραγδαία ανάπτυξη και διάχυση των μικροδικτύων σε όλη την έκταση του κεντρικού δικτύου επέτρεψε την ανάπτυξη νέων στρατηγικών διαχείρισης ισχύος. Η παραδοσιακή αρχιτεκτονική της κεντρικής παραγωγής αντικαθίσταται με κατανεμημένη παραγωγή, ενώ οι στρατηγικές απόκρισης ζήτησης εισάγουν καλύτερη ευελιξία στα φορτία. Παράλληλα, τα ηλεκτρικά οχήματα επίσης γίνονται ολοένα και πιο δημοφιλή, δημιουργώντας έτσι νέες ευκαιρίες και προκλήσεις στο δίκτυο.

Λαμβάνοντας υπόψη τα παραπάνω, στο πλαίσιο αυτής της Διπλωματικής εργασίας αναπτύχθηκε ένας αλγόριθμος που επιτυγχάνει τη βέλτιστη λειτουργία ενός οικιακού μικροδικτύου με ηλεκτρικό αυτοκίνητο συνδεδεμένο στο δίκτυο και ηλιακούς συλλέκτες στην οροφή. Ο αλγόριθμος επιχειρεί την ελαχιστοποίηση της κύριας συνάρτησης κόστους μέσω της συνάρτησης fmincon της Matlab, ενώ τηρεί ταυτόχρονα όλους τους περιορισμούς που είναι εγγενείς στο παραπάνω σύστημα ισχύος. Επιπλέον, προσομοιώνονται πολλαπλά διαφορετικά σενάρια σχετικά με την εποχή, τις ώρες παρουσίας/απουσίας των ενοίκων στο σπίτι, καθώς και το κόστος ηλεκτρικής ενέργειας, προκειμένου να αναδειχθεί η αποτελεσματικότητα του αλγορίθμου σε ευρεία ποικιλία συνθηκών. Στόχος της παρούσας διπλωματικής είναι η εξοικονόμηση δαπανών η οποία μπορεί να επιτευχθεί μέσω της σωστής διαχείρισης του ηλεκτρικού οχήματος και των φορτίων στο οικιακό μικροδίκτυο.

Contents

1.	INTRODUCTION			8	
	1.1	Gene	eneral		
	1.2	Microgrid definition			
	1.3	Dissertation outline			
2.	MICROGRIDS				
	2.1	Distributed Generation			
	2.2	Microgrid Energy Production		13	
		2.2.1	Solar Power	13	
		2.2.2	Wind Power	14	
		2.2.3	Combined Heat Power - Cogeneration/Trigeneration	14	
		2.2.4	Internal Combustion Engine	15	
		2.2.5	Hydrogen Fuel Cells	15	
		2.2.6	Hybrid Renewable Energy Systems	16	
	2.3	Microgrid Energy Storage		17	
		2.3.1	Rechargeable Batteries	18	
		2.3.2	Ultracapacitors	20	
		2.3.3	Hydrogen Fuel Cells	20	
		2.3.4	Flywheel Energy Storage	21	
		2.3.5	Pumped Hydroelectric Energy Storage	21	
	2.4	Electric Vehicles		22	
		2.4.1	Types of Electric Vehicles	23	
		2.4.2	Charging modes of Electric Vehicles	25	
		2.4.3	Unidirectional V2G (V1G)	26	
		2.4.4	Bidirectional V2G	26	
	2.5	Load Management		27	
		2.5.1	Demand response	28	

		2.5.2	Energy efficient HVAC systems		
	2.6	Microgrid Control			
		2.6.1	Centralized control	34	
		2.6.2	Decentralized control	35	
		2.6.3	Hierarchical control	35	
		2.6.4	Power, Voltage and Frequency control		
		2.6.5	Microgrid sensors and meters		
3.	ME	METHODOLOGY			
	3.1	Model Description			
	3.2	Optimization Algorithm		42	
	3.3	Electric Vehicle Battery			
	3.4	Grid power			
	3.5	PV Panels			
	3.6	6 Load Management			
		RESULTS			
4.	RES	SULTS	5	50	
4.	RES 4.1		S		
4.				50	
4.		Case	Study	50 50	
4.		Case 4.1.1	Study Cost of Power	50 50 51	
4.		Cose 4.1.1 4.1.2 4.1.3	Study Cost of Power Solar Power	50 50 51 52	
4.	4.1	Cose 4.1.1 4.1.2 4.1.3	Study Cost of Power Solar Power Load modeling and management	50 51 52 53	
4.	4.1	Case 4.1.1 4.1.2 4.1.3 Scence	Study Cost of Power Solar Power Load modeling and management arios	50 51 52 53 54	
4.	4.1	Cose 4.1.1 4.1.2 4.1.3 Scenc 4.2.1	Study Cost of Power Solar Power Load modeling and management arios Morning shift – Summer – Peak/Off-peak cost of power	50 51 52 53 54 56	
4.	4.1	Cose 4.1.1 4.1.2 4.1.3 Scenc 4.2.1 4.2.2	Study Cost of Power Solar Power Load modeling and management arios Morning shift – Summer – Peak/Off-peak cost of power Morning shift – Summer – Variable cost of power	50 51 52 53 54 56 57	
4.	4.1	Cose 4.1.1 4.1.2 4.1.3 Scenc 4.2.1 4.2.2 4.2.3	Study Cost of Power Solar Power Load modeling and management arios Morning shift – Summer – Peak/Off-peak cost of power Morning shift – Summer – Variable cost of power Morning shift – Winter – Peak/Off-peak cost of power	50 51 52 53 54 54 54 54 54	
4.	4.1	Cose 4.1.1 4.1.2 4.1.3 Scenc 4.2.1 4.2.2 4.2.3 4.2.4	Study Cost of Power Solar Power Load modeling and management arios Morning shift – Summer – Peak/Off-peak cost of power Morning shift – Summer – Variable cost of power Morning shift – Winter – Peak/Off-peak cost of power Morning shift – Winter – Variable cost of power	50 51 52 53 53 54 54 56 57 58 60	
4.	4.1	Cose 4.1.1 4.1.2 4.1.3 Scenc 4.2.1 4.2.2 4.2.3 4.2.4 4.2.5	Study Cost of Power Solar Power Load modeling and management arios Morning shift – Summer – Peak/Off-peak cost of power Morning shift – Summer – Variable cost of power Morning shift – Winter – Peak/Off-peak cost of power Morning shift – Winter – Peak/Off-peak cost of power	50 51 52 53 54 54 56 57 58 60 61	

	4.2.9	No constraint on SoC before departure	65
	4.2.10	Dumb charging and no load shifting	67
	4.3 Cost	68	
5.	CONCLU	JSIONS	70
6.	REFEREN	NCES	71

1. INTRODUCTION

1.1 General

The world is currently facing a global energy crisis, as conventional power plants are failing to moderate the ever increasing demand for power. However, the ever worsening environmental issues prevent the expansion and addition of further conventional plants. As such, the integration of Renewable Energy Sources (RES) into the grid develops into an absolute necessity.

RES, however, are infamous for their volatility and intermittency. The large scale integration of RES in a power grid leads to instability without the proper operational control systems. Nonetheless, it is an incredibly difficult task for a control system to cover an entire grid, handling all its energy sources, loads and storage systems, while simultaneously optimizing energy production, power flow and power quality.

Under those circumstances, the Divide and Conquer method of problem solving is employed, introducing the concept of smaller, self-controlling components of the grid, the so-called **Microgrids**.

1.2 Microgrid definition

A microgrid is defined as a group of locally controlled interconnected loads and distributed energy resources (DERs) within clearly defined electrical boundaries.

Microgrids can feature a connection with the main grid through the Point of Common Coupling (PCC) (grid connected microgrids) or be entirely independent, with no connection to the main grid (isolated microgrid).

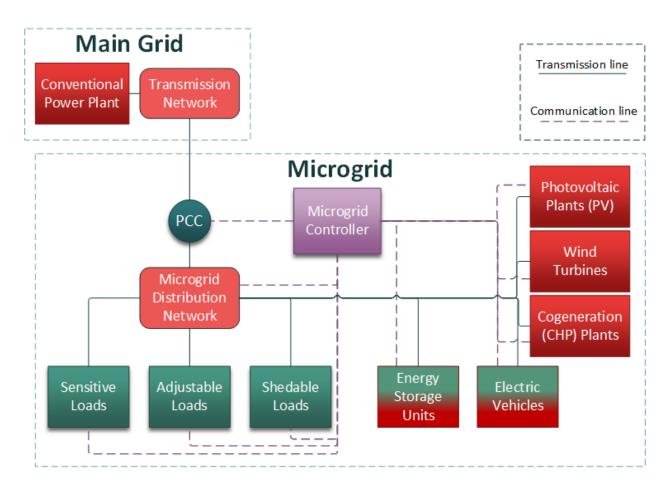


Figure 1.1 – Microgrid architecture.

This dissertation focuses on grid-connected household scale microgrids, with electric vehicles as the main energy storage system. While the most common household scale DERs are PV panels and diesel backup generators, the following literature review evaluates all possible Microgrid DERs.

1.3 Dissertation outline

This dissertation is a detailed study on the optimization of household microgrids that include RES and electric vehicles.

Chapter 2 covers all Microgrid related information that is necessary before moving on to the experimentation.

In Chapter 3, the optimization algorithm is showcased, along with all its constraints and variables regarding the different profiles of the simulated household.

Chapter 4 lists all the results of the different iterations of the algorithm, as well as analyses on the meaning of the aforementioned results.

Using these analyses, Chapter 5 is about the conclusions that can be drawn regarding household microgrids incorporating PV panels and electric vehicles.

2. MICROGRIDS

2.1 Distributed Generation

Distributed generation (DG) refers to the existence of Distributed Energy Resources (DERs) throughout the low voltage distribution network. DERs, compared to the conventional power plants, typically feature a higher Levelized Cost of Energy (LCOE). This essentially means that on a kilowatt/hour basis, the energy they produce is costlier. However, DG improves on a plethora of issues that are present in centralized generation:

- Reduced energy waste on transmission lines. Since DER units are positioned throughout the distribution grid, the distance to the consumer is shortened, and thus the thermal losses of transmission lines (Fig. 2.1) are mitigated.
- 2. **Improved stability and grid robustness**, since failure of a unit results in the loss of a small fraction of the total power output, which can then be restored through the remaining DER or the energy reserves of storage systems (unlike the catastrophic consequences of a failure of a conventional power plant).
- 3. **Reduced environmental impact**, as the majority of DERs are also RES, resulting in cleaner energy production with no carbon footprint.

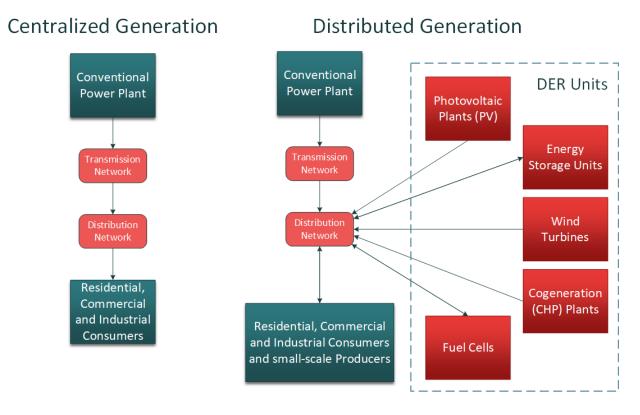


Figure 2.1 – Centralized and Distributed Generation.

