



TOR VERGATA
UNIVERSITÀ DEGLI STUDI DI ROMA

Ph.D. PROGRAM IN
ENGINEERING FOR INDUSTRIAL DESIGN AND PRODUCTION

XXXIX cycle

Implementation of the firm photovoltaic generation strategy

**From outdoor module characterization
to sizing optimization and prototype validation**

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A.Y. 2025/2026

Ph.D. program funded by the European Union – NextGenerationEU

Project ECS 0000024 Rome Technopole



Sommar

L'integrazione massiva del fotovoltaico (PV) nel mix energetico sta trasformando i mercati elettrici, ma la sua variabilità pone sfide di stabilità della rete, gestione del dispacciamento e *curtailment*. Per superare queste difficoltà senza ricorrere a capacità di accumulo proibitive, questa tesi analizza e valida la strategia firm-PV. Combinando sovradimensionamento fotovoltaico (OVS), accumulo a batteria (BESS, misurati in giorni di carico accumulato, NDY) e *curtailment* proattivo, il solare si trasforma da fonte intermittente in risorsa dispacciabile, minimizzando, contestualmente, il costo dell'energia.

La ricerca adotta un approccio a più livelli, dall'analisi di componente, all'ottimizzazione computazionale, fino alla prototipazione sul campo. Per caratterizzare i moduli bifacciali in condizioni operative reali, è stato sviluppato e validato un protocollo di test *outdoor* in tre fasi. Esso estrae in modo affidabile parametri elettrici, coefficienti di temperatura e il guadagno da irradianza posteriore (BiFi), con risultati in linea con specifiche nominali e benchmark *indoor*, offrendo un'alternativa accessibile per le strutture prive di strumentazione per test al chiuso.

A livello di sistema, è stato implementato un modello di ottimizzazione finalizzato alla minimizzazione del costo dell'energia (LCOE) per la Macroarea di Ingegneria dell'Università di Tor Vergata (caso studio per il campus del Rome Technopole). Le simulazioni evidenziano che, fino ad una autoproduzione (SP) target dell'86–87%, l'LCOE rimane sostanzialmente costante e competitivo rispetto al Prezzo Unico Nazionale (PUN). Con target più elevati si innesca un rapido aumento sia della capacità della batteria necessaria sia dei tassi di *curtailment*.

Infine, per colmare la mancanza di validazione reale, il prototipo Infinity è stato messo in esercizio e monitorato per un intero anno (aprile 2025 – marzo 2026). Basato su componenti commerciali e con carico emulato, Infinity ha raggiunto una SP annua del 98,6% e un tasso di *curtailment* del 68,5%. Tuttavia, i dati sul campo hanno rivelato significative non-idealità fisiche: le condizioni notturne di basso carico (30–50 W) hanno ridotto l'efficienza media di scarica del BESS al 58,4%. Sebbene un modello Matlab a efficienza statica abbia stimato con precisione i valori annui di SP e *curtailment*, l'analisi dei flussi ha evidenziato disallineamenti nei flussi di potenza della batteria. Tali evidenze empiriche hanno permesso la formulazione di una funzione di efficienza di scarica dipendente dal carico, e sottolineato la necessità di incorporare efficienze dinamiche nei futuri strumenti di modellazione predittiva.

Abstract

The massive integration of solar photovoltaics (PV) into the energy mix is fundamentally transforming power markets, yet its intrinsic variability poses challenges to grid stability, dispatch management, and power curtailment. To overcome these barriers without relying on prohibitive storage capacities, this dissertation explores and validates the firm photovoltaic (firm-PV) generation strategy. By combining PV oversizing (OVS), battery energy storage systems (BESS, measured in days of load stored, NDY), and proactive curtailment, this concept transforms intermittent solar into a dispatchable asset while minimizing energy costs.

This research adopts a multi-scale engineering approach spanning component-level analysis, computational optimization, and experimental prototyping. First, to characterize bifacial PV components under real operating conditions, a three-phase outdoor testing protocol was developed and validated. The protocol reliably extracts electrical parameters, temperature coefficients, and the rear-irradiance-driven power gain (BiFi), aligning with nominal specifications and indoor laboratory benchmarks while offering an accessible alternative for facilities lacking indoor testing equipment.

Moving to system-level design, an optimization model targeting levelized cost of electricity (LCOE) minimization was implemented for the Engineering Macro-area at Tor Vergata University (a case study for the Rome Technopole campus). Simulations highlight that up to an 86–87% self-production (SP) target, LCOE remains virtually constant and competitive against the Italian National Price (PUN). Pushing for higher targets triggers a sharp rise in both battery capacity and curtailment.

Finally, to address the gap in real-world firm-PV validation, the Infinity prototype was operated over a full year (April 2025–March 2026). Composed of commercial components and an emulated load, Infinity achieved an annual SP of 98.6% and a curtailment rate of 68.5%. However, field data revealed significant physical non-idealities: operating under low nighttime baseloads (30–50 W) reduced the average BESS discharge efficiency to 58.4%. While a static-efficiency Matlab model accurately matched annual SP and curtailment, granular power flow analysis exposed localized battery misalignments. These empirical findings enabled the mathematical formulation of a load-dependent discharge efficiency function, highlighting the necessity of dynamic efficiencies in future predictive modeling.

Contents

Nomenclature	8
1 – Introduction	13
1.1. Overview of energy supply worldwide	14
1.2. The role of renewable energy	16
1.3. The Rome Technopole framework and the Res4Tech project	18
1.4. Research topic and questions	19
1.5. Thesis outline	20
2 – Overview of the photovoltaic sector	23
2.1. The state of photovoltaics	24
2.1.1. Market expansion and investment dynamics	24
2.1.2. Grid integration challenges: the "duck curve" phenomenon	27
2.1.3. Photovoltaic technology classifications	28
2.1.4. Emerging applications	30
2.1.5. Integration with energy storage systems	35
2.2. Bifacial photovoltaics	36
2.2.1. Working principle and characterization of bifacial PV	36
2.2.2. Market expansion and applications of bifacial PV	37
2.3. The firm-PV generation strategy	40
2.3.1. The mentality shift about curtailment	41
2.3.2. Simulation firm-PV case studies	42
2.3.3. The experimental framework	44
3 – Outdoor characterization of bifacial PV modules	46
3.1. Normative framework on bifacial PV characterization	47
3.2. Overview of the equipment	48
3.3. Description of the procedure	49
3.3.1. Phase one – Acceptance	50
3.3.2. Phase two – Temperature coefficients	54
3.3.3. Phase three – BiFi	56

3.4. Outdoor characterization results	58
3.4.1. Results for Phase one – Acceptance	58
3.4.2. Results for Phase two – Temperature coefficients	62
3.4.3. Results for Phase three – BiFi	66
3.5. Summary of uncertainty analysis for the procedure	70
3.6. Long term performance and degradation testing	71
3.6.1. Experimental setup	71
3.6.2. Results	73
4 – Firm-PV simulation in Tor Vergata	78
4.1. Overview of the simulation case study	79
4.2. Construction of the input datasets	81
4.2.1. Solar irradiance and weather datasets	81
4.2.2. Electricity demand	84
4.2.3. Cost learning curves	87
4.3. Optimization process – LCOE minimization	87
4.4. Results and discussion	90
4.4.1. Simulation results	92
4.4.2. Land occupation analysis	96
4.4.3. Economic feasibility (PBP)	97
5 – The “Infinity” prototype	99
5.1. From simulations to sizing	100
5.2. Final plant components and layout	101
5.3. Load emulation setup	102
5.4. Prototype fine-tuning and final settings	105
5.5. Data acquisition, processing and analysis	106
5.5.1. Data acquisition	106
5.5.2. Data filtering	109
5.5.3. Data reconstruction and consistency verification	111
5.5.4. Data analysis	112
5.6. Prototype performance in the first year of operation	114
5.6.1. PV metrics	115
5.6.2. Firm-PV indicators	116

5.7. BESS efficiency analysis	118
5.8. Analysis of the battery's state of charge	121
5.9. Matlab energy flows simulation model	123
5.9.1. Description of the model	123
5.9.2. Validation of the model	125
6 – Final remarks	132
6.1. Bifacial PV characterization and testing	133
6.1.1. Conclusions	133
6.1.2. Limitations	134
6.2. Contribution to the firm PV landscape	135
6.2.1. Conclusions	135
6.2.2. Limitations	137
6.3. Answer to the research questions	137
6.4. Directions for future research	140
Appendix A	142
Appendix B	146
Appendix C	147
Phase 1 – Acceptance test uncertainty analysis	147
Phase 2 – Temperature coefficient uncertainty analysis	149
Phase 3 – BiFi coefficient uncertainty analysis	151
References	153
List of publications	172

Nomenclature

Acronyms and abbreviations

Agri-PV	Agrivoltaics	
AM	Air Mass	
AOI	Angle of Incidence	[°]
ARPA	Agenzia Regionale per la Protezione Ambientale	
a-Si	Amorphous Silicon	
AVG	Average	[unit*]
BESS	Battery Energy Storage System	
BFPV	Bifacial Photovoltaics	
BG	Bifacial Gain	[%]
BiFi	Rear-Irradiance-Driven Power Gain Yield	[W/(W/m ²)]
BIPV	Building-Integrated Photovoltaics	
BMS	Battery Management System	
BNPI	Bifacial Name Plate Irradiance	
BSTC	Bifacial Standard Test Conditions	
CAGR	Compound Annual Growth Rate	[%]
CAMS	Copernicus Atmosphere Monitoring System	
CAPEX	Capital Expenditure	[€]
CIEMAT	Centro de Investigaciones Energéticas, Medioambientales y Tecnológicas	
CNR	Consiglio Nazionale delle Ricerche	
c-Si	Crystalline Silicon	
DNI	Direct Normal Irradiance	[W/m ²]
DSO	Distribution System Operator	
DSSC	Dye-Sensitized Solar Cell	
E	Energy	[Wh]

EPR	European Primary Standard/External Power Ratio	
ESS	Energy Storage System	
EU	European Union	
Firm-PV	Firm Photovoltaic Generation Strategy	
FF	Fill Factor	[-]
FPV	Floating Photovoltaics	
G_E	Effective Irradiance	[W/m ²]
GHI	Global Horizontal Irradiance	[W/m ²]
GPOAI	Global Plane-of-Array Irradiance	[W/m ²]
GTI	Global Tilted Irradiance	[W/m ²]
GUM	Guide to the Expression of Uncertainty in Measurements	
HJT	Heterojunction Technology	
H_{POA}	Total incident plane-of-array solar radiation	[kWh/m ²]
HVAC	Heating, Ventilation and Air Conditioning	
I	Current	[A]
I₀	Initial Investment	[€]
IEA	International Energy Agency	
IEC	International Electrotechnical Commission	
IRR	Internal Rate of Return	[%]
ITRPV	International Technology Roadmap for Photovoltaics	
k	Coverage Factor for Expanded Uncertainty	[-]
KPI	Key Performance Indicator	
L	Load	[W]
LCA	Life Cycle Assessment	
LCC	Life Cycle Cost	
LCOE	Levelized Cost of Electricity	[€/kWh]
LCOS	Levelized Cost of Storage	[€/kWh]
MAE	Mean Absolute Error	[unit [*]]
MFPV	Monofacial Photovoltaics	

MPPT	Maximum Power Point Tracking	
m-Si	Monocrystalline Silicon	
NDY	Number of Days of Electrical Demand Stored	[days]
NEM	National Electricity Market (Australia)	
NLR	National Laboratory of the Rockies (formerly NREL)	
NPV	Net Present Value	[€]
NREL	National Renewable Energy Laboratory (now NLR)	
OPEX	Operational Expenditure	[€/year]
OVS	Oversizing Factor	[-]
OPV	Organic Photovoltaics	
O&M	Operation and Maintenance	
P	Power	[W]
PBP	Payback Period	[years]
PCHIP	Piecewise Cubic Hermite Interpolating Polynomial	
p_E	Electricity price	[€/kWh]
PERC	Passivated Emitter and Rear Cell	
PHES/PHS	Pumped-Hydro Energy Storage	
PNRR	Piano Nazionale di Ripresa e Resilienza	
POA	Plane of Array	
PR	Performance Ratio	[% or -]
p_s	Electricity selling price	[€/kWh]
PSC	Perovskite Solar Cell	
p-Si	Polycrystalline Silicon	
PUN	Prezzo Unico Nazionale (Italian Single National Price)	[€/kWh]
PV	Photovoltaics	
PVNB	Photovoltaic Noise Barriers	
R²	Coefficient of determination	[-]
RH	Relative Humidity	[%]
RMSE	Root Mean Square Error	[unit*]

RTI	Rear Tilted Irradiance	[W/m ²]
SAPM	Sandia Array Performance Model	
SCPI	Standard Commands for Programmable Instruments	
SEM	Standard Error of the Mean	[unit [*]]
SNL	Sandia National Laboratories	
SOC	State of Charge	[%]
SP	Self-Production	[%]
STC	Standard Test Conditions	
STD	Standard Deviation	[unit [*]]
T	Temperature	[°C]
TOPCon	Tunnel Oxide Passivated Contact	
TSO	Transmission System Operator	
u	Standard Uncertainty	[%/unit [*]]
U	Expanded Uncertainty	[%/unit [*]]
V	Voltage	[V]
VISA	Virtual Instrument Software Architecture	
VRE	Variable Renewable Energy	
WACC	Weighted Average Cost of Capital	[%]
Y_F	Final Yield	[kWh/kWp]
Y_{Ref}	Reference Yield	[kWh/kW]

* the unit of measurement depends on the variable for which the parameter is calculated

Greek symbols

γ	Normalized temperature coefficient	[%/°C]
η	Efficiency	[%]
φ	Bifaciality factor	[% or -]

Subscripts and superscripts

active	Referred to active power
amb	Ambient
batt	Battery
BOM	Back of module
chg	Charge/Charging
Curt	Curtailed or referred to curtailment
dchg	Discharge/Discharging
disc	Discounted
firm, firmPV	Firm-PV generation contribution
feed	Including remuneration of energy fed into the grid
front	Front side of a bifacial photovoltaic module
imp	Imported
inv	Referred to the inverter
load	Load/Electrical demand
MAX	Maximum or referred to the maximum-power point
meas	Measured quantity
n	Nominal
OC	Open-circuit
rear	Rear side of a bifacial photovoltaic module
residual, resLoad	Load covered through grid support
RT	Round-trip (referred to efficiency)
SC	Short-circuit
sensor	Referred to the smart power sensor
stored	Energy effectively stored in the battery
released	Energy effectively released by the battery
tot	Total
wind	Referred to wind energy

1

Introduction

This first introductory chapter is designed to shape the framework in which this thesis and the whole Ph.D. program fit. The motivation will be outlined in these pages, presenting a snapshot of the energy supply worldwide and highlighting the increasing contribution of renewable sources. The Rome Technopole framework, and the Res4Tech sub-project, will also be presented as the innovation ecosystem in which the research discussed in this work falls. Finally, the questions that this thesis attempts to answer will be introduced, thereby highlighting its significance in the context of this research field.

1.1. Overview of energy supply worldwide

The global energy sector is currently experiencing a profound structural transformation, characterized by a dual reality: an unprecedented expansion of low-carbon technologies alongside a persistent and absolute growth in fossil fuel consumption. According to the data from the Energy Institute, the global total energy supply surpassed the historical threshold of 600 EJ, registering a 1.7% increase that reflects the continuous upward trend in worldwide energy demand [1]. **Figure 1** plots the total energy supply from 2015 and shows its distribution by type of fuel.

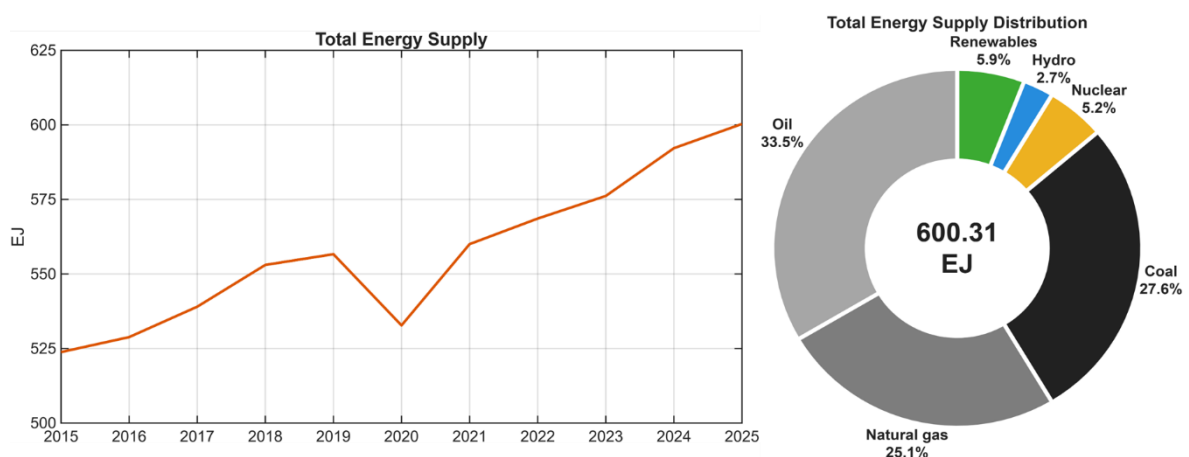


Figure 1 – Total energy supply trend from 2015 and distribution by type of fuel [1].

While the long-term trajectory outlines a progressive transition towards electrification, the current primary energy mix remains heavily carbon-dependent. In absolute terms, fossil fuels continue to expand, accounting for 86% of the global total energy supply. Oil remains the largest single component, with global consumption increasing to 103 million barrels per day, driven by road transport, aviation, and petrochemical feedstocks. Natural gas experienced the second-largest absolute rise among fossil fuels, growing to a global demand of 4186 billion m³,

whereas global coal consumption reached 166 EJ, maintaining a dominant yet highly concentrated role centered primarily within the Asia-Pacific region.

Concurrently, the architectural framework of global power generation has reached a historic milestone. For the first time outside of a global recession, renewable energy sources represented the largest driver of total energy supply growth, with photovoltaics (PV) accounting for over 71% of this clean technology expansion. Driven by a record-breaking addition of 511 gigawatts (GW) of new installed capacity worldwide, solar power generation achieved a 30% year-on-year growth (650 TWh), capturing an 8.7% share of total global power generation and effectively surpassing wind power (8.4%) while converging with nuclear energy (8.8%) [2]. This massive influx of clean generation has fundamentally altered the dynamics of the electricity sector, steering it into what is globally recognized as the "Age of Electricity" [3]. Electricity demand is currently expanding at a rate twice as fast as overall energy consumption, fueled by the rapid build-out of dynamic sectors such as advanced manufacturing, electric mobility, and digital hyper-scale infrastructures including data centers and Artificial Intelligence (AI).

Despite these milestones, this rapid shift towards an electrified and renewables-dominated paradigm has exposed several critical structural vulnerabilities and geopolitical dependencies across major energy networks. Major global demand centers remain profoundly exposed to supply shocks and maritime chokepoint disruptions. For instance, India relies on net imports for 86% of its oil consumption, while China and Europe remain structurally vulnerable, importing 73% and 75% of their respective liquid fuel supplies. These high levels of fuel import dependence have been dramatically laid bare by recent geopolitical disruptions. The structural vulnerability of major global energy corridors was critically exposed in late February 2026 following the sudden closure of the Strait of Hormuz, which instantly severed core Persian Gulf hydrocarbon export routes and triggered a severe global supply shock [4].

Furthermore, since 2015, global capital expenditure on renewable power generation has charged ahead by nearly 70%, reaching an unprecedented 1 trillion USD per year. In stark contrast, annual spending on transmission and distribution grids has risen at less than half that pace, stabilizing at approximately 400 billion USD. A decade ago, for every dollar invested in generation capacity, 0.60 USD was allocated to network infrastructure. Today, this ratio has dropped to just 0.40 USD, reflecting a severe capital underinvestment in power grid modernization.

This profound misalignment between fast-scaling variable generation and lagging infrastructure capacity has led to escalating network congestion and a dramatic rise in negative pricing events within wholesale markets. Consequently, power utilities worldwide are experiencing an unprecedented surge in the curtailment of wind and solar outputs, as existing grids lack the necessary operational flexibility and storage solutions to absorb peak renewable generation. Millions of kilowatts of clean capacity are frequently curtailed, creating severe economic penalties and dampening the real-world mitigation potential of solar technologies.

Ultimately, these grid integration barriers demonstrate that scaling up solar capacity is no longer a sufficient condition for a secure energy transition. Rather, the critical challenge lies in the system's ability to manage, stabilize, and integrate these variable flows. Within this engineering framework, transforming intermittent solar power into a reliable, predictable, and dispatchable asset is an urgent necessity. This context establishes the baseline and directly underscores the scientific relevance of this thesis, which addresses field non-idealities by developing and validating the firm-PV generation strategy.

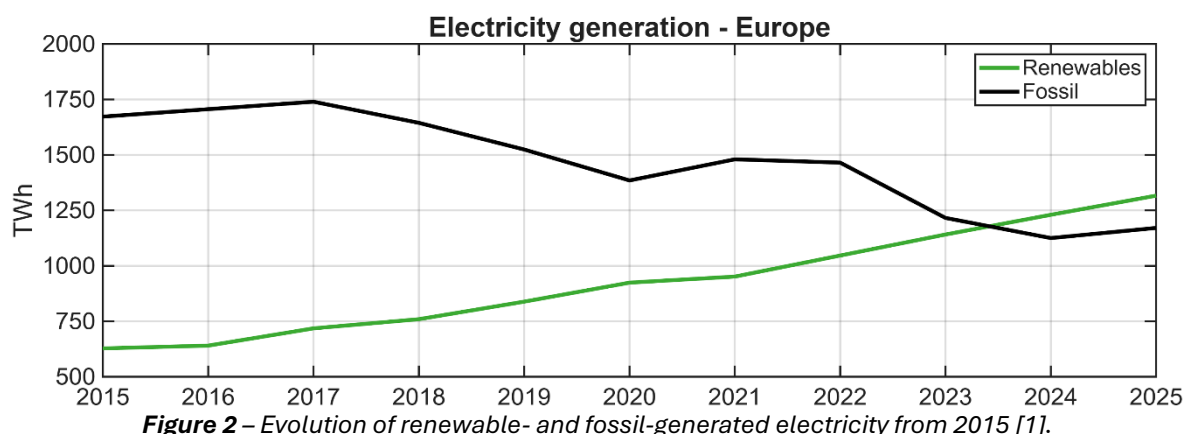
1.2. The role of renewable energy

In the current global energy transition, renewable energy is evolving from a supplementary power source to a critical asset for energy security and economic resilience. The rapid expansion of PV and wind power is not merely a response to climate change, but also a strategic tool to mitigate dependency on volatile international fossil fuel markets. The regulatory landscape has shifted significantly in recent years, moving towards integrated policy frameworks that combine emission reduction targets with industrial security and energy independence.

At the international level, the COP28 [5] pledge to triple global renewable capacity by 2030 remains the primary benchmark for policy ambition. However, the 2026 assessment confirms that while the deployment rate is historically unprecedented, with 800 GW of new capacity added globally in 2025, the pace must be sustained to bridge the investment gap between generation assets and grid flexibility.

Within this context, key regional policy instruments are defining the trajectory of this evolution. The European Union continues to lead through the Green Deal [6] and the Fit for 55 [7] package, which have now been complemented by the Clean Industrial Deal [8]. This latest

policy instrument represents a strategic shift, aiming to improve industrial competitiveness by providing more affordable energy from renewable sources while making access to critical raw materials easier. In 2023, renewable-generated electricity surpassed that coming from fossil fuels for the first time (**Figure 2**), effectively validating the regulatory push toward a decarbonized power sector.



Increasingly, renewable deployment is framed within national security legislation. Countries are pivoting away from imported fossil fuels by leveraging domestic renewable resources to stabilize long-term energy costs. The integration of renewables is no longer an isolated objective but is intrinsically linked to energy system flexibility, with 2025 witnessing a 66% growth in global grid-scale battery energy storage systems (BESS) as a direct response to grid-security hazards.

Current normative trends are forcing a transition from passive renewable integration to active, firm generation strategies. Emerging regulations are starting to value flexibility, ancillary services, and demand-side response as essential grid components, moving beyond the simple "feed-in" model. This shift is critical for the implementation of firm-PV generation strategies, which align regulatory requirements for power stability with technical solutions for energy storage and proactive curtailment management.

In this context, the IEA Renewables 2025 [9] report underlines that global renewable electricity capacity is projected to double by 2030, increasing by 4600 GW. This expansion represents a fundamental shift in the global power mix. By 2030, renewables are expected to surpass coal as the largest source of electricity generation globally, with variable renewable energy (VRE) sources, specifically wind and solar PV, covering nearly 30% of global electricity supply.

The transition is further characterized by two essential technological shifts. As the penetration of variable renewables grows, the focus is shifting toward "firming" intermittent supply. This is reflected in the rapid deployment of battery storage. In 2025, 108 GW of new battery storage capacity was deployed worldwide, and the market is projected to continue its exponential growth to support grid stability. The report also emphasizes that rising VRE shares are increasing integration challenges, with curtailment levels already rising in major markets such as China, Germany, and Brazil. To bridge the gap toward the COP28 pledge of tripling renewable capacity, countries must accelerate grid infrastructure investments and implement flexible market mechanisms, such as "firm-capacity" auctions, which incentivize coupling renewables and storage.

Ultimately, VRE sources, and photovoltaics in particular, are establishing themselves as pillars of the global energy transition. Capturing every fraction of available solar radiation directly translates into an increase in efficiency, promoting solutions such as bifacial photovoltaic technologies to the forefront of modern installations, as they are capable of harvesting both direct and reflected light. However, the rise of bifacial PV in both land-based and more specific applications (like agrivoltaics) introduces critical characterization and normative challenges in the definition of their potential under real operating conditions.

In conclusion, the role of renewable energy is being redefined: it is no longer just a climate-neutral alternative, but the primary instrument for maintaining economic competitiveness in an era of geopolitical volatility. The ability to harmonize massive VRE (Variable Renewable Energy) deployment with robust regulatory frameworks for system firmness will be the defining feature of the next generation of energy policy.

1.3. The Rome Technopole framework and the Res4Tech project

Rome Technopole [10] represents a strategic institutional and industrial network funded by the European Union under the NextGenerationEU program, specifically within the framework of the Italian National Recovery and Resilience Plan (PNRR) [11]. Formally established as a regional innovation ecosystem, this collaborative R&D initiative involves the public and private universities of the Lazio region, national research bodies (EPR), industrial associations, local enterprises, the Lazio Region, the Municipality of Rome, and regional Chambers of Commerce. Its goal is to catalyze a structural advancement in the regional innovation sector by focusing

on smart specialization, industrial revitalization, and sustainable development. To effectively drive this socio-economic transformation, the Technopole concentrates its research and development capabilities across three core thematic areas:

- Energy Transition;
- Digital Transition;
- Health & Bio-Pharma.

The primary objective of the Rome Technopole project is to foster a dynamic innovation environment capable of delivering three key macro-goals for the Lazio region. First, it aims to facilitate the strategic repositioning of regional industrial and productive entities towards high-added-value market segments by adapting cutting-edge technologies and expertise. Second, it seeks to position the region as a leading European innovation hub with a global reach, fostering international academic and industrial collaborations. Finally, it drives internationalization efforts by leveraging the renewed competitive strength of the local industrial fabric to target key foreign markets for sustained economic growth.

Within this institutional framework, the research presented in this thesis is directly embedded in the Energy Transition thematic area, operating under Spoke 1 (FP1). Specifically, this work aligns with the strategic objectives of the project titled "100% Renewable for Rome Technopole" (Res4Tech). By evaluating the techno-economic viability of firm photovoltaic generation and validating its implementation through advanced characterization and real-world prototyping, this work provides a scalable methodology that directly supports the Rome Technopole's mission to transition large-scale public and industrial infrastructures toward deep decarbonization and complete energy self-sufficiency.

