Mitigating the Duck Curve by Optimization Using Battery Storages

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NOMENCLATURE

Symbol	Meaning	Units
Solar power generation system		
A_{pv}	Area of solar panel	$[m^2]$
N	Number of solar panels	$[-]$
R	Solar radiation	$[kW/m^2]$
η_{pv}	Efficiency of solar panel	$[-]$
P_{pv}	Output power of PV system	$[kW]$
Energy storage system		
Cap_{bat}	Capacity of battery	$[kWh]$
$P_{s,ch}$	Power exchange during battery charging	$[kW]$
$P_{s,dis}$	Power exchange during battery discharging	$[kW]$
$\eta_{s,ch}$	Battery efficiency during charging	$[-]$
$\eta_{s,dis}$	Battery efficiency during discharging	$[-]$
SOC	State of charge of battery	$[-]$
$L_{cyc}^{80\%}$	number of full equivalent cycles	$[-]$
AGE_{cyc}	Cyclic aging of battery	$[-]$
AGE_{cal}	Calendric aging of battery	$[-]$
AGE_{tot}	Total aging of battery	$[-]$
SOH	State of health of battery	$[-]$
$SOH_{initial}$	Initial state of health of battery	$[-]$
SOH_{end}	Final state of health of battery	$[-]$
Objective function		
W_t	Weight on operating time	$[-]$
a	Weight on flattening the duck curve	$[-]$
b	Weight on reducing the battery degradation	$[-]$
P_1	Input power to the network from the grid	$[kW]$

ABSTRACT

The rapid expansion of solar photovoltaic (PV) installations worldwide is significantly reshaping energy generation and consumption patterns. While solar PV is highly productive during midday, its output is minimal during evening hours when energy demand peaks. This imbalance creates power ramping challenges for electrical grids, potentially leading to instability and increased reliance on conventional power sources. The resulting ramp-up at the evening (duck curve) poses economic and environmental concerns, necessitating innovative solutions [1].

In this study, we present an optimization strategy for a solar-PV-integrated region designed to address the challenges of the duck curve. The core objective was to flatten the power demand curve by reducing rapid ramp-up events during peak periods. To achieve this, we present in the thesis a distributed optimization approach (based on the Proximal Atomic Coordination (PAC) methodology) for a grid. Our enhanced framework accounted for peak demand, battery state of health (SOH), and carbon emissions, aiming to prolong battery life and reduce the environmental impact.

The study was conducted in California using real-world data from a residential network integrated with solar panels and a storage system. These data included load demand, solar radiation, and electricity prices specific to the region. We applied three lithium-ion batteries for storage and a High-Density Mono PERC Module (HIDM) for the PV system, using an IEEE13 bus network as our testbed.

significantly flattened the duck curve by leveraging optimized power procurement from the grid and utilizing battery storage. This resulted in a 30% reduction in yearly power ramp-up (430.7 MW saved) and enhanced grid reliability.

Additionally, the strategy conserved 1.1 million m^3 of natural gas, reducing CO2 emissions by 3,043 tons during peak demand periods.

Battery optimization strategies mitigated both cyclic and calendric ageing phenomena, extending the lifespan of the storage system by approximately three years and yielding an estimated cost savings of $1.2 million over a 25-year PV lifespan. These findings highlight the efficacy of our approach in addressing the duck curve challenge while promoting sustainability and cost efficiency in microgrid operations.

1. INTRODUCTION

1.1. The Current Trends in the European Energy Market Towards Renewable Energy Introduction

With the transformation in the energy market before this decade, Europe was destined for an incredible future and since renewable energies arrived to make a real revolution. This transition is a stimulus by a combination of policy drives, technology innovations, and socio-economic forces to limit greenhouse gas emissions and promote sustainable development (Figure 1). In this section, we will dive into the present trends seen in the European energy market and how part of this includes an emphasis on the merging and growth of renewable energy sources [2].

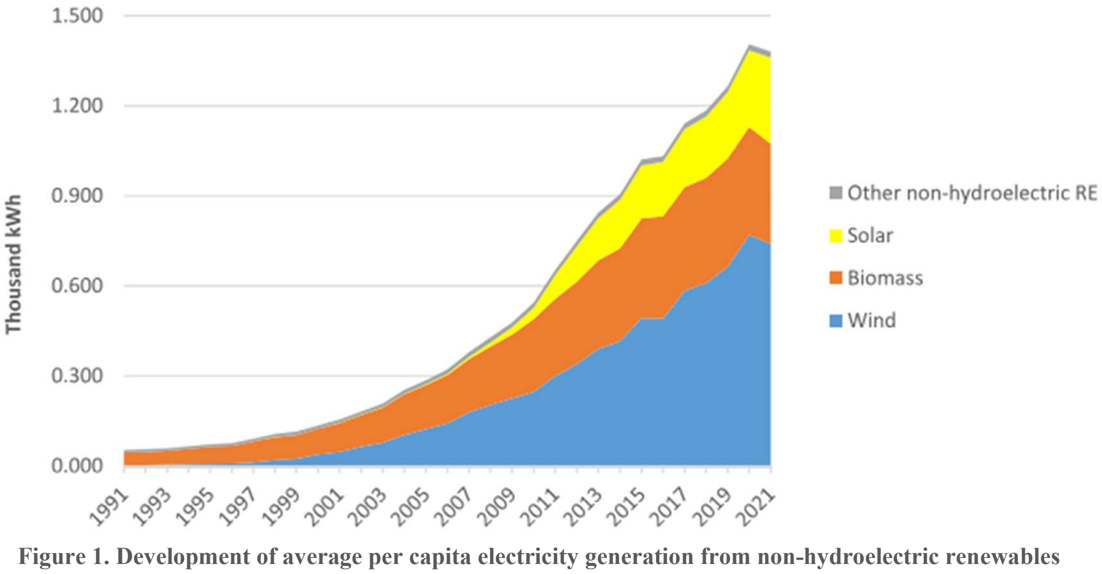

Figure 1. Development of average per capita electricity generation from non-hydroelectric renewables

<u>Policy Drivers:</u>

Also, as part of its ambitious climate and energy policies, the European Union (EU) has established clear objectives for the transformation of its energy system to renewable energies. The European Green Deal, which is the frame to ensure that the Green New Deal fulfills its promise of the EU becoming the first climate-neutral continent by 2050, has clear implementation methods to obtain mammoth CO2 reductions. At the core of this strategy is the determination to always grow the portion of renewable energy in the energy pool [3].

The Renewable Energy Directive (RED II), agreed in 2018, requires that at least 32% of the EU´s final energy consumption must come from renewables by the end of the decade. The directive has driven member states to create national renewable energy action plans (NREAPs) which in turn have stimulated major investments in those first four technologies – wind, solar, biomass and hydro Figure 2.

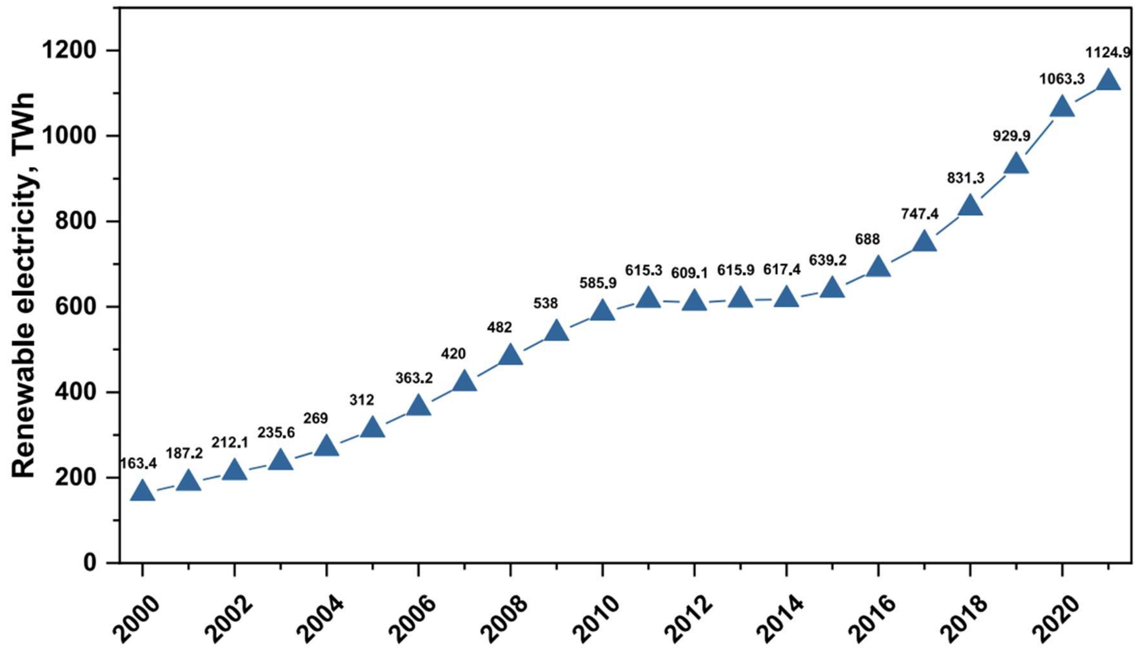

Figure 2. Renewable electricity production for 27 EU countries + UK for the year of 2000–2021

The RED II — Renewable Energy Directive of 2018 stipulates that the EU must have a renewable quota in gross final energy consumption of 32% by 2030 (30% in the project). This led to the establishment of wind and solar and bio and hydro power and a series of national renewable energy action plans by member states.

Expansion of Renewable Energy Capacity:

Europe enjoyed a marked increase in spectrum of renewable energy capacities, in particular wind power and solar. Moreover, with 230.2 GW of wind power capacity and 155.2 GW other solar PV at the end of 2023, the total installed renewable energy capacity in European Union now tops 500 GW.

Wind Energy: Particularly offshore wind remains a global leader in wind energy. Countries like the United Kingdom, Germany, and Denmark have made substantial investments in offshore wind farms, benefiting from the region's favorable wind conditions and technological advancements in turbine efficiency and grid integration.

Solar Energy: Solar PV has witnessed exponential growth across Europe. Germany, Spain, Italy, and the Netherlands are at the forefront, driven by decreasing costs of solar technology, favorable regulatory frameworks, and innovative financing mechanisms such as feed-in tariffs, auctions, and net metering schemes.

Biomass and Hydro: While wind and solar dominate the renewable landscape, biomass and hydroelectric power continue to play crucial roles, particularly in countries with abundant natural resources. Biomass is extensively utilized in Scandinavia and Eastern Europe, whereas hydroelectric power remains a significant contributor in countries like Norway, Austria, and Switzerland.

Technological Advancements:

The renewable energy transition cannot proceed without technological innovation. Reliability and utilization of interrupted renewable sources have been increased by emerging energy storage solutions, specifically by lithium-ion batteries. Beyond that, storage is also needed to market solar and wind and provide grid stability and enable energy consumers to optimize self-consumption.

Smart grid technologies and digitalization are transforming the energy landscape as well. By doing so, the efficiency and flexibility of energy systems are, which makes it easier to realize higher shares of renewable energy with enhanced grid management systems, real-time data analytics, and demand response mechanisms.

Market and Economic Factors:

The past decade has witnessed a remarkable and rapid decline in the cost of renewable energy technologies, leading to their rising competitiveness with conventionally power generation – initial capital cost of the renewable energy projects is high, but their operational and maintenance costs are substantively lower than fossil fuels. Public and private sector investment has been attracted by the steady fall in the levelized cost of electricity (LCOE) from wind and solar projects, driven by economies of scale, technological advances, and competitive auction mechanisms.

In addition, decarbonization of the energy system is for meeting broader economic and social goals, including job creation, energy security, and public health. The renewable energy sector is a huge employer and could generate millions of jobs in manufacturing, installation, maintenance, and indirect services.

Expansion of PV Usage in Europe:

Over the past decade, PV systems have been rapidly moving into European countries and is predicted to spread gradually Figure 3 with countries setting ambitious renewable energy targets, the price of solar technology continuing to fall, and unspecified government policies to support rollout. Below is an overview of where and how PV has been used in Europe, and how use has developed installation in the EU.

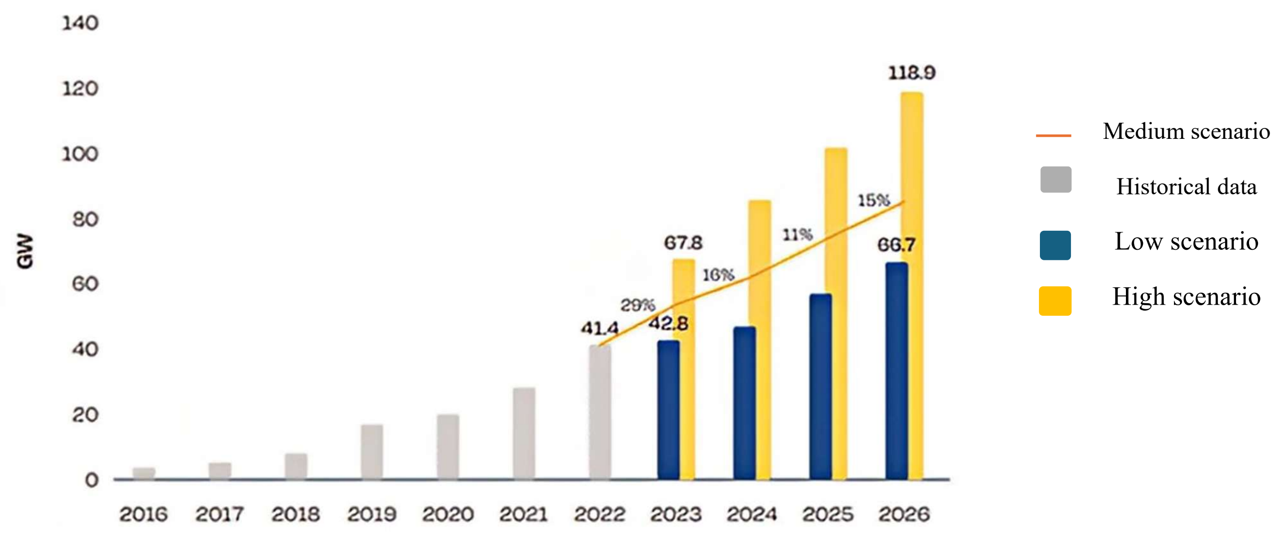

Figure 3. Prospective scenarios over the period 2023-2026 – Solar Power Europe, 2022

Installed Capacity:

Germany: Germany will retain the title of Europe's top market by the end of 2023, surpassing 60 GW of cumulative installed capacity. This is due to the energy transition policy.

Spain: One of the markets where Solar PV installations have increased is Spain, which reached almost 20 GW by the end of 2023. Solar investment rises on removal of 'sun tax,' favorable auction systems

Italy: Italy has cumulative installed capacity of 25 GW PV. The country is adding a slew of new incentives and net metering schemes to its ever-growing solar capacity.

France: PV capacity in France has surged to around 15 GW, backed by a robust governmental support in general and an emphasis on solar coupled with other renewable sources in this month Law.

Netherlands: The Netherlands has more than 15 GW of solar PV capacity, thanks to a supportive subsidy environment and an elevated level of residential and commercial installations.

1.2. Duck curve phenomenon

The Duck Curve is a graphical depiction of electricity demand on days with high solar energy production and low grid demand. The graph's lines and curves resemble a duck. It is used to describe the time-dependent net value of electricity generated by solar photovoltaics (PVs) that results from the integration of a large amount of solar PV power onto the grid, representing the amount of conventional generation that may need to be dispatched, curtailed, or stored due to an over-generation over-supply event [4]. The image below Figure 4 — referred to as a duck curve illustrates the challenge of solar variability and timing.