All DERs can be sorted into multiple categories depending on their interface with the grid, and the control over their power flow:

Depending on their interface with the grid:

- **Conventional or Rotary units** Rotary units are connected to the grid through a synchronized rotating generator. Examples include reciprocating engines, small hydro, fixed-speed wind turbines, etc.
- Non-conventional units Non-conventional units are electronically coupled with the grid through power converters (DC-DC converters, Inverters etc.). Examples include variable speed wind turbines, PV panels, fuel cells, etc.

Depending on power flow control:

• **Dispatchable unit** – Dispatchable units are equipped with the ability to provide control over their power flow through a higher level control system. Reciprocating engines are an example of this category.

• Non-dispatchable unit – Non-dispatchable units lack the ability to have their power flow controlled, as it is usually dependent on the optimal operating condition of their primary energy source (external factors). The most common RES belong to this category (PV panels, wind turbines, hydroelectric stations).

2.2 Microgrid Energy Production

2.2.1 Solar Power

Photovoltaic panels (PV Panels) exploit the photovoltaic effect of semiconductors to convert the solar power of the sun into electricity.

Solar is one of the most swiftly evolving renewable sources, with the price of €/watt of PV panels dropping by around 35% in the last 5 years. PV panels are environmentally friendly, noise-free and of low maintenance. Additionally, the installation is incredibly scalable, from small units positioned on household roofs to large solar parks. This scalability establishes solar panels as the RES of choice in the simulation model of the proposed optimization algorithm, since they are the most common DER found in households.

The production of PV panels is relatively predictable with complex model simulation and accurate weather predictions. Efficiency-wise, PV systems usually reach the 15-20% mark, but this has also been improving over the last years.

Solar units are frequently combined with energy storage systems, such as lead-acid or lithium-ion batteries. This practice helps smooth out their noon-focused output, as the unused energy during the day can be used at night.

2.2.2 Wind Power

Wind Turbines convert the wind's kinetic energy into electricity through the use of generators (the wind's power rotates the rotor to produce electricity).

Microgrid-scale wind turbines are generally less used than PV panels, as they have high capital costs and require a large amount of free space. One of the applied types of residential-scale wind generators is the Gorlovtype helical wind turbine, positioned on the roof of buildings in similar fashion with solar panels.



Figure 2.2 – Gorlov wind turbine, Source: <u>https://www.electricalelibrary.com/en/2019/03/26/gorlov-turbines/</u>

2.2.3 Combined Heat Power - Cogeneration/Trigeneration

Combined Heat Power (CHP) or otherwise referred to as Cogeneration is the practice of saving the heat byproduct of heat engines or power stations to be used for heating. This operation increases the efficiency of electricity generation by reducing the wasted energy in thermal losses. Micro-CHP units are a recent development in DER systems, but are already proven to be a very valuable technology in reducing the carbon footprint of non-renewable fuels.

Another concept comparable to Cogeneration is that of Trigeneration, which refers to the utilization of heat engines of power stations for electricity, heating and cooling. The system is similar to cogeneration, except for the fact that medium-scale heat (100-180°C) is instead used by absorption chillers for cooling.

2.2.4 Internal Combustion Engine

An Internal Combustion Engine (ICE) is a heat engine which exploits the high temperature and high pressure gasses of the fuel combustion to apply force on a piston or a rotor and produce electricity.

Most commonly found Diesel or Gas engines, the fuel that is used is not environmentally friendly. However, there are types of ICEs that use renewable fuels, such as biodiesel, bioethanol or hydrogen.

Microturbines are also ICEs frequently used in microgrids, with the force of the combustion being applied to a turbine (instead to a piston) to produce electricity.

As far as household-scale microgrids are concerned, diesel engines (portable generators) are commonly used as backup in case the microgrid disconnects from the main grid due to a fault. The diesel engine exhibits high energy density, low fuel costs and minimal maintenance requirements, which all designate it as a satisfactory backup system.

2.2.5 Hydrogen Fuel Cells

A hydrogen fuel cell converts the energy created through the redox reaction of Hydrogen and Oxygen into electricity. Optimal Power Management of Residential Microgrids

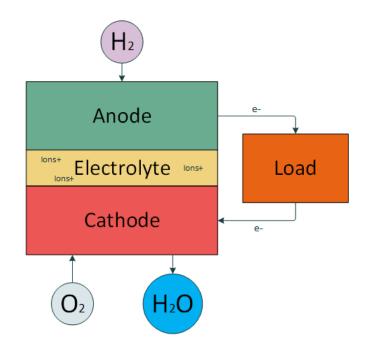


Figure 2.2 – Hydrogen Fuel Cell Design.

Similarly to ICEs, the conversion of chemical energy to electrical energy takes place, but unlike ICEs, fuel cells' only byproduct is water. The above fact, combined with the process of producing hydrogen by electrolyzing water, designates fuel cells as significantly more environmentally friendly.

Fuel cell systems are lightweight, compact and contain no moving parts, making them very reliable standalone electricity sources of microgrids (especially isolated ones). The equipment necessary for their use, however, is expensive and requires highly trained personnel, which complicates their use in residential microgrids.

2.2.6 Hybrid Renewable Energy Systems

Most RES have glaring disadvantages that need to be considered in their implementation. However, since many of those disadvantages are timeoriented, they can be covered by using different types of RES systems in combination.

A widely known example of this practice is to combine Wind Turbines and Solar Panels, since both of them usually have power peaks at different hours, better covering the load throughout the day. Numerous combinations can be made from just solar, wind, biomass and hydrogen plants, with the latter two not having time-of-the-day restrictions.

A Hybrid RES (HRES) system combined with an energy storage system can provide even greater energy balance and system efficiency.

2.3 Microgrid Energy Storage

Energy storage refers to all devices/mechanisms that can be used to store energy. With the exception of capacitors, the energy is not stored in electric form, due to the highly transient behavior of the electric charge. Instead, the Energy Storage Systems (ESSs) convert the electric energy to other forms to store it, and then back to electric once there is need for it.

Energy storage provides a wide range of utilities to the microgrid:

RES Support

Energy storage systems assist microgrids with the intermittency of the produced energy of RES. Specifically, excess energy produced during high production hours can be stored and later used during peak demand/low RES production.

• Voltage and Frequency support

The microgrid can manage energy reserves to increase or decrease voltage and frequency. With the use of proper control architecture, ESSs can increase the stability of the microgrid and make it less prone to the voltage/frequency fluctuations caused by RES, new loads or even faults of conventional power plants.

• Islanded Microgrid support

Microgrids that are by default isolated or had to disconnect from the grid (due to a fault) can rely on their ESSs to remain powered. Without the main grid's support, however, ESSs require strenuous amounts of control to maintain power balance, as well as high capacity, should the microgrid have to remain disconnected for an extended period.

The following subchapters list the most common ESSs used in microgrids:

2.3.1 Rechargeable Batteries

Batteries are devices that use high-energy chemical reactants to produce electricity through redox reactions. Batteries can be **primary** (no recharging) type or **secondary/rechargeable**. Since the focus of the chapter is about energy storage systems, any mention of batteries will naturally be about *rechargeable* ones.

Electric batteries are a very efficient and flexible way to provide energy storage, being scalable enough to cover the needs of any system. In a €/Wh ratio, however, they are among the most costly energy storage solutions.

Additionally, most types of batteries require extensive control to remain healthy. This is attributed to the fact that each battery needs specific handling of its charging and discharging cycles. Storage control systems aim to prevent batteries from reaching below 10% State of Charge (SoC) or above 90% to increase their lifespan.

Different sequences of electrodes and electrolytes used in batteries lead to multiple different battery types, each with their own unique characteristics.

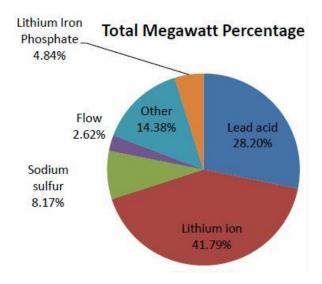


Figure 2.3 - Percentage of Battery storage systems deployed in the U.S. by 2019. Source: http://energyskeptic.com/2019/how-safe-are-utility-scale-energy-storage-systems/

The most prominent ones in the microgrid market are mentioned below:

• Lithium-lon

The most promising battery technology, lithium-ion (Li-ion) batteries' price has been dropping exponentially since their emergence in the 1990s. Currently being used in almost all laptops, electric vehicles, cell phones and other similar mobile devices, their low weight but high energy density sets them as the frontrunners for microgrid energy storage applications. They also feature very little loss of charge while not in use and lack the memory effect found in other types of batteries. Since their cost has been steadily decreasing, the only other notable drawback of Li-ion batteries is the high heat generated while in heavy use. Any danger however can be mitigated through proper design and safeguards. A recent upgrade of the lithium-ion technology is the Lithium-ion Polymer batteries, improving on energy density and flexibility regarding the battery's shape.

• Lead-Acid

Mostly found in motor vehicles, lead acid batteries are the oldest technology of rechargeable batteries. It is a mature technology with low cost, and they can provide high surge currents, which is the reason they are popular in combination with combustion engines and starter motors. Like lithium-ion, they exhibit no memory effect. For microgrid purposes, however, lead-acid batteries are infamous for their limited cycling capability, resulting in the need for frequent replacement. Additionally, since one of the purposes of a microgrid is to be environmentally friendly, the heavy metal elements of this battery pose a serious issue.

• Flow Batteries

Flow batteries utilize the ion exchange of two chemical components in two tanks separated by a membrane. Their operation is similar to fuel cells, in the way that the two tanks can be resupplied with fuel. This ability rids the flow batteries of the aging effect (prominent on conventional rechargeables).

2.3.2 Ultracapacitors

Ultracapacitors (or supercapacitors) are capacitors with much higher capacity than the common ones found in small-scale circuits. Compared to batteries, Ultracapacitors have much higher charge/discharge rates and more lifecycles, but significantly less energy density.

This behavior makes Ultracapacitors great balance support units, with their ability to discharge power quickly into the grid to mitigate voltage or frequency drops, or absorb power for the opposite effect.

Ultracapacitors are rarely installed as stand-alone units, usually being combined with electric battery systems to form what is known as Hybrid Energy Storage Systems (HESS). The capacitors therefore provide short term support, while the batteries help with long-term power deficits.

2.3.3 Hydrogen Fuel Cells

Hydrogen Fuel Cells, similar to batteries, are also electrochemical energy storage systems. Their rechargeable factor is attributed to the fact that

the main byproduct of the reaction is water. This water can then be fed to an electrolyzer powered by the electricity the microgrid wants to "store", creating hydrogen that can be used in fuel cells again. The round-trip efficiency of a fuel cell energy storage system is about 40%, but it can be increased to 80% if combined with a Cogeration (CHP) system mentioned in Chapter 2.2.3.