1.4. Research topic and questions

The core research topic of this dissertation is embedded within the challenge of large-scale renewable energy integration into the global power grid. While solar energy represents a central pillar for the ongoing energy transition, its intermittent and non-dispatchable profile prevents it from acting as a reliable primary source for power delivery. To mitigate these volatility challenges without relying on massive and economically unsustainable utility-scale battery storage configurations, this research investigates the implementation of the firm photovoltaic

(firm-PV) generation strategy. This operational framework combines photovoltaic oversizing (OVS) and proactive power curtailment with properly-sized battery energy storage systems (BESS) to transform variable solar generation into a fully dispatchable energy asset capable of continuously meeting a defined electricity demand profile.

Characterizing and validating such a multi-level strategy requires shifting the focus from numerical simulation and laboratory modeling to real-world industrial and environmental complexities. Therefore, this research adopts a transitional engineering approach spanning from individual component metrology, through computational optimization, to small-scale field prototyping. To systematically address the scientific, technical, and economic barriers encountered across this development path, this thesis formulates and investigates the following research questions:

- RQ1. What are the techno-economic trade-offs between battery storage capacity (BESS), implicit storage achieved through photovoltaic oversizing (OVS) and proactive curtailment when aiming for high energy self-production targets while minimizing energy costs (LCOE)?
- RQ2. To what extent can a properly designed PV system utilizing commercial components effectively guarantee continuous power demand coverage (firm power generation) under real, highly dynamic operating conditions?
- RQ3. What are the primary operational deviations that emerge when transitioning from simulations to actual hardware performance, and how can these field non-idealities be addressed to calibrate predictive sizing tools?
- RQ4. At component level, in light of their growing prevalence, is it possible to reliably assess the performance and electrical parameters of advanced bifacial photovoltaic modules directly under real, highly variable outdoor operating conditions?

1.5. Thesis outline

This thesis is conceived as a path toward the implementation of the firm photovoltaic (firm-PV) generation strategy. It starts from the characterization of the fundamental building block in one of its most innovative forms (the bifacial photovoltaic panel), proceeds through numerical simulation, used as an optimization tool, and culminates with the validation in a laboratory setting, with the construction of a functioning prototype and the analysis of its results.

Chapter 2 paints a picture of the photovoltaic sector, identifying the key players and trends in both the research and enterprise fields. It also discusses rising innovative products and concepts that were central in the development of this thesis, such as bifacial PV technologies and agrivoltaics. Finally, it presents the firm-PV concept, based on the overbuilding of the photovoltaic capacity and curtailment of the excess energy generation, which will be the central point of the entire work. It retraces the concept's evolution from its inception to its current status which still sees it as a promising idea, mostly explored through numerical case-studies.

Chapter 3 opens the discussion on the research activity performed during this Ph.D. program by outlining a three-phase outdoor characterization protocol designed specifically for bifacial PV modules in the framework of this thesis, in an attempt to propose a standardized procedure similar to that provided by the existing technical specifications for indoor testing. The chapter discusses the validation of the proposed procedure on 13 sample bifacial modules for agrivoltaic application. Furthermore, it presents the results of long term performance and degradation testing on four of these modules. This chapter essentially represents the component-level analysis in the broader framework of this study on firm-PV, since it provides useful insight on the bifacial PV technology, which has become a major player in the PV market in the last years.

Chapter 4 discusses the numerical simulation of the firm-PV generation strategy applied to the Engineering Macro-area of Tor Vergata University, as a representative case for the future Rome Technopole campus. The results for the least-cost optimization are presented for different targets of self-production, and a roadmap for the progressive implementation of the firm-PV concept is outlined, complemented by a land-occupation analysis. The importance of this chapter also lies in the use of the outcomes of the simulation study as a starting point for the laboratory prototype sizing.

Chapter 5 represents the largest contribution of this thesis in the PV research field, describing the real-world firm-PV prototype Infinity. The plant's configuration is outlined, the deviations from the original sizing are presented and explained, as well as the data acquisition and processing phases. Along with the presentation of results after one year of operation, the system's deviations from the expected outcomes are thoroughly discussed in terms of PV performance, firm-PV indicators and battery storage efficiency. Furthermore, a Matlab energy

flows simulation model is presented and validated with the real-world data recorded by the Infinity prototype.

Finally, chapter 6 draws the conclusions of this work, reviewing the research questions and presenting the answers that this thesis was able to provide. It also acknowledges the limitations of the results obtained and paves the way for future development on this topic and research field.

2

Overview of the photovoltaic sector

This chapter serves as the state-of-the-art review of this dissertation. A thorough analysis of the relevant and recent literature will be conducted to paint a picture of the current state of the photovoltaic industrial and research sector.

The literature review will initially focus on photovoltaics as a technology, highlighting its growing penetration in the energy mix, together with the challenges that arise with it, and its central role in the current energy transition. Specific applications of PV technologies, such as building-integrated photovoltaics, floating PV and agrivoltaics will also be briefly discussed in the first section. The last two sections of this chapter will specifically focus on innovation fields that are of particular interest for this thesis, namely bifacial photovoltaics and the firm-PV generation concept. The working principle and characterization methods of bifacial PV modules will be documented, together with their recent market growth and some of their most popular applications. Finally, a comprehensive overview of the firm-PV generation strategy will be presented. Given its centrality within this work, this concept will be presented from its inception in the early 2010s, through its evolution in the research field, up to its current status, from which the activity presented hereby aims at taking a step forward.

2.1. The state of photovoltaics

The photovoltaic (PV) technology has transitioned from a rapidly growing alternative energy source to the primary driver of the global power sector's expansion [12], [13], [14]. This milestone is underscored by a dramatic acceleration in deployment: while it took nearly seven decades (1954–2022) to install the first TW of solar power globally, the second was achieved in just two years between 2022 and 2024 [15]. By the end of 2025, cumulative global solar PV installations reached approximately 2.974 TWp [16]. This massive capacity influx meant that renewable additions successfully met two-thirds of the increase in global power demand by 2024, although deployment rates could not entirely keep pace with the massive surge in global electricity consumption driven by climate extremes and industrial expansion [17].

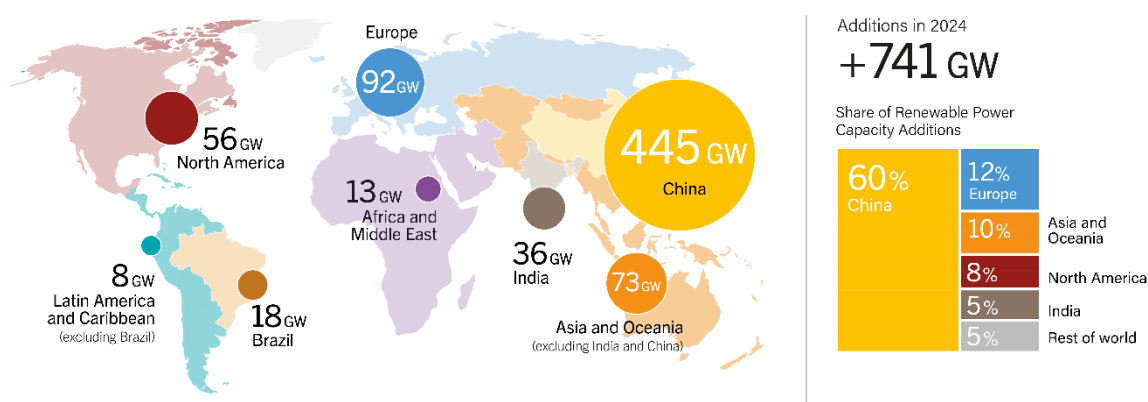
2.1.1. *Market expansion and investment dynamics*

On a global scale, the compound annual growth rate (CAGR) of cumulative PV installations reached approximately 27% between 2015 and 2025. This rapid expansion has been heavily concentrated in specific regions, leading to geographic disparities within the global energy

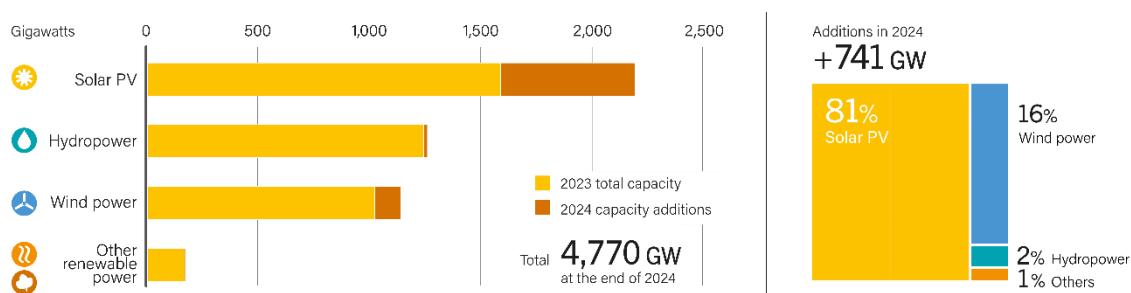
2.1. The state of photovoltaics

25

transition. As of 2025, China represents the dominant force in the PV sector and in renewables in general, accounting for 51% of total cumulative global installations and over 60% of new capacity additions (**Figure 3**). Europe follows as the second-largest contributor, representing 17% of cumulative installations. In contrast, regions such as Africa and the Middle East collectively accounted for only 1.7% of renewable power capacity additions in 2024, demonstrating that many parts of the world remain significantly underserved due to tight financial conditions and a persistently high cost of capital [16], [17].



REN21 GSR 2025 GLOBAL OVERVIEW

Figure 3 – Renewable power capacity additions by region in 2024 [17].

REN21 GSR 2025 GLOBAL OVERVIEW

Figure 4 – Renewable power total installed capacity and additions by technology in 2024 [17].

Figure 4 shows how solar drives the renewable energy sector growth, which perfectly reflects the investment table. Total global investment in renewables reached 728 billion USD in 2024, with solar PV securing the largest share at 521 billion USD, outpacing all other technologies and experiencing a 22% investment surge year-on-year (**Figure 5**). A significant macroeconomic structural driver within this funding landscape is the severe overcapacity across the manufacturing chain [18]. By the end of 2024, global solar module manufacturing capacity expanded to over 1,100 GW, more than doubling actual global deployment demand.

2.1. The state of photovoltaics

26

This supply surge triggered intense price competition, causing average prices for modules to fall by more than half since early 2023, stabilizing at an unsustainable historic low of under 0.10 USD/Wp (**Figure 6**). While these compressed margins forced manufacturers into the negative, they drastically lowered the levelized cost of electricity (LCOE) and the total installed cost for project developers. In 2024, the global weighted average total installed cost for large-scale utility PV systems dropped to 639 €/kWp, enabling utility-scale installations to outcompete conventional fossil-fuel technologies on cost grounds alone [19].

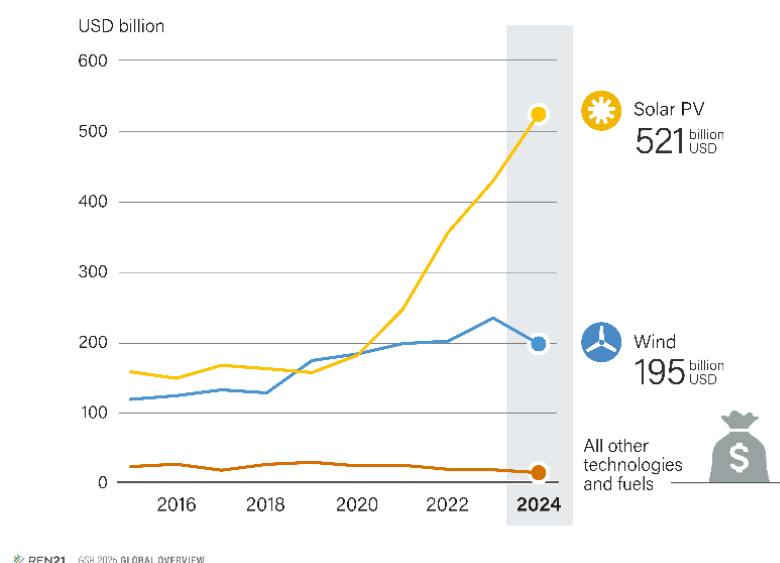


Figure 5 – Global investment in renewable power by source from 2015 [17].

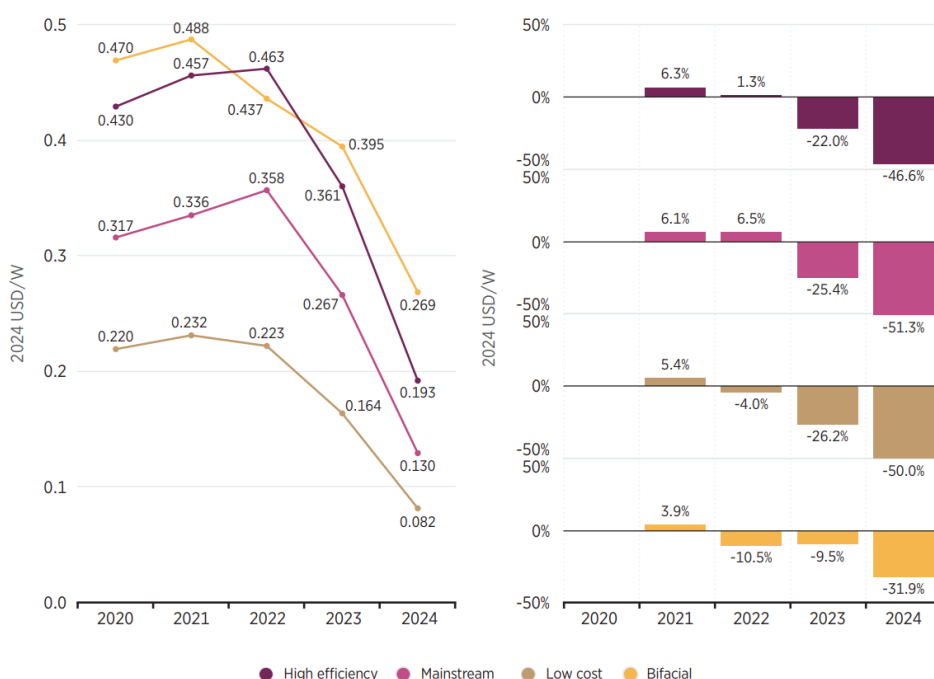


Figure 6 – Evolution of photovoltaic module prices [19].

2.1.2. Grid integration challenges: the "duck curve" phenomenon

The rapid escalation of PV penetration has introduced significant operational complexities, primarily characterized by the temporal mismatch between solar generation and peak electricity demand. This challenge is illustrated by the "duck curve" phenomenon (**Figure 7**), which maps the net load profile, representing the total power demand minus VRE generation [20].

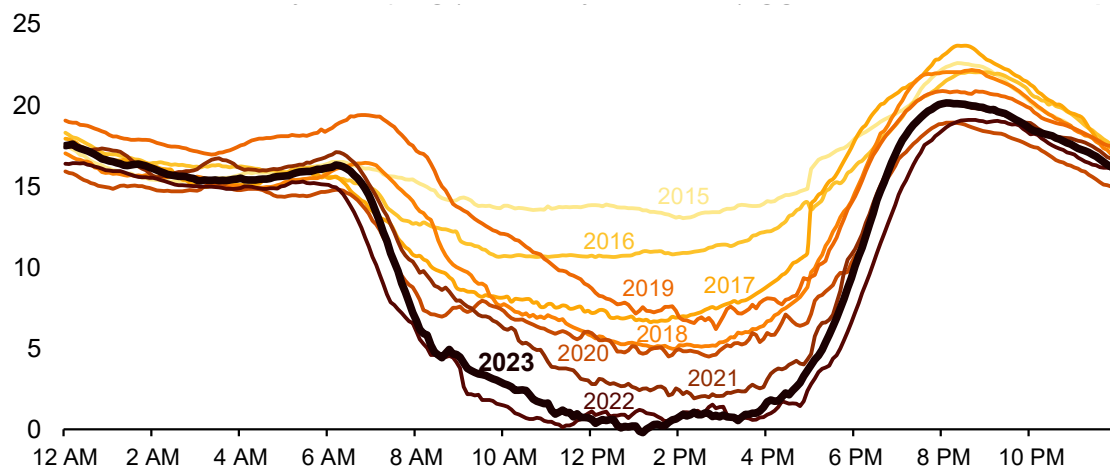


Figure 7 – Representation of the duck curve – California's lowest net-load day each spring (March-May, 2015-2023) [21].

During the day, a massive solar generation surplus causes the net load to fall, creating the deep "belly" of the curve, which poses severe risks of overgeneration and subsequent energy curtailment. At sunset, with evening consumption peaks, the grid experiences extremely steep upward ramps (the "neck" of the duck), forcing conventional dispatchable power plants to cycle rapidly and operate under suboptimal conditions.

To mitigate these grid imbalances, potential solutions have been proposed in the form of operational flexibility and active load management. At the macro-grid level, strategies focus on "fattening the duck" by lowering the minimum generation thresholds of conventional thermal fleets, alongside the deployment of utility-scale storage [20]. Simulations utilizing demonstrate that integrating energy storage technologies can drastically reduce curtailment rates and optimize system costs at high PV penetration levels [22].

However, managing the duck curve is not merely a utility-scale hardware challenge. It extends to the local distribution level, demanding a socio-technical transition. Energy management programs involving the community represent a vital pathway to flatten the curve locally by shifting residential demand to match midday solar peaks. Successful participation

2.1. The state of photovoltaics

28

in these load-shifting initiatives is heavily dictated by social and individual norms within eco-conscious neighborhoods rather than material wealth or financial incentives alone [23].

Within this dual context of macro-grid balancing and localized demand-side management, the firm-PV generation strategy could serve as an ideal bridge. By coupling PV oversizing (OVS) with battery energy storage systems (BESS) directly at the generation source, this approach systematically flattens the net load profile, absorbing excess midday energy to reliably cover evening ramp demands without relying solely on consumer behavioral changes or fossil-fuel spinning reserves.

2.1.3. Photovoltaic technology classifications

Contemporary photovoltaic technologies are categorized into structural generations based on material composition and manufacturing methodologies [24], [25]. Progress is mainly driven by the desire to push the boundaries in terms of conversion efficiency [26], the evolution of which is well documented by the NLR (Figure 8) [27].

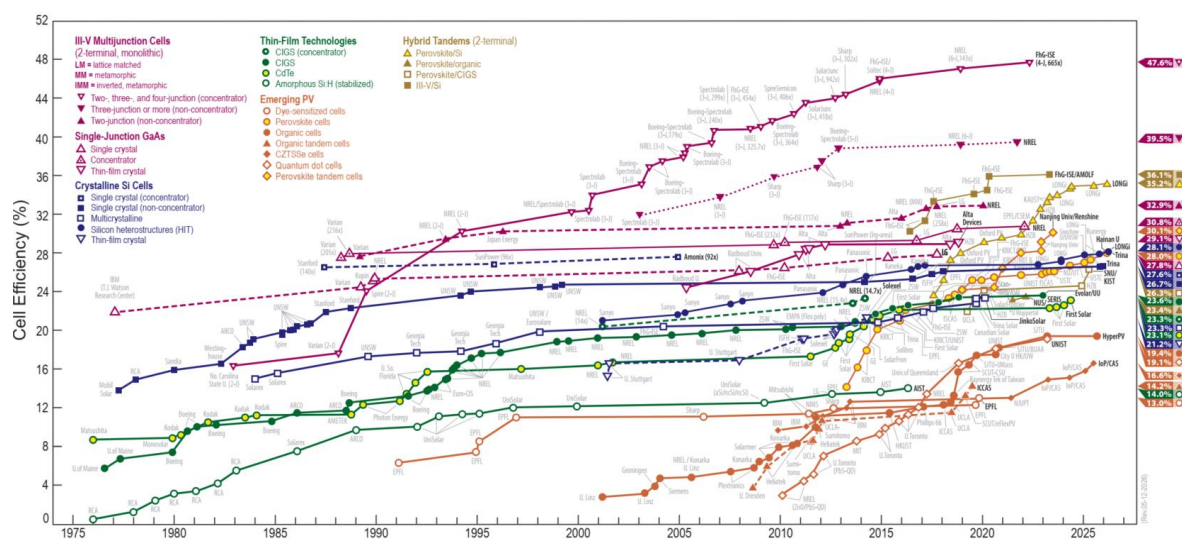


Figure 8 – Best research-cell efficiency chart, NLR [27].

- The first generation is constituted by crystalline silicon (c-Si) [28]. Silicon wafer-based technology remains the absolute dominant commercial architecture, accounting for approximately 98% of total global production [16]. These are subdivided into:
 - Monocrystalline silicon (m-Si), formed from single, high-purity silicon crystals. They currently represent the standard for commercial performance and longevity. Within this category, multiple cell architectures are included. The Passivated Emitter and Rear Cell (PERC) technology has been the industry's workhorse for

2.1. The state of photovoltaics

29

many years, with module efficiencies up to 20-22%. The Tunnel Oxide Passivated Contact (TOPCon) architecture has become the preferred choice for new production lines due to its higher efficiency potential, surpassing 24% at the cell level, and its relative ease of integration into existing PERC manufacturing facilities. Finally, Heterojunction Technology (HJT) offers some of the highest efficiency potentials for single-junction devices, but requires more complex and costly manufacturing processes. The total weighted average efficiency of commercial modules reached 22.7% at the end of 2024, with laboratory cells peaking at a record 28.1%.

- Polycrystalline silicon (p-Si), manufactured from ingots containing multiple silicon crystals, offer lower production costs but display reduced efficiencies (typically 15% to 18% for modules) and have virtually disappeared from primary utility-scale markets due to the superior economics and dominance of monocrystalline cells (such as TOPCon).
2. The second generation consists of thin-film technologies, formed by depositing ultra-thin semiconductor layers onto glass, metal, or plastic substrates [29]. These materials represent about 2% to 3% of the contemporary global market [16] and include Cadmium Telluride (CdTe), Copper Indium Gallium Selenide (CIGS) and amorphous silicon (α -Si). They feature lower temperature coefficients and better performance in diffuse light, though their commercial module efficiencies are typically lower than crystalline silicon, ranging from 13 to 20% depending on cell architecture and material.
 3. The third generation are emerging photovoltaic technologies, highly innovative architectures currently undergoing intensive laboratory and pilot scaling [30]. These include organic photovoltaics (OPV) using polymer blends [31], dye-sensitized solar cells (DSSC) mimicking artificial photosynthesis [32], [33], and perovskite solar cells (PSC) [34], [35]. Perovskites have achieved unparalleled research-cell efficiency gains, reaching a lab record of 26.9% for single-junction cells and up to 35.2% for perovskite-silicon tandem configurations [36]. In this context, tandem architectures represent a pivotal evolution [37], [38]: by stacking a perovskite top cell with a silicon bottom cell, researchers can harvest a broader portion of the solar spectrum, effectively bypassing the thermodynamic limitations of single-junction devices. However, these hybrid structures still face significant challenges regarding long-term moisture sensitivity, UV degradation, thermal stability, and material toxicity [39], [40], [41].

2.1. The state of photovoltaics

30

Table 1 resumes the information presented in this paragraph, providing an overview of the photovoltaic technologies mentioned so far, highlighting their research-cell efficiency, their main features and their position within the PV market.

Table 1 – Overview of photovoltaic technologies.

Table 1. Overview of photovoltaic technologies.			
PV technology	Cell efficiency	Features	Market position
First generation			
Monocrystalline silicon (m-Si)	28.1%	Good compromise between performance and longevity	Most widespread technology
Polycrystalline silicon (p-Si)	23.3%	Low production costs. Reduced efficiencies.	Virtually disappeared
Second generation			
CdTe	23.1%	Lower temperature coefficients and better performance in diffuse light. Efficiency lower than crystalline silicon.	2-3% of global market, mostly CdTe
CIGS	23.6%		
Amorphous silicon (α-Si)	14.0%		
Third generation			
Organic PV	19.4%	Light and flexible. Suffer from high degradation.	Applications requiring flexibility, lightweight design, transparency or performance in low-light conditions (interiors).
DSSC	13.0%	Good performance in diffuse light. Uses liquid electrolytes with possible retention problems.	
Perovskite	28.0%	High efficiency and low production cost. Stability and material toxicity problems.	Mainly at research level.
Tandem	35.2%	High efficiency. Complex production process.	

2.1.4. Emerging applications

As solar penetration increases, the primary engineering focus is shifting from standard ground-mounted or basic building installations toward advanced integration architectures.

Building-integrated photovoltaics (BIPV – **Figure 9**) represents a concept in urban energy production, where solar components are directly embedded within the building envelope, serving as active elements like roofs, shingles, facades, or windows [42], [43]. This architectural integration serves a dual purpose: it fulfills essential structural and aesthetic roles while simultaneously generating clean electricity on-site [44]. By utilizing building

2.1. The state of photovoltaics

31

surfaces for localized power generation, BIPV systems significantly enhance grid resilience and assist in decarbonizing the urban environment, reducing the dependence on centralized fossil fuel-based infrastructure and cutting city-level emissions [45].

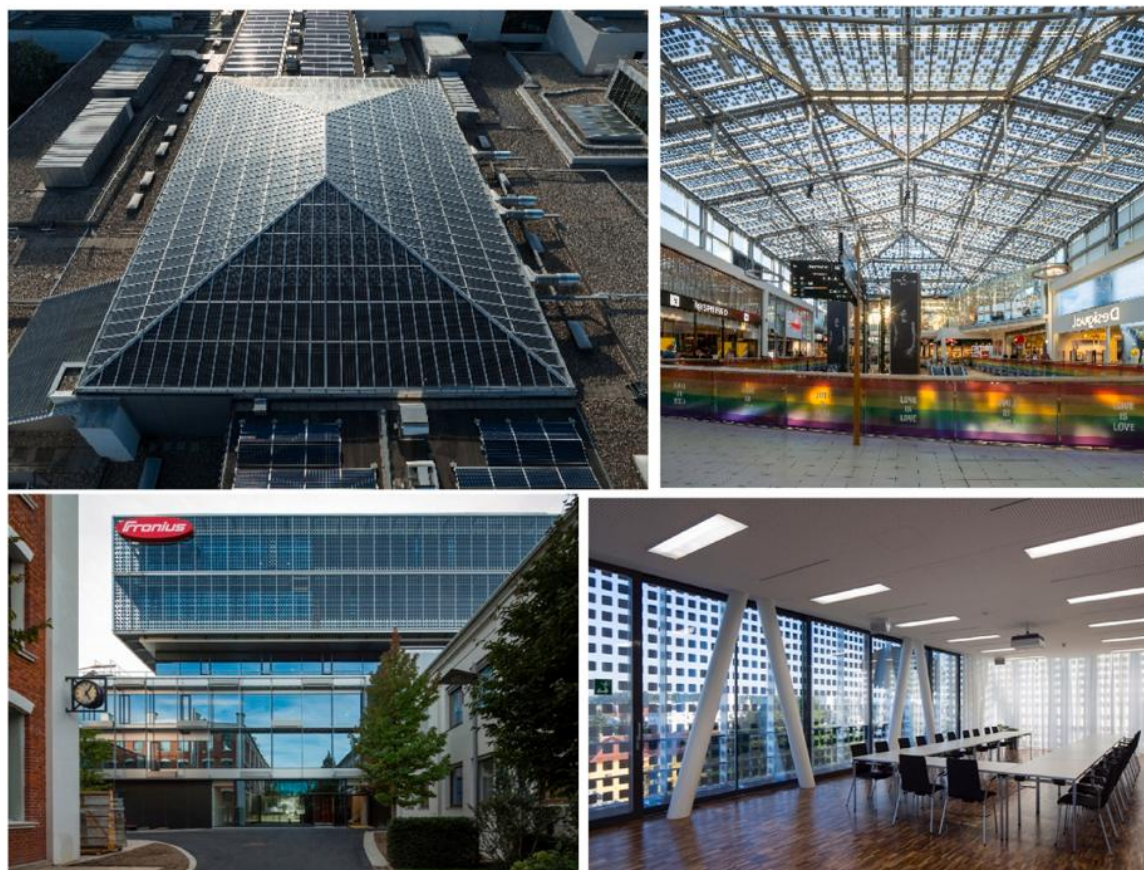


Figure 9 – Examples of BIPV [42].