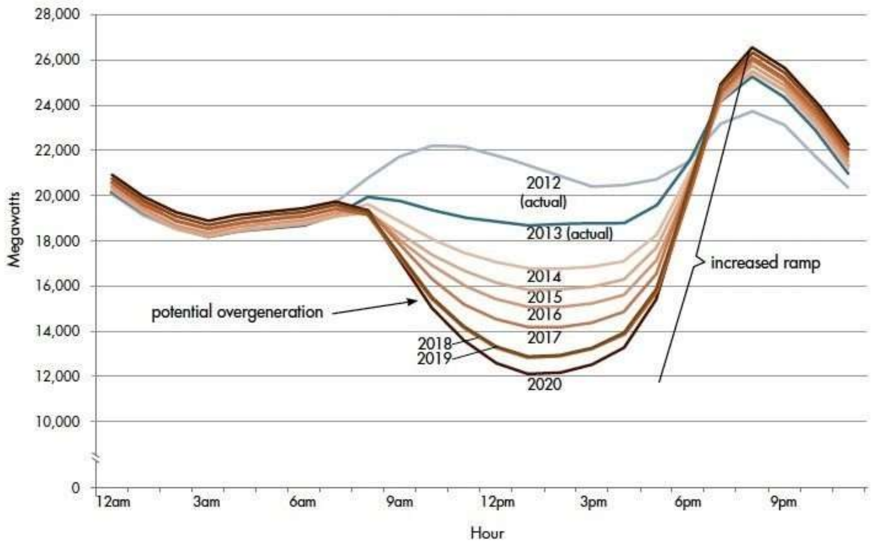

Figure 4. Duck curve

In 2010, the California Independent System Operator (CAISO) [5] started to illustrate the effects of enhanced photovoltaic (PV) solar energy on the net load, which is the anticipated electrical demand minus the estimated PV solar energy generation up to 2020. The duck curve was first introduced in 2008 by the National Renewable Energy Laboratory (NREL) and by 2013, CAISO produced a chart with a similar shape. This term quickly became popular in the energy industry, especially as new energy and environmental policies advocated for increased solar PV penetration.

As a result of the duck curve, CAISO and other system operators realized the need to adapt and adopt new operating procedures to address supply and demand balance with high levels of renewable energy. This marked a significant milestone in the advancement of utility-scale solar deployment from the conceptual stage to implementation. The system operators started realizing the need for more and more planning to accommodate higher levels of PV in the future and California led this initiative.

The expansion of solar generation and the enhancement of the duck curve posed technical and financial issues. In reality, the grid had to manage step changes in net load, especially the ramp-up of demand as solar production declines in the evening. Conventional power plants were also affected economically in terms of operational costs and profitability because of reduced running hours and the requirement of quick startup capabilities [6].

What is the Duck Curve?

The two phases of the duck curve [7]:

The Midday Overgeneration: During midday hours and for the most parts of the year, solar PV systems produce more electricity than needed. This considerable production minimizes the net electricity consumption from the conventional power plants during the sunshine hours. As a result, the consumption of conventional sources of energy is reduced during these peak times of solar energy production. Nevertheless, this midday overgeneration often results in challenges like grid overloading and curtailment of solar energy as supply outruns demand.

Evening ramp-up: As the sun sets, solar generation plummets dramatically, causing a sharp increase in net electricity demand. This sudden surge in demand, often referred to as the "evening ramp-up," requires conventional power plants to rapidly increase their output to compensate for the loss of solar energy. The challenge lies in the need for these plants to adjust their power output quickly and efficiently, which is inherently difficult and economically unfeasible. Conventional power plants, such as coal, natural gas, and nuclear facilities, are typically not designed for rapid ramping up or down, making large fluctuations in power output challenging to manage. This situation not only strains the operational capabilities of these plants but also leads to increased operational costs and potential During the evening ramp-up, grid operators must rely heavily on conventional power sources, which can result in higher emissions and fuel consumption. Additionally, the sudden need for increased output can lead to mechanical stress on the power plants, reducing their operational lifespan and increasing maintenance costs. The economic inclusion of this rapid ramping includes higher electricity prices for consumers and increased operational expenses for utilities. Furthermore, the reliance on conventional power plants during the evening ramp-up underscores the need for more flexible and responsive energy solutions. Energy storage systems, such as batteries, can play a crucial role in bridging the gap between solar generation decline and peak demand periods. By storing excess energy generated during midday and releasing it during the evening, these systems can help smooth out the fluctuations in power supply and demand.

The evening ramp-up phenomenon highlights the critical need for innovative solutions and strategic planning to ensure a stable and efficient power grid. Integrating advanced technologies, such as smart grids, demand response programs, and renewable energy storage, are essential to mitigate the challenges posed by the evening ramp-up and to promote a more sustainable and resilient energy system. Addressing these issues will be crucial for the successful transition to a renewable energy future and for maintaining grid reliability in the face of increasing solar power integration.

Challenges and Problems Caused by the Duck Curve

Grid Stress:

It can be a significant problem for conventional power plants as solar has a major impact on baseload power demands (which generally fluctuate most around midday and late evenings as demand falls slightly from midday and late evening demand remains high but sunlight falls) can cause quick ramp-up demands in generation for conventional plant, which specifically plagues natural gas-fired plants in high solar penetration grids. This extra load placed on the grid causes those older power plants (gas turbine power plants) that have been idling to fire up again - and quickly - something which takes a considerable bit of effort to make happen, and as such is not easy, cost-effective, nor sustainable.

In addition, the short-term power generation increase presents a challenge to grid operators as they seek to balance the grid supply - the power they are generating - to balance with the grid demand. Managing power supply is no mean task since operators have to deal with varying energy inputs and even outputs.

Furthermore, operators might have to curtail solar power to prevent overgeneration when the grid is saturated or if too much solar power is fed in at one time legitimately the grid can handle. It perfectly demonstrates how a high level of solar energy can be available, but its practical utility significantly curtailed due to constraints in the available grid architecture. Limiting renewable energy generation, being wasteful as it is, also diminishes sustainability of the grid [8].

Economic:

The other challenge is economics. The characteristics of duck curve may affect the economics of dispatchable power plants because the factors that cause the curve led to a decrease in the time that conventional power plants are operational and therefore the revenue from energy sales. This reduction in operational time has a significant effect on these plants' profitability since they are earning less revenue while continuing to spend on maintenance and operation.

If the reduced revenues are such that the plants become uneconomical to run, the plants may close without a dispatchable replacement. This condition poses a major challenge in the electricity supply chain given that fewer dispatchable plants result in limited options for managing the grid. Lower levels of dispatchable generation means that grid operators have less ability to balance supply and demand in a system with large variations in net demand.

Lack of adequate dispatchable power exposes the grid to instabilities and hence high chances of blackouts and other failures. The economics of conventional power plants are therefore significant not only for their continued running but also for the stability of the power system. Given the financial constraints that these plants face, it becomes crucial to seek viable economic measures that can guarantee a stable energy supply [8].

Environmental:

During the evening ramp-up, when the solar power is not available to the same extent, other sources like natural gas or coal-fired power must be used to provide energy. These plants emit greenhouse gases (GHGs) and other pollutants to the atmosphere thus impacting the quality of air and climate. This can lead to the plants being less efficient in terms of starting up and shutting down, which in turn could result in higher emissions than when the plant is operating at a steady rate.

The need to quickly increase or decrease power output to balance the grid results in frequent cycling for these conventional plants that are not built for this purpose. This mode of operation may lead to less efficient fuel combustion in the plants, and thus higher per-unit emissions of GHGs and other pollutants. Furthermore, the higher stress from more frequent ramping may lead to higher rates of degradation of the plants and thus require more frequent maintenance and could lead to more emissions from replacement processes.

Moreover, the emissions from these conventional plants are most problematic during the evening ramp-up, because this is usually a time when air quality is already poor owing to other factors, including traffic growth. It can worsen local air quality problems and have negative impacts on the health of people living in the vicinity.

Hence, the utilization of conventional power plants to address the gap created by the decline in solar energy hampers the fight against emissions while underlining the necessity of cleaner, more versatile options for grid management. Advancements in energy storage, demand-side management, and cleaner peaking technologies are crucial for reducing emissions and enabling a transition to cleaner power systems.

Duck Curve Mitigation Strategies

In the previous part, the duck curve was explained which leads to several problems such as grid stress, economic problems, and environmental effects. Therefore, scientists and engineers have spent a lot of time researching different approaches and measures to address the duck curve problem. In this section, we will give a brief overview of these methods. But we will discuss them and the relevant literature in more detail in the "State of Art" section.

1. Using Battery Storages

Both stationary battery storage and EVs are quite useful in dealing with the duck curve problem. This involves storing energy that has been produced during off-peak hours and then feeding it into the network during the peak hours to equalize the load on the network. Battery storage refers to the charging and discharging of batteries when energy demand is low and high respectively in an attempt to match supply and demand. This decreases the grid stress and increases the stability as well as reliability of the power system as well. In essence, battery storage is like a buffer that helps to regulate electricity usage and supply throughout the day [9] [10] [11] [12].

2. Pricing Strategies

Another method to mitigate the duck curve is through the implementation of a pricing strategy. In this method electricity prices are adjusted with the goal of influencing energy consumption and demand. By changing prices based on the time of day, consumers are encouraged to shift their energy usage to periods when renewable energy is abundant (midday in the case of solar), therefore it helps to balance the load on the grid [13] [14] [15].

3. Optimization and control approaches

Optimization and control methods are in fact also other promising techniques for addressing the duck curve problem because they rely on higher levels of algorithms and more accurate data for the power grid management. Of these, some of the methods include application of intricate software systems and algorithms to enhance the functionality of power stations, energy storage and renewable energy systems. This means that the output of such resources can be regulated to match the current circumstances that prevail in demand and supply of energy, hence striving to achieve a more balanced distribution of energy. Also, control systems can counteract the state of the grid and regulate the increase or decrease of power production as well as controlling or initiating demand response. It is also important to note that these approaches contribute to the objective of enhancing the reliability and stability of the utility grid as well as increasing the penetration of renewable power generation which helps to minimize the use of fossil fuel power plants thus addressing the problem of environmental degradation [1] [16].

1.3. Aim of thesis

In this study, we devised a multi objective distributed optimization strategy for the Solar-PV Integrated distribution grid model, integrating storage mechanisms to address the challenges posed by the duck curve phenomenon. Our aim was to flatten the duck curve, thereby mitigating the rapid ramp-up of energy demand during peak hours. Subsequently, we enhanced the objective function to encompass considerations of both high-demand periods and the state of health (SOH) of batteries.

The first part of our optimization objective function aims to minimize ramp-up events by reducing the differences in electricity purchases from the main grid between two consecutive time intervals. Using different weights for different hours of the day makes this approach more effective compared to using a constant weight for the entire day. Increasing the lifetime of the battery storages is the goal that be gained by the second part of the objective function. Minimizing the cyclic age of the battery storages is the method we used to achieve this goal.

Charging and discharging power of the battery storages and state of the charge of batteries are the decision variables we consider for these aims.

In this endeavor, the studies were conducted in the California region integrated of residential network with solar panels and storage system. We used the real load data, solar radiation, and electricity prices for this region. Three lithium-ion batteries for storage system and high-density mono perc module (HIDM) for PV system were applied over a IEEE13 bus network.

Here's a more detailed version:

In the following chapter of this thesis, we will start with a comprehensive literature review on the Duck Curve phenomenon and the various strategies proposed to mitigate its effects. Next, we will introduce and discuss the proposed optimization problem. Finally, we will demonstrate the practical application of our optimization approach through a detailed case study, highlighting the effectiveness and benefits of the proposed solution in a real-world scenario.

2. STATE OF THE ART

2.1. Introduction

The challenge of the "duck curve" the mismatch between energy generation and demand due to high solar output during midday and sharp ramping requirements in the evening—is driving innovation in grid management. A variety of strategies, ranging from distributed decision-making to battery energy storage systems (BESS) and demand response, are emerging to mitigate this issue.

One approach involves distributed decision-making frameworks. As demonstrated by [1] a distributed optimization framework in a San Francisco case study led to a 23% reduction in generator ramping requirements compared to more centralized approaches. This outcome underscores the potential of decentralized strategies to enhance grid stability and flexibility, which are crucial in managing the rapid changes in energy demand.

Battery energy storage systems (BESS) are pivotal in smoothing the fluctuations caused by the duck curve. In [9] the Whale Optimization Algorithm (WOA) was used to optimize the placement and sizing of BESS in distribution networks, resulting in reduced system losses and smoothed load profiles. This reduction in load variability allows for a more balanced energy flow, alleviating some of the stress on grid infrastructure. However, battery degradation is an important factor to consider, as [17] points out, noting that the optimization of PV-battery systems must consider life cycle costs and the optimal battery capacity to ensure sustainability and economic efficiency.

Beyond distributed frameworks and BESS, the exploration of energy storage technologies is vital for addressing the inherent variability of renewable energy sources. Study [18] discusses a range of storage technologies, highlighting the ongoing need for innovation to manage intermittent energy generation. This need is further underscored in [19], which demonstrates how BESS can be utilized to fill the generation-to-net-load gap while providing peak shaving capabilities, offering a versatile solution to multiple grid challenges.

Peak shaving itself plays a key role in mitigating the duck curve. In [20], researchers focused on optimal BESS sizing for industrial peak shaving, using a linear aging model to extend battery lifespan and simplify optimization. The study's findings suggest that while depth of discharge cycling has a minor impact, charge control strategies must consider the state of charge (SOC) to ensure battery longevity.

Demand response is another effective strategy for addressing the duck curve. Study [21] showed that by selectively switching off household loads during peak demand, energy consumption could be reduced by 36.87%, providing a significant buffer against grid instability. This demand-side management approach complements other techniques aimed at reducing ramping stress.

Market-based strategies also offer promising solutions. In [22], cost-minimizing dispatch strategies for grid-scale lithium-ion batteries resulted in substantial cost savings and efficiency gains by integrating model-based optimization. These findings suggest that market-oriented approaches could drive more efficient energy storage strategies at a larger scale, fostering a more resilient grid.

Finally, innovative grid management approaches are gaining traction. Study [10] proposes a bonus-based framework for managing flexibility in multi-agent distribution systems with high renewable energy integration. This Stackelberg game-based approach reduces severe ramping events, contributing to greater system flexibility. Meanwhile, [23] highlights the statistical relationship between rooftop PV output and wholesale energy prices, indicating the significant effects on midday energy prices, thus advocating for more targeted markets and improved inverter functionality.

Together, these diverse approaches and studies point toward a multi-faceted solution to the duck curve, combining technology, market incentives, and innovative frameworks to ensure a stable and flexible energy grid in the face of growing renewable energy integration.

In the remainder of this section, we will spend time exploring many of the key articles called upon by the different tools/strategies used to panel back the duck curve. We will take an in-depth look at each method to see how it works in practice, how it can be deployed, and what kind of effect it can have for solving the duck curve. In reviewing these articles, we hope to give a detailed view of what is being done to overcome or possibly avoid obstacles presented by the duck curve.

2.2. Pricing Strategy

One of the ways of tackling the duck curve is through the implementation of a pricing strategy. This approach entails changing the prices with the aim of controlling the consumption of energy and its demand. The following articles are great examples of how this strategy is put into practice and demonstrate various techniques and results in different situations. From these examples, it is possible to learn more about how pricing strategies can help to address the duck curve. In [14], the authors develop a new method to apply a bilevel programming algorithm to tackle the dynamic model for a city. This issue is formulated as a new noncooperative Stackelberg game to find out the best dynamic pricing strategy for leveraging air conditioning systems and electrical storage by using end-users as the decision maker. The study proves that both demand-side air conditioning and distributed storages can help balance the load curve and carry the optimal dynamic pricing profile. Concluding this section, it must be noted that the non-cooperative Stackelberg game algorithm used and introduced in this work is described in full. To assess the economic viability of the proposed system, three economic metrics were employed: The first one is the Levelized Cost of Energy (LCOE) of the solar power plant; the second one is LevelizedCost of Storage (LCOS) of the Residential Battery Storage Systems (BSS); the last two are Simple Payback Period (SPBP) of both the solar power plant and Smart Houses Energy Management System (EMS), including Smart House Automation (SHA) systems, and Batteries.