2.3.4 Flywheel Energy Storage

A Flywheel Energy Storage (FES) system employs an accelerating rotor's mechanical inertia to store mechanical energy. An electrical motor accelerates the flywheel, storing the electrical energy as kinetic energy. Once the microgrid requires power absorption, the same motor acts as a generator, transforming the kinetic energy of the flywheel into electricity. Similar to supercapacitors, flywheels are able to provide high bursts of power.

FES systems are prone to loss of energy, even if magnetic bearings are used to minimize friction. Therefore, their main application is to support the power quality of the microgrid and not long term power supply.

All in all, FES systems are generally costlier compared to other alternatives, and find uses only in select microgrids with specific niches, such as the need to support high load spikes.

2.3.5 Pumped Hydroelectric Energy Storage

Pumped hydroelectric energy storage (PHES) is comprised of two water reservoirs of differing altitude, connected through pumps and power generating turbines. During low demand hours, the plant receives power to drive the pumps and transport water from the lower to the higher reservoir. Once the microgrid encounters high demand, the high altitude water is dropped through turbines to provide electricity to the grid. Hydroelectric energy storage boasts a great 80% round-trip efficiency, higher than most other energy storage forms. Due to its great energy capacity, it accounts for more than 90% of the installed energy storage systems in GW rater power [Figure 2.4] in the US.

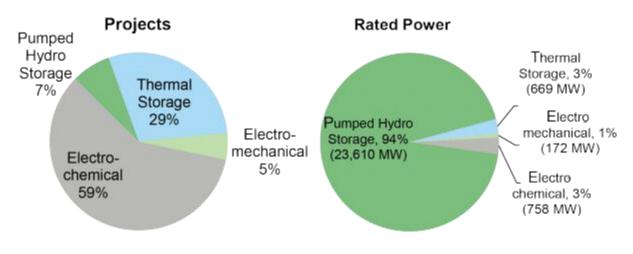


Figure 2.4 – U.S. Energy storage Projects compared to their Rated Power, 2018. Source:[33]

However, the scale of any Pumped Hydro project is significantly larger than the energy storage needs of even the largest microgrid. Thus, pumped hydro remains as proof of concept in microgrids so far.

2.4 Electric Vehicles

With the world's supply of fossil fuels slowly depleting, and the cost of liquid fuels increasing, conventional vehicles are no longer seen as longterm sustainable transportation solutions. The next step for the vehicle industry is the replacement of combustion engines with electric motor cars, known as Electric Vehicles (EV).

Electric vehicles feature many advantages over conventional vehicles, such as:

• Little to no air pollutants – All air pollutants from EVs come from the micro particles created by tire friction, but, comparatively to conventional vehicles, this amount is negligible. One could also argue that the production of the energy used by EVs has its own carbon

footprint, but, again, it is lower in comparison to conventionals and it can also be diminished through the use of RES.

- Generate less noise Noise pollution due to vehicles is a significant issue in major cities. Many EVs are so quiet that the producing company adds artificial noise to the engine to alert nearby pedestrians[50].
- Cheaper to operate and maintain The cost/mile of electricity is usually cheaper compared to the cost of gas/mile. Additionally, the cost of electricity is generally more stable compare to the market-sensitive fluctuating cost of gas. Finally, since an EV contains less moving parts, it is also cheaper to maintain and breaks down less often.
- **Improved efficiency** Electric motors reach an efficiency of 60%, compared to the 20% of conventional combustion engines.
- Lithium-Ion battery technology Lithium-Ion batteries that EVs primarily use have underwent great advancements over the last few years, such as increased energy capacity and density and, most importantly, exponentially decreasing cost.

2.4.1 Types of Electric Vehicles

Electric vehicles are split into three different categories:

1. Hybrid Electric Vehicles (HEV)

Hybrid EVs contain an ICE that is connected with an electric generator. The generator takes advantage of the movement of the vehicle to charge a battery. The battery can then supply an electric motor with power, with the motor assisting the ICE in the movement of the vehicle. The battery of HEVs is usually of limited capacity and cannot be charged/discharged externally, thus HEVs are unable to interact with the microgrid in any way.

2. Plug-In Hybrid Electric Vehicles (PHEV)

Plug-In Hybrid EVs have the same general topology with HEVs, but feature larger batteries that allow for more reliance on the electric motor by itself.

Additionally, the battery can be charged externally, which means they can be used by the microgrid for peak shaving and valley filling purposes. However, the battery capacity is still a fraction of that of BEVs, establishing their use as grid energy storage systems as circumstantial.

3. Battery Electric Vehicles (BEV)

Battery EVs lack an ICE, relying solely on an electric motor for movement. As such, they also feature a high capacity battery that is rechargeable by the grid. BEVs will be the main focus of electric vehicles in the simulation modeling on Chapter 3 below.

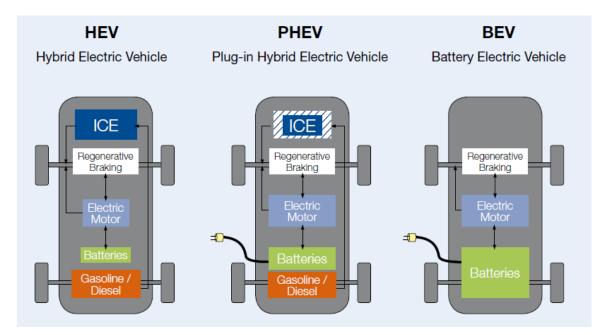


Figure 2.5 – Comparison between different types of electric vehicles, source: https://www.swingelectric.com/buyers-guide/picking-an-electric-car/

2.4.2 Charging modes of Electric Vehicles

The recharging of the batteries of the cars is categorized in the following ways:

• AC Charging

The EV is charged through the standard socket found in all households. Typical power ratings sit between 3.7kW and 7kW for single phase, but there are also chargers that carry three phase power for 22kW. Alternatively, the same socket can be used with a cable-incorporated protection device, for higher safety but also higher cost due to the more specialized cable.

Instead of standard sockets, there are also specialized sockets with dedicated circuit lines to better protect both the EV and the other household appliances. These sockets additionally provide load shedding utility, for a more optimized charging schedule.

• DC Charging

The EV is charged using rectified DC current. The power electronics that convert AC to DC also include all the control and protection utilities required. By using DC current, specialized charging locations and parking lots can reach power ratings from 50kW up to 350kW.

The diffusion of EVs throughout the grid can create both issues and opportunities for a microgrid. The main concern caused by the swift spread of EVs is the increased power demand. An unprepared grid could potentially face demand issues if the rate of increasing loads is not matched with an equally increasing power output.

However, EVs also provide unique opportunities to the microgrid. There are three facts to consider regarding electric vehicles:

 For the majority of the daytime, the average vehicle is parked, either at a household or at a parking lot near the workplace (with EV charging spots).

- Electric charging spots have the necessary power flow to charge an empty car battery to full in 6~ hours, while DC charging ports can reduce that to less than 2 hours (usually only in commercial buildings/parking lots however).
- 3. The **battery of an electric vehicle has** relatively **high capacity**, as it can cover more than the daily demand of an average household.

The combination of the above factors allows the microgrid to utilize parked EVs either as adjustable loads or as energy storage systems for the grid, a technology known as Vehicle to Grid (V2G). V2G is applied in two main ways, as follows:

2.4.3 Unidirectional V2G (V1G)

Unidirectional V2G (V1G), also known as Smart Charging, is the process of controlling the time and rate with which an EV's battery is charged, in order to assist the microgrid with peak shaving and valley filling. The aggregator (parking facility, household controller or the microgrid itself) takes into account the future departure time of the vehicle and tries to optimize the charging timespan. Thus, the battery is recharged optimally, using the excess energy generated from RES while avoiding peak demand time zones in order to assist the microgrid with demand management.

V1G is a simpler and less invasive procedure compared to bidirectional V2G, with guaranteed cost efficiency and less controversy surrounding it.

2.4.4 Bidirectional V2G

Bidirectional V2G essentially uses the parked vehicle like any other energy storage system, with the additional requirement of the battery to be charged by departure time. The energy of the battery is supplied to the grid during peak demand, and refilled during low demand. Additionally, as with other storage systems, it can be used for voltage/frequency support, or to power an islanded microgrid. Bidirectional V2G, however, faces scrutiny on multiple fronts. The battery is the most expensive component of the vehicle. As batteries have limited cycles before they need to be replaced, owners of EVs are understandably reluctant to allow their vehicles battery to be used in such manner, despite the economic incentive. Studies on this front are inconclusive, with some saying the battery degradation is not worth the economic gain [46,47] and others claiming this procedure actually increases battery life [44]. Additionally, it is equally inconclusive on whether bidirectional V2G is yet economically viable as a project, considering that cost of batteries and losses due to low round-trip efficiency finally negate any economic benefits [45].

Nonetheless, it needs to be noted that most EVs use Lithium-ion batteries, and, as mentioned in Chapter 2.3.1, Li-on's prices have been dropping exponentially the past few years. It is safe to assume that if this trend continues, the economic viability of bidirectional V2G will be indisputable.

2.5 Load Management

Since the energy challenges the world is facing demand all components of a grid to become "smarter", loads are no exception to this rule. All loads, from industrial facilities, to commercial buildings or residences can be categorized in three main categories:

• Sensitive/Critical Loads

Sensitive loads consist of all devices that exhibit a relative necessity for them to remain powered. This necessity can range from basic survival (healthcare buildings) to simple recreational use (personal computers, TVs). Regardless, failing to provide power to these loads is detrimental to the quality of life of the microgrid consumer, and should be avoided in all, except for the direst of circumstances.

• Adjustable Loads

Adjustable are considered all the devices that can operate in a wide range of intensity (i.e. dimmable lights), and/or their output (i.e. heat) has high enough inertia thus shutting them down for a limited amount of time would not result in major issues.

The most power consuming adjustable load in every household/commercial building is Heating, Ventilation and Air Conditioning (HVAC). All HVAC loads have different modes of intensity, which can be adjusted to assist with peak shaving on the grid.

• Shedable -Shiftable Loads

Shedable loads are comprised of electrical devices that can be time scheduled into different time slots of the day. This fact designates them as priority candidates to be turned off in case of a major power peak.

Washers, dryers, water heaters and electric ovens treated as shiftable, meaning that their operation can be halted and resumed with the purpose of minimizing their use during peak demand. Fridges are also roughly included in this category, assuming that the offline period is limited and their door is not repeatedly opened so as to keep the interior sufficiently cool.

Electric vehicles can be considered both shedable and adjustable, as their recharging process can be either fully interrupted or limited with a reduced power flow rate.

2.5.1 Demand response

Usually, whenever there is an imbalance of supply-demand in a grid, the utilities adjust the supply side to match the demand. This practice comes with a plethora of issues, as the supply side is not always flexible enough. Conventional generators usually require downtime before they can be started again and uptime before they can be shut off, without mentioning the extra monetary costs of these procedures. Demand Response (DR) management is the direct or indirect adjustment of the grid's loads by the utility operators. This adjustment can be approached by a multitude of ways:

 Tariffs – The least invasive way to encourage consumers to avoid using unnecessary power during power peaks is with off-peak tariffs. Consumers are thereby prompted to shift adjustable and shedable loads during the off-peak hours to save money, while simultaneously lightening the load of the grid during the peaks.