From a technical and economic standpoint, BIPV technology has reached a high level of maturity [46]. Recent studies highlight that, within the European context, BIPV systems often demonstrate a positive net present value, confirming their economic viability as an alternative to conventional cladding or glazing materials. Furthermore, the evolution of BIPV has moved well beyond the traditional appearance of standard modules. The emergence of advanced aesthetic solutions, including colored foils, digital ceramic printing, and interferential optical coatings, now allows for a broad range of architectural expressions that can mimic traditional construction materials or offer entirely new visual textures without significantly disrupting the clean exterior view [47].

Despite these advancements, the global penetration of BIPV remains relatively low, accounting for less than 1% of installed photovoltaic power. This limited adoption is primarily hindered by a lack of early-stage awareness and specialized expertise among design teams,

coupled with concerns regarding perceived risks and a persistent gap in the digitalization of construction workflows. Furthermore, while modular crystalline silicon technologies remain the dominant BIPV solution due to their high efficiency and cost-effectiveness, emerging solutions like semitransparent organic PV [48] and semi-transparent perovskite solar cells [49] are opening new frontiers for power-generating windows.

To move BIPV toward widespread adoption, it is essential to shift from a component-based approach to a systemic design framework, where BIPV is recognized as a standard building material integrated directly into Building Information Modeling (BIM) systems. Backed by advanced 3D-GIS mapping and high-precision shading computational engines, design teams can model solar potential across complex urban morphologies to mitigate power losses.

Floating PV (FPV – **Figure 10**) consists in deploying solar modules directly onto bodies of water such as industrial reservoirs, lakes, and canals [50] or offshore [51]. This architecture avoids land-use constraints, which represents a crucial advantage in small island nations or countries where the landmass is constricted or highly contested by agriculture, nature reserves, and urban development. Furthermore, covering water surfaces with floating arrays structurally reduces water evaporation rates by up to 60-70% [52] and significantly limits the occurrence of harmful algal blooms by blocking the penetration of solar radiation into the water column [53].



Figure 10 – Example of floating PV [54].

On a thermodynamics level, the system benefits from the natural cooling effect of water, which lowers operational cell temperatures and increases net energy generation efficiency. However, field-measured data have recently revealed that this cooling mechanism is highly site-specific and dependent on the structural geometry of the floating platform. Water-cooled FPV configurations, where modules maintain direct thermal contact with the water surface or utilize partially submerged designs, achieve exceptionally high heat loss coefficients, allowing them to operate at lower temperatures even when the underlying water body is warmer than the ambient air [55]. Conversely, air-cooled floating designs, where panels are elevated above the water, rely predominantly on wind-driven convection rather than water-surface cooling. Consequently, if an FPV array is deployed in low-wind conditions, features a massive close-structure footprint, or is positioned too low inside a sheltered basin, it can experience severe heat trapping, resulting in panel temperatures higher than traditional land-based PV systems [56].

From an electrical perspective, FPV systems must also endure wave-induced movements, which dynamically alter panel tilt and azimuth angles [57]. These rapid fluctuations create shifting patterns of plane-of-array irradiance that can introduce non-negligible wave-induced losses. Numerical simulations and field experiments indicate that total wave-induced losses scale directly with wave steepness, causing electricity generation drops ranging from 3.3% up to 6.7%.

Despite these technical hurdles and higher initial CAPEX, offshore and inland FPV systems remain highly cost-competitive across global energy markets [58], [59]. Their levelized cost of electricity (LCOE) is remarkably optimized when integrated within existing hydropower basins, where FPV arrays utilize pre-existing grid connection infrastructure, or when land-saving and water conservation benefits are fully monetized. Backed by rapid lifecycle sustainability indicators, contemporary FPV projects demonstrate a short energy payback time of 1 to 3 years and excellent end-of-life material recyclability.

Agrivoltaics (Agri-PV – **Figure 11**) consists in the coexistence of PV and agricultural production on the same portion of land, creating a dual-use system that optimizes land productivity and directly addresses localized land-use conflicts [60], [61], [62]. This concept can be effectively implemented either directly on open fields or within greenhouse systems.

2.1. The state of photovoltaics

34



Figure 11 – Examples of open-field [63] and greenhouse agrivoltaics.

In open-field designs, systems range from overhead structures to interspace configurations and vertical solar rows [64], [65]. Among these, East/West-faced vertical bifacial solar farms are particularly promising, yielding the smallest seasonal variation for shade-sensitive crops while providing high structural safety and allowing the unobstructed movement of heavy farming machinery [66]. In greenhouse applications, examples can be found in the literature both for modules mounted on the roof [67] and inside the greenhouse itself [68], with the former benefitting from unfiltered solar radiation and the latter from a simpler installation configuration that leverages the existing structure of the building. Greenhouse applications also benefit from emerging third-generation technologies, such as semitransparent organic photovoltaics (OPV) and perovskites [69], that transmit the key visible wavelengths necessary for plant growth while converting non-absorbed spectral bands into clean electricity. Within this context, the European REGACE project aims at validating the integration of innovative solar tracking systems into greenhouse environments to optimize the light-sharing mechanism [70].

In both open-field and closed-greenhouse cases, the physical presence of solar arrays alters the crop environment, creating a managed microclimate that impacts solar irradiation, evapotranspiration, photosynthesis, wind velocity, and local rain distribution patterns [71]. Shading from the panels protects crops from excess heat and reduces soil water evaporation rates, which can lower localized irrigation water budgets by up to 29% [72]. This is particularly relevant in regions that are particularly prone to drought situations.

Evaluating agrivoltaics from a life cycle perspective confirms that these multi land-use systems result in a reduced environmental footprint compared to standalone utility-scale PV installations [73]. Life Cycle Assessments (LCA) indicate that while the manufacturing of PV modules in fossil-dominated grids remains a major carbon hotspot, vertical layouts improve

sustainability by significantly lowering the structural steel demand compared to heavy stilted overhead frames. Economically, agrivoltaic installations entail higher initial CAPEX due to specialized racking and elevated structural requirements. However, the long-term cost-effectiveness is balanced by the secondary revenue stream of agricultural.

2.1.5. *Integration with energy storage systems*

The inherent variability and intermittence of solar energy has led to their integration with multiple forms of energy storage, which is seen as one of the enablers not only for PV, but also for VRE in general, to become a dispatchable resource [74]. As already anticipated in section 2.1.2, energy storage systems (ESSs) can be an effective tool for mitigating the energy generation imbalance and flatten the duck curve, which is, in fact, one of the key decision factors in their design [75], [76].

When it comes to ESS solutions, multiple options are available for coupling with PV systems, such as pumped-hydro, compressed air, thermal storage and, most notably, battery energy storage systems (BESS) [77], [78]. Studies highlight the role of BESS in improving distribution system performance, particularly in voltage regulation, peak demand shaving, and power loss reduction [79], [80], [81], and demonstrate that a “critical storage zone” exists, beyond which further increases in battery capacity offer negligible improvements [82].

The deployment of energy storage technologies must be evaluated within a rigorous techno-economic framework [83]. While traditional economic assessments often focus exclusively on total capital expenditures, contemporary analyses increasingly rely on the Levelized Cost of Storage (LCOS) and Life Cycle Cost (LCC) as the primary indicators of economic performance [84]. The LCOS method is highly relevant for design optimization because it accounts for all expenditures incurred over the storage asset's lifespan, including capital, operations, maintenance, and cycle-driven battery degradation, divided by the total energy effectively delivered to the load. This indicator allows system designers to identify the exact threshold where battery capacity becomes economically competitive against market electricity prices.

To demonstrate the real-world viability of this techno-economic framework, recent case studies have evaluated the performance of fully integrated PV-BESS architectures within community contexts. A notable application is the development of a 2 MWp grid-connected PV facility coupled with a 1.5 MWh BESS and optimized through automatic dispatch strategies

[85]. By storing surplus solar energy during peak production hours and distributing it to decentralized local communities when solar generation is absent, this real-world application has proven highly effective. The system successfully achieved a 45% reduction in annual electricity bills for the integrated prosumers, returning a levelized cost of energy (LCOE) of 0.04 €/kWh and a discounted payback period of 8.8 years, while simultaneously abating 1150 tons of CO₂ emissions in its first year of operation.

Furthermore, literature suggests that a strategy involving both traditional energy storage and overbuilt VRE capacity, also defined “implicit storage” is the approach that gives the most promising results both in terms of energy management and system cost [86]. This paves the way for discussion about the validity of the firm PV generation strategy that is central in this dissertation.

2.2. Bifacial photovoltaics

Within the photovoltaic landscape, bifacial PV technologies (BFPV) are quickly becoming the standard thanks to an increased potential productivity against an only slight increase in cost. The rapid growth of this technology is fueled by the push to overcome the efficiency limits of traditional monofacial photovoltaics (MFPV). The peculiarity of this innovative solution lies in the ability to harvest solar radiation both from the front and back of the panel. This section will introduce the working principle and characterization methods of BFPV and will discuss both its current status within the PV market and its main practical applications. A comprehensive overview is provided by the International Energy Agency (IEA) in the Task 13 report titled “Bifacial Photovoltaic Modules and Systems: Experience and Results from International Research and Pilot Applications” [87].

2.2.1. Working principle and characterization of bifacial PV

The operational principle of bifacial PV modules relies on their ability to capture solar radiation on both their front and rear surfaces, thus outperforming traditional monofacial panels under equivalent environmental conditions. While the front side continues to absorb direct and diffuse components of incident solar irradiance, the rear surface generates additional electrical power by harvesting radiation reflected from the underlying ground or surrounding structures.

When it comes to cell architecture, similarly to what happens for traditional MFPV, monocrystalline silicon (PERC) is the dominant choice. Advanced cell designs, such as TOPCon and HJT technologies, possess an inherently symmetric structure that provides excellent rear spectral response with minimal carrier recombination losses, which is consolidating their role within the bifacial PV landscape [88].

To characterize this behavior under real operating conditions, the performance of the rear side is evaluated relative to the front through a specific parameter known as bifaciality factor (ϕ), which assess the rear-to-front ratio for short-circuit current (I_{sc}), open-circuit voltage (V_{oc}), and maximum power (P_{MAX}). Standard commercial modules usually exhibit stable bifaciality values localized within the 77-80% range [89].

Given the fundamental difference compared to traditional PV panels, generally tested under Standard Test Conditions (STC – 1000 W/m², $T_{BOM}=25^{\circ}\text{C}$), bifacial photovoltaic technologies have posed a new challenge in module characterization. From as early as 2014, methods were proposed stemming from the ones consolidated on monofacial modules [90] or combining indoor and outdoor evaluation [91]. In this phase, studies and reviews painted a picture of the state and challenges of bifacial PV characterization in a framework that still lacked established standards [92], [93]. In 2019, the perspective changed with the publication of the IEC TS 60904-1-2 [94], that established precise rules for the characterization (especially indoor) of bifacial modules and defined the Bifacial Standard Test Conditions (BSTC – 1000 W/m² on the front and 135 W/m² on the rear, resulting in an equivalent irradiance of $G_E = 1000 + \phi \cdot 135 \text{ W/m}^2$, $T_{BOM}=25^{\circ}\text{C}$), which, as of today, are integrated on a regular basis in module datasheets as Bifacial Name Plate Irradiance (BNPI). Within this newly-established normative framework, the validity of the standardized procedure under controlled conditions both for single and double-side illumination was verified [95] and the importance of the determination of the bifaciality coefficient was underscored [96] as a key element for the determination of BNPI.

2.2.2. Market expansion and applications of bifacial PV

In recent years, bifacial PV technology has transitioned from a niche research interest to the dominant industrial standard for utility-scale installations and large-scale projects. According to the IEA [87], as of 2020, bifacial architectures already accounted for approximately 20% of the PV cell market, and commercial panels sold with transparent rear

covers represented around 12%. Data from the ITRPV [97] show that, in 2025, bifacial modules had reached about 69% market share, with the remaining 31% split between monofacial featuring bifacial cells (28% of the total) and monofacial with monofacial cells (3%). Projections for 2036 see the bifacial share grow to about 84%, with the remaining 16% covered by monofacial with bifacial cells, while monofacial with monofacial cells is set to exit the picture (**Figure 12**).

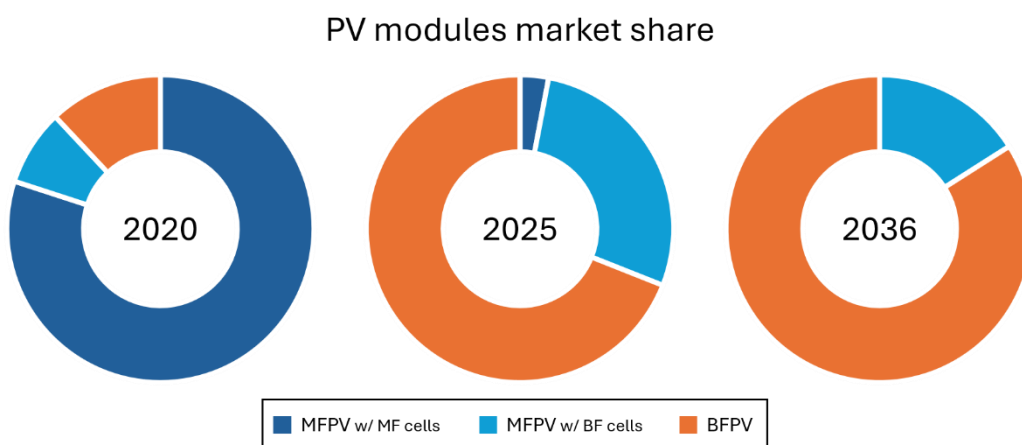


Figure 12 – Market evolution of monofacial and bifacial modules [97].

On a macroeconomic scale, the global bifacial solar panels market was valued at 2.50 billion USD in 2020 [98]. The recent surge brought it to about 30 billion USD in 2025 and projections place it at about 65 billion USD in 2034 [99] (**Figure 13**). Within this market structure, glass-glass configurations and utility-scale applications represent the absolute majority of global market shares, mostly concentrated in the Asia-Pacific region and expanding across Europe and America.

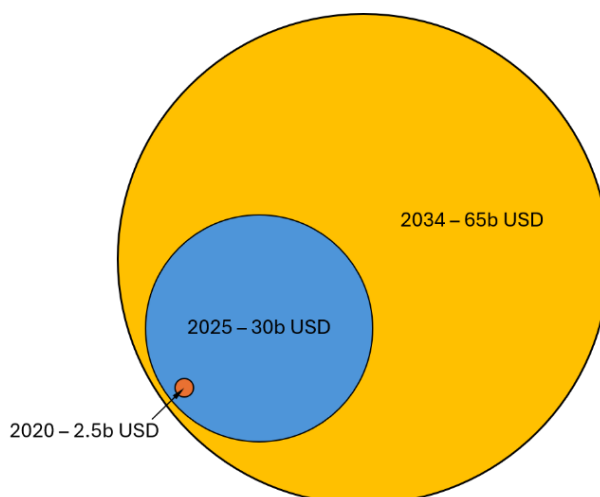


Figure 13 – Evolution of the BFPV market size [98], [99].

Project developers increasingly select bifacial modules for new utility installations on account of their superior economics and lower LCOE. This is largely confirmed by multiple literature studies over the years [100], [101], [102], that point at the replacement of monofacial with bifacial technologies as one of the motors towards reducing energy costs.

In terms of applications, early BFPV technologies were mainly used in space exploration, telecommunication and rural electrification [103]. In modern times, their dominance means that bifacial modules represent the absolute majority of new capacity additions. Their use in solar farms and PV power plants has become standard practice worldwide, mostly for their ability to enhance energy generation especially on cloudy days, with examples found in Asia [104], Europe [105], North [106] and South [107] America and the Middle East [108] among others. Furthermore, bifacial technologies are particularly common in agrivoltaics, also in vertical or tracking (variable-tilt) configurations [109], floating PV, benefitting from the water's albedo [110], [111], and BIPV, integrated in facades or with the use of transparent organic PV in windows, roofs and railings [112]. One final application worth mentioning is the one constituted by photovoltaic noise barriers (PVNB), installed vertically along railways or highways with the dual purpose of sound insulation and electricity generation [113], [114] (Figure 14).



Figure 14 – Photovoltaic noise barriers in Lithuania [115].

2.3. The firm-PV generation strategy

The concept of "firm power generation" traditionally describes the capability of an energy facility or portfolio to continuously and reliably satisfy a defined electricity demand profile 24/365. In conventional grid architectures, firm capacity has historically been provided by dispatchable thermal plants, nuclear facilities, or hydroelectric reservoirs. Furthermore, under traditional operational paradigms, increasing solar penetration exposes the grid to severe supply-demand mismatches, steep evening ramps (the "duck curve" phenomenon described in section 2.1.2), grid congestion, and unpredictable market imbalances.

Firm photovoltaic (firm-PV) generation represents the transformative idea of covering the electricity demand 24/365 using energy-flexible PV plants with battery storage, effectively transforming solar from a variable and generally unreliable source into a dispatchable asset. The firm-PV concept was fully established within the scientific community in 2019, with the pivotal work of Perez et al. [116], where the authors showed that the combination of PV overbuilding, energy storage and proactive curtailment of the excess generation represents the most technologically and economically efficient way to achieve dispatchability with solar energy. By overbuilding solar capacity, the system guarantees sufficient power delivery even during low-irradiance winter days, thereby drastically suppressing the battery storage volume needed to cover multi-day solar deficits. Even before this milestone in the research landscape, the idea of firming variable renewable energy generation had been explored [117], concluding that a combination of physical electrochemical storage and excess renewable generation capacity was the most promising option, yielding the lowest system cost for ultra-high supply reliability. The central role of implicit storage was also reiterated in more recent years [118], [119], consolidating its importance in achieving lowest-cost 100% renewable generation.

The economics and policy mechanisms of firm-PV have been further explored in recent times to definitively establish its cost-effectiveness and market viability [120], [121]. In this context, international initiatives such as the IEA PVPS Task 16 [122] have played a central role, establishing a dedicated global research framework focused specifically on firm power generation and its integration strategies. Novel market design frameworks, such as "generation and market splitting" were also proposed [123], demonstrating that incentivizing flexible PV systems to feed baseload power into a dedicated firm market can economically reduce grid-induced variability and eliminate price cannibalization.

The most recent milestone in the evolution of the firm power concept is its formal institutional recognition with the publication of the 2026 IRENA report “24/7 renewables: The economics of firm solar and wind” [124]. The report introduces the concept of Firm LCOE as a project benchmark to quantify the cost of reshaping variable renewable output into a continuous energy supply at high reliability targets (90–95%). IRENA confirms that PV+BESS systems have already proven capable of delivering firm power at levelized costs below fossil fuels in high-irradiance regions. Additionally, the “firming premium” is continuously narrowing thanks to the declining costs of hardware, establishing firm power generation as a commercially viable, scalable concept for high VRE penetration worldwide.

The operational principles of flexible PV systems with storage also play a vital role in grid-level ancillary services and imbalance mitigation. In high-penetration energy markets, day-ahead solar forecast uncertainties introduce significant supply-demand imbalances, forcing Transmission System Operators (TSOs) to maintain expensive, carbon-intensive spinning reserves.

The integration of firm generation strategies with advanced solar forecasting offers an effective bridge toward complete grid decarbonization. Studies in Italy demonstrated that operating flexible PV fleets equipped with BESS and smart inverters allows solar assets to actively participate in dispatch markets, providing secondary frequency regulation and voltage support [125], [126]. By managing power reserves through proactive curtailment and real-time remote control, PV systems can effectively compensate for forecast errors [127], eliminating solar-induced imbalances at costs lower than traditional thermoelectric balancing.

This concept was further evolved into the “firm solar forecast” methodology [128], [129]. By using properly sized storage buffer capacity to absorb or supplement deviations between predicted and real-time PV generation, solar plants can deliver guaranteed, error-free day-ahead power schedules. Achieving a “perfect operational forecast” eliminates balancing risk for grid operators and represents a crucial step toward full 24/365 firm-PV generation.

2.3.1. *The mentality shift about curtailment*

A fundamental prerequisite for implementing the firm-PV strategy is a profound paradigm shift regarding the operational definition of curtailment. In traditional PV grid integration, curtailment is universally viewed as an energy loss or an administrative penalty caused by local network bottlenecks. Under current intraday market regulations, therefore, excessive

curtailment could make PV projects economically unfeasible [130]. Recent studies [131], [132] argue the firm-PV framework could redefine curtailment from "wasted energy" to "unused system output", promoting a much-needed shift of mentality. As the penetration of VRE, and specifically PV, inevitably grows, the focus will have to shift to seeking the optimal level of curtailment, rather than minimizing it.

During summer peak production hours, an oversized PV array generates vast amounts of excess energy, far exceeding load demand and battery absorption capacity. Proactively curtailing this surplus power at the inverter level prevents local grid congestion and eliminates the need to over-dimension transmission lines or buy market-prohibitive battery storage. When evaluated from an LCOE standpoint, the economic cost of discarding excess production is far lower than the capital expenditure required to store them. Thus, curtailment serves as an active optimization variable that minimizes overall energy delivery costs. Furthermore, viewing curtailment as "unused potential" could reframe surplus solar generation as a valuable by-product. This shift opens new pathways to redirect non-harvested energy toward flexible secondary applications, unlocking additional economic value without compromising grid stability [133].

2.3.2. *Simulation firm-PV case studies*

Over the past decade, the techno-economic viability of firm renewable generation has been extensively confirmed worldwide through computational modeling and regional optimization studies.

In the North American context, multiple works have demonstrated the techno-economic feasibility of firm- PV generation across diverse regulatory and climatic frameworks. Studies focusing on the New York Independent System Operator (NYISO) footprint [134] proved that combining oversized solar arrays with short-duration battery storage and proactive curtailment enables a cost-effective transition toward ultra-high renewable penetration. Expanding the scope to the Midcontinent Independent System Operator (MISO) region [135] further confirmed that overbuilding PV capacity, particularly when optimally paired with regional wind resources, provides dispatchable power profiles at levelized energy costs that are fully competitive with wholesale thermal generation. Pushing this paradigm into colder, high-latitude environments, recent research in Nova Scotia, Canada [136], highlighted that firm variable renewable energy strategies remain highly effective even under severe winter resource

constraints, where strategic oversizing suppresses the massive battery storage capacities that would otherwise be required to bridge seasonal generation deficits.

In Europe, firm generation modeling has been evaluated at continental, national and regional scales. At a continental level, the Pan-European Intermittent Renewable Overbuilding and Curtailment Optimization Model (PEIROCOM) [137] demonstrated that optimal overbuilding paired with batteries and hydrogen storage drastically reduces the firm kWh premium across 37 European countries. National case studies further validate this approach under specific regional constraints. In Switzerland, evaluations of high-penetration solar scenarios highlighted how oversizing PV capacity, leveraged alongside existing hydroelectric storage, provides a cost-effective pathway to support the ongoing nuclear phase-out and guarantee winter energy security [138]. In Italy, initial macro-scale research formulated national protocols to transition from solar imbalance regulation toward firm 24/365 power delivery [139]. This national perspective was subsequently downscaled to regional dynamics in the Lazio region [140], confirming that strategic PV overbuilding combined with battery storage can economically unlock high self-production targets. These findings directly paved the way for simulating the firm-PV generation strategy applied to the Engineering Macro-area at Tor Vergata University, serving as the benchmark case study for the future Rome Technopole campus [141].

In Asia and island settings, firm power generation modeling addresses unique geographical, climatic, and land-availability constraints. In high-latitude, cold-climate environments such as Harbin [119] and Northeastern China [142], simulation studies confirmed that combining oversized PV arrays with battery storage and proactive curtailment drastically reduces firm energy delivery costs under severe winter solar deficits. Further Asian studies explored multi-technology storage integration, demonstrating that pairing overbuilt solar fields with pumped-hydro storage or green hydrogen electrolyzers offers cost-effective long-duration balancing. A study conducted in Japan [143] demonstrated that a hypothetical 100% renewable grid driven mainly by solar PV and floating offshore wind, balanced by vast off-river pumped hydro energy storage and localized green hydrogen produced from curtailed electricity, can achieve complete electrical self-sufficiency at fully competitive costs. On Reunion Island [144], multi-step transition pathways underscored that strategic solar oversizing acts as the primary economic enabler to eliminate fossil-fuel thermal generation and transition isolated island grids toward complete renewable autonomy.

Finally, in Australia, long-term modeling of firm power within the National Electricity Market (NEM) highlighted the strategic value of overbuilding solar and wind capacity across diverse climatic conditions. Research demonstrated that combining oversizing with short-duration battery storage offers a firm 100% renewable generation system that significantly lowers production costs compared to recent wholesale energy prices [145]. Crucially, this overbuilding strategy generates a substantial surplus of low-cost clean energy, transforming potential curtailment into an opportunistic resource to power energy-intensive regional industries, support sector coupling, and drive broader economic decarbonization across Australia.

Complementing these macro-scale studies, recent research has extended the evaluation of firm renewable power down to the neighborhood and household level [146]. Investigating smart meter data from residential consumers in Flanders, Belgium, researchers evaluated the feasibility of applying PV oversizing, curtailment, and implicit storage to micro-scale profiles. The study highlighted that achieving 100% firm solar power for single-site households requires prohibitively large storage capacities due to the strong mismatch between individual demand and PV generation timing. However, aggregating individual households into energy communities and integrating secondary wind resources significantly smooths out both generation and consumption profiles, substantially reducing per-household storage requirements and confirming the operational scalability of firm power principles across local distribution networks.

2.3.3. *The experimental framework*

Despite the extensive body of literature validating the firm-PV concept through numerical simulations, a critical scientific gap persists: the scarcity of long-term experimental validation on real-world hardware.

To date, physical testbeds investigating flexible PV integration have primarily focused on short-term dynamic control or localized energy management. For instance, the ELECTRA project demonstrated the practical feasibility of dynamic inverter curtailment [147], active/reactive power setpoint control, and load-following within a tertiary nanogrid, confirming that commercial smart inverters can execute TSO/DSO dispatch commands. Similarly, small-scale prototypes combining PV generation with battery storage coordinated by

Building Energy Management Systems (BEMS) have proven effective in maximizing local self-consumption under emulated building demand profiles [148].

However, virtually all established firm-PV models rely on idealized, steady-state mathematical assumptions regarding system component performance. Storage assets are typically assigned constant efficiencies (typically 90-95%) [149], [150], inverter losses are either modeled as flat percentages or ignored, and internal standby power draws are frequently neglected.

Real-world systems operate under dynamic, non-ideal environmental and electrical conditions. Commercial components generally exhibit non-linear efficiency curves, thermal sensitivities, communication latencies, and, in some cases continuous auxiliary overhead consumption. When an energy-flexible plant operates under partial-load conditions, these internal losses can dominate the energy balance, causing real-world results to significantly differ from theoretical expectations.

To bridge this gap between theoretical modeling and physical operation, this Ph.D. dissertation establishes an experimental testing framework centered on the physical prototyping of a firm-PV system. By designing, commissioning, and operating the Infinity prototype under real outdoor conditions over a full operational year, this work provides empirical field data to quantify physical non-idealities, evaluate curtailment control strategies, and calibrate predictive firm-PV design tools.

3

Outdoor characterization of bifacial PV modules

This chapter describes the design and validation of a full outdoor characterization protocol for bifacial PV modules and the results of long term testing performed on those. It is partially based on the paper “*Full outdoor characterization procedure for bifacial PV modules*” [151], published in *Energy Conversion and Management* (2026). Text, figures, and tables are adapted and reproduced here in accordance with the reuse rights.