Article [13] is a study that focuses on the use of up to 400 MW of solar systems in 60,000 smart houses –the technical and economic analysis of integrating smart grid. There presents a new non-cooperative Stackelberg game that aims at solving profitability for the supply side of the PV market along with the problem of overgeneration and photovoltaic curtailment. This game has the objective of identifying the best real-time pricing of power with demand-side distributed storage to help balance the grid. The analysis is based on ten cases wherein five models of photovoltaic plant and two models of battery are considered. A new quantitative assessment evaluates the technical potential of high resource penetration level in terms of the solar percentage of total electricity demand. A bilevel programming model is used in this paper with leader objective function which comprise of supply side those is solar photovoltaic plants and demand side that is smart houses in the overall optimization problem. This approach presents the new non-cooperative Stackelberg game for dealing with flattening the duck curve. Through the dynamic pricing strategy of deploying demand side management to increase penetration of solar energy, the model addresses the problems of over-generation and photovoltaic curtailment by adopting attributes from the supply side economic and demand side management models.

According to the conclusions made by the study, it is critical for the policymakers to embrace dynamic pricing profiles that would encourage the end-users to optimize the grid by storing electrical energy and ensure smart home automation. High levels of solar penetration and solutions to any overgeneration that may arise could thus be supported by such investment by the demand side.

In other hand study [15] introduces a new market mechanism called the Substitute Energy Price (SEP) market mechanism to address the objective market value, new supply-demand relationships, and the continuous power balance characteristics of RE power systems. The SEP mechanism, which represents the market price of per-unit substitute energy, is proposed for the first time, enabling energy curves to be traded as substitutes at the vector level. Through a designed regulation responsibility mechanism, any entity, particularly RE generators, can convert the energy curve with regulation demands into substitutes through indirect payment. In this substitute energy market, each generator sells the energy it plans to produce in the following 24 hours as a whole and as a substitute. Another important rule is that each energy curve must satisfy the regulation responsibility mechanism, which is consistent with the load curve shape and total energy. For non-compliance, the generator is required to pay the regulation cost based on the shape difference, which is referred to as the regulation demand for that generator.

The SEP mechanism is suitable for tradable commodities with quantitative market value, which covers many GES and DG as well as the market value orientation and new supply-demand relationship of the RE power systems. This approach enables the evolution of today's power systems to RE-based power systems that do not emit carbon dioxide. Comparative tests show that the SEP mechanism correctly captures the cost-based nature of regulation need, properly measures the regulation capability of GES, and reasonably balances the energy market, which is superior to the current LMP scheme. The results indicate that while both SEP and LMP mechanisms have the potential to induce the development of GES, only the SEP mechanism optimizes welfare and solves the duck curve issue. This is due to the substitute effect and the designed regulation responsibility mechanism, which makes individual interest consistent with the overall interest of power balance in the system.

Article [24] is another article that addresses solutions for flattening the load curve and tackling minimum system load issues through several approaches: tariff reform, new ancillary services, automation, storage, and energy productivity improvements. Also, it aims at designing markets that can facilitate the integration of energy supply with the new demand side and integrating enabling technologies including inverters with improved capabilities and control systems. First, the paper examines whether there is a statistical correlation between rooftop PV output and wholesale energy prices in the WEM to validate the WEM case study. A statistical analysis approach was chosen for the hybrid model that is parsimonious as statistical models easily examine the relationships between independent variables with a reduced complexity.

A bonus-based approach for controlling RU/RD in multi-agent distribution systems is introduced in [25]. While each agent controls its resources autonomously, the DSOs seek to optimize the highly variable RU/RD of the MADS net electricity demand. The approach is modeled as a Stackelberg game, and strong duality is applied to reformulate the game into a single level optimization problem to obtain the equilibrium point. This strategy can enable the local flexible resources (LFRs) to support the RU/RD management in systems with high levels of variable renewable energy (VRE). DSOs need to modify the initial scheduling of LFRs to smooth the net electricity demand and handle extreme RU/RD. This means that there is a need for an efficient mechanism for re-scheduling the LFRs to meet the MADS's net electricity demand variation with the available flexibility capacity.

2.3. Using Electrical Storage

Battery storage, which includes both stationary systems and electric vehicles, can be very useful in flattening the duck curve. This strategy entails putting energy from other sources into the grid during off-peak hours and using it during the peak hours to equalize the load on the grid. The following articles are good examples of how this approach is applied, as they present various methods and their results in various settings. Through these examples, it becomes possible to understand the potential of battery storage solutions in addressing the issues of the duck curve.

The main goal of [10] is to cover the gap between the real generator output and net load demand using Battery Energy Storage (BES). The BES is set to charge and discharge to meet the generation output and the net load demand. Moreover, BES is used for peak shaving which means that it meets the part of the net load demand that is above a specific level. Because the BES discharge is carried out more often than charging, the BES is scheduled to charge from the generator when the net load is low. The study findings show that BES can solve the duck curve problem and carry out peak shaving through the right control of charging and discharging.

The demand side management potential of large numbers of electric vehicles (EVs) is analyzed in [11] by shaping their charging demand to reduce the electricity duck curve due to integration of solar energy. The scheduling problem is modeled and solved in the light of an extra objective function that involves the charging level of EVs. The first goal is to reduce the system's ramp-up time, while the second goal is to address the quality of service and the revenue-generating potential of charging stations. One of the main components of the proposed model is the effect of total charging capacity on both objectives. The study uses a quadratic programming model to find the Pareto Front of the objectives involved. The Quadratic Program (QP) model works in a bi-directional manner with the goal of determining the best EV charging schedule. The model's goals are twofold: first, to help the power system operators to avoid periods of high ramping requirements; and second, to ensure that the energy is fully transferred to the EVs.

A coordinated charging system for large-scale electric vehicles (EVs) and utilizes a fuzzy logic algorithm to level the duck curve is studied in [12]. To assess the charging system, various expected data are employed. This approach seeks to minimize the Start-Up Cost (SUC) of dispatchable thermal units and electric vehicle charging costs through Time of Use (ToU) pricing, thereby improving the reliability of the power system. This paper proposes a park-and-ride charging system implementing Level-II off-board EV charging infrastructure; all charging stations are connected to the power distribution company through smart meters.

To assess the model, two primary objectives are established: maximizing the difference between average demand and relative grid demand, and to charge the vehicles as fast as possible. The proposed fuzzy logic-based charging system achieves these objectives and provides better performance than conventional PID controlled systems in the presence of nonlinearities. The fuzzy logic controller features two input functions and one output function: The first input is the difference between average load demand and relative demand divided by the average load demand, and the second input is the State of Charge (SOC) of the battery.

2.4. Optimization and control approaches

Using Artificial Intelligence, Internet of Things, and advanced control methods is a novel way of dealing with the duck curve problem. This strategy utilizes AI algorithms, IoT devices, and complex control systems to manage energy consumption and distribution in real time. The following articles can serve as examples of how this approach is used, presenting various methods and their results in different contexts

An unsupervised learning technique based on LSTM with attention mechanism to help in clarifying Duck Curve forecasts and identify causes of differences is used in [26] . This comprehension can help the decision makers in properly understanding the curve and effectively combating the problem. Renewable energy is dependent on Information and communication (ICT) and internet of things (IoT) in its implementation. Thus, data from different sensors can be used to confirm information at the local production level and help address the Duck Curve problem in an efficient and specific manner.

Using smart load shedding devices in micro and nano grids are proposed to mitigate the duck curve problem in [16], where demand is shifted during peak hours to the national grid. ICT and IoT technologies have been used to implement smart load shedding in nano grids. Voltage transformers (VT) and current transformers (CT) are ICT-enabled and provide inputs to a heuristic rules-based multifunction smart relaying system. Smart meters, instrument transformers, and status monitoring field devices produce a large amount of data.

Article [27] Describes the methodology developed to tackle the challenges of higher penetration of solar photovoltaic power, keeping in mind the physical limitations. BESS, load shedding, and solar curtailment are employed to handle the quick ramping events that are characteristic of the duck curve. The proposed system is tested on a 24-bus RTS system through a case study. Flexibility analyses reveal that the energy management and control system can address the fast-ramping events of the duck curve. The model predictive control (MPC) based EMS handles these fast ramps by using BESS, load shedding, and PV curtailment techniques.

Developing a learning-based control approach to mitigate the duck curve using standard-sized batteries is subject of [28]. By employing deep learning with model predictive control (MPC), we predict solar power and demand and then allocate the storage over the time horizon. Their approach is based on load consumption behavior and the objective function that resembles the Peak-to-Average power ratio. For a system with multiple houses and time slots, the aim is to regulate the battery charging/discharging rates to minimize power ripples.

An advanced ramp rate-limit (ARRL) control with battery energy storage (BES) for a grid-tiled rooftop solar photovoltaic array (SPVA) based microgrid is the object of [29]. The control leverages BES's power leveling feature to ensure continuous power supply during renewable energy source (RES) intermittent or high load demand. Additionally, it presents a modified adaptive third order interweaved generalized integrator (MATOIGI) control to enhance microgrid power quality during grid voltage or load current distortions/unbalance, complying with IEEE standard 1547.

A demand response system that can mitigate the duck curve problem through real-time energy pricing of household appliances was studied in [30]. Certain household loads are disconnected during peak demand to help lower the overall demand. The process starts when the consumer pairs the application with a management device through Bluetooth. The management device gets the current energy price from a database via the mobile application.

Employing a cross-sectional study to investigate the concept of local energy management in a particular setting by collecting both qualitative and quantitative data, as well as to examine the propositions proposed in the literature were done in [31]. Thus, mixed-methods research is desirable for asking both exploratory and confirmatory questions in the same study. The study employed a sequential exploratory design where data collection involved stakeholder interviews, a community workshop, and focus group discussions. This was succeeded by quantitative data collection through an internet-based questionnaire to the residents.

And finally [32] proposes and discusses several models for proactive prediction of city-wide energy demand based on different machine learning algorithms. The study created several ML models that can estimate the energy demand only by using the weather data and the price of the electrical energy. These include the linear auto regressive with exogenous inputs model (L-ARX regression), the nonlinear auto regressive with exogenous inputs model (N-ARX regression), and the nonlinear auto regressive with exogenous inputs neural network (N-ARX neural network).

2.5. Other Strategies

For a good example of applying demand response/flexibility strategy [33] is suggested that the excess energy from the PV panels can be used to heat water in electric water heater tanks beyond the normal set point during mid-day hours. In this paper, EnergyPlus (EP) simulations and average hot water consumption profile in the US with altered water heater schedules are used to show the applicability and effectiveness of this approach. In California, this technique could be capable of storing up to 59 GWh of energy per day during midday hours thus reducing the need for costly storage technologies such as batteries to level the duck curve.

On the other hand, [34] focuses on the pre-cooling strategies in the residential households to counter the duck curve. Thermal models and simulations of typical houses are developed using the Smart Residential Load Simulator (SRLS) from the University of Waterloo to show the technical viability of pre-cooling. An aggregation technique is then used to evaluate the impacts of different levels of PV integration and pre-cooling for a big grid in California and Texas, thus demonstrating that these measures can help to reduce the variability and improve the predictability of the system net demand.

The [35] offers a two-step analytical approach that would help in evaluating the impact of the duck curve and that can be potentially used to lessen the negative effects produced by this phenomenon. This approach leverages two well-known open-source platforms: including the System Advisory Model (SAM) and the IRENA FlexTool, as well as the IRENA Global Atlas. Firstly, data related to the energy capacity addition is obtained from system advisor model (SAM). After that the tool goes through optimization process with the FlexTool applied. The aforementioned methodology is then used to select a suitable system for the analysis and the application of a sample load profile and different energy sources. Afterwords, several case scenarios are discussed to evaluate the efficiency of the proposed approach, and the overall performance is summarized to prove its applicability.

The [36] focuses on the outcomes in relation to the flattening of the duck curve and the related ramping issues that can potentially be addressed through the mirror irradiation and the orientation of solar panels when mounting them. Overall, the implication of grid-friendly panel orientation in the identification of the findings presented below: a reduction of ramping by 25–30%; a reduction of over generation during the mid-day; and a slight increase of net load. This approach is noted to be a preferred strategy for future solar operations as sustainable practice that can help to improve the status of grid control and reliability.

2.6. Challenges and Limitations

Despite the valuable insights provided by existing studies, several challenges and limitations persist in mitigating the duck curve, highlighting a critical research gap that this thesis aims to address.

One significant challenge is **integration complexity**. Implementing distributed decision-making frameworks and multi-agent systems requires intricate coordination and robust control systems. Studies have shown that while these approaches offer potential benefits, their scalability to larger grids poses significant hurdles. This includes managing increased complexity and ensuring consistent performance. The need for enhanced control systems that can adapt to the dynamic nature of energy grids is paramount.

Economic viability and cost are also major concerns. The financial investment required for battery storage and optimal placement can be substantial, impacting the overall economic feasibility of these approaches. Current research, such as [25], emphasizes the importance of cost-effective solutions, considering varying tariff structures and financial constraints. However, these studies often overlook the long-term economic sustainability and the potential financial risks involved.

Technological limitations add another layer of complexity. Energy storage technologies, critical to addressing the duck curve, face inherent limitations regarding efficiency, capacity, and aging. Although innovations are being made, as highlighted by [18], there is still a significant need for advancements to improve reliability and performance. These technological constraints hinder the widespread adoption and effectiveness of current solutions.

Scalability and adaptability are further challenges. Solutions must be scalable to accommodate different grid structures and adapt to varying levels of renewable energy penetration. This necessitates tailored approaches that can adjust to specific regions and unique grid configurations. Flexibility and adaptability are crucial, yet existing studies often provide generalized solutions that may not be applicable across diverse contexts [37].

In summary, while research aimed at mitigating the duck curve has introduced promising strategies—from distributed decision-making and battery energy storage optimization to demand response and innovative grid management frameworks—challenges like integration complexity, economic viability, scalability, and technological limitations remain. Addressing these challenges will require a collaborative approach, innovative technologies, and flexible regulatory frameworks to build stable and sustainable power grids in an era of growing renewable energy integration.

Main Novelties of This Study

The primary contributions of this study with respect to the existing literature are:

- Investigation of the impact of battery capacity on system performance, addressing a gap in understanding the long-term implications of varying capacities.
- Analysis of Battery State of Health (SOH) and its integration into optimization strategies, a relatively unexplored area in current research.
- Establishing a balance between duck curve optimization and battery health, offering a novel approach to ensure sustainable energy storage solutions.
- Examination of strategies for maximum reduction in CO2 emissions and dependency on fossil fuels, contributing to environmental sustainability goals.
- Allocation of varying weights for the optimization of different peak and over-generation hours, providing a more nuanced and effective approach to energy management.

By addressing these gaps, this thesis aims to contribute to the development of more efficient, cost-effective, and sustainable strategies for mitigating the duck curve.

3. THE PROPOSED OPTIMIZATION PROBLEM

3.1. Introduction to optimization

Single-Objective Optimization Problems

A single-objective optimization problem (General Single-Objective Optimization Problem) is presented as follows: It involves either minimizing or maximizing a single scalar function $f(x)$, where x represents a vector of n decision variables $x = \{x_1, ..., x_n\}$ within a defined domain Ω. This optimization is subject to inequality constraints $g_i(x) \leq 0$ for $i = \{1, ..., m\}$, and equality constraints $h_j(x) = 0$ for $j = \{1, ..., p\}$. The decision variable vector x can encompass both continuous and discrete variables, just as the objective function f and constraints g_i and h_j can be either continuous or discrete. The constraints, which may be either explicitly defined or require an algorithm for evaluation, must be satisfied to optimize $f(x)$. It's important to note that the number of equality constraints p should be less than the number of decision variables n to avoid an over-constrained scenario ($p \geq n$), which would eliminate any degrees of freedom for optimization. The available degrees of freedom are calculated assuming all equality constraints are independent and none of the inequality constraints are effectively equality constraints [23].