A more advanced solution made possible by the recent application of smart meters is that of fully variable tariffs. Smart metered households are supplied with an In Home Display (IHD), by which the utility companies can alert the consumer in real time on the need to reduce their power consumption.

- 2. **Agreements** Utilities reach agreements, usually with high-end industrial users. The aforementioned industrial users comply to limit their electricity usage during peak demand timeslots.
- Targeted Blackouts Utilities operators disconnect specific areas/neighborhoods from the grid, in order to avoid cascading grid failures or a potential total blackout. This is a last resort solution saved only for situations that it is deemed absolutely necessary.

This procedure is often applied to the Crete power system during the hottest days of summer, since the increased demand from tourism infrastructure and HVACs overwhelms the grid's energy production ability.

2.5.2 Energy efficient HVAC systems

The primary purpose of the HVAC system is to maintain the comfort of the indoor environment. Demand-controlled HVAC uses sensors to provide feedback control that automatically adjusts the output rates of all HVAC components. Additionally, smart HVAC systems also include sensors that

estimate occupancy and adjust accordingly, further increasing energy efficiency.

Air quality can easily be measured and kept within an acceptable level. CO₂ concentration must not be allowed to reach values above 1000ppm, and comfortable humidity is roughly around 40%.

Comfortable temperature, however, is a significantly more complicated matter, and cannot be approached solely by means of temperature sensors.

A proposed solution on combining all related factors into one variable is the **Predicted Mean Vote (PMV)**. PMV works on a scale of +3 (hot) to -3 (cold), and incorporates the multitude of elements that affect the human body's comfort in a certain temperature:

- Room temperature, humidity and air velocity
- Metabolic rate, mechanical work done by the human body
- Thermal insulation of clothing

As one can notice, many of the aforementioned input variables cannot be measured by sensors. They are instead assigned depending on current season, type of building and the amount of physical activity of the average person present.

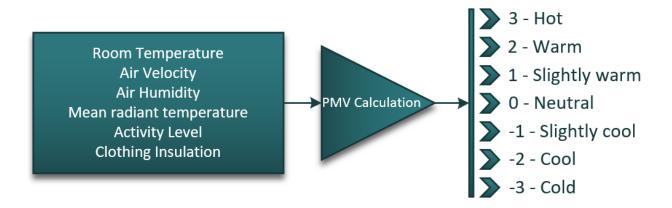


Figure 2.6 – PMV calculation approach.

Furthermore, the amount of energy used by electric space heaters and electric chillers does not linearly relate to the room temperature. For efficient energy use, it is crucial to analyze the **Thermal Model** of the building [42]:

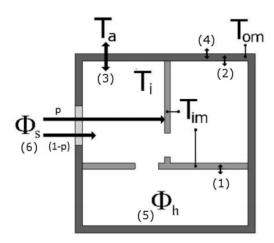


Figure 2.7 – Heat Exchange of building

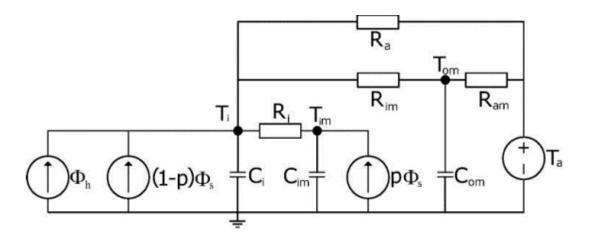


Figure 2.8 – Equivalent RC diagram of building

To better simulate heat flow, the heat dynamics can be modeled as an electrical network, as shown in Figures 2.7 and 2.8. Temperature is equivalent to voltage, heat flow to current, thermal resistance to resistors and heat capacity to capacitors. Analysis of the above system produces the following equations:

$$C_{i} \cdot \frac{dT_{i}}{dt} = \frac{1}{R_{a}} \cdot (T_{a} - T_{i}) + \frac{1}{R_{i}} \cdot (T_{im} - T_{i}) + \frac{1}{R_{im}} \cdot (T_{om} - T_{i}) + A \cdot (1 - p)$$

$$\cdot \Phi_{s} + \Phi_{h}$$
(1)

$$C_{im} \cdot \frac{dT_{im}}{dt} = \frac{1}{R_i} \cdot (T_i - T_{im}) + A \cdot p \cdot \Phi_s$$
⁽²⁾

$$C_{om} \cdot \frac{dT_{om}}{dt} = \frac{1}{R_{im}} \cdot (T_i - T_{om}) + \frac{1}{R_{am}} \cdot (T_a - T_{om})$$
(3)

- *T_i* : Indoor air temperature in the building (°C)
- *T_{im}*: Temperature in interior walls of the building (°C)
- *T_{om}*: Temperature in the house envelope (°C)
- T_{α} : Outdoor temperature (°C)
- $\boldsymbol{\Phi}_{s}$: Solar radiation (kW/m²)
- ϕ_h : Heat input from electric space heaters (kW)
- *R*_α: Thermal resistance between indoor air and ambient environment (°C/kW)
- *R_i*: Thermal resistance between interior walls and indoor air (°C/kW)
- *R_{im}*: Thermal resistance between indoor air and house envelope (°C/kW)
- *R_{am}*: Thermal resistance between house envelope and ambient environment (°C/kW)
- *C_i* : Heat capacity of indoor air (kWh/°C)
- Cim: Heat capacity of interior walls (kWh/°C)
- Com: Heat capacity of house envelope (kWh/°C)
- *p*: Fraction of solar radiation absorbed by interior walls
- A: Effective window area (m²)

Equation 1 describes the heat flow between indoor air, interior walls and house envelope, while taking into account the heat produced by the solar rays reaching the house as well as the electric heaters. Equation 2 is about the heat flow between interior walls and indoor air and Equation 3 is about the heat flow between the house envelope, interior walls and the outside environment.

Since temperature can be within a certain range without affecting the PMV, HVAC systems can exploit the heat capacity of walls and air to create an additional energy storage system. Such system can store thermal energy (or the lack of it) during low demand, and then reduce its operation during peak demand without affecting the overall comfort level.

2.6 Microgrid Control

The whole control process of a microgrid involves many microprocessors (controllers), with each one having its own responsibility of controlling a specific part of the microgrid.

The Microgrid supervisory control architecture is split in three hierarchical levels, each one communicating with the rest in a top-down tree topology.

The main components of microgrid control are as follows:

• Distribution network operator (DNO)

DNO is the operator responsible for providing power to the microgrids. Intended to be used in an area where multiple microgrids exist.

• Market Operator (MO)

MO is the operator responsible for selling power to the microgrids.

• Microgrid Central Controller (MCC)

Located in the middle of the hierarchy, the MCC facilitates communication between the microgrid and the MO/DNO nodes.

• Local Controller (LC)

An LC is allocated for every DER and adjustable load that is contained within a microgrid. Depending on the type of control, it communicates with the MCC or both the MCC and other LCs.

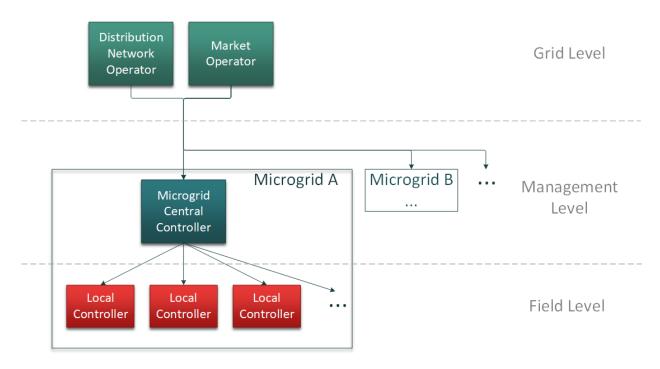


Figure 2.9 – Microgrid Control Architecture.

MCCs and LCs communicate in thoroughly different ways depending on the focus of the control architecture (Centralized, Decentralized or Hierarchical).

2.6.1 Centralized control

Centralized control of microgrids focuses on optimizing the amount of power sold or purchased to/from the grid. This architecture establishes the MCC as the main control unit of the microgrid.

The MCC receives information on market prices from the MO, production bids from the DER LCs and load bids from the load LCs. With all this information available, the MCC processes it and instructs control set points to all LCs with the intention of minimizing the cost of power.

The information exchange requires a bidirectional communications network, usually through Power Line Carriers (PLC), telephone lines or a wireless medium (i.e. RF networks).

The focus of Centralized control on the MCC leaves the LCs with little autonomy. While having lower costs as the only focal point might be

profitable in the short run, it also introduces different issues in the overall performance and longevity of the Microgrid.

2.6.2 Decentralized control

Decentralized control of microgrids allows more autonomy on the Local Controllers, compared to centralized control. LCs are more intelligent and communicate with each other in order to make decisions that are not necessarily focused on just the market aspect of energy. The MCC acts mostly as a communication node between the LCs, providing them with information on the market and the weather, but allowing them to act autonomously.

This bottom up architecture requires more robust communication networks and a Multi Agent management System (MAS) capable of organizing economic functions, environmental factors, and technical requirements.

2.6.3 Hierarchical control

In-between the extreme cases of centralized and decentralized control exists the Hierarchical Control. This control scheme implements the best of both worlds, allowing the relative autonomy of decentralized control with the better economic performance of centralized control.

The way Hierarchical Control works is by splitting the control responsibilities into three main categories, and assigning each category on different parts of the grid.

1. Primary Control

Primary control is responsible for stabilizing voltage and frequency by providing reference points to the voltage and current control loops of all DERs, also referred to as zero-level-control. The actual stabilization procedures are further detailed in Chapter 2.6.4.

Additionally, primary control offers plug-and-play capability to DERs while also sharing the active and reactive power among them. Furthermore, it is also important for the reduction of circulating currents to avoid damage in power devices.

Primary control is located hierarchically in the bottom level and is handled mainly by the LCs (each Local Controller runs its own primary control algorithm).

2. Secondary Control

Secondary control is performed less regularly compared to primary, and is run by the MCC. It is responsible for fixing voltage and frequency deviations caused by primary control or variations of loads and renewable sources.

Secondary control provides primary control with the voltage and frequency setpoints, essentially handling the "how much" part of the equation and leaving stabilization to the LCs themselves.

3. Tertiary Control

Tertiary control is responsible for optimizing the operation of the microgrid in the long term, through the thorough consideration of economic constraints, future loads and weather for RES production.

It is the slowest level of control compared to the aforementioned two, sampling relatively infrequently. It is also responsible for the power exchange of the microgrid and the main grid, assuming the microgrid is not in islanded mode.

2.6.4 Power, Voltage and Frequency control

All DERs are connected with the microgrid through power electronic systems (inverters and rectifiers). A microgrid's power, frequency and voltage can be controlled depending on the control strategy utilized by the power system. All control schemes take advantage of the almost linear relationship between active power-frequency, and reactive power-voltage. This is accomplished by altering one of the values to adjust the other, depending on the control type.