The three-phase procedure was developed in the framework of this thesis and tested on 13 samples specifically manufactured for agrivoltaic application in the pilot greenhouses of the REGACE project [70]. To integrate the characterization procedure, the modules also underwent 7 months of long term testing, which allowed to assess their performance over a prolonged period and their degradation month by month.

This research topic aims at integrating the well-established normative framework for the indoor determination of PV module parameters with an outdoor integrated procedure that allows to reliably estimate them and verify the manufacturer’s specifications. This is especially useful for facilities lacking the equipment needed for indoor characterization, mainly a solar simulator and a way to control module temperature.

The rise of bifacial PV as the standard technology for photovoltaic installations (section 2.2) and their use for the Infinity prototype, that will be described in chapter 5 are the main contributors to the relevance of this chapter in the present work.

3.1. Normative framework on bifacial PV characterization

The first IEC Technical Specification directly focused on bifacial PV is the IEC TS 60904-1-2 [94], first published in 2019, which presents ways to characterize PV modules both indoor and outdoor. Indoor characterization is described in much deeper detail, while only general indications are given for execution outdoors. This technical specification is, also, often used alongside the IEC TS 60891 [152], last updated in 2021, which provides guidance on the correction of measured I-V characteristics and on the calculation of temperature coefficients. In addition, temperature coefficient determination is addressed within the IEC 61215-1-2 standard [153], which defines procedures under controlled indoor conditions as part of module design qualification. However, these procedures rely on stabilized operating conditions that are not easily reproducible in outdoor environments.

Although several outdoor studies and repeatable measurement approaches have been reported in the literature, they generally focus on specific aspects of bifacial characterization, such as outdoor I–V measurements, bifaciality coefficient assessment under real operating conditions, or long-term performance analyses under specific installation geometries [154], [155].

In this framework this chapter aims at addressing the lack of a standardized step-by-step protocol to fully characterize bifacial PV modules in outdoor settings by providing a three-phase procedure to determine the electrical parameters, FF, ϕ , temperature coefficients and BiFi.

This three-phase procedure was developed to define an operational outdoor workflow integrating measurement sequencing, acquisition constraints and data-processing steps for full parameter extraction, building upon existing outdoor characterization studies, the IEC TS 60904-1-2, IEC TS 60891 and IEC 61215-1-2.

3.2. Overview of the equipment

The Ester Lab facility [156], [157], [158], located on the rooftop of the Industrial Engineering building at the University of Tor Vergata in Rome, Italy (41.85498 N, 12.62263E), hosted the measurements necessary for the protocol's validation. The lab features a south-oriented (**Figure 15a**), adjustable-tilt stand (hereafter “fixed stand”) and a two-axis sun tracker (hereafter “tracker”) (**Figure 15b**).

For data acquisition, EsterLab uses two independent measurement systems, both based on the Campbell CR1000. The first system, hereafter “main system”, records data from the sensors every minute, while the second system, hereafter “portable system”, has an adjustable acquisition frequency.

For the measurement of both Global Tilted Irradiance (GTI) and Reflected Tilted Irradiance (RTI), EKO MS-802F pyranometers were used, while PT100 sensors were employed to measure the back-of-module temperature. Finally, the electrical parameters of the modules (V_{MAX} , I_{MAX} , I_{SC} , V_{OC} and P_{MAX}) and the I–V curves were measured using 5A MPPT-3000 devices manufactured by SUPSI. **Table 2** summarizes the main features of the experimental set-up.

Table 2 - Experimental set-up main features.

Variable	Instrument	Uncertainty	Scan rate
I_{MAX}	MPPT-3000	0.5 %	1 min
V_{MAX}	MPPT-3000	0.5 %	1 min
P_{MAX}	MPPT-3000	0.5 %	1 min
T_{bom}	PT100	0.3 °C	15s
IV curves	MPPT-3000	-	15 s
GTI/RTI	EKO MS-802F	3 %	1 min
T_{amb}	Rotronic Hygroclip	0.3 °C	1 min
RH	Rotronic Hygroclip	2%	1 min

Since the protocol also involves verification of temperature uniformity through thermal imaging, a Flir TS865 thermal camera is also featured at Ester Lab.



Figure 15 – Equipment used for the execution of the procedure

The modules, as anticipated, are custom-made bifacial units designed by Trisolar for agrivoltaic application in greenhouses for the REGACE project, funded by the Horizon Europe program. They feature Mono-PERC cells with increased spacing to limit shading on the crops growing underneath. Modules of 4 different power ratings were used: 55W (2 samples), 75W (5 samples), 105W (4 samples in 2 layouts) and 125W (2 samples).

3.3. Description of the procedure

The procedure comprises three phases, denominated as follows:

- Phase one – Acceptance (Acc)
- Phase two – Temperature coefficients (TC)
- Phase three – Rear-irradiance-driven power gain yield (BiFi)

3.3. Description of the procedure

50

Table 3 summarizes the experimental phases performed on each module, identified by its serial number, and indicates whether each phase was executed once (X), twice (XX) or not performed (-).

Table 3 - Summary of the experimental phases executed on each module.

Power rating	Serial Number	Rear active area (m ²)	Number of cells	Cell arrangement (row by column)	Acc	TC	BiFi
55 W	E002	0.2646	24	(3x8)	X	X	XX
	E010	0.2646	24	(3x8)	X	X	X
75 W	B075	0.3528	32	(4x8)	X	-	X
	B106	0.3528	32	(4x8)	X	X	-
	B109	0.3528	32	(4x8)	X	X	-
	B130	0.3528	32	(4x8)	X	-	X
	B274	0.3528	32	(4x8)	-	-	X
105 W	A007	0.4851	44	(4x11)	X	X	-
	A027	0.4851	44	(4x11)	X	X	-
105 W	D013	0.4631	42	(3x14)	X	-	X
	D047	0.4631	42	(3x14)	X	-	X
125 W	C121	0.5733	52	(4x13)	X	-	X
	C145	0.5733	52	(4x13)	X	-	XX

3.3.1. Phase one – Acceptance

Figure 16 shows the workflow for phase one – Acceptance. This phase consists of measuring 5 I-V curves of the modules in bifacial and in both monofacial configurations (front and rear) and using them to assess the module's electrical parameters. The number of curves was chosen as a compromise to obtain a representative sample of curves while limiting the acquisition time.

The measurement is performed on the fixed stand. Before the acquisition, the stand tilt is manually adjusted for the module to operate at near-normal incidence during a selected time window around solar noon (between 11:40 and 12:20), which allows for the angle of incidence (AOI) to be 0±5 degrees. This window also gives the operators reasonable time to complete the procedure and accounts for seasonal variability. Furthermore, the measurements must be performed during a clear-sky day to guarantee consistent irradiance throughout the test.

3.3. Description of the procedure

51

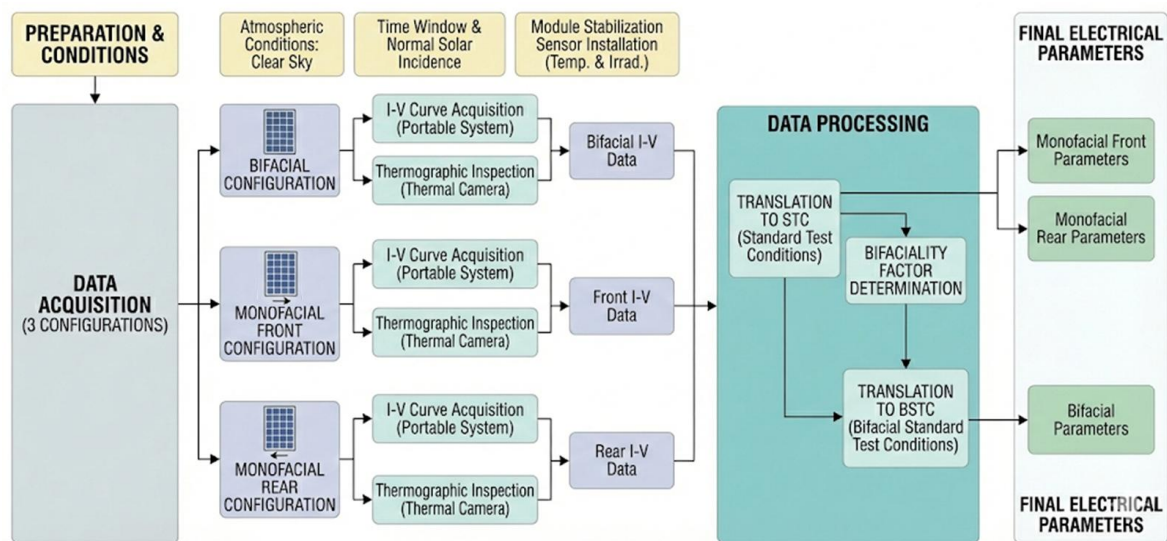


Figure 16 – Workflow of phase one (Acceptance)

The portable system is used for the acquisition of the I-V curves with a frequency of 15 seconds, for a total acquisition time of 1 minute per configuration. GTI and RTI are measured by the main system.



Figure 17 – Acquisition of I-V curves for bifacial (a), monofacial front (b) and monofacial rear (c) configurations.

Before testing, the module is placed in the sun for its temperature to stabilize, in this case at about 35-40°C. After this, the unit is positioned on the stand for the acquisition of the I-V curves in bifacial configuration (**Figure 17a**). Once completed, a black plastic sheet is used to cover the rear side of the module and the acquisition is repeated for the monofacial front

configuration (**Figure 17b**). The sheet was chosen in black with a matte, non-reflective finish to minimize radiation transmitted through the spaces between cells from being reflected back onto the covered side of the module [159], [160]. Then the sample is flipped and the back sheet is repositioned to test the monofacial rear configuration (**Figure 17c**).

During acceptance, a temperature sensor is attached to a central cell on the back of the module (**Figure 18**) [161]. When the module is flipped for the rear-side measurement, the sensor was reinstalled on the corresponding cell in order to maintain a consistency between configurations.

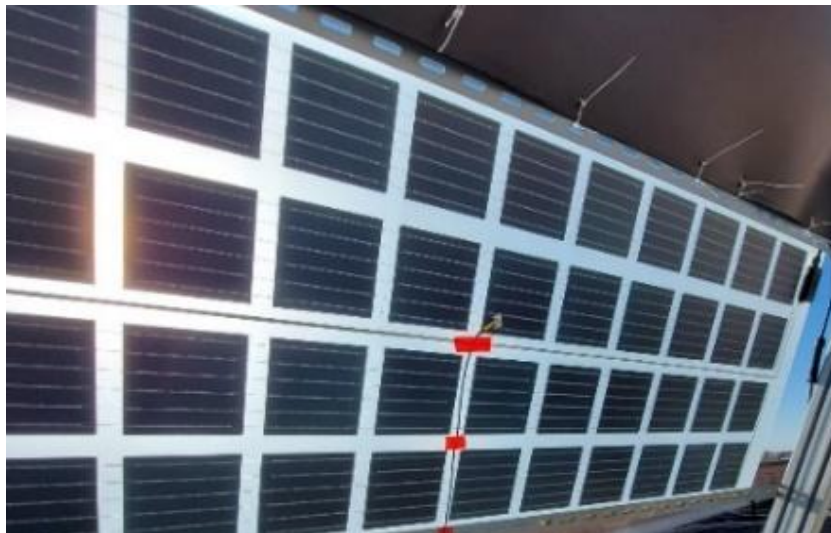


Figure 18 – Temperature sensor installed on the back of the module during testing.

When installing the temperature sensor, care is taken to limit the portion of cell surface covered to under 2%, making the resulting decrease in reflected irradiance negligible [161]. Additionally, the sensor is positioned close to the cell's edge to minimize shading caused by the cable, which is also routed so as not to shade any of the rear side cells during the bifacial configuration acquisition.

During the I-V curves measuring time, a thermal image of the module is taken for a thermographic inspection, with the aim of verifying temperature uniformity, which confirms the measurement's reliability even with the sensor not in the center of the cell.

Once the I-V curves are obtained for all three configurations, the data is processed to determine the electrical parameters. First, the curves for the two monofacial configurations are translated to Standard Test Conditions (STC – GTI = 1000 W/m² and T_{BOM} = 25°C) using Anderson's method [162]. This method involves dividing the V_{OC} and I_{SC} calculated at STC by

the measured ones, respectively, to obtain a multiplier, which is then applied to every point of the original I-V curve to translate it. The 5 measured curves are individually translated, and the average I-V curve is obtained by averaging every point, including V_{OC} and I_{SC} . P_{MAX} is obtained as the maximum value of $V \cdot I$, which, consequently, correspond to V_{MAX} and I_{MAX} . Lastly, FF is calculated as

$$FF = \frac{P_{MAX}}{V_{OC} \cdot I_{SC}} \quad (1)$$

First, this process is performed for the front and rear monofacial configurations. Then, ϕ is determined as follows:

$$\phi_{I_{SC}} = \frac{I_{SC}^{Rear}}{I_{SC}^{Front}} \quad (2)$$

$$\phi_{V_{OC}} = \frac{V_{OC}^{Rear}}{V_{OC}^{Front}} \quad (3)$$

$$\phi_{P_{MAX}} = \frac{P_{MAX}^{Rear}}{P_{MAX}^{Front}} \quad (4)$$

$$\phi = \min(\phi_{I_{SC}}, \phi_{V_{OC}}, \phi_{P_{MAX}}) \quad (5)$$

The bifaciality factor is then used for the determination of the bifacial electrical parameters, which is achieved by translating the I-V curves to Bifacial Standard Test Conditions ($G_E = 1000 + \phi \cdot 135 \text{ W/m}^2$ and $T_{BOM} = 25^\circ\text{C}$). Anderson's method is used for this translation as well, adjusting the target irradiance. The rest of the process is unchanged compared to the monofacial configurations.

A comparable methodology for the determination of bifacial electrical parameters is proposed in [163], and experimentally validated on bifacial PERC modules. Measurements are performed under clear-sky conditions with irradiance levels above 800 W/m^2 and the I-V curves are translated using Anderson's equations. However, the curves in [163] are translated to STC conditions (1000 W/m^2), and the modules are installed at fixed tilt configurations (15° and vertical), relying on data filtering criteria to isolate representative operating conditions. Furthermore, in [163] the bifaciality coefficient is taken from manufacturer specifications, since whereas the present protocol leverages the monofacial electrical parameters to experimentally determine the value of ϕ .

3.3.2. Phase two – Temperature coefficients

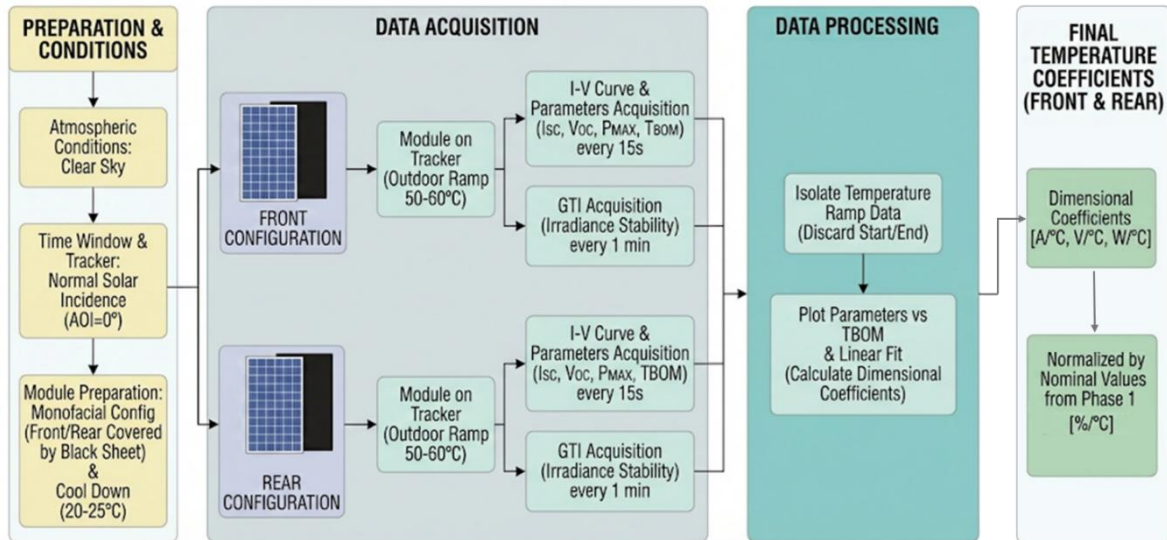


Figure 19 – Workflow of phase two (Temperature coefficients).

The second phase of the procedure (**Figure 19**) consists of subjecting the module to a controlled temperature ramp, monitoring the variation of I_{SC} , V_{OC} and P_{MAX} and calculating the corresponding temperature coefficients through linear regression.

The modules are tested only in their two monofacial configurations (front and rear), and therefore the non-exposed side is covered by a matte black plastic sheet (**Figure 20**). Conceptually, the proposed approach follows IEC 61215 international standard, deriving temperature coefficients from the variation of electrical parameters with respect to module temperature and obtained through linear regression, with subsequent normalization to nominal values. Given the outdoor setting, however, the experimental implementation had to be properly adapted. Instead of relying on steady-state measurements under controlled irradiance and stabilized temperature conditions, the present method employs a continuous temperature ramp while monitoring irradiance monitored to ensure stability.



Figure 20 – Front (a) and rear (b) view of the experimental setup for phase two.

Data acquisition is performed on the tracker ($AOI = 0^\circ$) and takes place on a clear-sky day in order to maintain consistent irradiance conditions throughout. T_{BOM} , I_{SC} , V_{OC} and P_{MAX} are monitored by the portable system with a frequency of 15 seconds. In particular, T_{BOM} is measured by a temperature sensor placed on the back of a cell between the module and the black sheet, while I_{SC} , V_{OC} and P_{MAX} are recorded by an MPPT device. GTI is monitored by the main system to verify the stability of the irradiance conditions: only acquisition windows where GTI remained within $\pm 2\%$ of its median value were considered suitable for temperature coefficient analysis.

The measurement needs to start with the module at low temperature. This is achieved by keeping it in an conditioned room until its temperature stabilizes (in this case at about 20-25°C). Then, the non-exposed side is covered, the module is brought outside and mounted on the tracker. The acquisition records the temperature ramp up to a new stable condition, which in this case was reached after 15-20 minutes at 50-60°C. Afterwards, the module is moved back inside and allowed to cool down naturally before repeating the procedure on the opposite side. No forced cooling was applied. Moving and mounting the module outside, including the installation of the temperature sensor and backsheet, generally took 2-3 minutes. During this time, the module temperature would rise by about 5°C, which was one of the reason why T_{BOM} values under 35°C were discarded, as will be explained later. Furthermore, two modules were alternated during measurements, so that while one was under testing, another one was cooling down. It was verified that this alternation provided enough time for the module to return to 20-25°C and for the back to be tested under conditions comparable to the front. Therefore, the cool-down time can be quantified in 15-20 minutes.

Lopez-Garcia et al. [164] documented a temperature coefficient analysis where the acquisition was similarly performed on a solar tracker and the samples were heated by natural sunlight under clear sky conditions. This method preserves consistency with the physical definitions adopted in IEC standards and can be implemented in facilities lacking climate-controlled equipment. However, outdoor conditions inevitably introduce environmental variability, which can result in higher measurement uncertainty, particularly for low-magnitude coefficients such as that of I_{SC} .

During the data processing phase, T_{BOM} values lower than 35°C and higher than 50°C are discarded, leaving mostly monotonic trends against time. I_{SC} , V_{OC} and P_{MAX} are then plotted against T_{BOM} and linear regressions are performed, the slopes of which constitute the

dimensional temperature coefficients ($[A/^{\circ}C]$, $[V/^{\circ}C]$, $[W/^{\circ}C]$). These are then normalized ($[%/^{\circ}C]$) by dividing them by I_{SC} , V_{OC} or P_{MAX} obtained in the corresponding monofacial configuration (front or rear) in phase one.

The choice to retain only the central part of the temperature ramp (35–50 $^{\circ}C$) was made for several reasons. First, it reduces the influence of the preliminary handling phase, which includes temperature sensor attachment, backsheet preparation, and module positioning on the tracker. These operations can introduce inconsistencies in the first part of the acquisition. Second, the 35–50 $^{\circ}C$ interval corresponds to the portion of the measurement where the temperature evolves monotonically and comparably across all tested samples. Beyond 50 $^{\circ}C$, the temperature tends to stabilize, and the data points provide limited additional information for the estimation of the temperature coefficients. Finally, restricting the analysis to the central part of the ramp avoids excessive concentration of data at the temperature extremes, which improves the robustness of the fitting procedure.

3.3.3. Phase three – BiFi

This final phase of the characterization (**Figure 21**) is designed to determine the rear-irradiance-driven power gain yield, otherwise known as BiFi. This phase aims at evaluating the power response of the modules under naturally varying rear-irradiance conditions representative of outdoor operation.

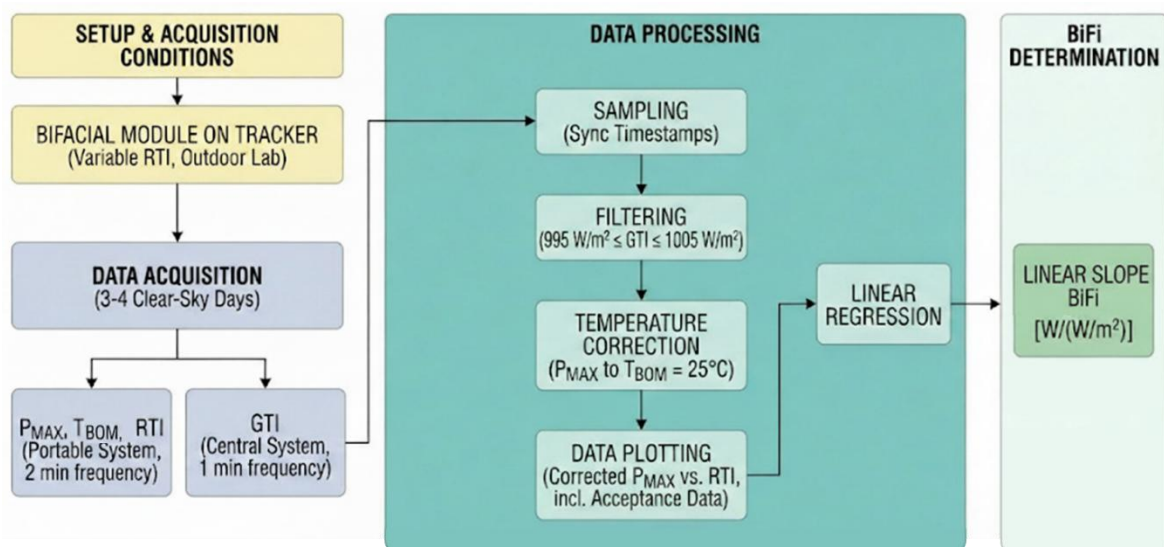


Figure 21 – Workflow of phase three (BiFi).

This quantity, as the name suggests, indicates the power gain per unit of rear irradiance, with the value at STC for the monofacial front configuration corresponding to an RTI of 0. The

IEC technical specification [94] suggests the use of a reflective cloth on the ground to enhance the RTI. However, due to the structural limitations of the setup at Ester Lab, this exact solution could not be recreated. It was, therefore, decided to perform the acquisition on the tracker, causing the elements reflecting the irradiance to the back of the module to be variable, and thus providing a range of different values for RTI (**Figure 22**). Although this necessary deviation may reduce control over the value of the rear irradiance, it should be seen as a practical adaptation for outdoor laboratories where accurate control of this quantity is not feasible.



Figure 22 – Front (a) and rear (b) view of the experimental setup for phase three.

In this phase, P_{MAX} , T_{BOM} and RTI are measured by the portable system with a frequency of 2 minutes, while GTI is acquired by the central system every minute and then sampled to match the other variables' timestamps.

The module is positioned on the tracker in its bifacial configuration in such a way that the structure does not shade the back of the cells, and data are acquired for 3-4 clear-sky days. Then, a filter is applied to isolate data points where GTI is close to STC ($995 \text{ W/m}^2 \leq \text{GTI} \leq 1005 \text{ W/m}^2$). P_{MAX} is then corrected in temperature (to $T_{BOM} = 25^\circ\text{C}$) using the temperature coefficient previously measured to fully meet the standard conditions. The power values obtained are then plotted against RTI, including the ones from acceptance for the bifacial ($\text{RTI} = 135 \text{ W/m}^2$) and monofacial front ($\text{RTI} = 0 \text{ W/m}^2$) configurations. At this point a linear regression is performed, and the value of BiFi is determined as the slope of the fit.

3.4. Outdoor characterization results

In this section, the results obtained from the execution of the procedure will be reported and discussed. Module E010 is used in this section as a representative example to illustrate the outputs of each phase of the procedure.

3.4.1. Results for Phase one – Acceptance

The first stage of acceptance was obtaining the average I-V curves for the three configurations (bifacial, front and rear). For module E010, these are shown in **Figure 23** together with the P-V curves, also highlighting the maximum power point (P_{MAX}). The bifacial I-V curve shows a small step at about 3.5 V. This behavior is common in bifacial modules and generally associated with rear-side partial shading caused by the junction boxes or cables and general non-uniformity of the rear irradiance [165], [166]. This can be experienced both in the bifacial and monofacial rear I-V curves.

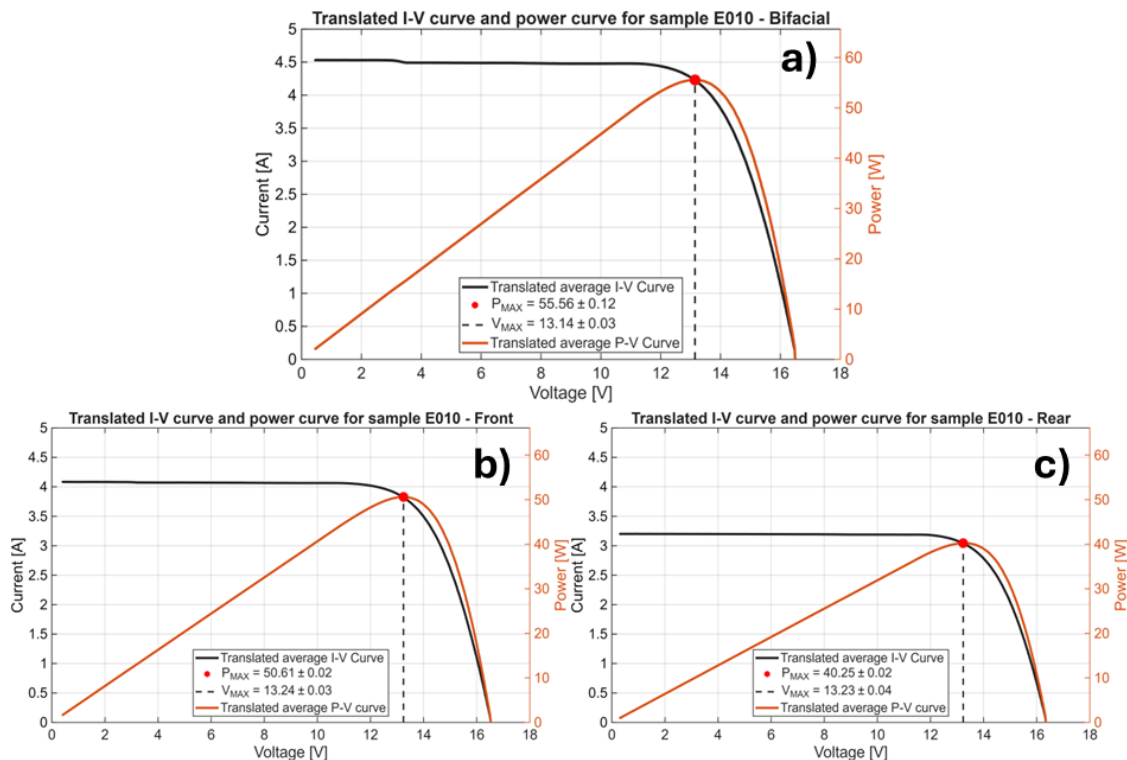


Figure 23 - Average I-V and P-V curves for module E010 in bifacial (a), front (b) and rear (c) configuration.