Global Optimization refers to the process of identifying the global optimum (which may not be singular) of a given function. Specifically, for a single-objective issue, the global minimum is defined as follows:

For a function $f : \Omega \subseteq \mathbb{R}^n \rightarrow R$, $\Omega \neq 0$, for $x \in \Omega$ the value $f^* \triangleq f(x^*) > -\infty$ is called a global minimum if and only if:

$$\forall x \in \Omega : f(x^*) \leq f(x) \qquad (1)$$

Here, x^* represents the global minimum solution, f denotes the objective function, and Ω signifies the domain where x is viable. The pursuit of the global minimum solution is known as solving the global optimization problem in the context of a single-objective challenge.

Multi-Objective Optimization Problems

Multi-objective problems aim to optimize simultaneously k objective functions, labeled $f_1(x), f_2(x),..., f_k(x)$, collectively represented by the vector function $F(x)$:

$$F(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ . \\ . \\ . \\ f_k(x) \end{bmatrix} \qquad (2)$$

Single-objective optimization problems may be solved with a single best answer, but multi-objective problems have a universe of solutions, in most cases virtually infinite). Two Euclidean spaces are considered for the multi-objective optimization settings:

- the space of the decision variables in which each coordinate axis corresponds to a component of vector x;
- the k-dimensional space of the objective functions where one component vector $f_k(x)$ efficiently dominates you on each coordinate axis.

Pareto Optimality Theory: The evaluation function in multi-objective optimization, $F: \Omega \rightarrow \wedge$, maps decision variables ($x = x_1,...,x_n$) to objective vectors ($y = a_1,...,a_k$). The mapping can span the entire objective function space, or it may only cover a fraction of it, depending on the form of the individual elements and constraints on the problem. Decision-makers must choose one or more solutions from these vectors, typically located in the Pareto front (representing the set of most efficient trade-offs between objectives). Decision-makers should find a balanced solution that at least meets all objectives well, that is, a set of Pareto optimal solutions.

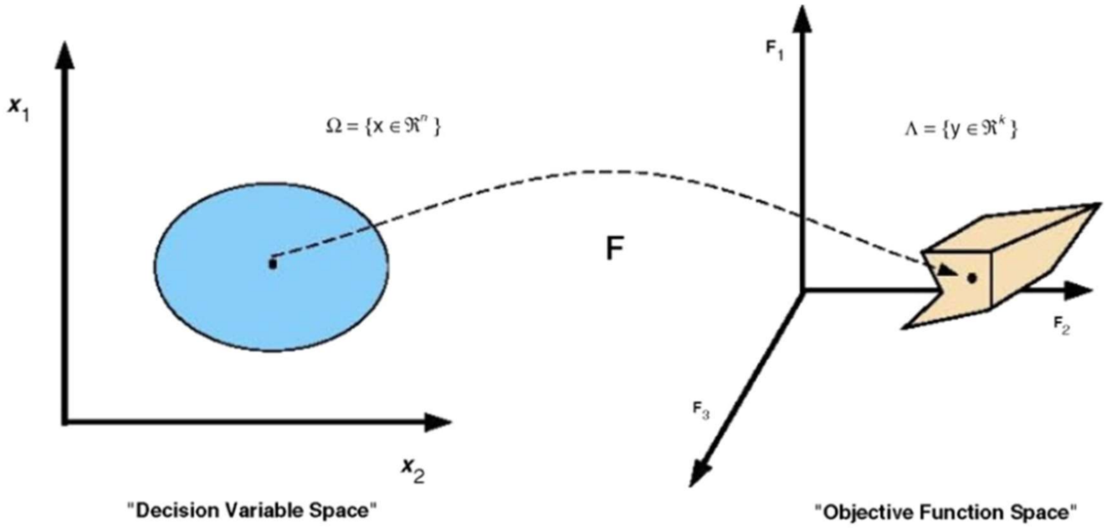

Figure 5. Decision variable space [23]

Thus, the challenge of multi-objective optimization, also known as multi-criteria, multi-performance, or vector optimization, involves finding a decision variable vector that meets constraints and optimizes a vector function representing conflicting objective functions.

The goal is to find a solution that achieves acceptable levels of performance across all objectives to the decision-maker.

General Multi-Objective Optimization Problem

A general multi-objective optimization problem involves minimizing or maximizing of the objective function set $F(x) = (f_1(x), f_2(x), ..., f_k(x))$, while adhering to inequality constraints $g_i(x) \leq 0$ for $i = \{1, ..., m\}$, and equality constraints $h_j(x) = 0$ for $j = \{1, ..., p\}$. The goal is to optimize the elements of vector $F(x)$, with x being a vector of n decision variables $x = (x_1, ..., x_n)$ within a defined universe Ω.A The constraints $g_i(x) \leq 0$ and $h_j(x) = 0$ must be satisfied during the optimization of $F(x)$, where Ω encompasses all viable x values for evaluating $F(x)$. The problem includes k objectives represented by k objective functions, constrained by $m + p$ conditions, and defined over n decision variables. These objective functions and decision variables might be linear or nonlinear, and either continuous or discrete.

Pareto Optimality

A solution x from the set Ω is considered Pareto optimal relative to Ω if there exists no alternative $x^{'}$ within Ω such that the vector $v = F(x^{'}) = (f_1(x^{'}),...,f_k(x^{'}))$ is superior to $u = F(x) = (f_1(x),...,f_k(x))$. Pareto optimality is generally understood in the context of the entire space of decision variables unless stated otherwise. Essentially, this means that a solution x^* is Pareto optimal if no other viable solution x can be found that improves any objective without simultaneously worsening at least one other objective (under the assumption of minimization).

Pareto Optimal Set

For a given multi-objective problem, $F(x)$, the Pareto Optimal Set, p^*, is defined as:

$$p^* := \left\{ x \in \Omega \middle| \exists x^{'} \in \Omega \;\; F(x^{'}) \le F(x) \right\} \qquad (3)$$

Pareto optimal solutions are those solutions within the decision space whose corresponding variables cannot be all simultaneously improved. These points are alternatively known as non-inferior, admissible, or efficient solutions, collectively denoted by p^*. The vectors related to these solutions are described as non-dominated. Choosing a vector from the set of these vectors, known as the Pareto front set pF^*, signifies the selection of viable Pareto optimal solutions and their decision variables. The only common feature among these solutions is their inclusion in the Pareto optimal set, as they represent all possible solutions with non-dominated associated vectors. The classification of solutions as Pareto optimal is determined by their functional value assessments.

Pareto Front

For a given multi-objective problem, $F(x)$, and Pareto optimal Set p^*, the Pareto front pF^* is defined as:

$$pF^* := \left\{ u = F(x) \middle| x \in p^* \right\} \qquad (4)$$

In the objective space, non-dominated vectors collectively constitute what is known as the Pareto front. p^* represents a subset of a larger solution set, with its objective vectors evaluated to form pF^*, where each vector is non-dominated across all objective vectors obtained by evaluating all potential solutions in Ω. Finding an analytical description for the line or surface encompassing these points is typically challenging and often not feasible. The usual method to construct the Pareto front involves calculating numerous points within Ω and their corresponding objective values $f(\Omega)$. With a substantial collection of these points, it becomes possible to identify the non-dominated ones, thereby delineating the Pareto front.

3.2. The System model

In this section, we delve into the intricacies of the model we have meticulously developed to analyze our energy system comprehensively. Initially, our investigation focuses on dissecting the model specific to each segment of the system under consideration. This involves a detailed examination of the decision variables and constraints that are integral to the optimization aspect of our study. Such an examination is crucial as it lays the groundwork for understanding how each component of the system contributes to the overall functionality and efficiency. Following this foundational analysis, the latter portion of our study will transition to a thorough discussion on the objective function. This discussion aims to illuminate the core goals that our model strives to achieve, accompanied by a comprehensive exploration of the detailed model itself. Through this approach, we ensure a holistic understanding of the model's structure, its operational mechanisms, and its pivotal role in enhancing our grasp of the energy system's dynamics.

PV Power Generation Source

The amount of power generated by photovoltaic (PV) systems depends on different factors; one of the most important factors is the irradiation intensity at the specific area, the coverage area (size of the PV arrays), and their power efficiency. In addition, the sum efficiency of the system takes into consideration various important efficiencies, comprising the power conversion efficiency of the PV arrays, the efficiency in the inverter system and the efficiency relevant to grid connection. These factors are taken together for considering and estimating in the subsequent equation:

$$P_{pv} = \eta_{pv} \, E_{rad} \;\; N \, A_{pv} \qquad (5$$

Where:

P_{pv}	Output power of PV system [kW]
η_{pv}	Efficiency of solar panel
E_{rad}	Solar irradiation [kW/m^2]
N	Number of solar panels
A_{pv}	Are of one solar panel [m^2]

Power Grid Model

In this section we present models of the electrical distribution grid in operational integrated within the proposed Energy Management System (EMS). To handle the active and reactive power flows in the distribution network, let us define $P_{i,j,t}$ (kW) and $Q_{i,j,t}$ (kvar) as the active and reactive power flows, respectively, for nodes i and j where $i, j \in N$ (where N is number of the nodes in the grid) for the time period $(t, t+1)$. The power flow equations are expressed in per unit values as $P_{i,j,t} = S_b p_{i,j,t}$ and $Q_{i,j,t} = S_b q_{i,j,t}$ in which S_b represents the power base in kVA. At each node, the balance equations for active and reactive power are provided in equations 9 and 10 [38]. To achieve the balance in the modeling process, the active and reactive power currents at each node are computed. This balance is crucial in supporting the structural integrity and functionality of the electrical distribution grid. These detailed equations and models of the EMS would allow for the interacting systems to be managed and optimized all throughout a grid to enhance the reliability and efficiency of power distribution.

$$\sum_{l \in H_{R,i}} P_{RES,l,i,t} + \sum_{k \in S_i} P_{S,k,i,t} + P_{grid,i,t} - P_{D,i,t} = \sum_{j \in A_i} P_{i,j,t} \tag{6}$$

$$\forall t \in \{1, \ldots, T-1\}, i \in N$$

$$\sum_{l \in H_{R,i}} Q_{RES,l,i,t} + \sum_{k \in S_i} Q_{S,k,i,t} + Q_{grid,i,t} - Q_{D,i,t} = \sum_{j \in A_i} Q_{i,j,t} \tag{7}$$

$$\forall t \in \{1, \ldots, T-1\}, i \in N$$

Where $\mathrm{H}_{R,i} = \{1, \ldots, \mathrm{h}_{r,i}\}$ represents the set of renewable generators (PV panels in our study) at node i Similarly, $S_i = \{1, \ldots, k_{s,i}\}$ denotes the set of storage systems at node

i. The active power produced by the ith renewable generator (here PV panels) at node i is $P_{RES,l,i,t}$. $P_{S,k,i,t}$ is the active power exchanged with the kth storage system at node i and $P_{D,i,t}$ indicates the overall power load at node i, while $P_{grid,i,t}$ represents the power exchanged with the main grid. Corresponding reactive power flows are denoted as $Q_{RES,l,i,t}$, $Q_{S,k,i,t}$, $Q_{D,i,t}$ and $Q_{grid,i,t}$ [38].

Comprehensive non-linear power flow equations are used in modeling the power flow between the grid nodes. Meanwhile, these equations represent the circuit quantities in Cartesian coordinates and the corresponding sinusoidal steady-state equilibrium of a power network.

$$p_{i,j,t} = G_{i,j}(v_{i,t} - v_{j,t}) + B_{i,j}(\delta_{i,t} - \delta_{j,t}) \qquad (8)$$

$$i, j \in N,\ i \neq j,\ t = 0, \ldots, T-1$$

$$q_{i,j,t} = B_{i,j}(v_{i,t} - v_{j,t}) - G_{i,j}(\delta_{i,t} - \delta_{j,t}) \qquad (9)$$

$$i, j \in N,\ i \neq j,\ t = 0, \ldots, T-1$$

In this model $G_{i,j}$ and $B_{i,j}$ denote the conductance and susceptance parameters of line connecting nodes i and j respectively. Where $v_{i,t}$, and $\delta_{i,t}$ are the voltage magnitude and angle at node i, respectively $\delta_{i,t}$ [38].

<u>Battery Storage System (BESS)</u>

While the transition to renewable resources continues to change the global energy sector in pursuit of a sustainable future. At the heart of this change is incorporating solar and wind power into our electrical grids, which are currently largely managed using various computer systems that store endless amounts of information about our energy consumption and generation. Nonetheless, the challenge of providing enough energy, reliably and all the time is immense due to the intrinsic variability of these resources. That is where battery storage systems come in - a game-changing technology that is said to be able to unite the intermittent nature of renewable energy generation with the constant demand of the grid. As a basic piece in capable of delivering sustainable and reliable power: these systems have the ability to retain electrical energy, which can be used later, are right now at the pulse of present-day energy plans.

No longer just secondary equipment, battery systems are critical and indispensable to capturing the full benefits and potential of renewable energy solutions. The systems act to prevent the randomness of wind and solar power from creating supply shocks, helping to store energy when it is needed and release it when demand surges or generation flags. This enables the conversion of renewable energy from an intermittent source to a reliable source making it available, on demand, with grid requirements and consumption patterns. Further, battery storage also goes far beyond just supply balancing, as it also contributes to grid stability, ancillary services, as well as enabling our energy systems to further decarbonize.

They are vital for frequency regulation, voltage control, and emergency backup power, and hence, increase the grid stability and efficiency.

Battery Storage Systems hold the same significance in enabling a sustainable, reliable, and efficient power grid on the verge of an energy revolution, as they will be the foundation, upon which, a smart grid is built on. In this article we will examine the function of these systems, their crucial function in enabling renewable energy to be fed into the grid and what they mean for the global energy consumption of the near future. Come along with us as we peer into the world of battery storage systems innovation and technology, and dream into the future of renewables supported by the quiet guardians of energy storage [9].

The technical specifications that matter most with regards to Battery Energy Storage Systems (BESS) involve how much power it can store and how effective it is at charging or discharging. State of Charge (SOC) is described as the stored electrical energy with respect to the total amount of the battery capacity. There is little self-discharge for a lithium-ion battery.

$$SOC_t = SOC_{t-1} + \left[\eta_{s,ch} P_{s,ch,t} - \frac{P_{s,dis,t}}{\eta_{s,dis}} \right] \Delta t \Big/ Cap_{bat} \qquad (10)$$

Where:

SOC_t	State of charge of battery at time t
$P_{s,ch,t}$	Power exchange during battery charging at time t
$P_{s,dis,t}$	Power exchange during battery discharging at time t
$\eta_{s,ch}$	Battery efficiency during charging

$\eta_{s,dis}$	Battery efficiency during discharging
Δt	Time interval
Cap_{bat}	Capacity of battery

State of charge of battery at time t ($SOC(t)$), Power exchange during battery charging at time t ($P_{s,ch}(t)$), Power exchange during battery discharging at time t ($P_{s,dis}(t)$), and two binary variables $x_{s,ch}$ and $x_{s,dis}$ are decision variables in the model of battery storage system. It should be mentioned that we use binary variables as ***decision variables*** to make our model linear.