There are three commonly used control strategies, each one with its own benefits and drawbacks:

• **P-Q Control** – P-Q control's purpose is to set the active and reactive output of the inverter to the specific reference values provided by the secondary control mentioned above.

PQ control adjusts active and reactive power by adjusting the frequency and voltage. This behavior however can affect the microgrid negatively by causing voltage or frequency drops and spikes. The above reason is why PQ control is optimally used on grid-connected microgrids, where the voltage and frequency of the main grid support those of the microgrid's, allowing it to focus only on the active and reactive power balance.

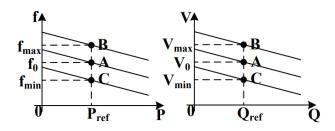


Figure 2.10 – P-Q Control, Source:[20]

• V-f Control – Consequently, the opposite action of adjusting the active and reactive power of the inverter is voltage and frequency control. V-f control forces the inverter's output to follow the reference values of voltage and frequency.

Nominally used on islanded microgrids, this control scheme results in the DERs providing voltage and frequency support to the islanded microgrid, sacrificing however the control on active and reactive power. V-f control thus struggles to respond to load changes.

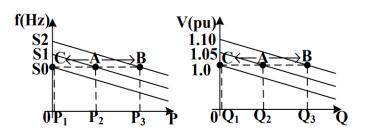


Figure 2.11 – V-F Control, Source:[20]

• **Droop Control –** Droop control works by simulating the droop characteristic found in synchronous generators and controlling the voltage and frequency depending on the variation of output power.

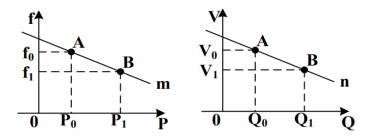


Figure 2.12 – Droop Control, Source:[20]

Frequency droop control follows the following equation regarding the inverse proportionality of power and frequency:

$$f = -R \cdot P + c \tag{1}$$

- *f* : Frequency of the DER (Hz)
- R: Slope characteristic of the DER (Hz/kW)
- P: Power production of the DER (kW)
- *c*: Droop constant (Hz)

Essentially, DERs are left to follow their droop characteristic without being forced to maintain a specific voltage, frequency or power level. However, in case of the **Hierarchical control** mentioned above, Secondary Control adjusts the c constant in equation (1) to fix any voltage or frequency variation that will inevitably occur. Droop control is the most flexible of the three control schemes, following the loads without needing any information fed to the inverter (thus cutting down communication network costs). It does however demonstrate poor behavior towards heavy transient events, requiring further PID controllers for smoother performance.

Since different control schemes work better for grid-connected and islanded microgrids, there have consequently been created inverters that can perform multiple of those control schemes.

The most optimal operation of a microgrid is to use P-Q control as long as it is connected to the grid, but in case of grid failure, switch to droop control. A multi-purpose inverter, with information on the grid's status, can seamlessly perform this switching, depending on the microgrid's connection. Such switching does obviously come with its own dangers, thus some microgrid utilities employ only droop control, regardless of the connection with the grid.

2.6.5 Microgrid sensors and meters

The microgrid control architecture consists of a closed-loop control system (negative feedback). An essential component of the system is the sensors unit.

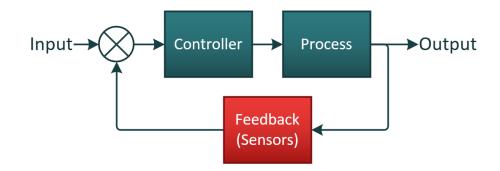


Figure 2.13 – Closed-Loop control system.

The most prominent type of sensor a household microgrid requires is the **Smart Meter**.

The Smart Meter accurately measures the power flow from the PV panels and from the EV's battery, the power exchange from the grid, as well as the load needs of the house.

Additionally, the In Home Display (IHD) that is supplied with the smart meter informs the household residents on their consumption, the PV Panels' production and the State of Charge of the vehicle's battery. IHD's are also able to inform the consumer on varying tariffs, such as the daynight price model. This would in turn incentivize the consumer to shift their loads to off-peak hours, assisting with the demand response mentioned above.

Besides the Smart Meter measuring power flow, a residential microgrid can comprise of a few other sensors:

- **Temperature, Humidity and Air Velocity sensors** The output of the aforementioned sensors can be used in the algorithm that optimizes the HVAC operation, in order to heat/cool the house without wasting energy.
- Human detection sensors Infrared sensors that detect human presence can assist with HVAC operation and automatic lighting management.
- Weather sensors While accurate weather prediction cannot be handled on a household scale, a residential microgrid can make use of weather predictions of the local forecast station to more accurately predict RES production and adjust its loads accordingly. In addition, local weather sensors, such as outdoor temperature, wind speed and direction, humidity, etc. could provide input to the heat loss model of the building, as described above.

3. methodology

3.1 Model Description

The simulated microgrid in the present dissertation is a **Residential Household Microgrid**, with the following features:

- Access to the grid (and to information about cost of power)
- Rooftop PV Installation
- Battery Electric Vehicle (BEV), connected in V2G mode
- Residential loads (shiftable and sensitive)

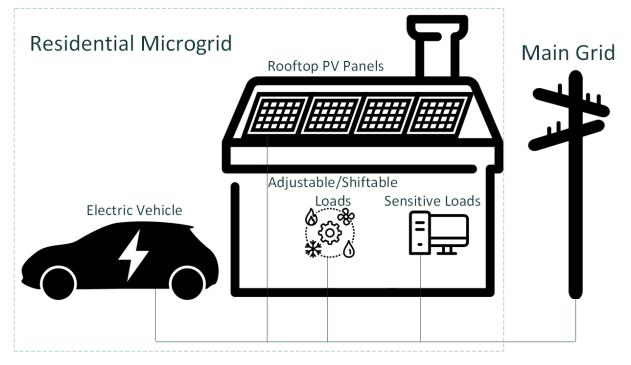


Figure 3.1 – The proposed Residential Microgrid Model.

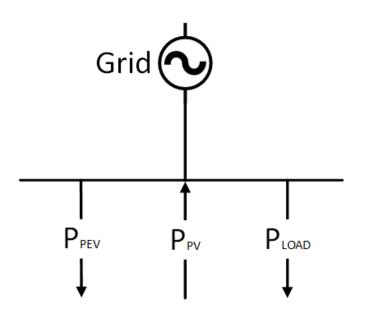


Figure 3.2 – Power Diagram of the residential microgrid

The battery of the EV is simulated using the <u>load convention</u>, hence the power flow of the battery being in the same direction with P_{LOAD} .

3.2 Optimization Algorithm

The following equation is the main <u>cost equation</u> of the optimization algorithm:

$$\min \sum_{t} \left(\left(P_{PEV}(t) + P_{LOAD}^{*}(t) \right) \cdot cost(t) - \left(P_{PV}(t) \cdot cost_{PV}(t) \right) \right) dt$$
(1)

Where P_{PEV} is the power transfer from the battery of the EV (kW), P_{LOAD} is the adjusted load (kW) (after the load shifting mechanism has been applied) and P_{PV} is the power production of the PV Panels (kW). The purchasing price of power produced by PV Panels is $cost_{PV}(t)$, and the purchasing price of power generally is cost(t). Depending on the net metering law, the two costs could be the same or different. For the purpose of the simulation, the selling price of solar panel power is considered to be lower.

The proposed algorithm tries to minimize the value of the formula as much as possible on a 24 hours period.

The battery's power flow is considered positive when it absorbs power and negative when it supplies power to the microgrid (load convention).

Considering all the above, by minimizing the value of the formula, the microgrid achieves its optimal operation, since the addition of these three values determines the amount of power that will be bought/sold to/from the grid (Equation 2).

$$P_{PEV}(t) + P_{LOAD}^{*}(t) - P_{PV}(t) = P_{GRID}(t)$$
(2)

The optimization of the above two equations is carried out using Matlab's **fmincon** function. Fmincon finds the minimum of constrained nonlinear multivariable functions, by applying the following concept:

$$\min_{x} f(x) \text{ such that} \begin{cases} c(x) \le 0\\ ceq(x) = 0\\ A \cdot x \le b\\ Aeq \cdot x = beq\\ lb \le x \le ub \end{cases}$$

In this case, f(x) is the cost equation (1), and x is a vector that contains both P_{PEV} and P_{LOAD} , since we need the function to calculate both of them. P_{PV} is a set range of values, since the generation of PV panels is not controllable (non-dispatchable unit).

$$x = \begin{bmatrix} P_{PEV} \\ P_{LOAD}^* \end{bmatrix}$$

The matrices A and b are used for any inequality constraints that apply to the system, and Aeq and beq are used for equality constraints. All four of the above matrices are created according to whether we want the constraint to apply to P_{PEV} , P_{LOAD} or both.

The matrices lb and ub are formulas that set the range of values P_{PEV} and P_{LOAD}^{*} are allowed to reach (bound constraints).

The nonlinear constraints c(x) and ceq(x) are not used in this scenario, since there is no need for nonlinear conditions.

3.3 Electric Vehicle Battery

The battery of the EV is modeled after the Tesla Model S 60kWh battery, with all its specifications copied from the real battery [54].

Total Capacity	Maximum Allowed Capacity	Minimum Allowed Capacity				
60kWh	54kWh	6kWh				

The function of minimum and maximum allowed power is to preserve the battery's health. It is known that batteries must not be allowed to reach their edge states (full or empty) in order to remain healthy for longer.

$$SoC(0) + \sum_{t=0:dt:T} P_{PEV}(t) \cdot dt \le SoC_{max}$$
(3)

$$SoC(0) + \sum_{t=0:dt:T} P_{PEV}(t) \cdot dt \ge SoC_{min}$$
(4)

Equations (3) and (4) set the constraints for preserving the battery's health as mentioned above. *SoC(0)* is the initial state of charge (kWh) and *SoC_{max}*, *SoC_{min}* are the set limits of the battery (kWh). *T* is the duration the algorithm runs for (24 hours).

Additionally, the battery obeys charging flow constraints, since the average residential AC charger of a household can only reach the power flow specified below:

Maximum Power Flow	Minimum Power Flow				
(charging)	(discharging)				
10kW	-10kW				

$$P_{PEV} \le P_{max} \quad \forall t \tag{5}$$

$$P_{PEV} \ge P_{min} \ \forall t \tag{0}$$

Equations (5) and (6) set the power flow constraints, with P_{max} and P_{min} being the maximum and minimum power transfer rate of the EV's battery. The minimum power flow essentially describes the maximum power rate when the battery is delivering power to the microgrid (hence the negative value).

For realism purposes, the battery is disconnected from the microgrid for 8 hours, according to the work shift of the owner of the EV. Once the battery is plugged in again, its SoC has been slightly depleted, since the vehicle was used for a certain amount of kilometers.