From the measured data and translated curves, the electrical parameters were determined, which are shown in **Table 4**, together with the corresponding values from the module datasheet and the relative error between the datasheet and outdoor measurements.

3.4. Outdoor characterization results

59

The errors are represented by the standard deviation of the average parameters from the ones obtained from the individual I-V curves. The table also includes, for comparison, the results of an indoor evaluation performed by the manufacturer. However, beyond the fact that this test happened at STC, further details about experimental setup and rear irradiance control were not disclosed. Additionally, only the bifacial configuration was tested by the manufacturer, and thus, no comparison can be drawn for the front and rear monofacial values. Equivalent tables are provided for all the samples in Appendix A (**Table A1 – Table A11**).

It should be noted that the P_{MAX} values reported in the datasheets correspond to the nominal power class of the modules. Therefore, they do not necessarily coincide with the product of the rounded V_{MAX} and I_{MAX} values reported by the manufacturer.

Table 4 – Acceptance results for module E010, tested on 01/10/2024 between 12:06 and 12:14

E010	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	55.00	55.56 ± 0.12	1.0	50.61 ± 0.02	40.25 ± 0.02	58.98
V_{OC} [V]	17.25	16.53 ± 0.02	-4.2	16.55 ± 0.01	16.36 ± 0.01	16.68
V_{MAX} [V]	13.14	13.14 ± 0.03	0.0	13.24 ± 0.03	13.23 ± 0.04	13.92
I_{SC} [A]	4.710	4.533 ± 0.003	-3.8	4.085 ± 0.003	3.201 ± 0.002	4.399
I_{MAX} [A]	4.290	4.227 ± 0.015	-1.5	3.821 ± 0.008	3.042 ± 0.007	4.237
FF	0.677	0.741 ± 0.0007	9.5	0.749 ± 0.0003	0.768 ± 0.0003	0.804
$\phi(V_{OC})$			0.9890			
$\phi(I_{SC})$			0.7838			
$\phi(P_{MAX})$			0.7953			

When compared to the datasheet, it is apparent that the values obtained in phase one are representative, especially in terms of P_{MAX} , V_{MAX} and I_{MAX} . V_{OC} and I_{SC} show a small discrepancy from the manufacturer's specifications, and the difference is larger for FF.

A cross-comparison with the manufacturer's indoor tests shows that these generally yield higher P_{MAX} values across all tested modules. Conversely, V_{MAX} demonstrated a closer agreement between the two methods, with outdoor BSTC values tightly scaling alongside or occasionally overlapping with the indoor benchmarks.

Regarding the bifaciality factor, it should be noted that $\phi(V_{OC})$ is expected to be higher than $\phi(I_{SC})$ and $\phi(P_{MAX})$, since the number of cells in series (which determines V_{OC} and V_{MAX}) does not change between configurations, and produces a value of $\phi(V_{OC})$ very close to 1. Conversely,

the ability of the individual cells to generate current decreases in the monofacial rear configuration, resulting in lower values of $\phi(I_{SC})$ and, consequently, $\phi(P_{MAX})$.

To provide a more systematic validation of the acceptance procedure across all tested modules, relative deviations from the datasheet values were evaluated for the main electrical parameters using all modules that underwent phase 1. Although module E010 is used as an illustrative example, the aggregated statistics presented below reflect the behavior of the tested module population. For each parameter, the relative deviation was calculated as:

$$\Delta (\%) = 100 * \frac{(X_{meas} - X_{datasheet})}{X_{datasheet}} \quad (6)$$

Relative deviations were adopted instead of absolute differences because the tested population included modules with different nominal power ratings (55, 75, 105 and 125 W), making normalized values more suitable for cross-comparison.

The datasheet values are reported under STC (1000 W/m², 25 °C, AM 1.5) using a standard solar simulator. During the measurements, the rear side of the bifacial modules was left uncovered and no dedicated rear-side irradiation was applied.

Across the tested population, P_{MAX} showed an average relative deviation of -3.95% (STD = 3.13%), while V_{MAX} and I_{MAX} exhibited average deviations of -2.33% (STD = 2.06%) and -2.33% (STD = 0.81%), respectively. I_{SC} showed a mean deviation of -4.44% with limited dispersion (STD = 0.83%), indicating consistent behavior across the tested modules. By contrast, V_{OC} presented an average deviation close to zero (-0.45%) but with larger variability (STD = 4.02%), reflecting differences among module families. A similar behavior was observed for FF, which showed the largest dispersion (average 1.19%, STD = 6.26%), as expected from the combined propagation of uncertainties affecting both current and voltage. These aggregated results support the overall robustness of the proposed protocol while highlighting the influence of module-specific characteristics on some parameters.

Although the deviations remain moderate, their origin is relevant for the interpretation of outdoor measurements. The observed deviations can be attributed to both methodological and physical factors inherent to outdoor characterization. The present procedure relies on the translation of measured I-V curves to STC and BSTC using Anderson's method [162], which inevitably introduces residual uncertainty because irradiance and module temperature cannot

be perfectly stabilized during field measurements. In addition, outdoor measurements are affected by spectral conditions, small short-term irradiance fluctuations, and residual thermal non-uniformities that differ from the controlled conditions typically achieved during indoor characterization. These effects are particularly relevant for parameters such as V_{OC} and I_{SC} , and consequently for FF, since the latter depends on the combined propagation of uncertainties affecting both voltage and current. Differences in instrumentation, spectral distribution, rear-side irradiance conditions and temperature control may therefore also contribute to the discrepancies observed between indoor and outdoor results. Although manufacturer indoor measurements were available, the lack of detailed information regarding the associated experimental conditions prevented a rigorous benchmark comparison with the present outdoor procedure.

It is worth noting that FF is not directly provided in the datasheet, and instead it is obtained from the values found in it using equation (1).

Overestimation in V_{OC} and I_{SC} , therefore, inevitably results in underestimation of FF, and vice versa, when P_{MAX} is comparable.

Data for the front and rear monofacial configurations are not provided in the datasheet. Therefore, the only comparison possible is with the bifacial configuration. ϕ was not stated either, and it is interesting to note that, for all modules, this parameter came out as 77-80% (or 0.77-0.80), which is in accordance with the $80 \pm 5\%$ generally seen in Mono-PERC bifacial PV modules.

Additionally, the thermographic inspection carried out in this phase showed a satisfactory level of temperature uniformity (**Figure 24**).

One final result worth mentioning is that the duration of the data acquisition phase was approximately 10 minutes per module including positioning it in bifacial configuration and installing the temperature sensor properly, covering the back side for the monofacial front configuration, flipping the module and re-installing the temperature sensor for the monofacial rear configuration and, obviously, considering data acquisition times. Furthermore, it only required two operators to carry out and the simplicity of the setup makes it possible to tailor it to different applications and stay within the time window of 11:40 to 12:20 defined in section 3.3.1.

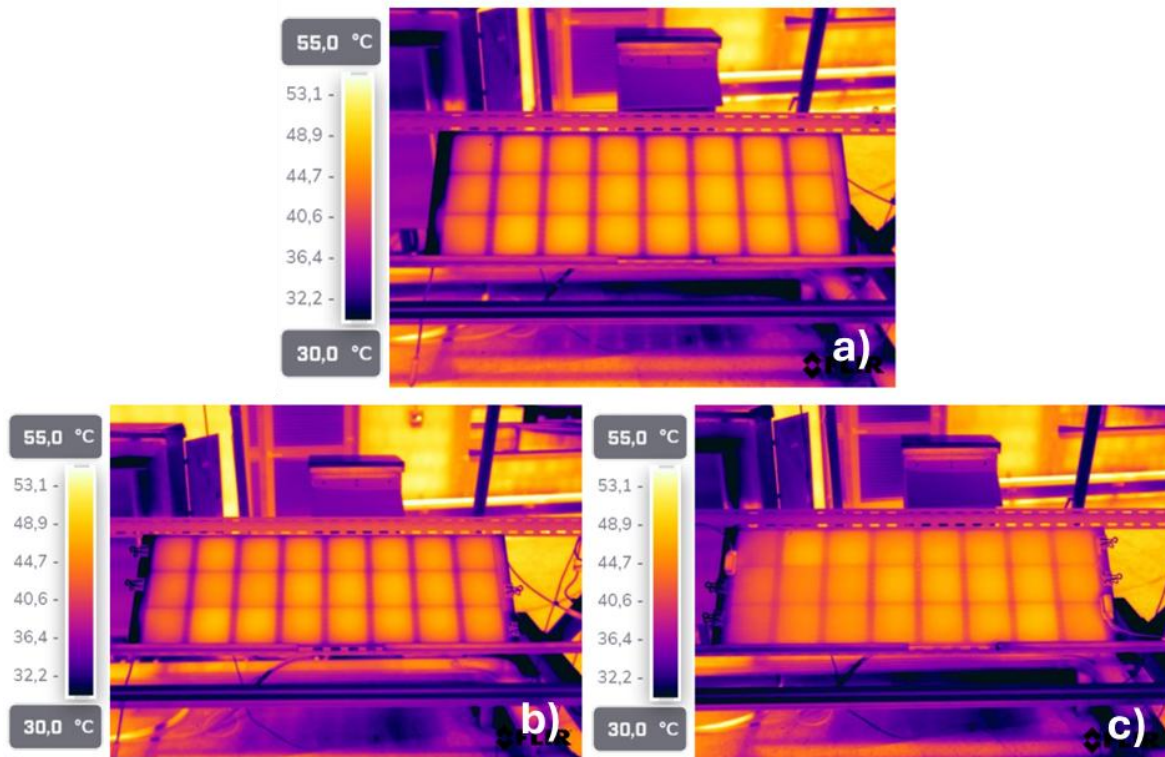


Figure 24 – Thermographic inspection for bifacial (a), monofacial front (b) and monofacial rear (c) configurations for module E010.

3.4.2. Results for Phase two – Temperature coefficients

The measurement of temperature coefficients consisted in determining the dimensional ones first ($[A/^{\circ}C]$, $[V/^{\circ}C]$, $[W/^{\circ}C]$) and then dividing them by the nominal I_{SC} , V_{OC} and P_{MAX} for the corresponding monofacial configuration respectively to obtain the normalized coefficients ($[\%/^{\circ}C]$).

As described in 3.3.2, the measurements started with T_{BOM} at 20–25°C and lasted 15–20 minutes per configuration, with a final T_{BOM} of 50–60°C. Considering the time to cool down the module between acquisitions, each unit could be tested in a time window of about 60 minutes. The temperature ramp was then cropped to the 35–50°C interval. This range was selected for several reasons, including ensuring consistency across all the samples tested, which all exhibited a satisfactory temperature ramp within these values. In outdoor settings, the lower and upper ends of the ramp are strongly dependent on ambient conditions (e.g. ambient temperature and wind) and were therefore not easy to stabilize with the available equipment. Future improvements of the procedure could include reliable methods to extend this temperature interval.

3.4. Outdoor characterization results

63

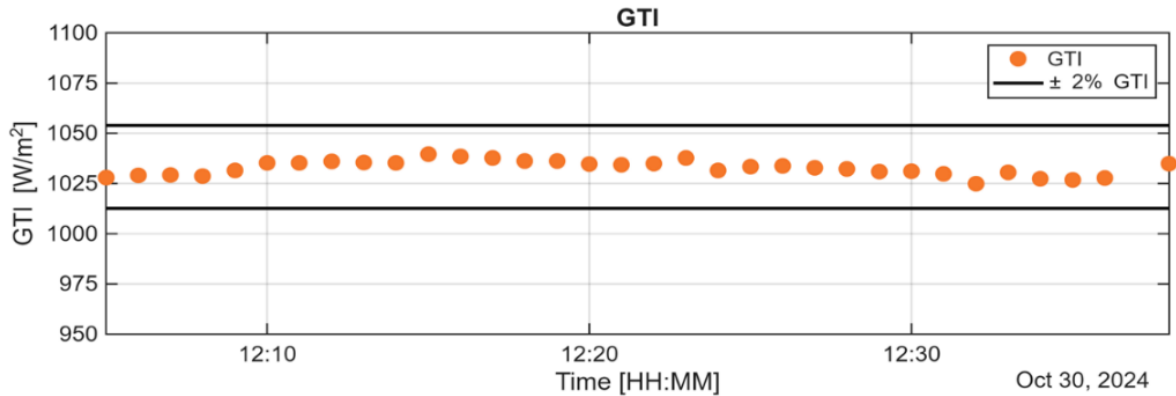


Figure 25 – Plot of the GTI during the temperature coefficients data acquisition window.

Another important aspect is irradiance stability during data acquisition. Therefore, only acquisition windows characterized by quasi-stationary irradiance conditions were considered suitable for temperature coefficient analysis. In the representative case of module E010, GTI remained within $\pm 2\%$ of the median value throughout the selected measurement interval (Figure 25).

Figure 26 shows, as an example, the cropped temperature ramp (T_{BOM}) and the evolution with time of I_{SC} , V_{OC} and P_{MAX} for module E010 in the front monofacial configuration.

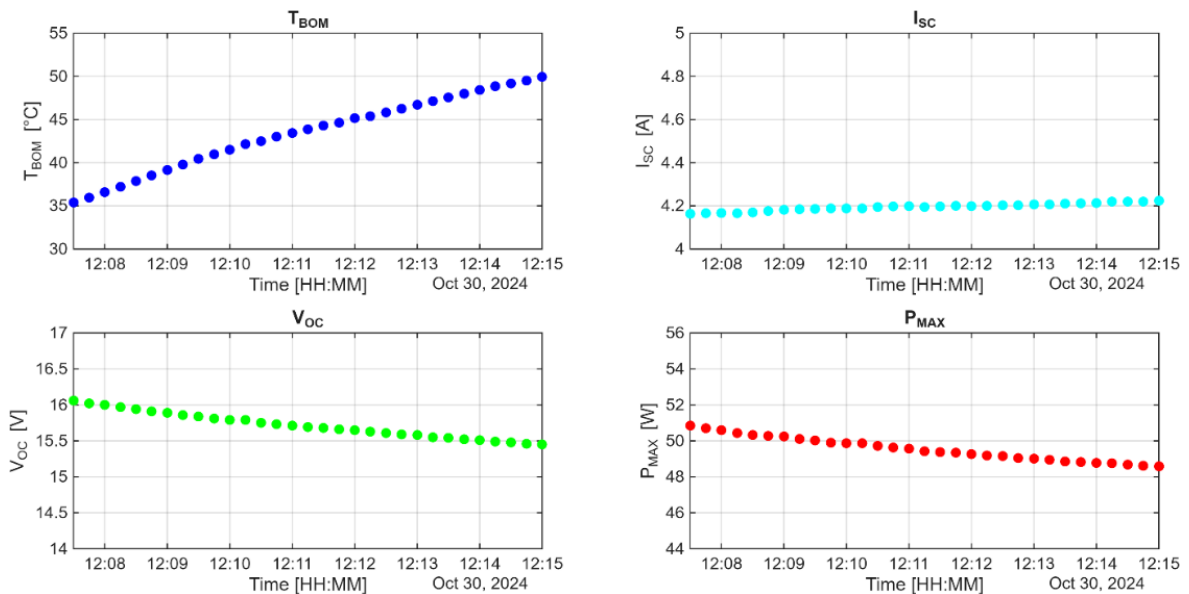


Figure 26 – Evolution of T_{BOM} , I_{SC} , V_{OC} and P_{MAX} with time for module E010 (front).

Figure 27 depicts the variation of I_{SC} , V_{OC} and P_{MAX} as a function of T_{BOM} for the same sample, with the slopes of the fits representing the dimensional temperature coefficients, while Table 5 lists the normalized coefficients for both monofacial configurations (front and rear). In Appendix B the values for all the tested modules and configurations are reported (

3.4. Outdoor characterization results

64

Table B3).

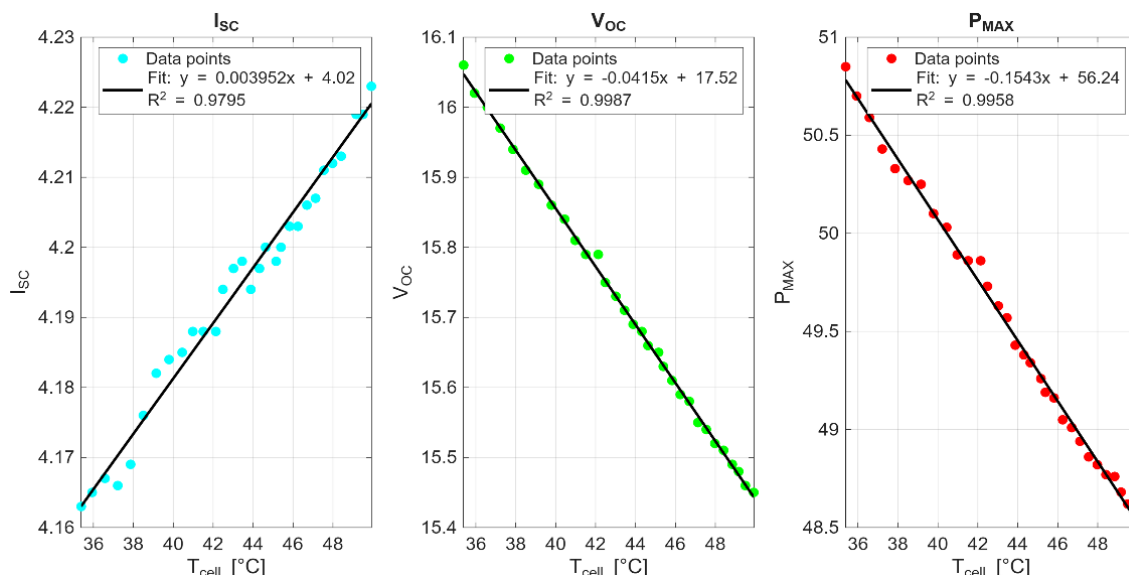
Figure 27 – Evolution of I_{sc} , V_{oc} and P_{max} with T_{BOM} for module E010 (front).

Table 5 - Normalized temperature coefficients for module E010.

	I_{sc} (%/ $^{\circ}\text{C}$)	V_{oc} (%/ $^{\circ}\text{C}$)	P_{max} (%/ $^{\circ}\text{C}$)
Front	0.097	-0.25	-0.30
Rear	0.069	-0.25	-0.31

It is important to note that cell technology is the same across all the modules, thus making the temperature coefficients theoretically equal. Similarly, no intrinsic difference is expected between the coefficients measured from the front and rear sides of a given module, since both measurements involve the same photovoltaic cells operating under opposite illumination directions. Therefore, the small discrepancies observed between front and rear configurations are attributed primarily to experimental uncertainty associated with outdoor measurements, including residual irradiance fluctuations, spectral variations, thermal non-uniformities, and regression-fitting sensitivity. This interpretation is supported by the individual results reported in Appendix B (

Table B3), where the front and rear values of V_{oc} generally show good agreement, while larger differences are observed for I_{sc} , the coefficient most sensitive to measurement noise. For this reason, the results for the modules tested were aggregated into a single average and standard deviation for each coefficient (Errore. L'autoriferimento non è valido per un segnalibro. and Figure 28).

Analyzing these results, it is evident that the determination of the I_{SC} temperature coefficient was the most critical. Although the final average value is close to the datasheet one, the observed variability is very large, as shown by the standard deviation being of the same order of magnitude as the coefficient itself. This can be attributed to the fact that I_{SC} coefficient is much smaller than the others in absolute value. Under outdoor conditions, the measured current remains directly sensitive to small residual irradiance variations, even within the quasi-stationary acquisition windows selected for the analysis. Slight fluctuations in irradiance, changes in spectral composition and minor thermal transients may therefore induce current variations of the same order of magnitude as the temperature-driven I_{SC} variation itself. Therefore, the linear regression used to estimate the coefficient becomes intrinsically more sensitive to experimental noise than in the case of V_{OC} and P_{MAX} . This explains why the observed variability is more pronounced for I_{SC} , while the average value remains consistent with the manufacturer's datasheet.

Table 6 - Aggregated results for the temperature coefficient analysis [%/°C] with standard deviation and comparison to the datasheet value.

	DATASHEET	AVG
V_{OC}	-0.26	-0.27±0.019
I_{SC}	0.046	0.057±0.069
P_{MAX}	-0.32	-0.36±0.071

3.4. Outdoor characterization results

66

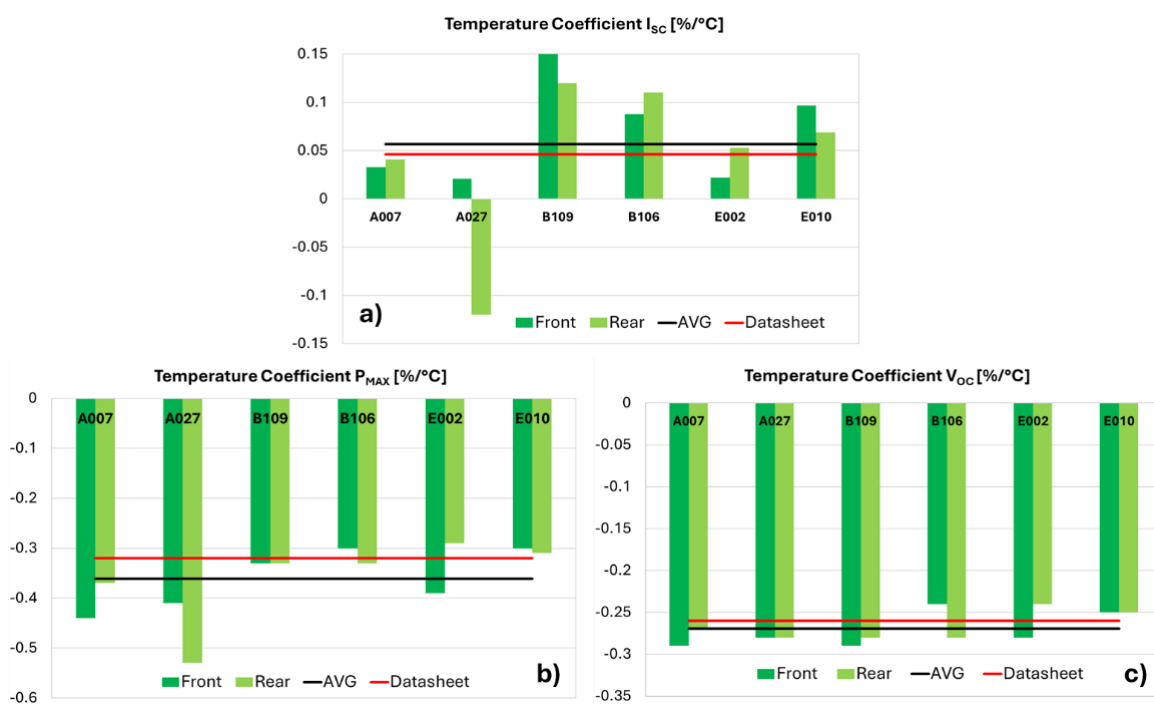


Figure 28 – Bar plots of the normalized temperature coefficients for all the modules tested and comparison to average and datasheet values: a) I_{SC} , b) P_{MAX} , c) V_{OC} .

The observed variability does not invalidate the procedure, but rather highlights the intrinsic limitations of outdoor determination of I_{SC} temperature coefficients. Recent studies have also shown that temperature coefficients may be influenced by device-related non-idealities, degradation mechanisms and correlations with other electrical parameters, rather than depending solely on temperature itself [167]. In particular, low-magnitude coefficients such as I_{SC} are more sensitive to residual irradiance fluctuations and measurement uncertainty under outdoor conditions [168], which is consistent with the relatively large dispersion observed in the present study. By contrast, the V_{OC} and P_{MAX} temperature coefficients appear more stable and their average values only slightly overestimate the corresponding datasheet figures.

It should be noted that the manufacturer datasheet reports normalized temperature coefficients for P_{MAX} , V_{OC} and I_{SC} . However, detailed information regarding the experimental procedure used to determine these coefficients was not available. Consequently, the comparison reported in **Table 5** should be interpreted as a comparison with nominal manufacturer specifications rather than as a validation against independently certified measurements.

3.4.3. Results for Phase three – BiFi

For the measurement of BiFi, P_{MAX} values measured at different RTI levels under GTI between 995 and 1005 W/m² were corrected in temperature and plotted against RTI. The slope of the resulting linear fit is assumed as the value of BiFi. For module E010, the fit equation (**Figure 29**) was found to be:

$$P = 0.0293 \cdot RTI + 50.61 \quad (7)$$

which therefore gives BiFi = 0.0293.

The intercept of the equation was fixed at the value obtained in Acceptance for the monofacial front configuration P_{MAX} , since in the TS 60904-1-2 [169] it is stated that the fit “shall be forced to cross the P_{MAX} axis at $P_{MAX,STC}$ ”. The results for all modules are reported in **Table 7**, where the BiFi values are provided together with the standard error of the fitted slope obtained from the constrained linear regression. Not following the technical specification’s indication on the intercept would result in a value of BiFi equal to 0.0266, with a predicted value of $P_{MAX,STC}$ of 51.01. These values suggest that fixing the intercept does not have a strong impact on the fit. However, R^2 falls from 0.8941 to 0.5480, confirming the need for a wider RTI spread in the data points. For this study, it was, therefore, decided to follow the TS’s prescription.

The variability observed among the BiFi values can be attributed to both experimental and physical factors inherent to outdoor characterization. First, although only data points satisfying the GTI filtering criterion were retained, the available RTI range was not identical for all modules and depended on the specific environmental conditions encountered during the 3–4 day acquisition periods.

3.4. Outdoor characterization results

68

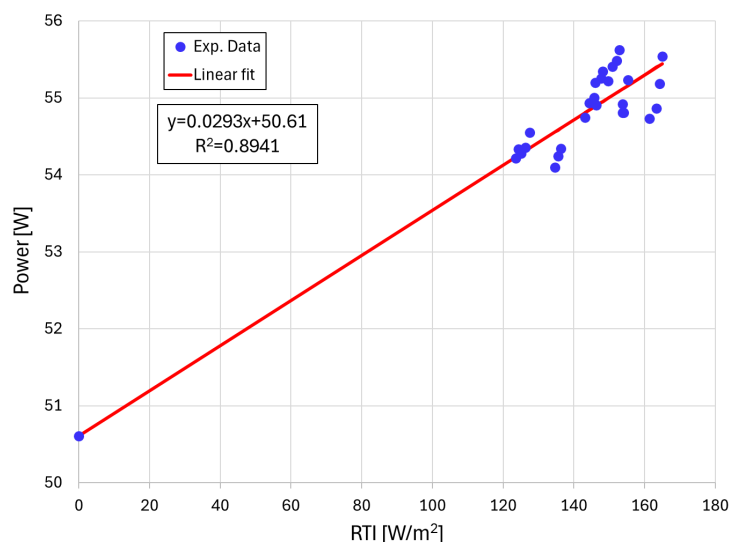


Figure 29 – Plot of P_{MAX} against RTI and linear fit of the data points to obtain the value of BiFi (slope of the linear trend) for module E010.

Since BiFi is obtained as the slope of the P_{MAX} –RTI linear regression, differences in the available RTI range may affect the robustness and sensitivity of the slope estimation, thereby contributing to the observed dispersion among modules.

Table 7 - BiFi values for the tested modules.

Power rating	S/N	BiFi	R ²
55 W	E002	$0.0358 \pm 1.6E-3$	0.8967
		$0.0255 \pm 4.2E-4$	0.8930
75 W	E010	$0.0293 \pm 3.9E-4$	0.8941
	B075	$0.0497 \pm 4.5E-4$	0.8953
	B130	$0.0387 \pm 3.4E-4$	0.9280
105 W	B274	$0.0346 \pm 3.3E-4$	0.9207
	D013	$0.0723 \pm 9.8E-4$	0.9023
	D047	$0.0643 \pm 7.8E-4$	0.9155
125 W	C121	$0.0813 \pm 5.5E-4$	0.9036
	C145	$0.0790 \pm 1.2E-3$	0.8580
		$0.0808 \pm 4.3E-4$	0.9056

Small variations in reflected irradiance distribution, spectral composition, ambient temperature and surrounding reflective surfaces may therefore affect the slope of the linear regression used to determine BiFi. In addition, differences in module geometry, rear active surface and layout configuration may contribute to the observed dispersion among samples.