Operation constraints for battery storage systems are listed in following:

- Ensuring that the state of charge at any time is greater than or equal to its minimum value:

$$SOC_t \geq SOC_{\min},\ \forall t \in \{1,...,T\} \qquad (11)$$

- Ensuring that the state of charge at any time is smaller than or equal to its maximum value.

$$SOC_t \leq SOC_{\max},\ \forall t \in \{1,...,T\} \qquad (12)$$

- Setting the state of charge at the start of each day matches the predefined initial value.

$$SOC_1 = SOC_0 \qquad (13)$$

- Setting the state of charge at the close of each day (when $t = T$) to match the predefined initial value. This approach guarantees that the stored energy from the previous day is not utilized on the following day.

$$SOC_T = SOC_0 \qquad (14)$$

- Ensuring that the charging power at any time remains at or above its minimum value.

$$P_{s,ch,t} \geq P_{s,ch,\min},\ \forall t \in \{1,...,T\} \qquad (15)$$

- Ensuring that the charging power of the storage at any time is either zero or does not exceed the maximum charging power, controlled by a binary decision variable $x_{s,ch}$ that enforces the storage to either charge or discharge, but not both simultaneously.

$$P_{s,ch,t} \leq P_{s,ch,\max}\ x_{s,ch}, \forall t \in \{1,...,T\} \qquad (16)$$

- To be sure that the discharging power at any time remains at or above its minimum value.

$$P_{s,dis,t} \geq P_{s,dis,\min}, \forall t \in \{1,...,T\} \qquad (17)$$

- To get sure that the discharging power of the storage at any time is either zero or does not exceed the maximum charging power, controlled by a binary decision variable $x_{s,dis}$ that enforces the storage to either charge or discharge, but not both simultaneously.

$$P_{s,dis,t} \leq P_{s,dis,\max}\ x_{s,dis}, \forall t \in \{1,...,T\} \qquad (18)$$

- A standard binary constraint, which, along with the non-negativity of $x_{s,ch}$ and $x_{s,dis}$, is inherently satisfied since binary variables can only take values of 0 or 1.

$$x_{s,ch} + x_{s,dis} \geq 0 \qquad (19)$$

- And finally, to be ensure that if the battery is charging ($x_{s,ch} = 1$), then it cannot be discharging ($x_{s,dis}$ must be 0), and vice versa. Because each x can only be 0 or 1, the sum being less than or equal to 1 enforces mutual exclusivity between charging and discharging states.

$$x_{s,ch} + x_{s,dis} \leq 1 \qquad (20)$$

Using binary decision variable (here $x_{s,ch}$ and $x_{s,dis}$) maintains linearity of the constraints, which is crucial for the efficiency of linear programming solvers used to solve this type of optimization problem. Nonlinear or integer constraints could complicate or slow down the solution process significantly, but by using binary decision variables and linear inequalities, we ensure that the problem stays within the linear programming domain, which is typically faster and easier to solve using standard optimization algorithms.

<u>Modelling Battery Degradation and State of Health (SOH)</u>

While it holds true that the phenomenon of self-discharge is associated with relatively minute magnitudes, its impact is considerably less pronounced, particularly in battery technologies that are founded on lithium-ion chemistries. Contrasting with the marginal influence of self-discharge, one cannot afford to overlook the progressive aging of energy storage systems. Indeed, the gradual decay and wear of storage components emerge as primary factors influencing the operational expenditures throughout the lifecycle of a storage system. A meticulous distinction is generally drawn between two predominant types of degradation processes: ***cyclic aging***, which occurs with the battery's charge and discharge cycles, and ***calendric aging***, which transpires over time regardless of the battery's use. This bifurcation in the aging taxonomy is thoroughly elucidated in existing literature.

To quantify the impact of these degradation mechanisms, indicators such as the cyclic and calendric lifetime thresholds ($life_{Cyc}^{80\%}$ and $life_{Cal}^{80\%}$, respectively) are deployed. These metrics delineate the anticipated lifespan of a battery under specified usage conditions until it exhibits a palpable decline in its capacity. The terminologies employed are indicative of the threshold at which the battery's ***state of health (SOH)*** is reduced to 80% of its nominal capacity—a threshold that is conventionally utilized as a benchmark for replacement in vehicular contexts.

In the discourse of this document, a straightforward approximation is adopted to represent the temporal progression of calendric aging, as well as a more intricate model that captures the influence of charge cycles on cyclic aging. Specifically, the metric of calendric lifetime ($life_{Cal}^{80\%}$) furnishes a baseline for estimating the deterioration of the storage's SOH to the 80% mark at a standardized temperature of 20 degrees Celsius in the absence of any charge-discharge activity. On the other hand, to articulate the cyclic aging ($life_{Cyc}^{80\%}$) that is a consequence of the energy exchanged within the battery storage, we refer to the correlation with the concept of ***full equivalent cycles (FEC)***. This approach to defining cyclic aging provides a nuanced understanding of how energy throughput begets wear in battery storage systems [37].

$$FEC = \alpha \times \frac{1}{t} \int SOC_t dt \approx \alpha \times \frac{\int |P_{bat}| dt}{Cap_{bat}^{nom}} \qquad (21)$$

The multiplicative aspect of $\alpha = 0.5$ is the result of a change in the way in which charge throughput is measured relative to a full cycle count methodology, one which incorporates an entire charge/discharge cycle [37]. On this, SOC stands for State of Charge (a measure of the current charge level of the battery compared to the maximum charge capacity). P_{bat} is the amount of power that can be drawn from the battery, and

Cap_{bat}^{nom} is the overall energy capacity of the battery, meaning the total amount of energy the battery can hold in theory, under perfect conditions.

Therefore, to provide a theoretical framework in which battery health can be evaluated, let us define a theoretical concept of maximum charge throughput. The unit root condition is written as $life_{Cyc}^{80\%}$, In summary, it is a value that indicates how many full equivalent cycles (FEC) the battery can perform under ideal conditions, i.e. without taking into account the effects of calendric aging and assuming a discharge of 100% down to 0% that will allow the battery to reach 80% of its manufacture original capacity. A theoretical figure, it helps communicate how long the battery will be useful in terms of having a long, active lifecycle, as affected by cyclic aging alone.

To this end and with the objective to incorporate battery aging awareness in future modeling efforts, a set of equations are derived. The goal is to generate equations that will characterize the complex electrochemical and mechanical impact of each of those conditions on the life of the battery pack in a quantifiable manner. The purpose of developing these equations is to create a detailed mathematical model of battery aging that can be relied upon to predict battery degradation over time and can be used to enhance battery maintenance schedules, battery replacement strategy as well as to plan for the economic aspects of battery usage and management.

$$AGE_{cal} = \frac{\Delta t}{life_{Cal}^{80\%}} \tag{22}$$

$$AGE_{cyc} = \frac{0.5 \times \int |P_{bat}| dt}{life_{Cyc}^{80\%} \times Cap_{bat}^{nom}} \tag{23}$$

A superposition principle is used to estimate the overall aging as:

$$AGE_{tot} = AGE_{cal} + AGE_{cyc} \tag{24}$$

Where is the battery-aging model parameterized in this framework, which AGE_{tot} serves as the quantified index to represent the total aging status caused by both time and load conditions. The parameter takes a value on a continuous scale and the starting point, $AGE_{tot} = 0$ represents a battery in a brand-new state having never been used before – it is a factory fresh battery sort of thing. On the other side of the spectrum, and completely on the flip side, there is $AGE_{tot} = 1$. This number is a somewhat crucial milestone in the life of the battery, it is a hint that the remaining energy capacity of the battery decreased to only 80% of the initial one. This lower power output is the result of several factors, such as degradation over time, as well as regular wear and tear during the battery's performance cycles.

Moreover, the operational benefit of the storage system can be utilized beyond the limit expressed by $AGE_{tot} > 1$. This possibility is high in instances where the replacement criteria have a higher tolerance level allowing the effective capacity of the replaced storage to fall below the typical 80% standard benchmark [37]. The details of how this methodology was carried out and the storage to be used long after traditional replacement might have taken place are then described in subsequent sections. This approach allows a wider flexibility in the conducted operations and thus generally leads to a more economically benevolent use of the storage system by extending the operational range of the battery before replacement is seen warranted.

The current condition or 'health' of the battery is quantifiable through a specific equation, designated as [17]:

$$SOH_t = 1 - (SOH_{initial} - SOH_{end}) \times AGE_{tot} \qquad (25)$$

This equation is used to find the State of Health (SOH) of a battery which determines the percentage of capacity left in a battery with respect to its original capacity at the time of new. By default, the parameters $SOH_{initial}$ and SOH_{end} are set to indicate full or diminished capacity values respectively. Like most batteries is set at 100% under normal circumstances which is where the battery's maximum capacity when new unused is referenced.

On the other hand, it is most common to set to 80%, which is the accepted floor at which a battery loses so much capacity that it might want to be replaced.

AGE_{tot} is the desired variable which is used to be the descriptor that the longer a battery has more extended overall degradation. The aging is a combination of two types of aging: calendric aging, which is the physical deterioration the battery undergoes just because of time passing, regardless of how much is used; and cyclic aging, which is based on the total number of charge/discharge cycles of the battery.

Also, it is also possible (using another formula that It calls), to know the battery State of Health each year

$$SOH_t = SOH_{t-1} - a \times (AGE_{cal}(t) + AGE_{cyc}(t)) \qquad (26)$$

Where a =0.2 (based on [37]). This equation provides a lifetime view for battery health in terms of how we calculate SOH in intervals along its lifespan, giving a more precise understanding of how the battery performs overall and over a long period of time.

Calendric aging, or $AGE_{cal}(t)$, is inherently influenced by external environmental conditions. The first state is the environmental conditions such as the ambient temperature indicated by T, and state of charge (SOC) of the battery which is when the battery has more energy, the SOC is higher.

A semi-empirical model has been developed to quantify and predict the degree of calendric long-term aging in some specified period. In fact, as shown above, this model is embedded in something resembling the following:

$$AGE_{cal,m} = a \cdot SOC^{b} + c \cdot (d \cdot T^{e} + f) \cdot m^{g} \qquad (27)$$

Where;

$a = 0.019, b = 0.823, c = 0.5195, d = 3.258 \times 10^{-9}, e = 5.087, f = 0,295$ *and* $g = 0.8$. This can be useful to understand the effects of ambient temperature and years (how many months it works) and what it does to the battery. In the next equation the model gets slightly more rigorous through defaulting the two remaining variables temperature 'T' and time 'm' (letting T=25 Celsius and m = 180 months i.e. 15 years) as;

$$AGE_{cal}(180) = a \cdot SOC^{b} + c \qquad (28)$$

Where; $a = 0.4089, b = 0.823$ *and* $c = 11.15738$. To make this model more practical and applicable to real-world scenarios, the linear progression of capacity reduction that a battery is expected to undergo over 15 years is recalibrated to reflect a short-term timescale of 1 hour. This recalibration is formulated as:

$$AGE_{cal,t} = a \cdot SOC_{t} + b \qquad (29)$$

Where; $a = 6.6148 \times 10^{-6}$ *and* $b = 4.6404 \times 10^{-6}$. Which effectively distills a long-term aging process into an abbreviated timeframe, making it more comprehensible and relatable to immediate observations and applications.

To go deep into the calculation of the SOH (Battery State of Health) analysis, we must take into account the equations on which we are based. As already explained in an earlier part of our report, these equations are mainly calibrated monthly. Although this temporal scale is convenient in many instances, we need to make a strategic adjustment to account for specific needs of our model, and temporal resolution. So, we must deal with windows at smaller timescales - our model goes over a period of 15 minutes (Δt), that allows us to focus on the right analysis and time management.

To implement the original equations in our model framework, it was necessary to modify them because of reasons with time scales. To fill this gap, we performed a complete re-formulation of the equations from monthly to 15-minute intervals. This adjustment wasn't just changing units, though, it was thoroughly re-evaluating the variables and the parameters in order to represent better the dynamics of battery operation and degradation at the minute-scale. These new equations allow us to obtain a more accurate and detailed analysis of the Battery State of Health (SOH), which troubleshoots us within our operational time, i.e. in time.

Also, this change improves the ability of our model to take decisions and to predict instantly or quasi-instantly. The 15-minute intervals SOH provides a clearer picture into the health of the battery, how quickly it is deteriorating, which maintenance it requires, and operational strategies that can be tuned for a longer life and continued performance efficiency of the battery. Here, 15 minutes resolution can be particularly useful by providing an almost real-time power performance data at time scales where battery performance can vary drastically, such as in renewable energy systems where solar irradiance can change significantly throughout the day.

In brief, our choice to adjust the SOH equations for a 15-minute analysis window is to a great extent influenced by the desire to excel and remain useful in our model. This change ensures our battery health assessment approach is not only theoretically justified, but also reflective of the way in which battery-based energy storage systems are operated.

$$AGE_{cyc,t} = a \cdot \frac{\left| \eta_{s,ch} P_{s,ch,t} - P_{s,dis,t} / \eta_{s,dis} \right| \Delta t}{b \cdot Cap_{bat}} \tag{30}$$

$$AGE_{cal,t} = c \cdot SOC_t + d \tag{31}$$

Where; $a = 0.5,\ b = 9000, c = 1.6537 \times 10^{-6}\ and\ d = 1.1601 \times 10^{-6}$

3.3. The Optimization Model

From previous sections of this thesis, we have delved deep into the various areas of our energy system - the batteries, PV panels and went on a comprehensive journey. This essential dialogue laid the foundation for us to examine the complex architectures and operational dynamics that comprise the underlying fabric of the relevant energy system.

In subsequent phases of our work, we will examine our energy system model that aligns to the least-cost optimization model on which it is based. In this segment, we will disassemble the optimization model.

Apart from this, we will also have a full-rounded talk about the decision variables that affect how well the system performs and operates. It will include an extensive foraging of the parameters that may be controlled or manipulated in the model to arrive at certain goals within the model.

In parallel, we will define constraints that are inherently present in our model. These constraints are the pragmatic ranges with which the application most realistically needs to function, usually including as a minimum constraint like physical and technical. The explanation of these constraints is also important as they specify the feasible region for the decision variables, and it is a reason why the optimization model cannot find any viable solution.

The overarching objective of our thesis is a multi-faceted challenge, primarily focused on coping with the duck curve that arises in response to the inclusion of the current photovoltaic (PV) panels in the power grid. This sharp evening ramp will prove to be a significant challenge for energy management; it represents the very real difficulty of ramping electricity demand up once the sun sets and solar power begins to wane. Our secondary research objectives are to reduce the cyclic age of battery storage systems on the network and increase the lifespan of battery storage systems on the distribution network. It is therefore essential to minimize this process to ensure the economic and environmental sustainability of energy storage solutions.

To accomplish these ambitious objectives, we designed a multi-objective function to account for these two goals. The first part works to strategically flatten the duck curve, a major challenge associated with the pronounced shifts in demand and supply of energy within the electricity system across the day due to solar generation. Component two addresses the extension of battery storage life by optimizing these system's cycle age in a similar smart manner. Both the immediate challenges faced by PV panel integration into the energy network and the long-term sustainability concerns of battery storage are addressed by this dual-faceted approach.

$$Objetive\ Function = a\sum_{t=1}^{T} W_t\,(P_{1,t-1} - P_{1,t})^2 + b\sum_{t=1}^{T}(AGE_{cyc,1,t} + AGE_{cyc,2,t} + AGE_{cyc,3,t})$$

(32)

This equation is given by minimization of purchased power and battery aging subject to equations (10-20) and equation (33).

$$P_{1,t} \geq 0 \quad \forall t \in \{1,...,T\} \qquad (33)$$

Where:

$P_{1,t}$	Power at node 1 at time t (node 1 is slack bus and connected to the main grid)
$AGE_{cyc,1,t}$	Cyclic age of battery storage 1 located at node 5
$AGE_{cyc,2,t}$	Cyclic age of battery storage 2 located at node 7
$AGE_{cyc,3,t}$	Cyclic age of battery storage 3 located at node 12

We have introduced 3 different weights in our objective function, where all weights are used in optimizing in and around the custom defined business goals.

- W_t is intricately designed to impose a heightened penalty on fluctuations during the critical ramp hours. By defining our time units in quarter-hours, we identified the morning ramp period as spanning from 6 AM to 9 AM and the evening ramp period from 6 PM to 9 PM. This delineation is instrumental in addressing the most significant shifts in power demand and supply, effectively smoothing out the abrupt changes that epitomize the duck curve. The strategic placement of W_t ensures that these critical periods are given precedence in our optimization efforts, while also affording greater flexibility during the less critical hours of the day.
- a is allocated to the component of the objective function that focuses on flattening the duck curve. This weight underscores our commitment to mitigating the disparities in energy production and consumption patterns that contribute to the duck curve phenomenon. By optimizing this aspect of our objective function, we

aim to foster a more stable and efficient energy network that can seamlessly accommodate the variable nature of solar power generation.