This specific model assumes a workplace at a distance of 40km, and thus the round-trip consumes about 15kWh from the battery (25% of the SoC).

$$SoC(0) + \sum_{t=0:dt:T} P_{PEV}(t) \cdot dt = SoC_{target} - SoC_{commute}$$
(7)

Equation (7) establishes one of the end goals of the algorithm, which is to reach the same SoC as the initial SoC, by the end of the 24 hour run period. $SoC_{commute}$ is the amount of kWh consumed by travelling to the workplace and back. This constraint is set in order to ensure comparison fairness, since it would be groundless to compare daily costs of different runs of the algorithm that reached dissimilar final states of charge.

$$SoC(0) + \sum_{t=0:dt:t'} P_{PEV}(t) \cdot dt = SoC_{departure}$$
(8)

Equation (8) forces the algorithm to charge the vehicle up to the specified level before the departure time. $SoC_{departure}$ is the SoC that the battery is

(6)

considered sufficiently charged and t' is the departure time for work (9:00 or 15:00, depending on the shift). This constraint dampens the efficiency of the algorithm, since keeping the vehicle fully charged is hardly ever necessary, considering the 330km mileage of the battery's full charge. Several scenarios, both with and without this constraint are evaluated on Chapter 4.

3.4 Grid power

The algorithm operates on a day-ahead market basis. As a day-ahead market case, the microgrid receives information regarding the cost of power for the following day time.

The optimization algorithm uses that information to most efficiently charge the EV, power the necessary loads and sell or buy the remaining power to or from the grid.

Maximum Grid power (buy	Minimum Grid Power (sell to			
from the grid)	the grid)			
10kW	-10kW			

$$P_{PEV}(t) + P_{LOAD}^{*}(t) - P_{PV}(t) < P_{GRID_{max}} \forall t$$
(9)

$$P_{PEV}(t) + P_{LOAD}^{*}(t) - P_{PV}(t) > P_{GRID_{min}} \forall t$$
(10)

Equations (9) and (10) detail the power flow constraints of the residential microgrid and the main grid. These constraints are usually set by the utility operator, and the values of $P_{GRIDmax}$, $P_{GRIDmin}$ can vary depending on the type of billing.

Regarding the cost of power, the model is simulated using two different scenarios:

• On-peak/Off-peak tariff

This tariff mode splits the day to two categories: *peak* and *off-peak* hours. Power consumption during peak hours is more expensive than power consumptions during off-peak hours, thus incentivizing the consumer to avoid unnecessary loads during peak demand.

The simulation follows the timetables and cost tables provided by PPC (Public Power Company, Δ EH) [51, 52]. It is important to note that offpeak hours differ between winter and summer periods.

• Variable tariff

The second tariff mode used is derived from the first, but instead of two different costs, the variable tariff displays a different value each hour of the day.

This tariff is not yet applied in Greece, thus its values have been created theoretically. However, for comparison fairness, it exhibits the same mean price with the two-zone tariff mentioned above.

3.5 PV Panels

The simulated PV Panels feature twenty eight (28) 370 kW LG Neon R Ace LG380A1C-V5 solar panels positioned on the residence's roof of 70m² area, as an array of rated power 10.36kW.

The power produced by the PV Panels is calculated from the following equation [55]:

$$P_{PV} = Y_{PV} \cdot f_{PV} \left[1 + a_P \left(T_C - T_{C,STC} \right) \right] \cdot \frac{\hat{G}_T}{\hat{G}_{T,STC}}$$
(11)

where Y_{PV} is the rated capacity of the PV module under Standard Test Conditions (STC) conditions (kW) and f_{PV} is the PV derating factor, influenced by real-world operating conditions such as soiling of the panels, wiring losses, shading, snow cover, aging etc. a_P is the PV temperature coefficient for the power (%/°C), T_c is the current module temperature and $T_{C,STC}$ is the module temperature under STC conditions.

 G_{T} is the incident total solar radiation (kW/m²), a variable of the model proposed by Hay and Davies, Klucher and Reindl (HDKR model). G_{T} takes into account a multitude of factors, such as distance between the earth and the sun, zenith angle, latitude, period between hour angles and combines direct radiation, diffuse radiation and reflected radiation. $G_{T,STC}$ is the incident total solar radiation in STC conditions (kW/m²).

Footnote - Standard Test Conditions (STC) are the following:

- Solar radiation H = 1 kW/m²
- PV cell temperature T_{PV}= 250°C
- Wind -> minimal to none

3.6 Load Management

The household daily loads have been generated using the algorithm provided from [53]. The algorithm allows for customization of all common house loads, as well as operating profiles regarding current season (summer, winter etc.) or the work schedule of the people present. The household is cooled through A/C in summer and heated through electric heaters in winter, thus both are considered electric loads.

Each simulated load profile is explained in its specific case.

Additionally, the optimization algorithm is given the leniency to transfer 30% of each hour's loads to a different hour, as long as the total load sum of the day remains the same. This essentially simulates the shiftable loads of the microgrid, such as washers, dryers, water heaters and electric ovens that can also be operated in different time slots.

$$P_{LOAD}^{*}(t) \le 1.3 \cdot P_{LOAD}(t) \tag{12}$$

$$P_{LOAD}^{*}(t) \ge 0.7 \cdot P_{LOAD}(t) \tag{13}$$

$$\sum_{t=1:24} (P_{LOAD}(t)) = \sum_{t=1:24} (P_{LOAD}^{*}(t))$$
(14)

Where P_{LOAD} is the shifted load (kW) and P_{LOAD} is the load before adjustment (kW), as was generated by [53].

Equations (12) and (13) showcase the aforementioned load shifting, and equation (14) guarantees that the sum of the shifted load will be equal to the initial one by the end of the day.



4.1 Case Study

The above described optimization algorithm is executed with different scenarios for many of its inputs, all of which are referenced in the following subchapters:

4.1.1 Cost of Power

As mentioned in Chapter 3.4, cost of power is simulated in two different scenarios: (a) two-zone and (b) variable tariffs. The values of €/kWh are taken directly from the PPC (<u>dei.gr</u>), and thus represent realistic data of the main grid that the residential microgrid is connected to.





Figures 4.1.a and 4.1.b – Cost of Power scenarios.

4.1.2 Solar Power

The PV production was generated with the model mentioned in Chapter 3.5. For the purpose of the simulation, two random days are selected from the yearly PV production, one in the middle of summer (high power yields) and one in the middle of winter (low power yields).

The fluctuations in power production could be a result of a multitude of factors, such as partial shading from nearby trees/buildings or cloud coverage.

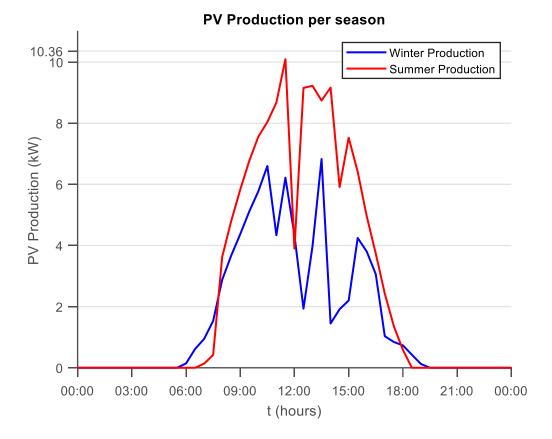


Figure 4.2 – Daily PV Production of a random summer and winter day

4.1.3 Load modeling and management

Using the algorithm of [53], the loads are generated according to the work shift of the house resident(s), as well as the current season.

Regarding shifts, two possible scenarios are examined: (a) morning (9:00-17:00) and (b) evening shift (15:00-23:00). The difference work-shifts achieve is shifting of loads throughout the day, as, for example, morning shifts result in the hours of 9:00 to 17:00 being relatively empty of loads.

As far as the effect of seasons, each of them creates different load variances. Winter season requires the use of electric heating (very significant power use) as well as lighting during daytime, while summer season exhibits power spikes due to the use of HVACs.

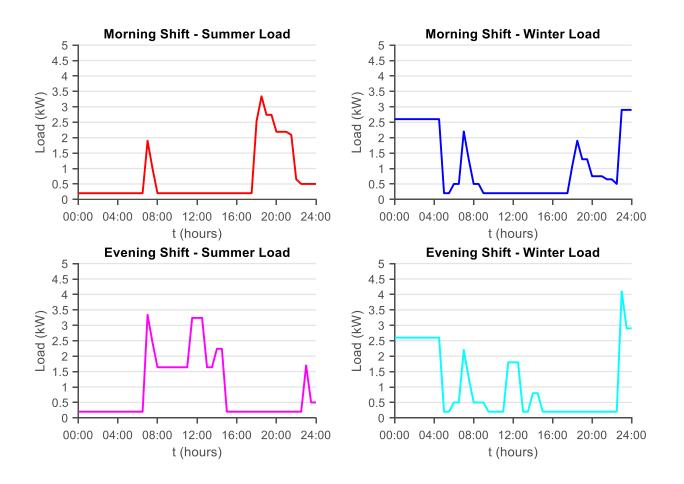


Figure 4.3 – All load scenarios of the simulation.

4.2 Scenarios

By combining all the aforementioned options, the algorithm is executed on a total of eight different scenarios, and an additional two, more specific ones. The plots and costs are as follow:



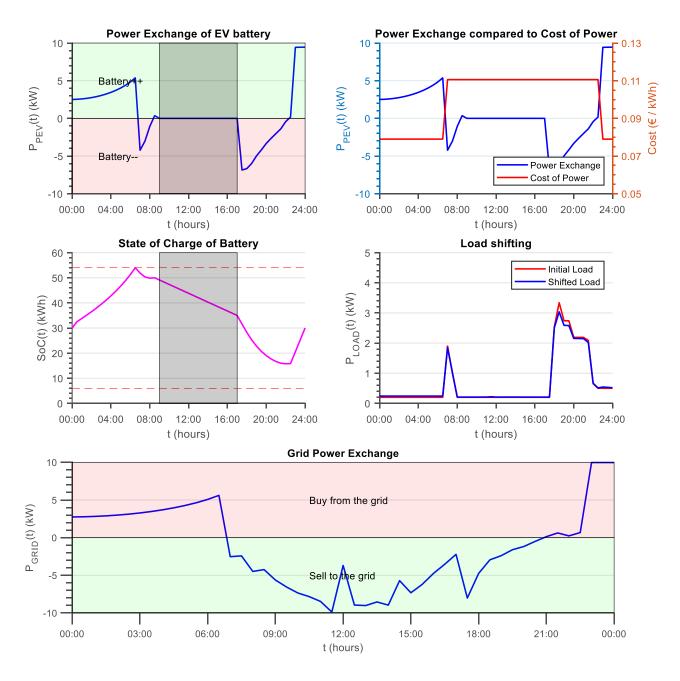


Figure 4.4 – Morning shift, Summer, Peak/Off-peak cost of power.

As has been noted before, due to modeling the battery with the load convention, positive values mean the battery is charging (draining power from the microgrid). The shaded area shows the time range during which the EV is not connected to the microgrid, and thus can't provide or absorb power. Comparing the battery power exchange and the cost of power, it is immediately obvious that the algorithm favors charging the battery during low price hours, and discharging it during peak demand.

As far as load shifting is concerned, the algorithm shifts the heavy loads of 20:00 to the off-peak hours of 23:00-7:00, as expected.

The power exchange with the grid clearly illustrates two functions of the model: the daylight hours feature the sale of large amounts of power, due to the excess production of PV panels, and the purchase of power only happens during off-peak hours, to take advantage of the lowered price.