3.4. Outdoor characterization results

69

It should be noted that the objective of this phase was conceived as an outdoor operational assessment of the module response to rear irradiance under realistic field conditions. Consequently, the use of naturally available RTI was a deliberate methodological choice aimed at capturing the module's behavior under actual operating conditions. The resulting measurements should therefore be interpreted as an assessment of field behavior rather than as a demonstration of equivalence with standardized indoor bifacial characterization procedures.

Table 8 – $BiFi/P_{MAX}$ comparison with available data from the literature

Producer	Identification	P_{MAX} [W]	BiFi	$BiFi/P_{MAX}$
Trisolar	E002	55	0.0358	6.51E-04
Trisolar	E002	55	0.0255	4.64E-04
Trisolar	E010	55	0.0293	5.33E-04
Trisolar	B075	75	0.0497	6.63E-04
Trisolar	B130	75	0.0387	5.16E-04
Trisolar	B274	75	0.0346	4.61E-04
Trisolar	D013	105	0.0723	6.89E-04
Trisolar	D047	105	0.0643	6.12E-04
Trisolar	C121	125	0.0813	6.50E-04
Trisolar	C145	125	0.0790	6.32E-04
Trisolar	C145	125	0.0808	6.46E-04
TRINA	M0	439	0.2747	6.26E-04
LG [170]	M1	434	0.3288	7.58E-04
LG [170]	M2	433	0.3326	7.68E-04
TRINA [170]	M3	439	0.2717	6.19E-04
TRINA [170]	M4	433	0.2749	6.35E-04
LG [170]	M5	430	0.3310	7.70E-04
TRINA [170]	M6	439	0.2688	6.12E-04
LG [170]	M7	435	0.3320	7.63E-04

The results in **Table 7**, normalized with respect to the rated power, were then compared with values provided by CIEMAT, obtained from the indoor characterization of the bifacial units used as reference modules in their rooftop experimental setup [170]. The figures, reported in **Table 8**, show good agreement between the two populations.

3.4. Outdoor characterization results

70

As prescribed by the IEC-TS 60904-1-2 [169], in **Errore. L'autoriferimento non è valido per un segnalibro.**, the P_{MAX} values for RTI equal to 100 and 200 W/m² are reported.

Table 9 – Calculation of $P_{MAX}(BiFi100)$ and $P_{MAX}(BiFi200)$.

S/N	BiFi	$P_{MAX}(BiFi100)$	$P_{MAX}(BiFi200)$
E010	0.0293	53.54 W	56.47 W

To provide an overview of BiFi analysis, **Figure 30** shows scatter plots of the values obtained for BiFi normalized by the bifaciality ϕ against power rating (**Figure 30a**) and rear active surface (**Figure 30b**). In both cases, the experimental points show a clear increasing trend. The linear fit reported in **Figure 30a** and **Figure 30b** yields a coefficient of determination (R^2) of 0.9519 and 0.9393 respectively, indicating that the available experimental data are consistent with an approximately linear dependence within the investigated range.

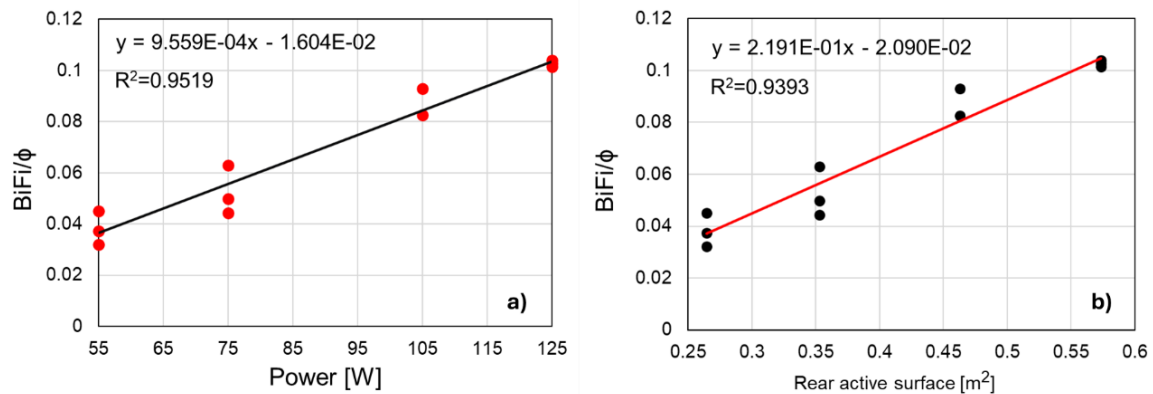


Figure 30 – Scatter plots of BiFi against power rating (a) and rear active surface (b).

Figure 31 integrates the scatter plots with the values BiFi/φ for the CIEMAT modules included in **Table 8**, providing a comparison with data extracted through indoor characterization. Including these data points only marginally modifies the parameters of the linear fit, while significantly improving R^2 to 0.9973 and 0.9971 respectively. This effectively aligns the trend obtained via the present outdoor method with indoor benchmarks, suggesting its robustness across a wide range of module power ratings.

3.5. Summary of uncertainty analysis for the procedure

71

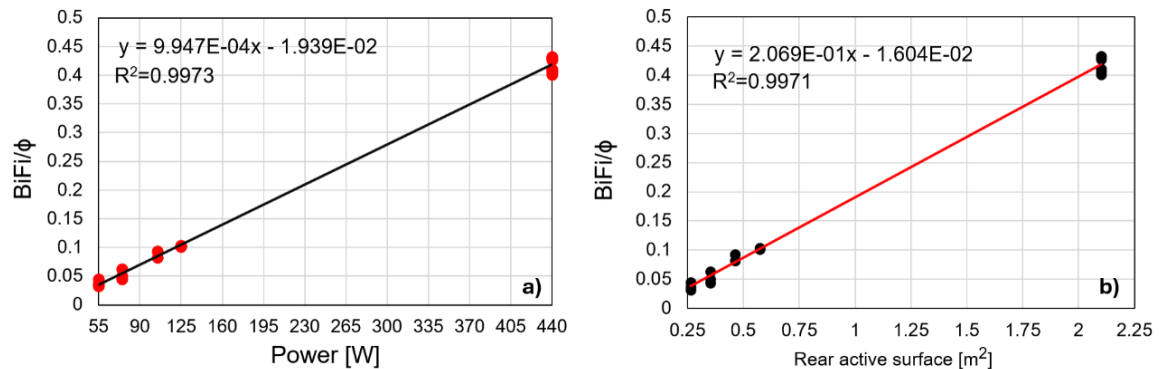


Figure 31 – Scatter plots of $BiFi$ against power rating (a) and rear active surface (b) with the addition of the data points provided by CIEMAT [170].

Nevertheless, the present dataset includes only a limited number of module sizes and repeated measurements on a small population of samples. Therefore, the observed trend should be regarded as preliminary and indicative only, and further experimental campaigns involving additional intermediate module sizes would be required to assess the generality of the relationship.

From a dimensional analysis standpoint, the scatter plot against the rear active surface is particularly interesting because, given how it is determined, the unit of measurement for $BiFi$ should be [m^2]. This would therefore suggest that a normalized parameter could be defined for specific cell technology and used as a multiplication factor for the rear active surface area to obtain the value of $BiFi$. Once again, however, the data available in this study are not sufficient to come to such a conclusion, and a more structured and detailed experimental campaign would be necessary to consider this possibility.

3.5. Summary of uncertainty analysis for the procedure

A comprehensive uncertainty assessment was carried out for all experimental datasets used for the validation of the procedure. The complete methodology, including uncertainty propagation procedures, regression-based contributions, and module-specific numerical results, is reported in Appendix C (**Table C1 – Table C3**). Briefly, the analysis combined Type A contributions arising from measurement repeatability and regression statistics with Type B contributions associated with instrumental accuracy and model-related effects, following the ISO/IEC Guide 98-1:2024 (GUM) [171]. For the acceptance-stage electrical characterization, the relative expanded uncertainty ($k=2$) remained limited across all investigated modules, with

typical values of approximately 1.0–1.4% for P_{MAX} , 0.7–1.0% for voltage-related quantities, and 1.3–1.6% for current-related quantities. For the normalized temperature coefficients, the expanded uncertainty remained generally low and was primarily governed by the statistical uncertainty of the linear-fit slope. Similarly, the bifaciality-factor determination exhibited limited expanded uncertainty for most modules, typically below 0.003, confirming the robustness of the adopted regression-based methodology. Overall, the uncertainty analysis supports the repeatability, consistency and practical applicability of the proposed outdoor bifacial characterization approach. However, a rigorous assessment of measurement accuracy relative to IEC TS 60904-1-2 would require a dedicated benchmark campaign against fully documented indoor measurements.

3.6. Long term performance and degradation testing

Along with the characterization procedure, four of the modules were subjected to long term testing to determine their performance and degradation over a prolonged period of time and compare the monofacial and bifacial configurations. The samples chosen for this test were B106 and B109, rated at 75W, A007 and A027, rated at 105W.

3.6.1. Experimental setup

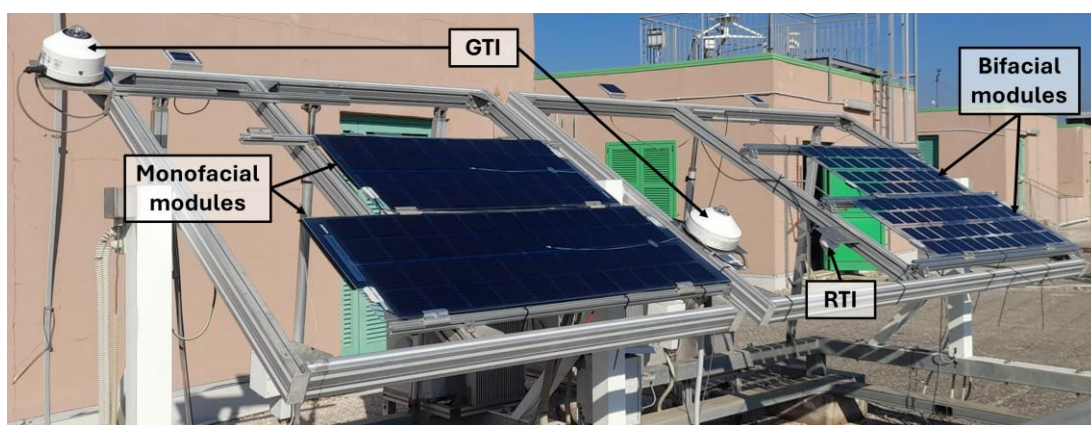


Figure 32 – Experimental setup for the long term performance and degradation testing.

The long term testing was performed on the fixed stand positioned at 30° tilt angle. As the samples were installed, a matte black plastic sheet was applied to cover the back of two of them, one per power rating, to simulate an equivalent monofacial unit. The setup (**Figure 32**) also includes the already described sensors for GTI, RTI and module temperature, and MPPT-

3000 devices for the acquisition of the modules' electrical parameters and I-V curves. Once every month, for 3-4 clear-sky days, the tilt angle is adjusted to give an AOI of 0° at noon. The I-V curves registered in this time frame are then used to evaluate the samples' monthly degradation.

For each module, I_{MAX} , V_{MAX} , P_{MAX} and back of the module temperature (T_{BOM}) are continuously monitored, along with the irradiance components of GTI and RTI, with a frequency of one minute. Furthermore, one I-V curve per sample is recorded every 10 minutes.

Data processing is divided into performance and degradation evaluation. Performance assessment leverages electrical parameters, T_{BOM} and irradiance to calculate representative metrics, namely energy production (E_{PV}), final yield (Y_F) and reference yield (Y_{Ref} and $Y_{Ref,BF}$) used to obtain the performance ratio (PR), and bifacial gain (BG), using the following formulas:

$$Y_F = \frac{E_{PV}}{P_n} \quad (8)$$

$$Y_{Ref} = \frac{H_{POA}}{G_{STC}} \quad (9)$$

$$Y_{Ref,BF} = \frac{H_{POA}}{G_{BSTC}} \quad (10)$$

$$PR = \frac{Y_F}{Y_{Ref}} \quad (11)$$

$$BG = \frac{E_{PV}^{Bifacial}}{E_{PV}^{Monofacial}} - 1 \quad (12)$$

In the calculation of Y_F , P_n is the nominal power obtained in the acceptance phase for the module's corresponding configuration. For Y_{Ref} and $Y_{Ref,BF}$, H_{POA} is the incident radiation on the module's active surface over the selected period of time, which includes the bifaciality-corrected rear irradiance for the samples in bifacial configuration. G_{STC} is equal to 1000 W/m², while G_{BSTC} is 1000 + $\phi \cdot 135$ W/m².

The IEC International standard 61724-1 on PV system performance monitoring [172] recommends the use of P_n in the calculation of Y_F , without providing any details about the conditions at which this metric is obtained. For this case in particular, the modules in bifacial configuration use the bifacial P_n values obtained through the outdoor characterization procedure, whereas the ones in monofacial configuration use the front side P_n . Furthermore,

the norm prescribes the use of “reference plane-of-array irradiance” for the calculation of $Y_{\text{Ref,BF}}$, without clarifying the entity of this parameter. It was therefore decided to use G_{BSTC} , which is the same value as the one used as reference for the bifacial I-V curves translation.

It is worth noting that this combination of parameters was only possible thanks to the preliminary parameter extraction through outdoor characterization, which gave access to specific metrics for bifacial and monofacial P_n and to the exact conditions at which these were obtained. Under normal circumstances, when only the manufacturer’s datasheet is available, it is of utmost importance that these conditions and parameters are as well-defined as possible in order to obtain representative and coherent results. This considerations will be particularly relevant in chapter 5 when discussing the results of the Infinity prototype, especially in terms of PR.

Monthly and overall values of these quantities are obtained to be used as KPIs for the samples and to compare the monofacial and bifacial configurations against each other.

For degradation, as anticipated, data from the 3-4 days where the tilt is adjusted to have an AOI of 0° at noon are used. In particular, I-V curves registered from 12:00 to 13:00 (solar time) are translated to STC and BSTC for the monofacial and bifacial configurations, respectively, using Anderson’s method. The average I-V curve is then determined and used to extract the electrical parameters at standard conditions, in an identical process to the one used in phase one of the characterization protocol (3.3.1). The evolution of the curve’s shape and that of P_{MAX} through the months is evaluated and used to assess the units’ degradation over time.

3.6.2. Results

Data acquisition for long-term performance and degradation testing was conducted from February to August 2025.

In terms of energy production (**Figure 33**), the modules in bifacial configuration show overall higher results. The 105W and 75W bifacial modules provided 9% and 11.8% more energy, respectively, compared to their monofacial counterparts. Monthly data show peaks in the summer, as expected, and figures for bifacial gain (**Figure 34**) indicate higher stability of this parameter for the 75W unit, with values concentrated between 11.4% in May and 12.4% in February. For the 105W samples, on the other hand, BG spans from 10.5% in February and March to as low as 7.2% in July.

3.6. Long term performance and degradation testing

75

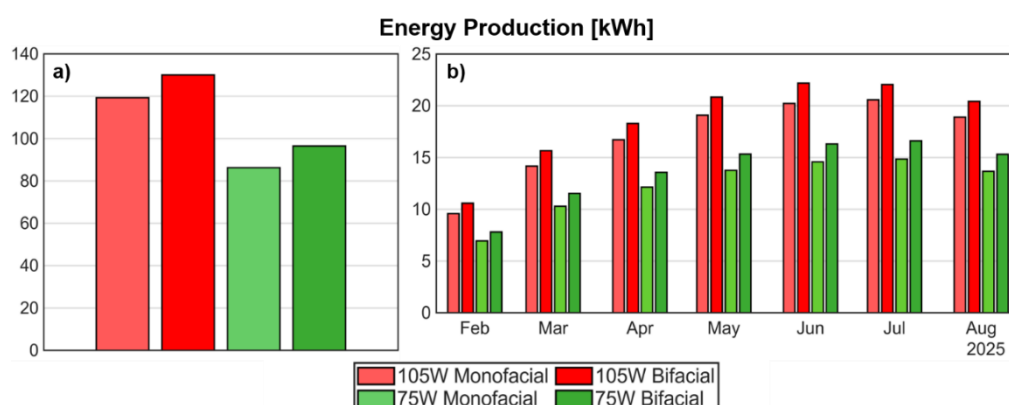


Figure 33 – Overall (a) and monthly (b) results for energy production after long term performance testing.

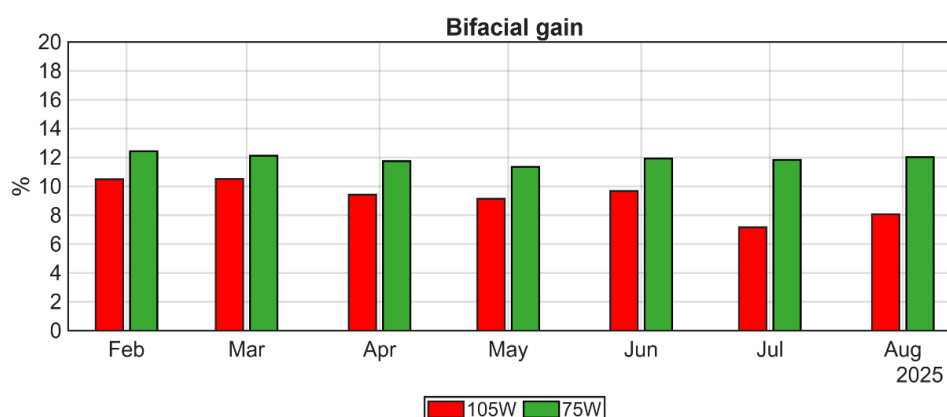


Figure 34 – Monthly values of bifacial gain

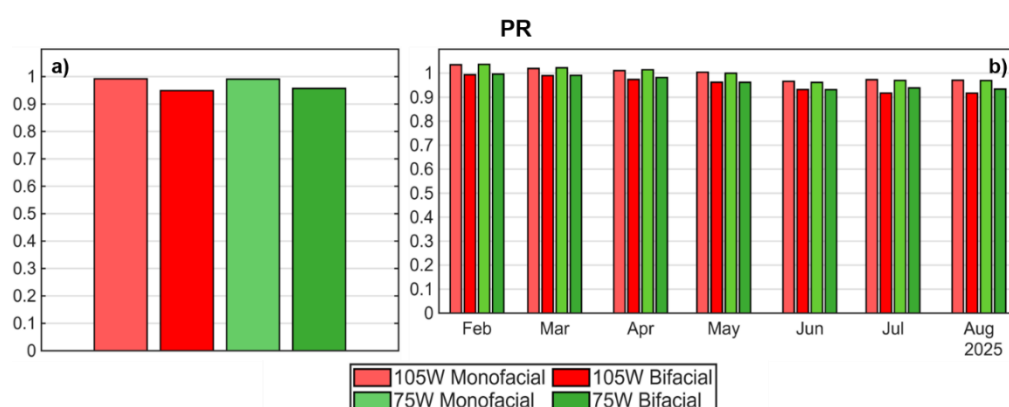


Figure 35 – Overall (a) and monthly (b) results for PR after long term performance testing.

Concerning PR (**Figure 35**), the values obtained are very high, which is compatible with the single-module configuration and with the absence of DC to AC conversion. The figures for the modules in bifacial configuration came out slightly lower. For the 105W-rated samples, the overall monofacial PR was 0.992, ranging between 0.966 in June and 1.035 in February, and the bifacial PR was 0.949, spanning from 0.917 in July and August to 0.994 in February. The 75W units generally registered similar values, showing an overall monofacial PR of 0.990, varying

3.6. Long term performance and degradation testing

76

from 0.962 in June to 1.037 in February, and a bifacial PR of 0.957, with values between 0.932 in June and 0.996 in February.

As evidenced by the results, the effects of seasonality manifest themselves with a reduction of this parameter during the summer months, which is associated with the higher ambient and module temperature reducing the energy conversion efficiency of the samples. This is also a partial justification for the values greater than 1 appearing in the winter and spring months for the monofacial modules. Another contributing factor might be that the black sheet covering the rear side of the module does not completely shield it from reflected radiation, thus causing a slight overestimation of the energy produced.

The evaluation of the degradation was carried out by monitoring variations in P_{MAX} and in the shape of the I-V curve at BSTC and STC. The power value and I-V curve registered during phase one of the characterization procedure were used as reference before any exposure of the samples to sunlight. At the end of each month a new measurement was performed and progressively added to the analysis.

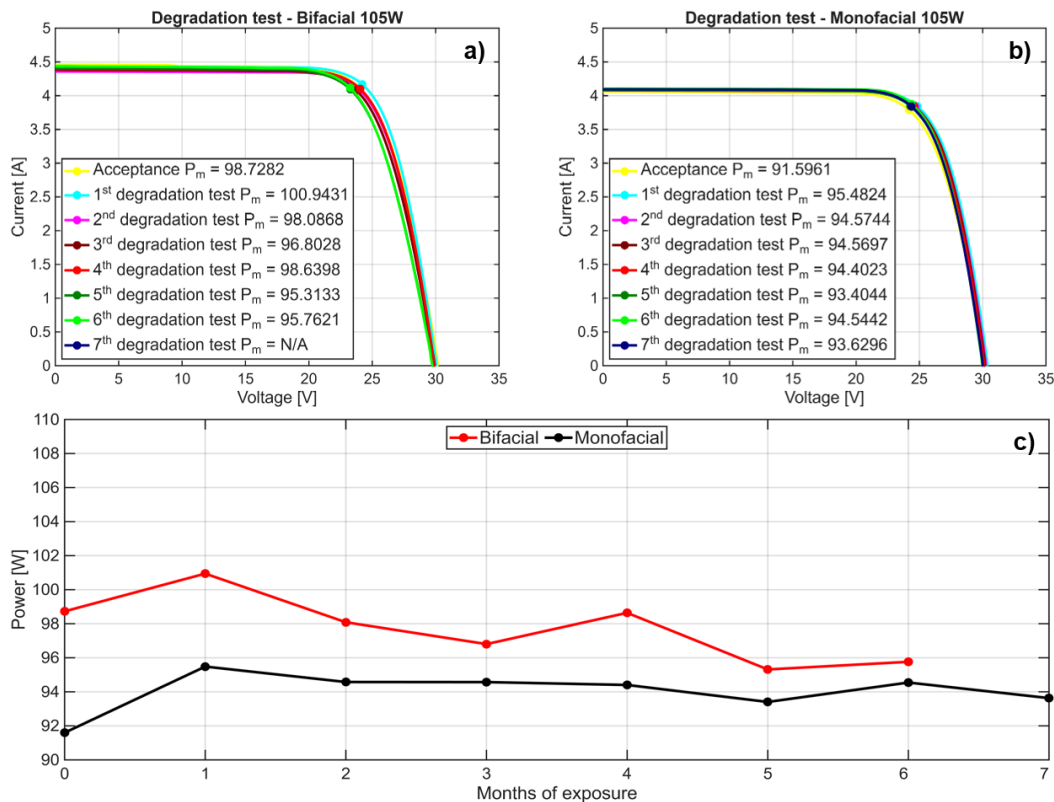


Figure 36 – Results of the degradation analysis for the 105W-rated modules: monthly I-V curves for the bifacial (a) and monofacial (b) configurations and evolution of P_{MAX} across the 7 months of exposure (c).

3.6. Long term performance and degradation testing

77

In the case of the 105W-rated modules (**Figure 36**), P_{MAX} showed greater stability in the monofacial configuration, with values from a minimum 91.6 W to a maximum 95.5 W and a standard deviation of 1.17. The bifacial power ranged between 95.3 and 100.9 W, with a standard deviation of 1.95. The shape of the translated I-V curves shows minimal variability across the months which, coherently with the results of P_{MAX} , is slightly more noticeable in bifacial configuration. Due to an error in the acquisition system, the value for the bifacial configuration after 7 month of exposure could not be registered and analyzed.

Similar conclusions can be drawn for the 75W modules (**Figure 37**). Once again, the monofacial configuration exhibits more stable P_{MAX} values, varying between 66.8 and 68.2 W with a standard deviation of 0.53. In bifacial configuration, the power spanned from 70.6 an 74.0 W with a standard deviation of 1.03. The I-V curves across the months overlap almost completely, with slight variations which are compatible with the fluctuation of P_{MAX} .

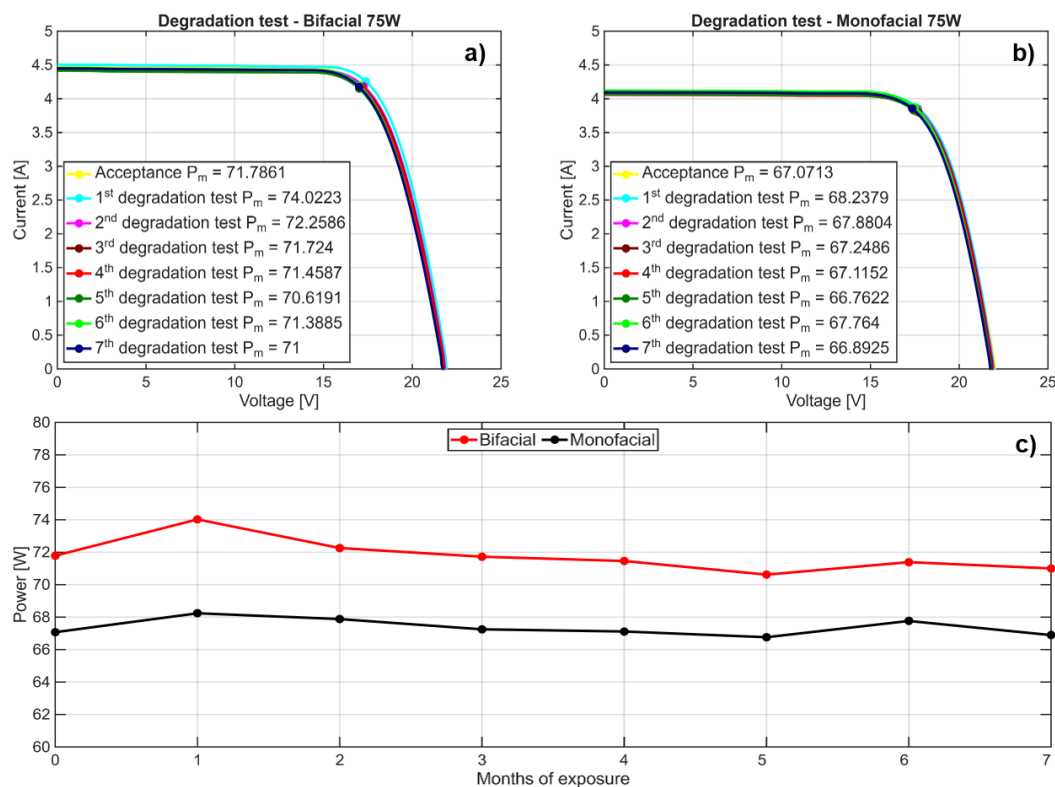


Figure 37 – Results of the degradation analysis for the 75W-rated modules: monthly I-V curves for the bifacial (a) and monofacial (b) configurations and evolution of P_{MAX} across the 7 months of exposure (c).

Overall, the results suggest very limited degradation in the testing period. A clear descending trend of P_{MAX} over time, which would indicate a loss of performance, could not be identified.

It is worth pointing out, however, that the evaluation was carried out using data measured in outdoor conditions which, as already extensively discussed in the description of the characterization procedure, are inherently variable. This introduces a degree of uncertainty in the results.

Nevertheless, long term performance and degradation testing was instrumental to assess the behavior of the samples in real operating conditions, and to perform a comparative analysis of the monofacial and bifacial configuration, complementing the information obtained from the characterization protocol.