- b is attributed to the enhancement of battery storage lifetime within our objective function. This weight highlights the importance of extending the operational lifespan of battery storage systems through optimized cycle management. By prioritizing the longevity of these systems, we not only enhance their economic viability but also contribute to the overall sustainability of the energy storage infrastructure.

4. APPLICATION TO A CASE STUDY

4.1. The Considered Case Study

In the previous section of this report, we have given all the equations and constraints pertaining to our optimization problem 'in general form', in the sense that the concrete values of the variables have not been assigned peculiar values. However, we did this in order to highlight the structural framework and theoretical structure of our analysis. Now, as we move into the next phase of our discussion here, we must tie some principles back to how they are used. As such, in this stage of our report, we will be explicitly focus on the numbers we give to these variables in the context of our project. Understand that these values are not randomly chosen but emerge after extensive analysis, collecting data from empirical evidence and vigorous testing to ensure that they are accurate depiction of the parameters of our study. The numbers to assign to all of these variables to get our optimization model up and running have been put into a table for clarity.

Variable	comment
T=96	• There is 96 fifteen minutes in each day
$Cap_{bat} = 2809$ [MWh]	• Based on nominal power of the installed photovoltaic panels
$\Delta t = 0.25$ [Hour]	
$\eta_{s,ch} = 96\%$	
$\eta_{s,dis} = 96\%$	
$SOC_{\min} = 10\%$	
$SOC_{\max} = 90\%$	
$SOC_0 = 50\%$	
$P_{s,ch,\min} = 0$	
$P_{s,ch,\max} = 2809$ [MW]	
$P_{s,dis,\min} = 0$	
$P_{s,dis,\max} = 2809$ [MW]	

Network

The IEEE 13-node test feeder is a benchmark model that was established by Institute of Electrical and Electronics Engineers (IEEE) to test and compare the algorithms and methodologies worked for power distribution system analysis. The feeder model in this paper is the most used in the electrical engineering study to emulate a miniaturized power network, an ideal platform to compare solutions in a common ground.

The IEEE 13-node test feeder consists of 13 nodes (buses) and is a much larger primary substation. network containing distribution lines, transformers, and load points. All these quantities are meticulously selected so that they replicate in a reasonable manner the system impedances, load schedules and configurations that occur in practice in real distribution grids. The IEEE 13-node test feeder is a typical radial structure in distribution networks, which brings challenges to voltage regulation, power flow management and reliability analysis [39].

During the extensive research, an electric distribution network was modelled in detail by relying on the structure of the test feeder IEEE 13 bus. It examines a prototype network that can serve as an adequate testbed for the analysis of flow and distribution of electricity within a network of a real urban power distribution system.

IEEE 13 bus system is an established benchmark in power systems and is typically used for simulating the distribution network to residential loads. In our instance of this network all nodes have a point of consumption, except node 1. These nodes are typical residential buildings that signify the 'Loads' or the electrical energy consumers. Our simulation relies on these loads, as they are a mirror of the energy consumption pattern of urban residential dwellings.

One special location exists within this structure: Node number 1, which is the slack node, where our modelled network meets the external electricity grid. The role of the slack node is critical in accomplishing power system analysis as it balances the system by compensating for losses that help in the stable operation of grid. Then, we read the data for node number 1 to understand how much power is being drawn from the main grid to satisfy the internal grid. The importance of local generation capabilities is supported by this measurement, a measure of how much the network needs to rely on outside sources for power.

The network we analyze is equipped with photovoltaic panels on three nodes we have previously defined in our model, our nodes number 5, 7, and 12. These panels are not mere static elements within the network; they are dynamic generators that convert solar energy into electrical energy. This, of course, is affected only when the sun is shining, and leaves for some period in which these nodes only handle a certain portion of the load. Choosing the city of Los Angeles was far from a random choice. Generally, Los Angeles is well known for its sunny weather, and it was a way to show an example in which urban conditions are suitable from such type of nodes deployment. From this point onward, we use real-world data in our analysis, from the irradiance specific to Los Angeles, to the load patterns in households. The IEEE 13 bus network, the fundamental object of our study, is strategically designed to be easily visualized through the topology shown in following figure, along with the corresponding number of residential buildings items the network carries.

This data was then organized into the table shown below, which does more than showing the load at every node. It also gives the reader an immediate impression of the scope and locations of the nodes we equipped with solar panels and at the scale of demand in each. Our analysis of a solar energy-integrating IEEE 13 bus network in Los Angeles, designed with real-world data in mind, therefore offers a deep insight into the promise and challenges of integrating renewable power sources in urban networks. With this focus in mind, we will then seek to contribute to the understanding of load-based energy optimization in urban environments, solar power integration, and the load delivery via the slack node to sustain the network.

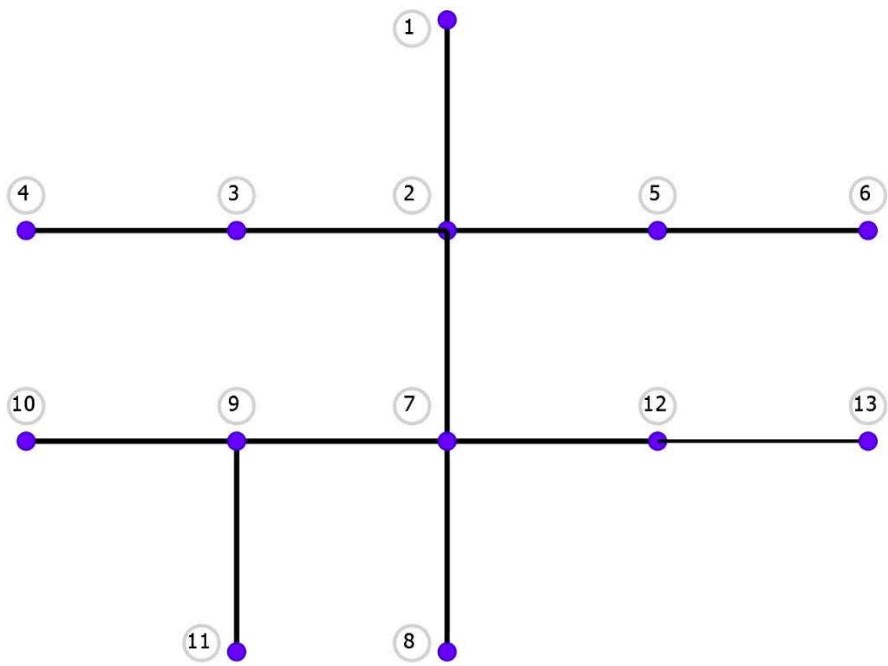

Figure 6 An IEEE 13-node sample showing the numbers of residentials

Node	1	2	3	4	5	6	7	8	9	10	11	12	13
No. of residential buildings in each node	0	200	220	297	200	209	497	626	150	140	165	266	0

Loads

In order to make the energy system model and its linked optimization process more realistic, a *detailed temporal disaggregation* was done. This included the determination of monthly average solar irradiance and energy consumption (load) profiles, which were reduced to fifteen-minute intervals throughout a standard day. A fine-grained manner of collecting data enables the capturing of diurnal and seasonal variability, which is built into both solar energy generation, and domestic energy consumption patterns as described above.

The purpose of inculcating these averages monthly was to essentially to create representative days. Each day is representative of its entire month. In this way, the methodology enables analysis to capture the varying levels of solar irradiance and energy demand through time of day - and the trajectory of the season.

Using these typical days provides a completer and more appropriate basis for optimization corresponding to the changes in seasons and seasonal variations. Solar irradiance is much higher during summer months, for example July, than during winter months, such as February, for example. Just as with the demand function, the load consumption patterns would also vary, in turn, the load consumption would follow the different usage habits of in-play residents.

To help make this seasonal mix clear, we chose example days of load consumption for four key months: February, April, July, and October. Winter, spring, summer, and autumn is purposely selected as the most representative profile of each energy category. The power and energy demands generated by residential buildings in our model for selected months are shown in the following figures. These sample months give an insight to the patterns and intricate interactions occurring. We chose to showcase these months to show the range of variability our system can handle and how it can perform with different seasonal set-ups in place.

By explicitly laying out the seasonal variations in flow, we make certain our strategies for optimization are not only sound in theory but applicable in practice. And it really emphasizes our desire to create a model that is not only academically accurate but also a model that could be used to produce actionable, practical tools for operating energy systems practically.

In addition, these representative days will be an important building block of further analyses, of which only a few will be simulating the model with extreme scenarios, stress testing the grid under peak demand and studying the potential of energy storage systems to balance supply and demand. Figures in the following provide visualizations of these representative days that will instantly help the reader understand the load consumptions trends during different seasons.

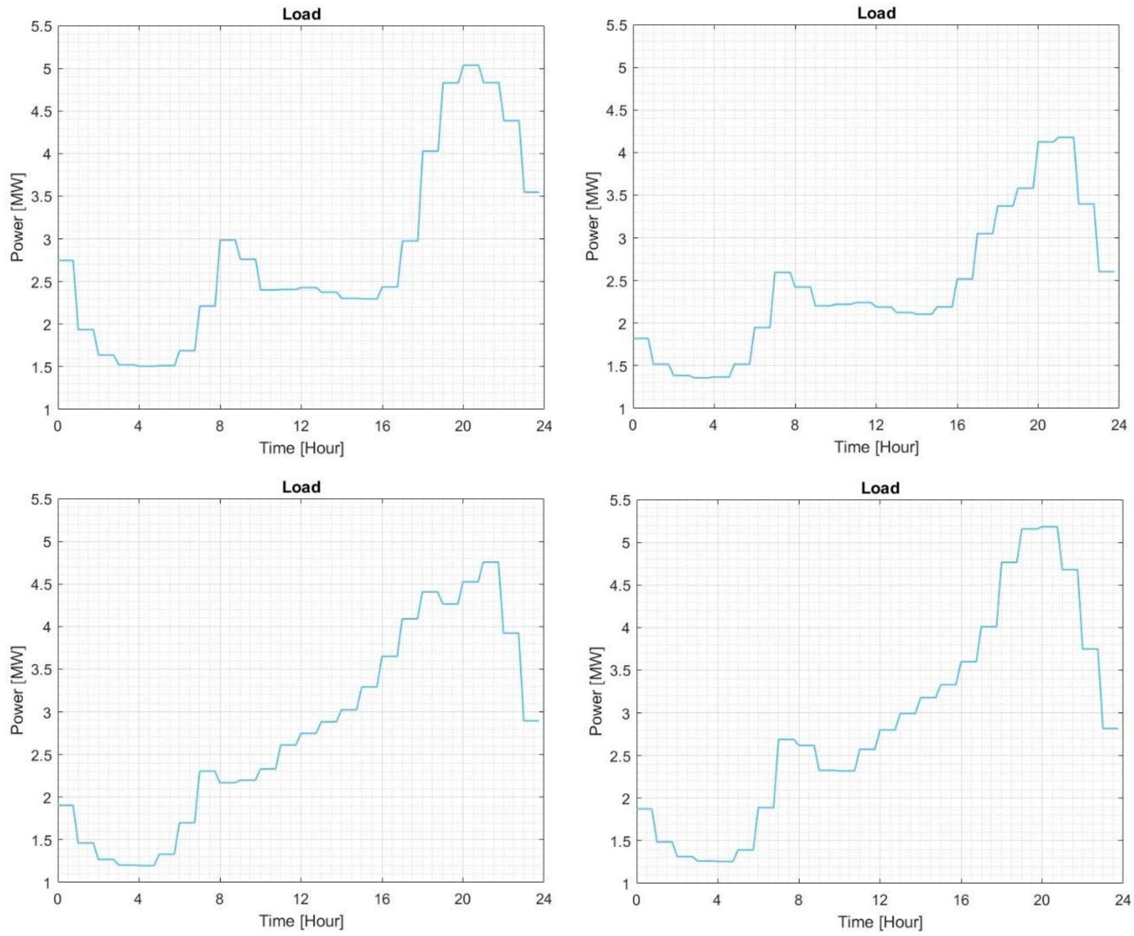

Figure 7. Loads profiles in February (first row left), April (first row right), July (second row left) and October (second row right)

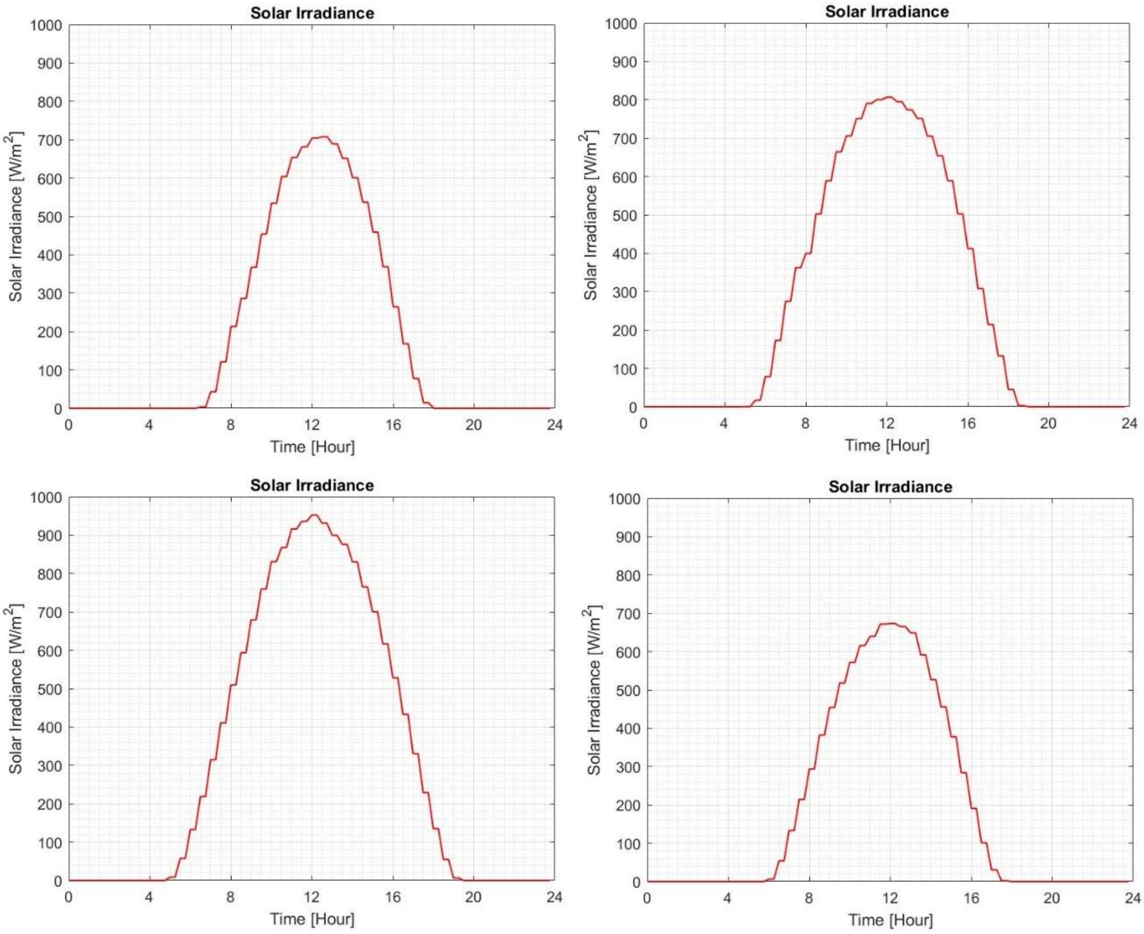

Figure 8. Solar irradiance profiles in February (first row left), April (first row right), July (second row left) and October (second row right)

PV Power Generation

In the comprehensive study and optimization of the network under our scrutiny, we meticulously selected the Canadian Solar HiDM High Density MONO PERC module [40] as the cornerstone photovoltaic panel. This decision was not made lightly; it was the culmination of extensive research, analysis, and comparison of various PV modules available on the market. The Canadian Solar HiDM module stands out for its high density and MONO PERC technology, which are critical attributes that enhance its efficiency and reliability in converting solar energy into electrical power. These features make it an ideal choice for our network, aiming to maximize energy output while maintaining a sustainable and eco-friendly energy solution.