The large power flow during the last hour is the result of forcing the algorithm to reach the initial SoC for comparison fairness. However, since it happens during off-peak hours, it does not considerably skew the final cost.



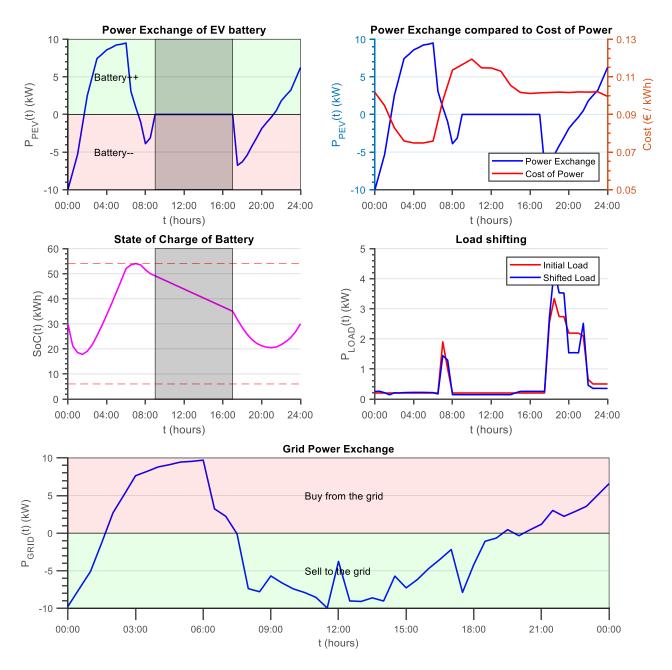
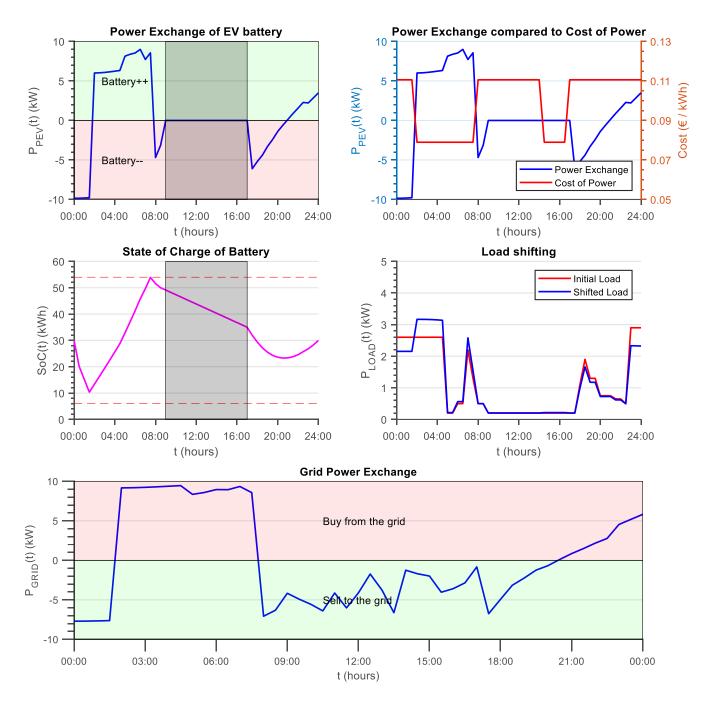


Figure 4.5 – Morning shift, Summer, Variable cost of power

Summer Morning 2-zone	Summer Morning Variable				
-2.03€	-1.93€				

Comparing scenarios 4.2.1 and 4.2.2, one can notice that while generally the power flow rates are different, the end result (total day cost) has a

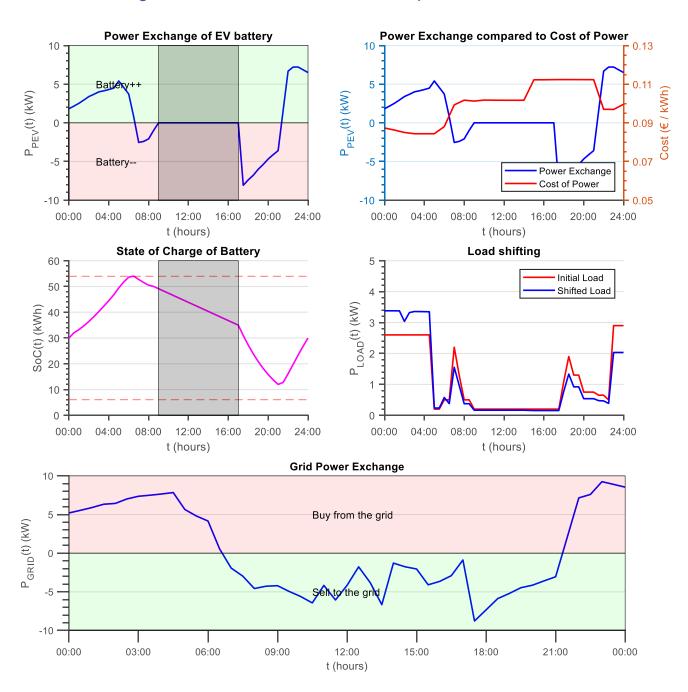
negligible difference. The lower value of scenario 4.2.2 is due to the EV being absent during the majority of the high power cost, thus missing the opportunity to sell energy to the grid.



4.2.3 Morning shift - Winter - Peak/Off-peak cost of power

Figure 4.6 – Morning shift, Winter, Peak/Off-peak cost of power.

The switch to winter introduces heavier loads due to electric heating. Additionally, the off-peak hours change, but the EV is absent in one of the cycles to take advantage of it. Equally notable is the load shifting, with the algorithm trying to shift the heavy winter loads to off-peak hours.



4.2.4 Morning shift - Winter - Variable cost of power

Figure 4.7 – Morning shift, Winter, Variable cost of power.

Winter Morning 2-zone		Winter Morning Variable				
	0.28€	0.78€				

The difference in cost of the two winter scenarios appears mainly on the starting hours, since scenario 4.2.3 is able to sell power from the battery while scenario 4.2.4 misses a large portion of peak hours due to the absence of the EV.

The comparison between summer and winter scenarios exhibits a steep difference in the daily total costs. This is to be expected, as winter has more significant load needs (electric heating) as well as reduced production from the solar panels.

4.2.5 Evening shift - Summer - Peak/Off-peak cost of power

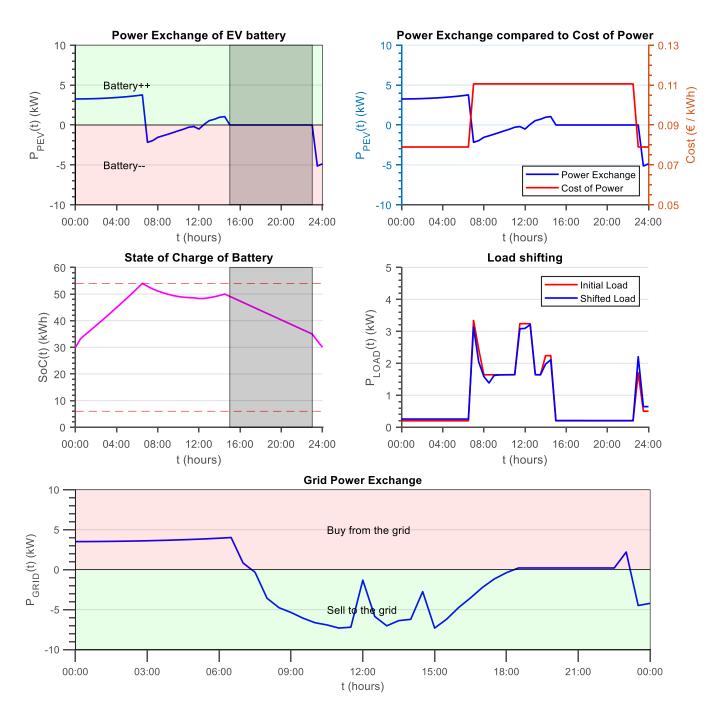
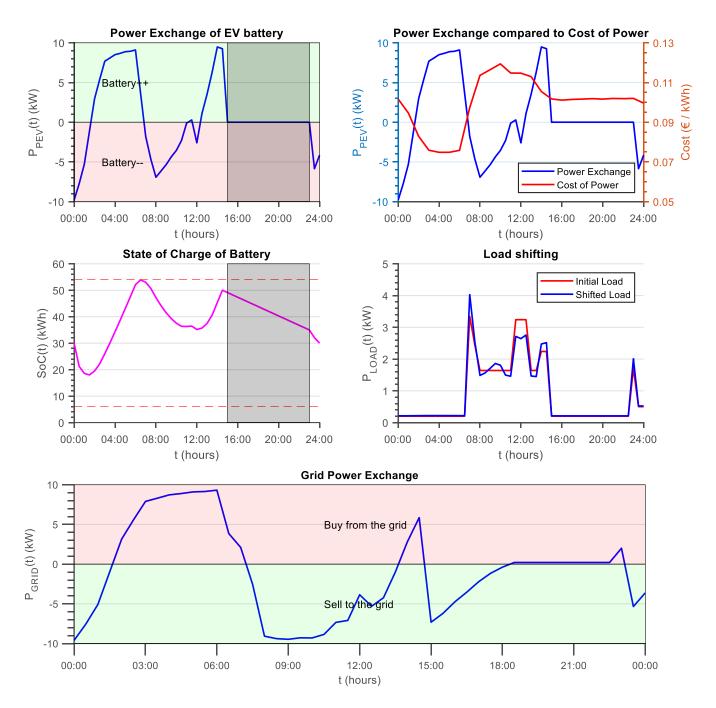


Figure 4.8 – Evening shift, Summer, Peak/Off-peak cost of power.



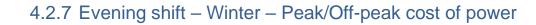
4.2.6 Evening shift - Summer - Variable cost of power

Figure 4.9 – Evening shift, Summer, Variable cost of power.

Summer Evening 2-zone	Summer Evening Variable			
-0.81€	-1.35€			

Evening shift introduces more freedom for the algorithm to sell power, since the overlap of peak demand hours present in morning shift scenarios is diminished. However, the household loads of evening shift are located mostly during peak demand hours, thus resulting in reduced efficiency and slightly higher costs.

Notable, however, is the better efficiency of the variable cost scenario, where in morning shift it was the opposite. This is attributed to the fact that the cost dip and peak are located more conveniently for the algorithm to sell and buy power.