Given the growing relevance of bifacial PV and the ongoing criticalities in determining their associated parameters and KPIs, the outdoor characterization protocol described in this chapter, alongside the experience acquired during this phase of the Ph.D. program, established a solid foundation for analyzing the results of the Infinity prototype (section 5.6). This stage was instrumental in underscoring the importance of clear manufacturer datasheet guidelines regarding the specific operating conditions under which nominal parameters are obtained. As anticipated in section (2.2.1), an evolution in this direction is already underway, with modern datasheets increasingly incorporating performance indications for bifacial panels not only at STC, but also at BSTC/BNPI.

4

Firm-PV simulation in Tor Vergata

This chapter discusses the numerical implementation and cost-optimization of the firm-PV generation strategy for the Engineering Macro-Area case study. The contents, methodologies, and figures presented are based on the paper “*Flexible photovoltaic generation strategy for Rome Technopole*” [141], published in *Energy Conversion and Management: X* (2025). The material is reproduced in accordance with the open-access reuse permissions of the journal.

This work is the evolution of a previous paper simulating the firm-PV concept for the Lazio region [140]. The present study was carried out with the Macro-area as a representative sample for the Rome Technopole campus, which, at the time of writing, is still under construction. The comparison is enabled by the similar function of the two buildings, both destined to teaching and research activities.

The Engineering Macro-Area of Tor Vergata is located in the eastern part of Rome, just outside the Grande Raccordo Anulare, the circular highway that encloses the city. It encloses multiple interconnected academic and research buildings dedicated to civil, industrial, electronic, and computer engineering departments. Functionally, the area handles an electrical load characterized by a continuous baseline demand for laboratories and server rooms, superimposed with fluctuating daytime loads driven by academic lectures, offices, and seasonal HVAC systems.

It is worth mentioning that the year 2023 will be cited multiple times throughout this chapter as a reference. This is due to the fact that the bulk of the activity described here was carried out between the end of 2023 and 2024, and thus, data from 2023 were the most updated.

The baseline for the transition from simulation to real-world testing is laid out in this chapter, presenting the case study around which the “Infinity” experimental prototype (presented in chapter 5) was designed.

4.1. Overview of the simulation case study

The study focuses on fine-tuning PV systems and battery storage (BESS) setups to address the energy needs of the Engineering Macro-area at the University of Rome Tor Vergata. The primary aim is to achieve this while simultaneously minimizing the LCOE. To accomplish this

objective, a comprehensive approach was adopted, considering various target self-production values. Each of these targets necessitates an accurate assessment of the optimal balance between PV oversizing (OVS), BESS size, and the resulting LCOE. OVS is a central parameter in the PV array design, since it constitutes the ratio between the potential energy production of the PV field and the total amount of energy consumed in the designated period (one year in the case of this study). BESS size is expressed as the "number of days of electrical demand stored" (NDY), indicating the consecutive days the system could operate solely on stored energy without relying on external sources. Both these parameters are strongly dependent on the electricity demand, which means that their design values are bound to differ from the ones that would be observed on the field. In section 4.2 the construction of the datasets that allowed to determine these quantities in this study is detailed, stating the reference periods for each dataset.

In view of the dynamic interplay between technological progress and economic factors, this analysis goes beyond current considerations. It integrates a forward-looking perspective by taking into account the evolution of parameters over the years and running simulations from 2023 to 2050. This time dimension ensures that the solutions discussed here remain adaptable and viable in the face of changing circumstances.

The main goal is to create a roadmap for the expansion of energy capacity in the Macro-area, aiming for a self-production rate of $\sim 100\%$. The LCOE shall remain below a threshold, that was defined as the value of the Italian National Unique Price of energy (PUN), which was 127 €/MWh in 2023 [173].

Building on the definition of the concept of firm PV power generation, introduced in section 2.3, this chapter first delves into the design process for generating a sample input dataset crucial for conducting comprehensive simulations. Then, it describes the algorithm used to methodically lower the cost of energy (LCOE), guaranteeing the economic viability of the suggested solutions.

Through this structured approach, this study aims not only to offer theoretical insights but also to provide practical strategies for achieving sustainable and cost-effective energy solutions tailored to the specific needs of the Macro-area of Engineering.

4.2. Construction of the input datasets

In order to apply the firm PV power generation to the Engineering Macro-area case study, various inputs are required spanning the period from 2013 to 2021, including:

- Solar irradiance and weather datasets
- Electricity demand
- Cost learning curves

4.2.1. *Solar irradiance and weather datasets*

Two primary sources were used to collect solar irradiance data: the “Copernicus Atmosphere Monitoring Service” (CAMS) [174] and the EsterLab facility, located within the Macro-area [156], [157], [158]. CAMS provides irradiation data derived from satellite observations for specific geographic locations and time periods. In this work, data were obtained for the period from January 1, 2013, to December 31, 2021, with hourly resolution. EsterLab's data, on the other hand, are acquired by ground-based pyranometers, with both one-minute and hourly measurements.

Since the data from EsterLab present gaps due to sensor malfunctions within the considered time frame, it was decided to use them only as a comparison parameter for the CAMS dataset. In the literature, the Root Mean Squared Error (RMSE) associated with the comparison between a dataset of irradiance estimated through satellite data and a dataset of irradiance measured by ground-installed sensors is typically reported to range between 50 and 100 W/m² [175]. The results of our comparison over the years 2013 to 2021 highlight the reliability of data obtained from satellites. Throughout the comparison period, the RMSE consistently remained below 55 W/m², except for 2015 (**Figure 38** and **Table 10**). During this particular year, the ESTER station encountered heightened occurrences of sensor and apparatus malfunctions.

For the weather dataset, ambient temperature and wind speed measured at EsterLab were integrated with data from station AL001 of ARPA Lazio, located within the CNR's Tor Vergata site [176]. Since the two measurement points are slightly apart from each other, the first step was to compare the two datasets. It was noticed that the temperature measured by the AL001 weather station is almost always lower than that measured by the EsterLab weather station (**Figure 39**).

4.2. Construction of the input datasets

83

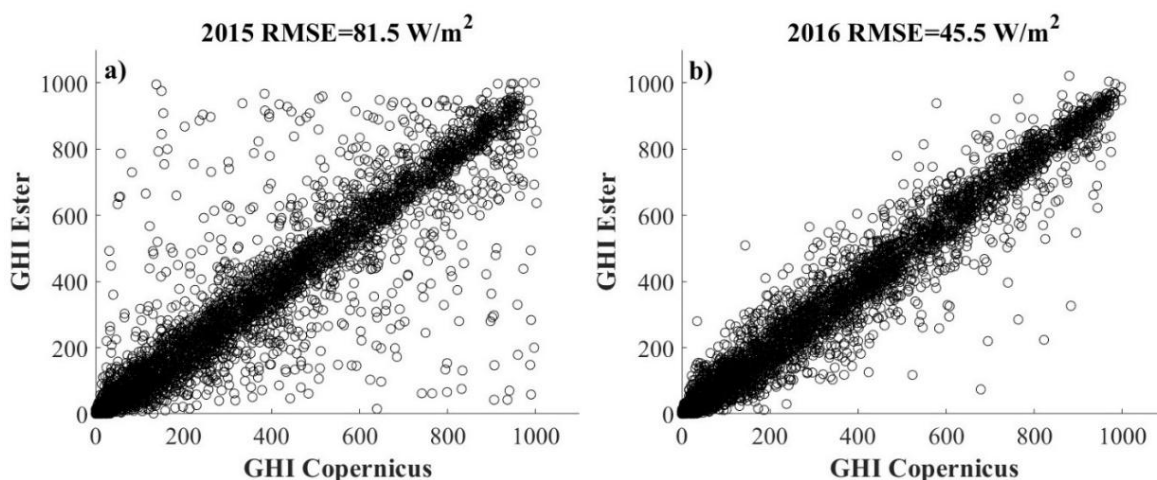


Figure 38 – GHI measured by ESTER and CAMS for 2015 (a) and 2016 (b).

Table 10 – Results of the comparison between the irradiance datasets of ESTER and CAMS.

Year	RMSE (W/m ²)
2013	46.3679
2014	45.7697
2015	81.4921
2016	45.5433
2017	52.1049
2018	52.5372
2019	47.6589
2020	46.1214
2021	45.7950

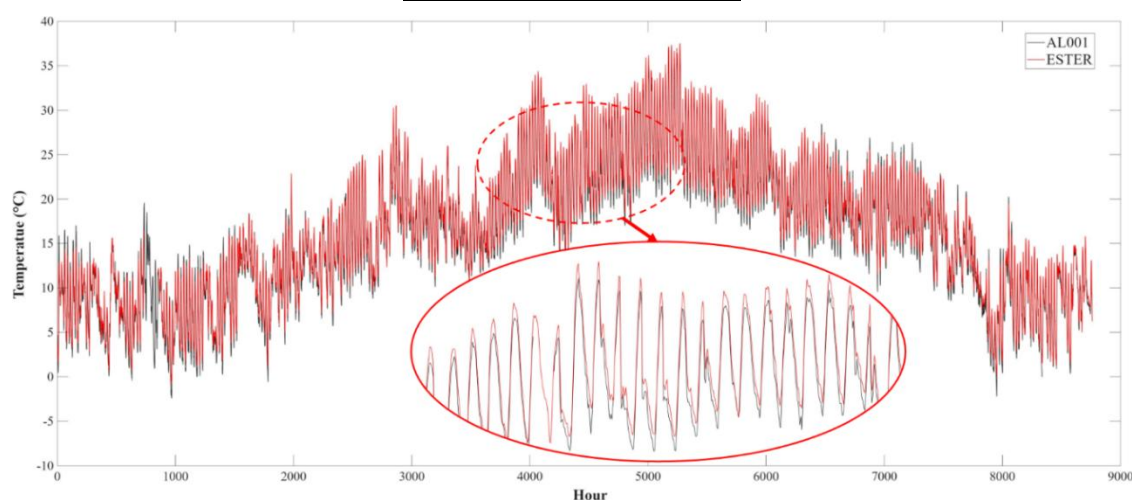


Figure 39 – Comparison of temperature datasets from the ESTER station (red) and the AL001 station (black). The enlargement highlights the differences between the two datasets.

The data from the AL001 weather station was therefore corrected by finding the following linear fit to serve as correlation between the two datasets:

$$T_{AL001,fit} = 0.932 \cdot T_{EsterLab} - 0.329 \quad (13)$$

The corrected temperature was then obtained using the equation:

$$T_{AL001,corr} = T_{AL001} + (T_{EsterLab} - T_{AL001,fit}) \quad (14)$$

Once the correction was applied, its effectiveness was verified by checking the correlation between the corrected AL001 data and the EsterLab ones, yielding a correlation coefficient of 0.995 (**Figure 40**).

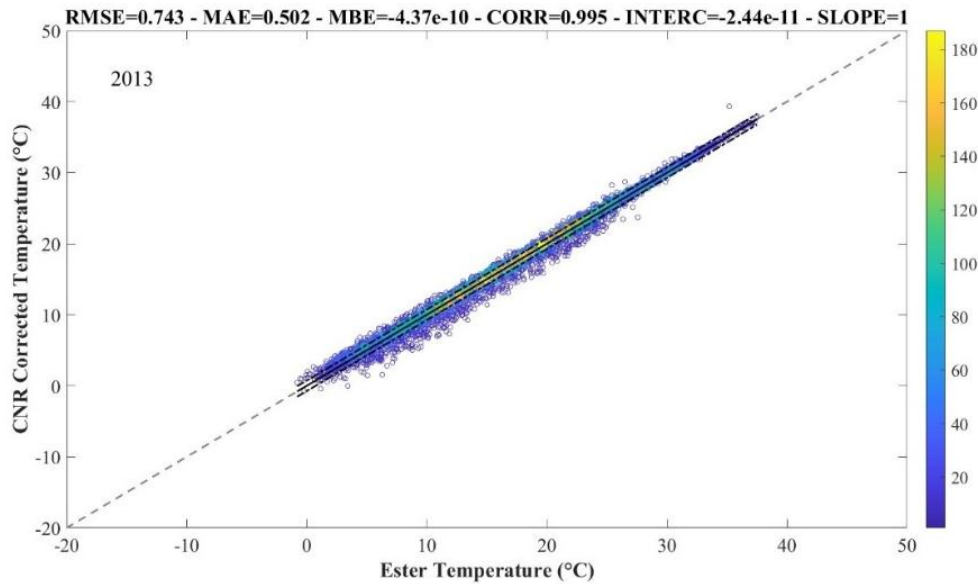


Figure 40 – Correlation between AL001 (corrected) and EsterLab temperature, color-legend represents the point density.

To translate the irradiance and meteorological datasets into photovoltaic power generation profiles, the industry-standard Sandia Array Performance Model (SAPM) was implemented. The simulation accounts for the physical and electrical behavior of the PV plant through the following modeling steps: first, GHI and DNI are transposed onto the module plane of array (GPOAI) incorporating solar geometry, absolute air mass corrections, and AOI losses. Second, module cell temperatures are dynamically computed using standard empirical thermal equations driven by ambient temperature, wind speed, and mounting-specific structural coefficients. Finally, DC power output is evaluated using empirical Sandia module performance coefficients, accounting for non-linear current-voltage responses under varying irradiance and spectral conditions, while AC power conversion and associated system efficiency losses are modeled via the Sandia National Laboratories (SNL) inverter database.

This modeling approach ensures high fidelity in reproducing long-term generation dynamics while minimizing potential transposition uncertainties in the subsequent optimizations.

4.2.2. Electricity demand

For the hourly electricity consumption of the Macro-area of Engineering only data for the year 2019 were available (**Figure 41**).

Since meteorological data span from 2013 to 2021 (included), an extrapolation of the hourly electricity consumption was conducted [27, 28], considering consumption variations with temperature and the associated day of the week, thus reconstructing the electrical demand for the missing years.

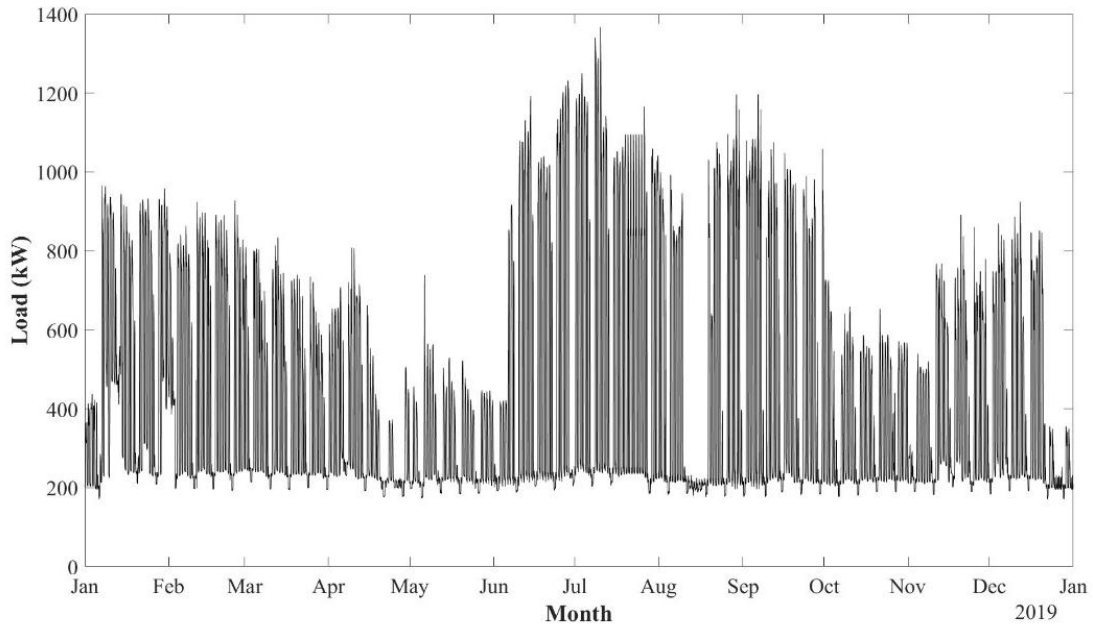


Figure 41 – Electricity demand of the Macro-area of Engineering in 2019.

Through statistical analysis, it became evident that over 55% of the annual hours consists of baseload (approximately 200 kW), and that instances of demand exceeding 1 MW are rare.

To understand the relationship between average daily energy usage, days of the week, and average daily temperatures, first, the daily energy usage and temperature for each day of the year were calculated. Following this, data for each day of the week were extracted from the two datasets and correlated using quadratic fits:

$$FIT_d = A_0 + A_1T + A_2T^2 \quad (15)$$

4.2. Construction of the input datasets

86

The fit parameters and RMSE for each day of the week are reported in **Table 11**.

Table 11 – Parameters of the quadratic fit performed between average daily load and temperature and RMSE for each day of the week.

Day of the week	A_0	A_1	A_2	RMSE [kW]
Monday	$1.12 \cdot 10^3$	-85.45	2.483	67.56
Tuesday	$9.51 \cdot 10^2$	-65.95	1.952	68.44
Wednesday	$8.36 \cdot 10^2$	-54.11	1.687	79.04
Thursday	$9.27 \cdot 10^2$	-62.08	1.851	64.10
Friday	$9.28 \cdot 10^2$	-64.32	1.923	71.62
Saturday	$6.48 \cdot 10^2$	-46.03	1.315	33.58
Sunday	$2.53 \cdot 10^2$	-4.763	0.112	10.96

This observation revealed that, on weekdays (Monday to Friday), the load increases as the average daily temperature deviates from 17°C in either direction. The fit levels off on Saturdays and becomes nearly horizontal on Sundays, when the educational and research activities are reduced or stopped and only the baseload remains, as evident from **Figure 42**. The plots for the days from Monday to Thursday are not reported since, as seen from the fit parameters, the one for Friday can be considered representative for all weekdays.

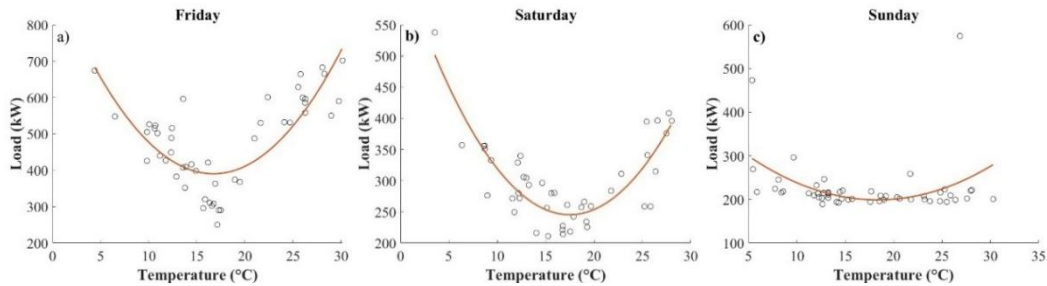


Figure 42 – Correlation between average daily load and average daily temperature in 2019.

The quadratic fits for average daily load and temperature are used to calculate the hourly load for a specific hour (h), day (d), and week (w) in the desired missing year using the following equation:

$$P_{year}(h, d, w) = P_{2019}(h, d, w) \cdot \frac{FIT_d(T_{year}(d, w))}{P_{daily\ avg, 2019}(d, w)} \quad (16)$$

The load associated with the corresponding moment in 2019 ($P_{2019}(h, d, w)$) is scaled by the ratio between the fit for the day of the week d under consideration (FIT_d), computed for the

4.2. Construction of the input datasets

87

average temperature in the selected day and week ($T_{year}(d, w)$), and the average load of the corresponding day in 2019 ($P_{daily\ avg, 2019}(d, w)$).

Table 12 – 2019 Electric demand compared to the extrapolated data (2013-2021).

	2019	2013-2021	Δ (%)
Average power [kW]	410	440	7.3
Maximum power [kW]	1367	1700	24.4
Minimum power [kW]	170	83.5	-50.9
Standard deviation [kW]	266	297	11.7
First quartile [kW]	220	225	2.3
Second quartile [kW]	247	310	25.5
Third quartile [kW]	560	597	6.6
Average annual consumed energy [GWh]	3.59	3.88	7.3

Equation (16) is used to calculate the hourly load for the missing years. Comparing extrapolated and available data, a 10% increase in the average load and energy consumed annually was observed on the reconstructed dataset. Regarding maximum power, an increase of about 25% was noticed, while minimum power saw a decrement of 50% (**Table 12**). These deviations can be attributed to the quadratic fit applied. For example, if a high load occurs at external average temperatures far from the abscissa associated with the vertex of the parabolic fit, the deviation will be more pronounced. Despite this, the reconstructed load profile aligns well with the reference year (2019), as the average power and the energy consumed annually are minimally affected. This is also apparent from the comparison between the duration curve of the consumed electrical power for 2019 (**Figure 43a**) and for the extrapolation (**Figure 43b**).

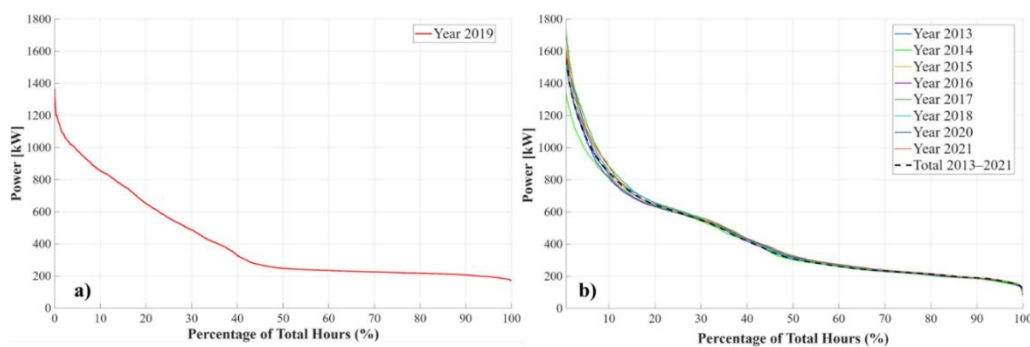


Figure 43 – Duration curves of electrical power consumption for the reference year (a) and for the extrapolated data of individual years (excluding 2019) along with the entire dataset (b).

4.2.3. Cost learning curves

The scenarios examined in this study are based on PV and BESS costs in 2023, with considerations extending to 2030, 2040, and 2050. These simulations leveraged the CAPEX values for PV and BESS provided by the National Renewable Energy Laboratory (NREL) [179]. The NREL delineates three distinct scenarios: conservative, moderate, and advanced. For the year 2023, the conservative values were adopted, while projections for future years were based on the moderate hypothesis.

Table 13 – CAPEX values used in the simulation.

Year	PV (€/kWp)	BESS (€/kWh)
2023	1037	312
2030	673	199
2040	613	175
2050	553	150

Table 13 summarizes the assumed values and **Figure 44** illustrates the CAPEX trends for PV and BESS across the three scenarios.

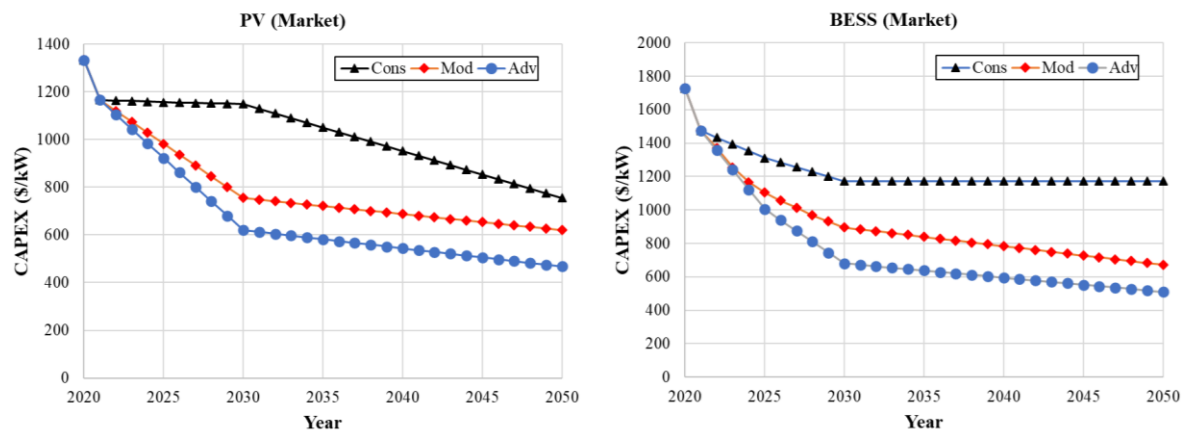


Figure 44 – PV and BESS CAPEX trends (moderate hypothesis) by NREL [179]

4.3. Optimization process – LCOE minimization

The ultimate objective of this study is to transform solar (PV) power generation into a reliable and cost-efficient energy source available 24/7, 365 days a year. This involves expanding the PV system beyond the usual size to reduce the BESS capacity needed. To do this

effectively, the optimization process aims at striking the perfect balance between lowering the necessary battery size and increasing the PV system's capacity. By reducing the cost of energy (LCOE) through this dual approach, the system becomes more economically feasible while ensuring consistent energy production, even when sunlight is scarce.

The optimization methodology utilized in this study is based on a brute-force approach, developed in MATLAB, which systematically explores the entire solution space to determine the optimal combination of PV and BESS capacity. The algorithm evaluates all possible combinations of PV oversizing (OVS) and BESS values within predefined intervals, enabling a comprehensive assessment of the trade-offs between OVS and storage capacity.

The Levelized Cost of Electricity (LCOE) is calculated using the following equation:

$$LCOE = \frac{E_{PVtoLoad} \cdot LCOE_{firmPV} + E_{BESStoLoad} \cdot LCOS_{firmPV} + E_{wind,imp} \cdot p_{wind,imp} + E_{resLoad} \cdot p_E}{E_{Load}} \quad (17)$$

where $E_{PVtoLoad}$, $E_{BESStoLoad}$ and $E_{resLoad}$ represent, respectively, the self-consumed PV energy, the energy supplied by storage, and the residual demand that must be covered by other dispatchable generators at the market price (p_E). E_{Load} is the total energy demand.

$LCOE_{firmPV}$ and $LCOS_{firmPV}$ refer to the levelized costs of PV and storage, respectively, considering only the portion of PV generation used to meet the firm demand. $E_{wind,imp}$ and $p_{wind,imp}$ indicate a possible contribution of imported wind energy and its associated price.

The production cost of PV ($LCOE_{firmPV}$) is computed as described in [180] while the cost of energy delivered by storage ($LCOS_{firmPV}$) is calculated using the detailed methodology developed in [181] which accounts for actual battery usage, including calendar aging, degradation through full equivalent cycles, and the resulting variable operation and maintenance (O&M) costs.

The algorithm, reported as a flowchart in **Figure 45**, begins by iteratively adjusting OVS values from minimum to maximum while simultaneously varying BESS values from maximum to minimum. Each combination of OVS and BESS is evaluated to meet the required level of self-production (SP), defined as the ratio between the electricity generated by energy-flexible PV systems with BESS and the total electricity demand ($0 \leq SP \leq 1$).

Battery capacity is expressed as the "number of days of electrical demand stored" (NDY), indicating the consecutive days the system could operate solely on stored energy without

Figure 45 – Flowchart of the algorithm.

4.4. Results and discussion

The simulations encompassed different levels of variable renewable energy (VRE) self-production (SP) to cover the electricity demand, ranging from 50% to 100%, highlighting the trend of LCOE with VRE penetration.

The calculation of LCOE was accompanied by determining the daily electric demand to be stored and the hours of operation for BESS. LCOE scenarios were computed as a weighted average of the constituent elements involved in the overall energy demand:

- The energy supplied to the grid by the batteries, multiplied by the Levelized Cost of Storage (LCOS) of the batteries.
- Any remaining electricity demand, if applicable, multiplied by the PUN.
- PV production utilized to fulfill the load or recharge the storage, multiplied by the LCOE of PV, which considers the requisite proactive curtailment.