To provide a clear and comprehensive understanding of why the CanadianSolar HiDM High Density MONO PERC module was chosen, we have included the data sheet of this module in our documentation. The data sheet serves as a vital resource, offering an in-depth look at the module's specifications, such as its physical dimensions, weight, maximum power output, efficiency, and temperature coefficients. Additionally, it outlines the module's electrical parameters, including its optimal operating voltage and current, as well as its maximum system voltage and series fuse rating. This information is pivotal for engineers, designers, and decision-makers involved in the PV network's planning and optimization process, as it enables them to assess the module's compatibility with the network's requirements and goals.

ELECTRICAL DATA | STC*

CS1U	400MS	405MS	410MS	415MS	420MS
Nominal Max. Power (Pmax)	400 W	405 W	410 W	415 W	420 W
Opt. Operating Voltage (Vmp)	44.1 V	44.3 V	44.5 V	44.7 V	44.9 V
Opt. Operating Current (Imp)	9.08 A	9.16 A	9.23 A	9.30 A	9.37 A
Open Circuit Voltage (Voc)	53.4 V	53.5 V	53.6 V	53.7 V	53.8 V
Short Circuit Current (Isc)	9.60 A	9.65 A	9.70 A	9.75 A	9.80 A
Module Efficiency	19.4%	19.6%	19.9%	20.1%	20.4%
Operating Temperature	-40°C ~ +85°C				
Max. System Voltage	1500V (IEC) or 1000V (IEC)				
Module Fire Performance	CLASS C (IEC 61730)				
Max. Series Fuse Rating	15 A				
Application Classification	Class A				
Power Tolerance	0 ~ + 10 W				

* Under Standard Test Conditions (STC) of irradiance of 1000 W/m², spectrum AM 1.5 and cell temperature of 25°C.

MECHANICAL DATA

Specification	Data
Cell Type	Mono-crystalline
Dimensions	2078 × 992 × 35 mm (81.8 × 39.1 × 1.38 in)
Weight	23.4 kg (51.6 lbs)
Front Cover	3.2 mm tempered glass
Frame	Anodized aluminium alloy
J-Box	IP68, 4 bypass diodes
Cable	4.0 mm² (IEC)
Cable length (Including connector)	1000 mm (39.4 in) (+) and 640 mm (25.2 in) (-) *; leap-frog connection: 1780 mm (70.1 in)**
Connector	T4 series or H4 UTX or MC4-EVO2
Per Pallet	30 pieces
Per Container (40' HQ)	660 pieces

* Adjacent two modules (portrait: left and right modules, landscape: up and down modules) need to be rotated 180 degrees.
** Need to confirm with the tracker suppliers there are no mounting or operation risks when cables go across the torque tube and bearing house.

ELECTRICAL DATA | NMOT*

CS1U	400MS	405MS	410MS	415MS	420MS
Nominal Max. Power (Pmax)	296 W	300 W	304 W	307 W	311 W
Opt. Operating Voltage (Vmp)	40.8 V	41.0 V	41.2 V	41.4 V	41.5 V
Opt. Operating Current (Imp)	7.26 A	7.32 A	7.37 A	7.43 A	7.48 A
Open Circuit Voltage (Voc)	49.9 V	50.0 V	50.1 V	50.2 V	50.3 V
Short Circuit Current (Isc)	7.75 A	7.79 A	7.83 A	7.87 A	7.91 A

* Under Nominal Module Operating Temperature (NMOT), irradiance of 800 W/m² spectrum AM 1.5, ambient temperature 20°C, wind speed 1 m/s.

TEMPERATURE CHARACTERISTICS

Specification	Data
Temperature Coefficient (Pmax)	-0.37 % / °C
Temperature Coefficient (Voc)	-0.29 % / °C
Temperature Coefficient (Isc)	0.05 % / °C
Nominal Module Operating Temperature	43±3 °C

Figure 9. Date sheet of photovoltaic panels

4.2. Optimal Results

This section of the report will detail the results of executing the optimization model on the IEEE 13-bus distribution network. In this paper, we provide an example where a battery energy storage system (BESS) is utilized to mitigate the duck curve in a photovoltaic-integrated grid. First, we study the simulation, highlighting the effects of the proposed optimization on mitigation of the duck curve, battery degradation, and environmental issues.

The simulation outcomes show that adding BESS to a photo voltaic integrated grid flatting the daily power supply from the main grid, which enables resisting the steep ramp-up periods that commonly emerge in the duck curve nature. The model manages the charge and discharge of the battery in a manner that provides a stable, secure power transmission, that is, it reduces the pressure of the on-grid hours.

The study also looks at the effect on battery life and degradation, calling into question the durability and economics of the BESS. Long battery life is achieved by minimizing the discharge and charge cycle of the battery, ensuring battery health with limited deterioration every single charge and reduction of maintenance costs. The correct optimization of this parameter is essential to the economic feasibility of large-scale BESS deployment on distribution networks.

Flattening the Duck Curve

Our in-depth study on the effect of different battery sizes of a PV-integrated grid in reducing the ramp-up between excess solar production and the evening peak demand exhibits following outcomes. The effectiveness of this strategy in tackling the duck curve challenge improved progressively as the battery capacity changed from 5% to 26% of the installed photovoltaic panel nominal power. Interestingly, a system that had a battery capacity of 26% turned out to be the best at mitigating the duck curve phenomena.

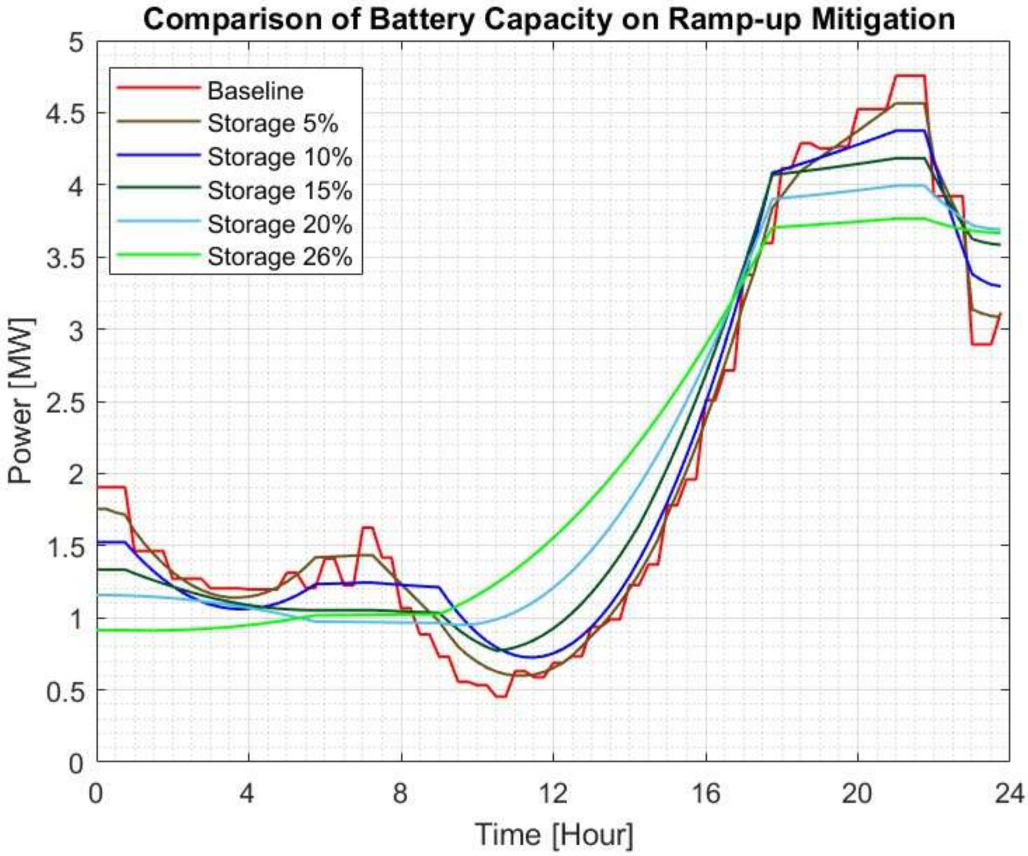

Figure 10 Effect of battery capacity on the Duck curve mitigation

According to figure 12 following facts can be seen:

- Referring to the baseline scenario shown by the red line, the duck curve is most noticeable, with a significant drop at midday and a spike in the evening. This scenario, with no battery storage, demonstrates the difficulty of dealing with the variability of solar power generation and the evening load peak.
- When incorporating battery storage in the system, even a fairly low level of 5% storage capacity (brown line) starts to help in flattening the sharp rise to some extent. Nevertheless, it is not significant, the line still has a rather sharp inclination. Further raising the battery capacity to 10% (dark blue line) offers a clearer improvement, albeit with issues in the initial charging phase.
- At 15% storage capacity (dark green line), the benefits are more obvious as the ramp-up period is less steep, signifying improved management of the duck curve. The 20% storage capacity (light blue line) helps in flattening the power output curve which primarily helps in reducing the stress on the grid during the critical ramp-up period.

- The largest improvement is seen at 26% storage capacity (light green line). At this level, the power output is the most stable throughout the day, and the steepness of the evening ramp-up is also reduced considerably. This capacity essentially affects the power supply from the main grid, highlighting the ability of BESS to support and strengthen the grid.

However, the effectiveness of increasing battery capacity in mitigating the duck curve is limited by factors such as battery health and economic feasibility. These considerations indicate that while larger battery capacities may offer potential benefits, they do not uniformly deliver superior performance across all metrics. Our analysis, based on comprehensive data on system loads and solar energy generation, identifies the 26% battery capacity as the most effective solution for mitigating ramp-up challenges within this PV integrated grid.

<u>Optimization approach on Ramp-up</u>

Analyzing the monthly average electricity purchases from the main grid during ramp-up across three scenarios—baseline (no optimization or storage), fully optimized network, and partially optimized network (excluding SOH optimization)—revealed varying reduction trends across different months (Figure 13).

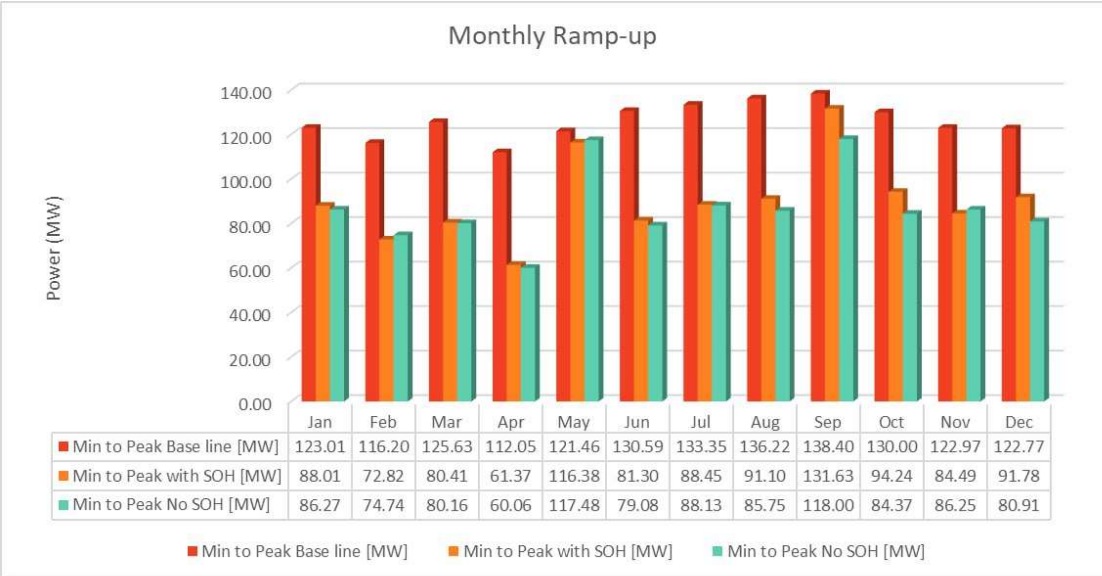

Figure 11. Monthly effect of duck curve optimization on ramp up reduction

As it can be seen in Figure 11 The fully optimized network, which includes SOH optimization and is represented by the orange bars, shows a substantial reduction in ramp-up power purchases across all months. This optimization strategy is particularly effective in reducing grid reliance, with the most significant reductions observed in April (61.37 MW) and March (80.41 MW). Despite seasonal variations, this fully optimized network maintains consistently lower grid reliance compared to the baseline, demonstrating the effectiveness of comprehensive optimization measures.

On the other hand, the partially optimized network, excluding SOH optimization and represented by the green bars, also shows a reduction in power purchases compared to the baseline, though not as pronounced as the fully optimized network. This scenario provides moderate improvements, with notable differences during high-demand months such as August (85.75 MW) and September (118.00 MW). While this partially optimized network offers substantial improvements over the baseline, it falls short of the performance seen with full optimization.

Finaly, the graph analysis reveals that optimization strategies, particularly those incorporating SOH considerations, significantly mitigate reliance on the main grid during ramp-up periods. The fully optimized network consistently demonstrates the lowest power purchases, indicating its superior effectiveness in managing ramp-up challenges. The partially optimized network, although less effective, still shows marked improvements over the baseline scenario. Seasonal variations underscore the importance of maintaining optimization efforts throughout the year to enhance grid stability, reduce main grid dependence, and effectively integrate renewable energy sources into urban distribution networks.

Battery Storage State of Health (SOH) Optimization

Through a comprehensive study focusing on battery State of Health (SOH) optimization, we have demonstrated significant benefits in terms of extending battery lifetime and achieving substantial cost savings. Considering the current price of Lithium-Ion Battery price 130 $Euro/kWh$ [41], our findings indicate a budgetary saving (replacement cost) of 1,092,000 Euro over a 25-year lifespan of the PV system, attributed to enhanced battery health optimization strategies. Furthermore, our approach has successfully extended the operational lifespan of each battery by an average of 3 years, representing a remarkable improvement of about 23% in the lifetime of the batteries as is shown in the following tables. They are calculated by equation (33) as:

$$Battery\ lifetime\ improvment\ [\%] = \frac{Battery\ lifetime_{Without\ SOH\ optimization} - Battery\ lifetime_{With\ SOH\ optimization}}{Battery\ lifetime_{Without\ SOH\ optimization}} \times 100 \quad (33)$$

Batteies lifetime improvment (%)	
Storage 1	21.22
Storage 2	22.72
Storage 3	22.76

Increased life of batteries in 25 years (year)	
Storage 1	3
Storage 2	3
Storage 3	3

The study also presents the average State of Health (SOH) improvement observed across three batteries that is calculated based on the equations (34), highlighting the monthly contribution to SOH optimization.