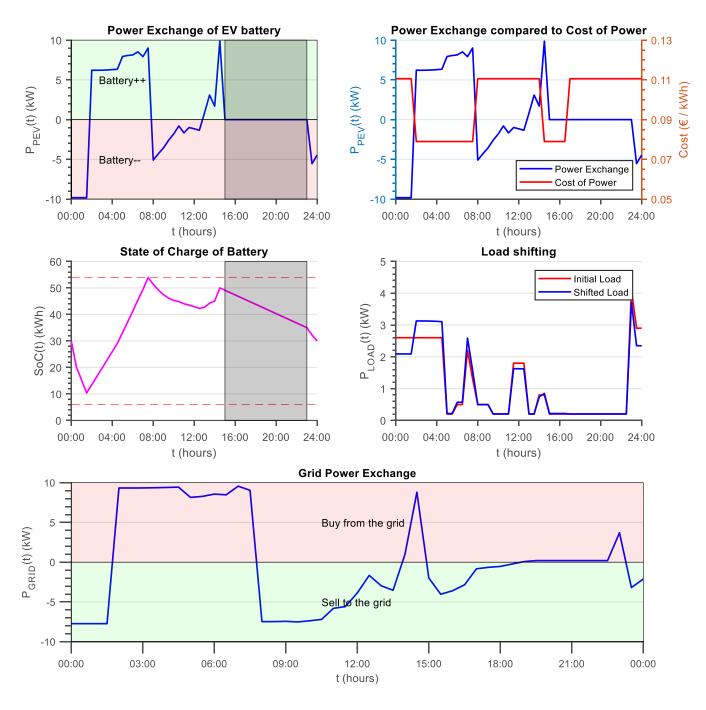


Figure 4.10 – Evening shift, Winter, Peak/Off-peak cost of power.



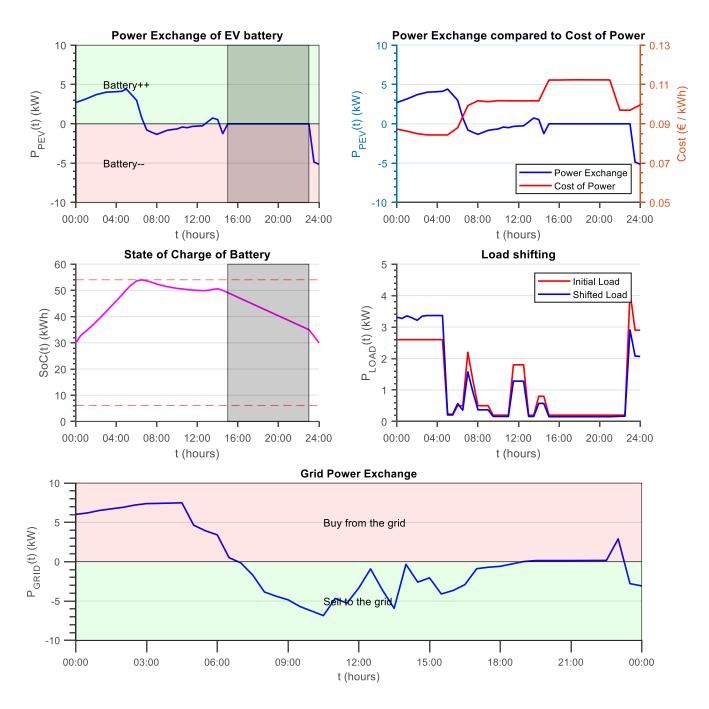


Figure 4.11 – Evening shift, Winter, Variable cost of power.

Winter Evening 2-zone	Winter Evening Variable			
0.11€	1.02€			

Similarly to scenarios 4.2.3 and 4.2.4, the winter scenarios produce higher total daily cost compared to summer scenarios due to the increased loads and reduced PV production. However, the two-zone cost of power aligns very conveniently with the absence of the battery, yielding the lowest winter cost yet, since the algorithm is able to sell large amounts of power to the grid.

4.2.9 No constraint on SoC before departure

As mentioned before, the algorithm is more efficient in most cases if the constraint to have the car fully charged before departure is removed.

For practical purposes of the algorithm, this matter is up to the user to decide. A distant workplace situation may require more certainty that the vehicle is sufficiently charged to make it back home, even in the worst case scenarios, such as traffic jams or long use of HVACs for heating.

All of the scenarios examined above force the battery of the EV to reach a level of at least 50kWh. However, the simulated workplace distance is an hour's drive away, which is already on the high end of acceptable workplace distances. Even with an hour's drive twice per day, the battery only dissipates 25% of its charge. Thus, the average user is not in great need to have the battery full by departure time.

Considering the above, the scenario of 4.2.5 is repeated without the aforementioned constraint:

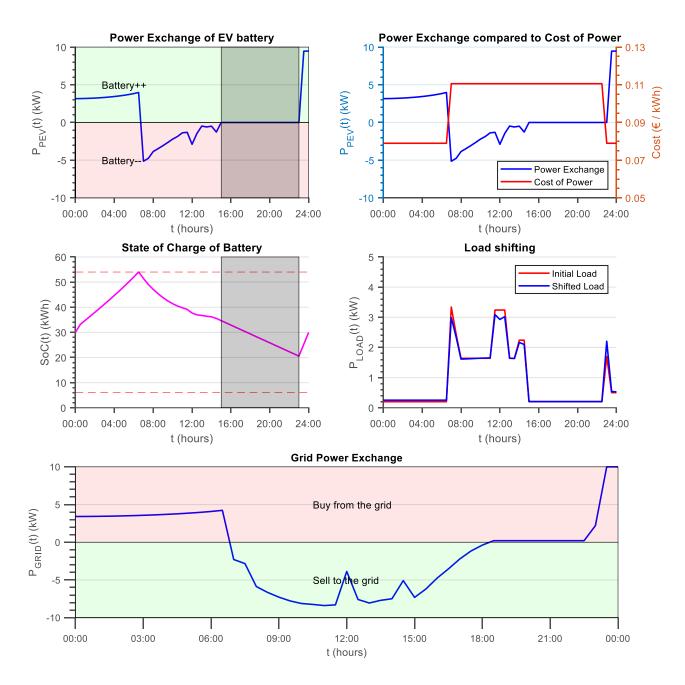


Figure 4.12 – Evening shift, Summer, Two-zone cost of power – No charge constraint.

Summer Evening 2-zone	Summer Evening 2-zone				
Full at departure	No constraint				
-0.81€	-1.30€				

It is thereby decidedly discernible that the algorithm operates more efficiently without the constraint. Nonetheless, the sacrifice of certainty over cost saving is a choice that is ultimately left up to the specific user.

4.2.10 Dumb charging and no load shifting

To better analyze the cost efficiency of the algorithm, it needs to be compared with the default case of no smart charging ("dumb" charging) and no load shifting. Scenario 4.2.1 is repeated without the optimizations:

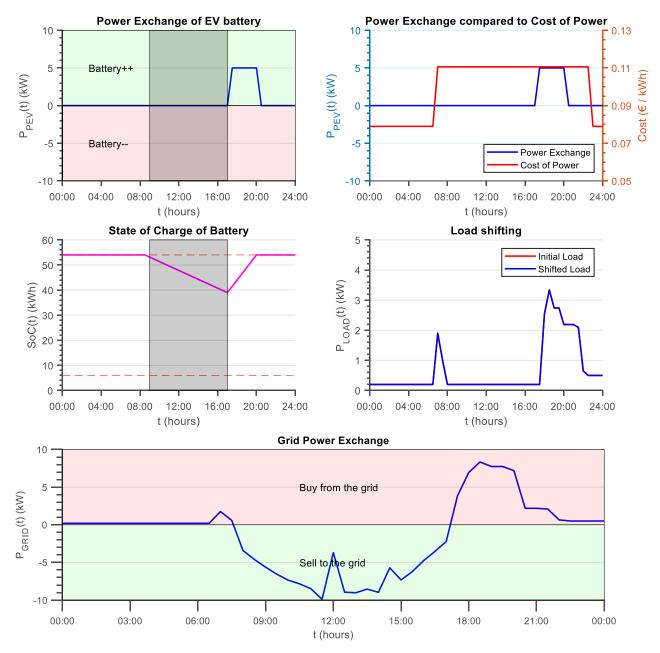


Figure 4.13 – Morning shift, Summer, Two-zone cost of power, Dumb charging and no load shifting.

Summer Morning 2-zone	Summer Morning 2-zone				
Algorithm	No algorithm				
-2.03€	-0.81€				

The efficiency of the algorithm is made clear by comparing the difference between the two prices.

4.3 Cost analysis

To analyze the cost efficiency of the operation, the 8 scenarios above are repeated with the same initial and final SoCs. Each scenario generates three price points, one with the algorithm with full charge departure constraint, one without, and one with dumb charging and no load shifting.

	Summer Morning 2-zone	Summer Morning Variable	Winter Morning 2-zone	Winter Morning Variable	Summer Evening 2-zone	Summer Evening Variable	Winter Evening 2-zone	Winter Evening Variable
Algorithm Full at departure	-2.03€	-1.93€	0.28€	0.78€	-0.81€	-1.35€	0.11€	1.02€
Algorithm No constraint	-2.12€	-1.87€	0.23€	0.81€	-1.30€	-1.49€	0.03€	0.89€
Dumb Charging, No load shifting	-0.81€	-1.03€	1.73€	1.66€	-0.69€	-0.39€	1.71€	1.29€

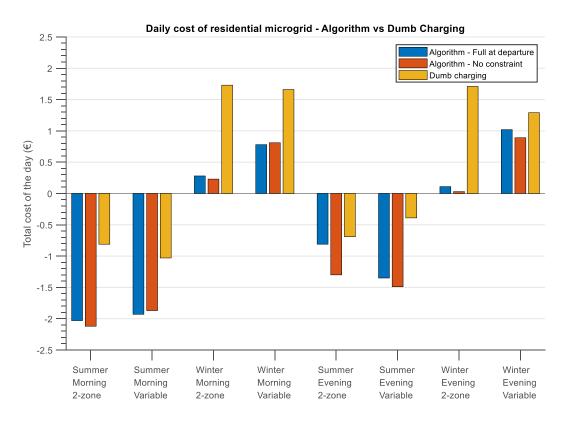


Figure 4.14 - Cost comparison over all scenarios

The total cost comparison proves what has already been mentioned in most comparisons above. Winter is costlier than summer, the algorithm behaves more efficiently with the morning shift, and the removal of the full charge at departure constraint improves the efficiency of the algorithm in most cases.

However, it can be noted that in two scenarios, the lack of the charge constraint is actually the (slightly) costlier option. While this cannot be explained by the rules of the simulated model, it can be attributed to the algorithm possibly selecting local minima, instead of the global minimum (an existing issue with nonlinear optimization algorithms).

5. conclusions

To summarize, the present dissertation simulated the optimization of power management of a residential microgrid with a plug-in Electric Vehicle connected in V2G mode, and solar panels connected on the rooftop.

The optimization algorithm was executed through the use of Matlab's fmincon function. The values and parameters of the EV's battery and the PV panels were both simulated realistically, by following actual real world products. The cost of power was imported through actual data from the Public Power Company, <u>dei.gr</u>, and the household loads were simulated through another dissertation's provided code.

After applying all the constraints related to power flows (both the battery's and the grid's), the SoC limits and targets and the constraints of load shifting, the algorithm was executed on a total of 24 different scenarios: (a) Season, (b) Shift time zone, (c) Two-zone or variable power tariff, (d) Charge constraint by departure and (e) Algorithm vs. dumb charging.

By analyzing the final daily cost results, the algorithm managed to save an average of 26.25€ per month in summer, and an average of 32.5€ per month in winter. It can thereby be concluded that handling smart charging of the EV and load shifting optimally, the average residential microgrid can considerably reduce its power costs.

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