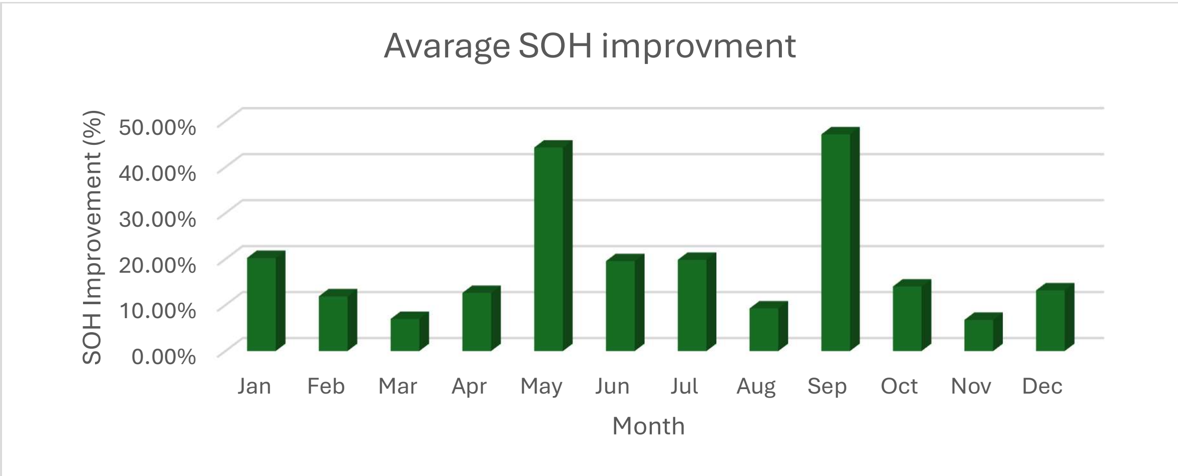

Figure 12. Monthly effect of battery optimization on battery health

Figure 12 illustrates the monthly average improvement in the State of Health (SOH) of batteries throughout the year. This data provides valuable insights into the monthly contributions of SOH optimization, complementing previous analyses on ramp-up mitigation and battery capacity in a photovoltaic-integrated grid.

$$SOH\ improvment\ [\%] = \frac{Battery\ SOH\ Change_{Without\ SOH\ optimization} - Battery\ SOH\ Change_{With\ SOH\ optimization}}{Battery\ SOH\ Change_{With\ SOH\ optimization}} \times 100 \tag{34}$$

In examining the graph, it is evident that May and September show the highest SOH improvements, with values approaching 50%. These significant peaks indicate that the optimization strategies implemented during these months are particularly effective in enhancing battery health. The substantial improvements during these periods suggest targeted optimization efforts can yield significant benefits for battery longevity and performance.

Several other months, including January, April, June, July, October, and December, demonstrate moderate SOH improvements, ranging between 20% to 30%. This consistency across different seasons indicates that ongoing optimization efforts provide beneficial results throughout the year. These moderate improvements highlight the sustained impact of optimization strategies on maintaining and improving battery health.

However, the graph also shows that February, March, August, and November exhibit lower SOH improvements, with percentages closer to 10%. While still beneficial, the impact of optimization during these months is less pronounced compared to others. These lower improvements suggest potential areas for further refinement in optimization strategies to achieve more consistent results across all months.

Overall, the analysis of the SOH improvement graph, in conjunction with the previous data on ramp-up mitigation and battery capacity, underscores the importance of comprehensive and adaptive optimization strategies. By enhancing the State of Health of batteries, these strategies not only improve grid reliability and reduce reliance on the main grid but also contribute to the economic feasibility and longevity of battery energy storage systems in urban power distribution networks. The seasonal variations in SOH improvements highlight the need for targeted optimization efforts to maximize the benefits of renewable energy integration in urban settings.

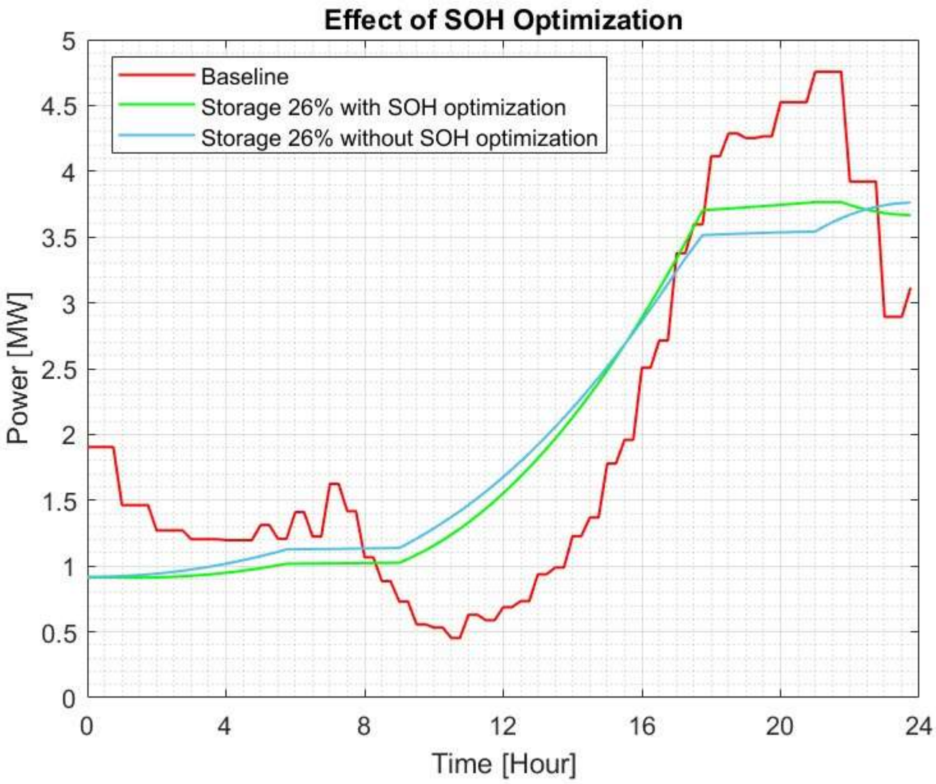

Figure 13. Effect of SOH optimization on ramp rate reduction

However, our analysis reveals that while SOH optimization yields notable benefits in terms of battery longevity and cost efficiency, it shows a minimal impact on ramp-up mitigation. Figure 13 illustrates this phenomenon, indicating that the emphasis placed on battery health optimization detracts slightly from the primary goal of reducing ramp-up periods. This observation underscores a trade-off where an increased focus on enhancing battery health may inadvertently reduce the efficacy of strategies specifically aimed at mitigating ramp-up challenges.

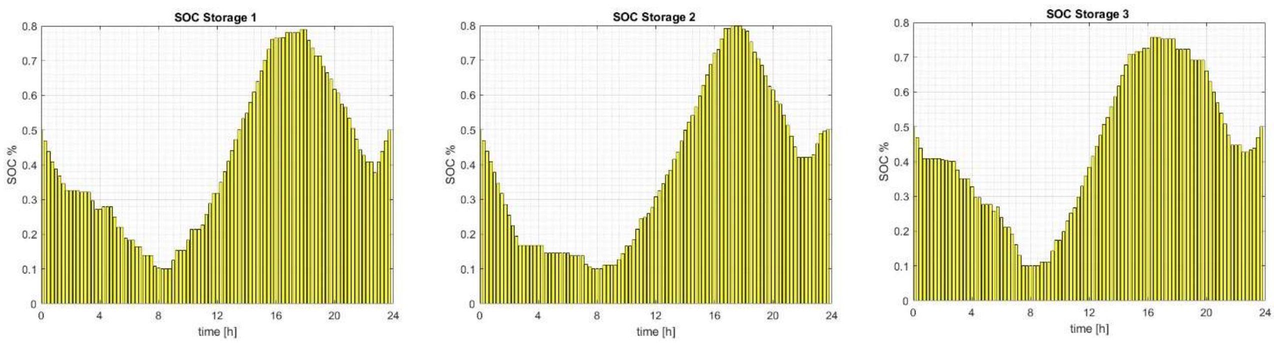

Figure 14. State of Charge of Batteries

In essence, while SOH optimization offers substantial advantages in terms of longevity and cost-effectiveness, careful consideration is necessary to balance these benefits against the specific objectives of optimizing ramp-up reduction strategies within PV integrated grid.

Environmental Effects

Our study on the duck curve mitigation contributes significantly to achieving a more reliable energy system by effectively mitigating the duck curve and enhancing battery longevity and health. This strategy also demonstrates a significant impact on the environmental issues in the form of fuel savings and CO_2 emission.

Considering the calorific value of natural gas equal to 47130 KJ/Kg [42] and the density of the natural gas as 0.68 Kg/m_s^3 we can calculate the consumption of natural gas for gas turbine with efficiency 35% per kWh as follows:

$$Energy\ input = \frac{Energy\ output}{Efficiency} = \frac{3600}{0.35} = 10285.74\ [KJ]$$

$$Mass\ of\ natural\ gas = \frac{Energy\ input}{Calorific\ value} = \frac{10285.74}{47130} = 0.218\ [Kg]$$

$$Valume\ of\ natural\ gas = \frac{0.218}{0.68} = 0.32\ [m_s^3]$$

The annual fuel saving of natural gas as the result of ramp-up improvement is calculated based on equation (35):

$$Annual\ fuel\ saving = Energy\ saved\ as\ the\ result\ of\ ramp-up\ improvment \times Gas\, turbine\ fuel\ consumption$$

(35)

Fuel saving [m^3 natural gas/year]	CO2 Emission reduction [ton/year]
1378206	3790

Based on the unique flexibility of gas turbine power plants in responding to the duck curve through quick adjustments of electricity production, this study seeks to explore the implications of this flexibility in relation to natural gas utilization and resultant CO_2 emissions. Gas turbines, powered mainly by natural gas, are vital in meeting the increased power demand in a particular region. However, such a dependence on natural gas leads to the release of a considerable amount of CO_2, which is dangerous for the environment. By optimizing the battery storages, we can greatly decrease the need for gas turbines during the peak hours. This optimization results in a significant reduction in the consumption of natural gas, and therefore a decrease in CO_2 emissions. The following table provides a breakdown of the results of our study to show the relationship between the optimized battery storage and the decrease in fuel usage and the associated CO_2 emissions. It should be noted that this numbers are rough estimation, and the actual CO_2 emission reduction would depend on additional factors including the ramping efficiency of the turbine – since the efficiency varies greatly in these dynamic operating regimes

The application of advanced battery storage systems is a viable solution to the problem of the duck curve since it is much more efficient and environmentally friendly than using gas turbine power plants. Thus, this work highlights the need for further research and development of battery technologies to meet the goals of a clean energy future.

CONCLUSION

This thesis proposes a detailed modeling and analysis of a PV-integrated electric distribution grid based on the IEEE 13-bus test feeder to address the mitigation of the duck curve. This work is a significant contribution to the field of integration of more renewable energy sources to grid. Using actual data for Los Angeles as the case study, such as solar irradiation and residential load profiles, we modeled a PV-integrated grid to study the effects of solar energy (PV) and energy storage systems.

Some of the findings include the integration of Battery Energy Storage Systems (BESS) was found to reduce the duck curve significantly especially when the storage capacity is at 26%, thus improving the stability of the grid (decrease the grid stress) and reducing the dependency on the main grid during peak hours. Furthermore, the State of Health (SOH) of batteries was improved to extend their lifespan, which brought about significant cost reduction while mitigating the ramp-up caused by the duck curve.

Environmental impacts were also seen through the decrease in natural gas use as the fuel for gas turbines and CO2 emissions which highlights the importance of using advanced battery storage systems for cleaner energy. This research adds to the knowledge in energy system optimization, renewable power integration, and the sustainable management of urban power distribution networks towards practical implementations and future studies.

FUTURE WORKS

This thesis has established a strong platform for comprehending the incorporation of renewable energy sources and battery energy storage systems in urban power distribution networks in order the increase the stability of the grid by mitigating the duck curve. In summary, the present work provides a foundation for additional research paths for further enhancing the integration of renewable energy sources into the grid. Our suggested future works are:

Using second-Hand EV Batteries as Energy Storage Systems in the grid:

Energy storage offers an ideal use case for recycled electric vehicle (EV) batteries. Future work will then consider the feasibility, performance and economics of directly reusing these batteries. The research in question would look at how much capacity, life and performance are still in used batteries compared to batteries that are new from the store. It would also investigate environmental advantages and expense reduction from using recycled batteries, thereby providing input into a circular economy.

Green Hydrogen Production and Utilization:

Further work could explore producing green hydrogen when there is a high production of electricity by PV panels, especially over the noon hours. The hydrogen is stored as a fuel to be used later in a fuel cell when the demand increases.

Exploring Alternative Optimization Objective Functions:

Though the thesis concerned specific optimization objectives, future work can investigate additional objective functions that complement the system performance. other desired high-level objectives, such as reducing the total system cost, increasing the fraction of renewable energy used in the system, and improving the system robustness.

Smart Grid Technologies Integration:

In the future works, advanced smart grid technologies can be integrated to automate monitoring, controlling and managing the power distribution network. This involves the use of smart meters, automated demand response systems, and enhanced communication infrastructure. Real-time data and analytics that can be deployed onsite allow us to balance the load, detect faults with less time lost and distribute energy.

Implementation of Machine Learning Algorithms:

Use of machine learning algorithms for demand forecasting, optimization of energy storage and optimization of energy distribution. Machine Learning can be used to create a model that processes millions of data points to predict patterns of consumption, optimizes cycles for charging and discharging of battery and improves system efficiency. Work in this area could help in creating smart energy management systems which dynamically respond to varying environmental conditions.

Further investigation of these pathways will allow future research to provide solutions for the integration of renewable energy technologies and storage solutions into the power distribution network in cities with a greater level of robustness, sustainability and efficiency.

APPENDIX 1

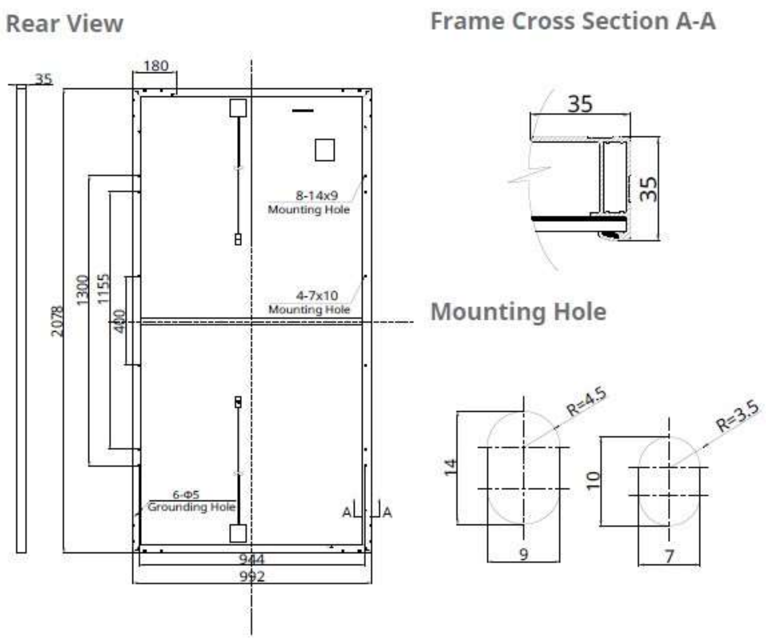

Figure 15. Dimensions of the photovoltaic panels

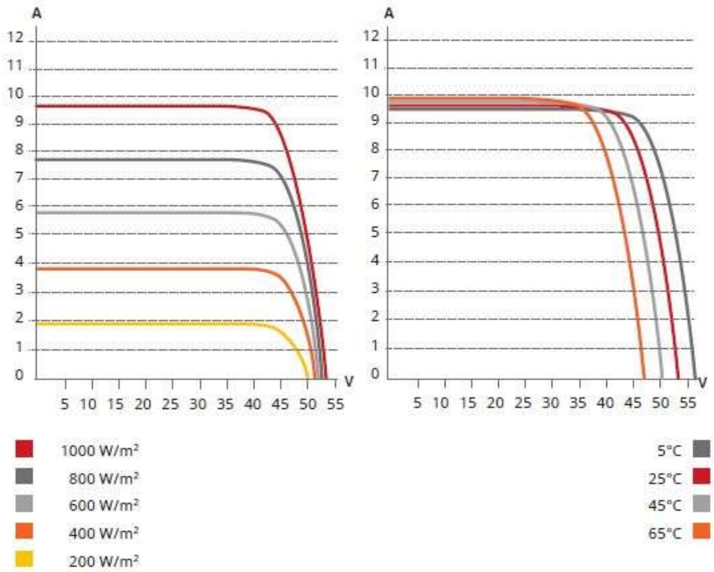

Figure 16. Temperature and PV's capacity on photovoltaics performance

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