Furthermore, an assessment of the available surfaces within the Macro-area was conducted to determine their extent, exposure, and possible shading. Finally, an economic analysis was performed for all simulated cases to calculate the pay-back period (PBP).

Before proceeding with the simulations, the minimum value of SP achievable by a photovoltaic system with just enough peak power to cover the energy needs of the Macro-area (no oversizing) without incorporating storage was verified. **Table 14** and **Figure 46** show the outcomes of the analysis.

It can be noticed that this scenario would require a PV system of approximately 2.5 MWp, which, however, would only cover about 49% of the electrical demand (SP = 49%), while the remaining 51% would be fed into the grid or curtailed, as it is produced when not needed. The corresponding LCOE for this setup is approximately €119/MWh.

These results underscore the critical importance of storage in aligning production with demand, thus minimizing reliance on the grid and ensuring optimal utilization of generated energy. Even increasing the OVS by 10 or 100 times, the maximum SP achievable would only increase to about 56%.

4.4. Results and discussion

92

Table 14 – Maximum self-production without storage

PV (MWp)	BESS (MWh)	SP (%)	OVS (-)	NDY (days)	Curtailment (%)	LCOE (€/kWh)
2.526	0	49	1	0	51	0.119

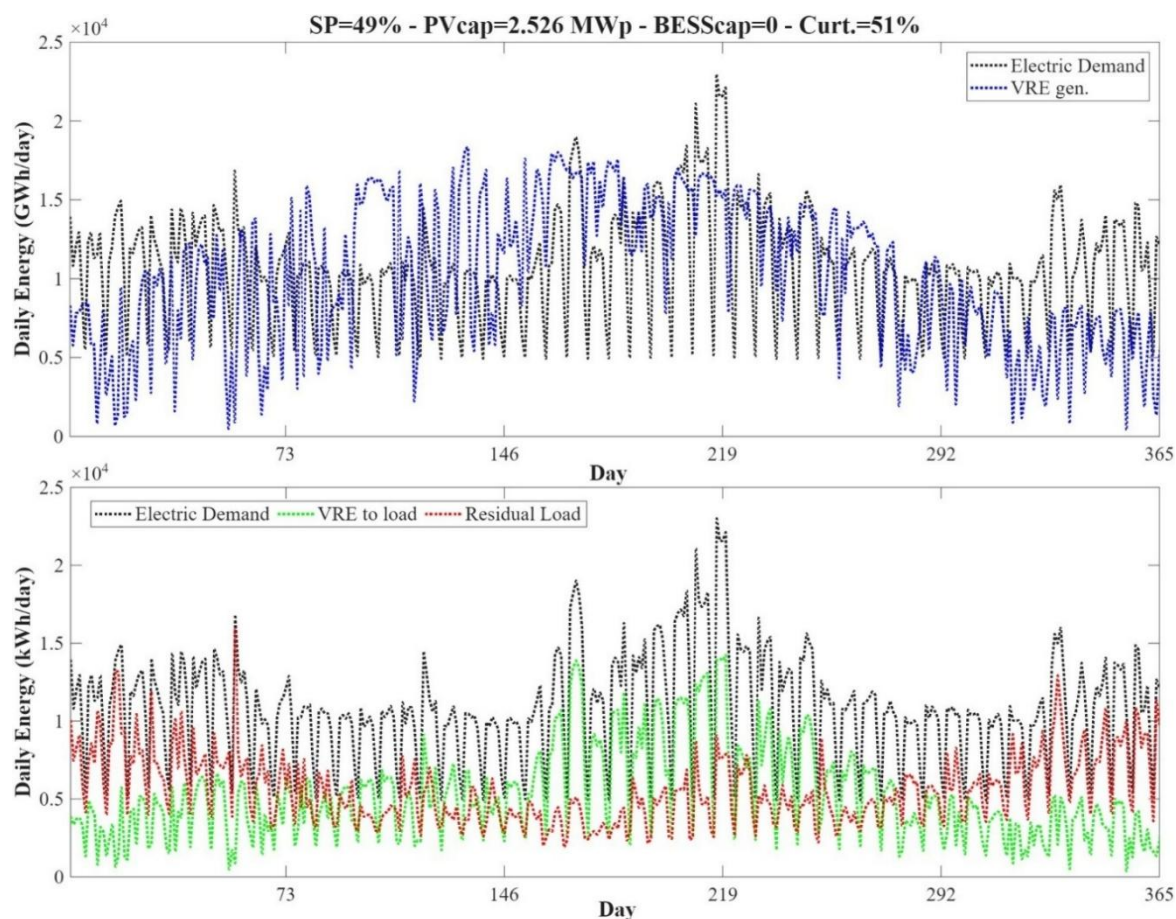


Figure 46 - Daily energy balance without storage and without oversize.

On the other hand, achieving 100% SP with a PV capacity sized to match annual demand (OVS = 1) would require an unrealistic battery capacity of approximately 3718.3 MWh (NDY = 350 days), resulting in an LCOE of around €4.2/kWh (**Table 15**). This value is clearly unsustainable, highlighting the need for a new methodology for sizing PV and BESS, aimed at minimizing LCOE.

Table 15 – BESS capacity and LCOE for SP=100% without PV overbuild (OVS=1).

PV (MWp)	NDY (days)	BESS (MWh)	Curtailment (%)	SP (%)	LCOE (€/kWh)
2.526	350	3718.27	0	100	4.2

4.4.1. Simulation results

The simulations presented here were conducted with varying degrees of self-production, ranging from 65% to 100%, while considering the CAPEX associated with both PV and BESS for the years 2023, 2030, 2040, and 2050. The outcomes of these simulations are summarized in **Table 16** and graphically depicted in **Figure 47**.

It is important to remember that the capacity values of PV and BESS have been determined through a minimization algorithm, that aims to identify the quantities of these two components that meet the required self-production while achieving the lowest possible value of LCOE among all combinations of PV and BESS.

Table 16 – Simulation results at different SP and Costs

SP (%)	PV (MWp)	BESS (MWh)	OVS (-)	NDY (days)	Curt. (%)	LCOE (€/kWh)			
						Year 2023	Year 2030	Year 2040	Year 2050
65	2.300	2.615	1.4	0.246	24	0.112	0.085	0.080	0.075
70	2.476	3.267	1.4	0.308	24	0.117	0.086	0.081	0.075
80	3.031	4.631	1.5	0.436	27	0.130	0.092	0.084	0.077
90	4.547	6.422	2	0.605	45	0.160	0.108	0.098	0.088
100	9.754	16.467	3.9	1.55	72	0.317	0.208	0.186	0.165

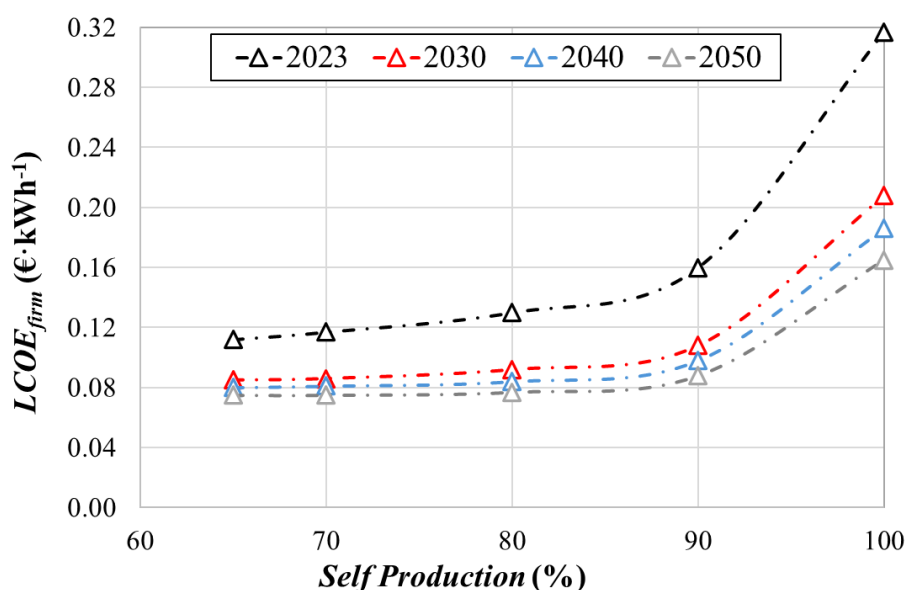


Figure 47 – PV and BESS CAPEX trends (moderate hypothesis used), by NREL.

The primary observation drawn from the analysis (**Figure 47**) pertains to the trend of LCOE against self-production, and CAPEX costs associated with PV and BESS. A distinct dual pattern

emerges. For self-production levels below approximately 87%, LCOE has a linear trend. Beyond this threshold, the slope of the trend increases sharply.

Notably, when focusing on the cost scenarios for the years 2030, 2040, and 2050, the slope of the linear trend (up to approximately 86%) appears very low. This suggests that it is feasible to increase self-production to higher levels without incurring significant increments in LCOE. For instance, considering the year 2030, transitioning from a self-production level of 65% to 80% results in an LCOE increase of approximately 8%. Further, extending to a self-production level of 87%, the corresponding increase in LCOE would amount to about 12% ($LCOE = 0.095\text{€/kWh}$, value extrapolated from the graph). However, beyond the 87% threshold, the increments in LCOE become more pronounced. Reaching a self-production level of 90% would increase the rise in LCOE to about 27% compared to 65% SP, while going all the way to 100% SP would mean an energy cost growth of 140%.

Figure 48 illustrates the relationship between curtailment and OVS against SP. It is noticeable that up to an SP value of 80%, both OVS and curtailment exhibit a relatively consistent pattern. This suggests that the increased capacity of the photovoltaic system resulting from oversizing predominantly boosts implicit storage in proportion to the SP increment. This becomes apparent when examining curtailment, which remains minimal during winter months with the increase in target SP, but grows during spring and summer (**Figure 49**).

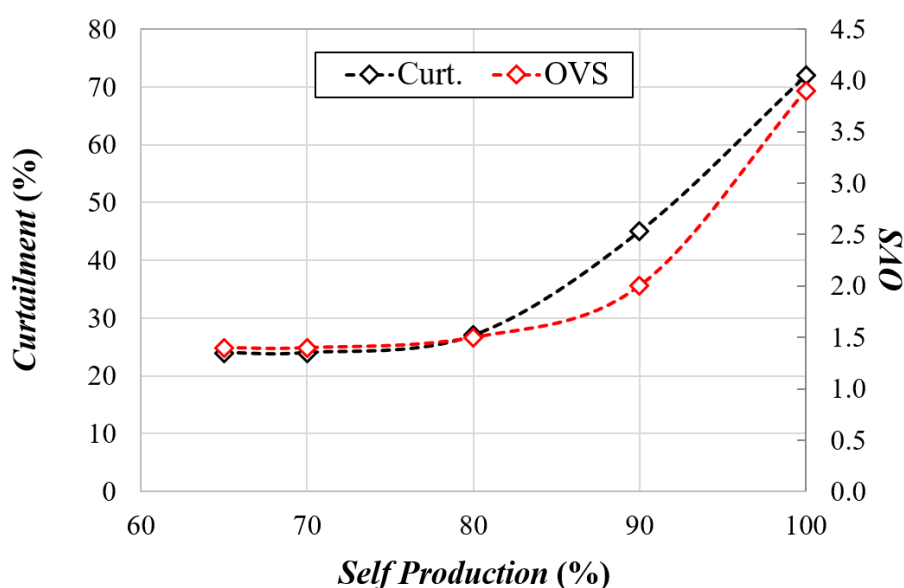


Figure 48 – Curtailment and OVS against SP.

4.4. Results and discussion

95

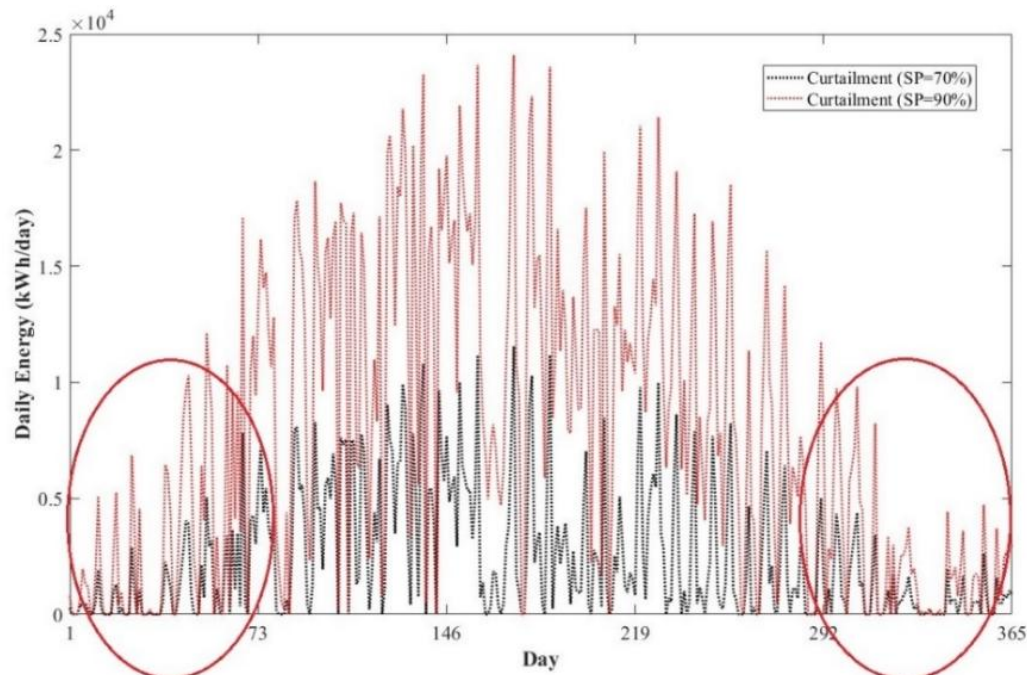


Figure 49 – Comparison between Curtailment for SP=70% and SP=90%.

For SP values exceeding 80%, the two curves in **Figure 48** diverge, suggesting that the overgeneration caused by OVS doesn't proportionately boost implicit storage. This results in an increase in curtailment even during winter months.

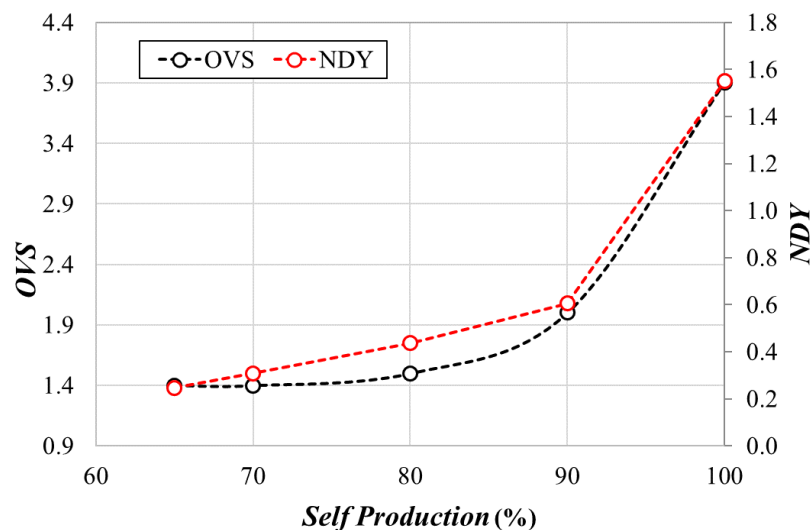


Figure 50 – OVS and NDY against SP.

It is also interesting to compare the trends of NDY and OVS as a function of SP (**Figure 50**). NDY essentially shows a trend with 2 slopes, the first, for SP < 90%, much lower than the second, for SP > 90%. The oversize of the photovoltaic system, as we said, is comparable to an implicit storage that assists the batteries in achieving a the target SP, and thus, the two quantities are closely related. Ideally, the coverage of electrical demand is completely

demanded to the PV system during daylight hours, and the battery mainly covers nighttime load. As SP increases, BESS capacity must grow to increasingly cover nighttime hours and minimize grid support. At the same time, OVS must also rise significantly to reduce battery usage during the day.

The results of the simulations served as the basis for crafting a strategic plan aimed at maximizing renewable energy integration within the Rome Technopole. This roadmap delineates four distinct steps (**Figure 51**), each marking a milestone towards reaching self-sufficiency in energy production.

The roadmap sets self-production targets of 65%, 80%, 90%, and 100% for the years 2023, 2030, 2040, and 2050, respectively. Additionally, it specifies the required capacities of PV and BESS, along with the LCOE compared to the average Italian national energy price (Prezzo Unico Nazionale – PUN) for 2023.

From the roadmap, it is clear that the first three milestones are easily attainable by comparing the LCOE to the average PUN of 2023. However, we also see that the 100% milestone is not economically feasible due to the high LCOE (165€/MWh compared to 127€/MWh). Nevertheless, it is possible to calculate the maximum SP achievable, matching the value of the PUN from **Figure 47**. By intersecting the calculated LCOE trend for 2050 with the PUN value, the maximum achievable SP is 95.5%.

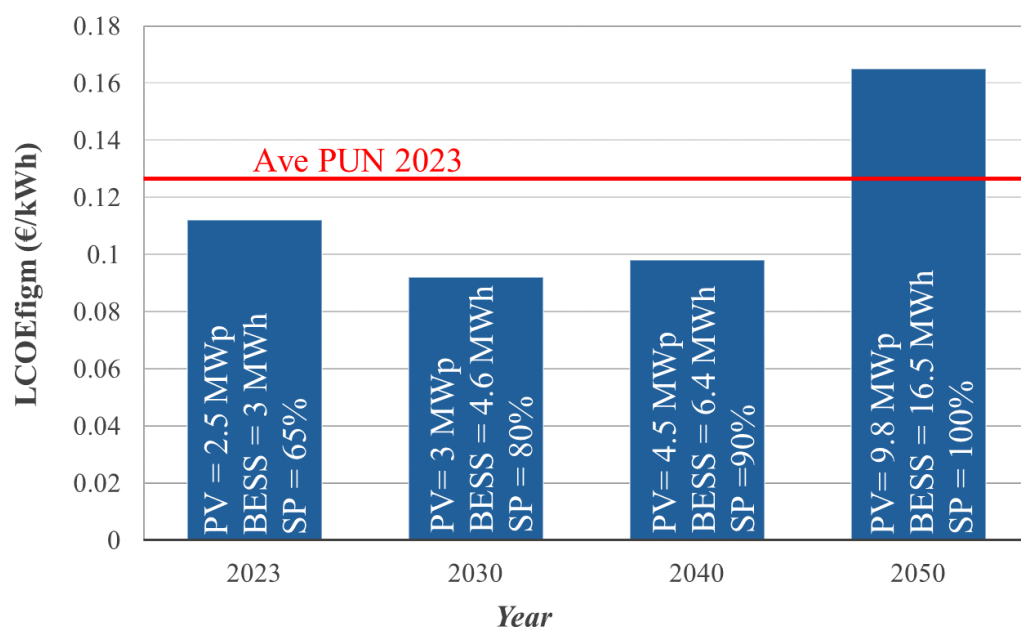


Figure 51 – Roadmap for the progressive implementation of the firm-PV generation strategy at the Engineering Macro-area of Tor Vergata.

4.4.2. Land occupation analysis

The subsequent step following the simulations involved assessing the availability of surfaces suitable for installing photovoltaic panels. A comprehensive analysis of all surfaces within the Macro-area was conducted, encompassing ground-level areas and rooftops (**Figure 52**). Potentially, there are around 110000 m² of usable spaces in the Macro-area (**Table 17**).

Table 17 – List of the available surfaces in the Engineering Macro-area.

#	Area (m ²)	#	Area (m ²)	#	Area (m ²)	#	Area (m ²)
1	33600	7	4700	13	1900	19	1050
2	7500	8	4800	14	1650	20	1500
3	11000	9	4800	15	2000	21	1100
4	14600	10	2000	16	610	22	1650
5	7500	11	500	17	1460		
6	3800	12	1250	18	1070		

Subsequently, these surfaces underwent a more detailed analysis, filtering out those susceptible to shading throughout the year or those with sub-optimal terrain conditions, among other factors. This process yielded approximately 65000 m² of suitable surfaces, more than adequate for the purposes of this study.



Figure 52 – Satellite image showing available surfaces in the Engineering Macro-area.

Surfaces 1 and 2, presently designated as parking areas for student vehicles, collectively span approximately 4 hectares. Assuming a PV-to-surface ratio of about 1 MWp per hectare, given that about 4.5 MWp are necessary to reach 90% self-production rate, it stands to reason that with optimal utilization of these surfaces, this target could, indeed, be met. To achieve 100% self-production, however, approximately 10 MWp are necessary, a rather high value that would require a much more intensive, almost complete exploitation of the available surfaces.

4.4.3. Economic feasibility (PBP)

Table 16 summarizes all the values obtained from the simulations, including PV and BESS capacities and the LCOE for various SP values with varying assumed costs.

LCOE is calculated considering the curtailed energy as lost, and not as fed into the grid and compensated (equation (17)). Considering that Italy currently allows selling unused energy production, a new parameter, named $LCOE_{feed}$, can be computed to study this scenario:

$$LCOE_{feed} = \frac{E_{PVtoLoad} \cdot LCOE_{firmPV} + E_{BESStoLoad} \cdot LCOE_{firmPV} + E_{wind,imp} \cdot p_{wind,imp} + E_{resLoad} \cdot p_E - E_{Curt} \cdot p_S}{E_{Load}} \quad (18)$$

Equation (18) is identical to equation (17) with the addition of E_{Curt} , which is the excess energy produced, that would otherwise be curtailed, and p_S , representing its selling price.

The results of this analysis are presented in **Table 18** for two typical years, 2023 and 2050.

Table 18 – LCOE comparison for firm PV generation and in 2023 and 2050.

2023			2050	
SP	LCOE (€/kWh)	LCOE _{feed} (€/kWh)	LCOE (€/kWh)	LCOE _{feed} (€/kWh)
65	0.112	0.086	0.075	0.045
80	0.130	0.098	0.077	0.051
90	0.160	0.094	0.088	0.051
100	0.317	0.103	0.165	0.054

As evidenced, the cost of electricity produced by the system strongly depends on the grid's capacity to accept excess power flows. To assess the feasibility of implementing a firm PV system considering the current ability to feed surplus energy into the grid, it is necessary to compare the $LCOE_{feed}$ value with the tariff per kWh at which energy is purchased from the grid by the user.

4.4. Results and discussion

99

To understand the profitability of a potential investment in the implementation of a firm-PV system, it is necessary to evaluate the net present value (NPV) and the pay-back period (PBP) associated with it. The initial investment (I_0) serves as the baseline for these evaluations. For the calculation of the NPV, a weighted average cost of capital (WACC) of 5% was used, along with the electricity price currently paid by Tor Vergata University, equal to 0.12 €/kWh, a plant lifespan of 30 years, and a selling price of excess electricity produced equal to 0.1 €/kWh. For the discounted PBP assessment, the year in which the NPV changes sign, from negative to positive, was identified.

The Internal Rate of Return (IRR) was calculated by assessing the WACC value that nullifies the NPV. The profitability analysis of the investments shows that the implementation of a firm-PV system capable of ensuring 65% SP is already profitable today. Achieving an 80% SP entails a discounted pay-back period of 28 years if implemented in 2023: despite the investment being characterized by a positive NPV, the pay-back period is too long. It is therefore advisable to wait to implement such a system (**Table 19**).

Using the values associated with the purchase and sale prices of electricity mentioned earlier, achieving self-production rates greater than 80% is currently not economically feasible.

Table 19 – Economic parameters related to the profitability of the investment in a firm-PV plant.

SP	Cost	I_0 (M€)	NPV (M€)	NPV _{rel} (M€)	PBP (years)	PBP _{disc} (years)	IRR (%)
65	2023	3.88	3.32	0.856	7	11	13
65	2050	2	5.66	2.83	3.5	5	27
80	2023	5.65	0.27	0.05	12	28	6
80	2050	2.89	3.76	1.27	6	9	16
90	2023	8.24	-3.55	-	-	-	-
90	2050	4.16	1.51	0.36	9.5	17	8
100	2023	18.9	-17.2	-	-	-	-
100	2050	9.57	5.6	-	-	-	-

5

The “Infinity” prototype

In this chapter, the firm-PV real-world prototype “Infinity” will be presented, along with the results of its first year of operation, which spans from April 2025 to March 2026. Infinity was designed using the previously discussed Engineering Macro-Area case study as a starting point, with the idea of verifying the simulation results under real operating conditions. In doing so, the prototype also helps to fill a gap in this scientific field, represented by the almost complete absence of experimental work within the firm-PV framework.

Infinity owes its name to the acronym “**IN**novative **F**irm **ge**NeRatIon proto**TY**pe” and it is fully composed of commercial PV plant elements (bifacial PV panels, smart inverter and Li-Ion battery energy storage system) plus a Matlab-controlled load emulator.

The relevance of this chapter in the framework of this work lies in depicting the transition from a simulation case-study to the implementation of a real-world testbed, enabling direct comparison between numeric and experimental results. This transition can be considered as the largest contribution of the work carried out during this PhD program.

5.1. From simulations to sizing

The sizing process started from the analysis presented in chapter 4, specifically on the results for the target 100% self-production for the Engineering Macro-Area of Tor Vergata, to be achieved while minimizing the LCOE. The two defining parameters are the oversizing factor, or OVS, which represents the plant’s annual energy production capability over the annual energy consumption, and the number of days of electrical demand stored, or NDY. The OVS, therefore, essentially defines the PV power installed, while the NDY determines the battery capacity needed. The simulation study found that an OVS of 3.9 and an NDY of 1.55 can provide 100% self-production with a curtailment rate of 72% while minimizing the LCOE (**Table 16**).

These values were, then, used to determine the reduction factor for the load. The system, as its first experiment, was set to run on the electrical demand of the Engineering Macro-Area of Tor Vergata from the year 2019, on which the simulations are based as well. The load needed to be scaled down to comply with the limitations of the load emulator (which will be discussed in the next section) and to have a suitable plant size to be installed at EsterLab, on the rooftop of the Industrial Engineering building at Tor Vergata. The choice of the reduction factor

happened by fixating the OVS and NDY values and repeating the simulations until suitable values were obtained.

The selected load reduction factor was 6185 which, combined with an OVS of 3.9 and an NDY of 1.55, results in 1.6 kWp PV power installed and 2.5 kWh battery capacity.

5.2. Final plant components and layout

The choice to rely solely on commercial equipment for the installation of the prototype required some adaptation of the parameters just discussed, since budget restrictions and market availability also had to be taken into account.

The final configuration of the plant consists of a DC-coupled system featuring three 605-W JA-Solar JAM72D40 MB bifacial PV panels [182], for a total installed power of 1.815 kWp, and a 5 kWh Huawei LUNA2000-5-S0 battery storage system (BESS), which comprises a LUNA2000-5-E0 battery module and a LUNA2000-5KW-C0 battery management system (BMS) [183]. The BESS features adjustable values for its state of charge (SOC) limits. In particular, the SOC floor can be set anywhere from 0 to 20%, while the SOC ceiling can be adjusted between 90 and 100%. This, effectively, allows to reduce the available battery capacity from 5 kWh down to 3.5 kWh. In the current configuration, for reasons that will be clarified in section 5.4, the SOC floor is set to 20%, while the SOC ceiling was left at 100%, giving a total available capacity of 4 kWh. This value, together with the PV power installed, results in an OVS of 4.56 and an NDY of 2.51 which, according to simulations, should provide 100% self production and a curtailment rate of 78% when applied to the electrical demand discussed above.

Along with the PV panels and BESS, the prototype also comprises other elements. The energy flows are managed by a Huawei SUN2000-2KTL-L1 smart inverter [184], which acts as the center of the system. The DC power generated by the PV array is distributed to the battery, the load and the grid. The inverter also requests power from the battery when the PV is not producing (e.g. at night) to continue covering the electrical demand. The connection between the inverter and the battery is DC/DC, while power sent to the load and to the grid is converted into AC. The inverter is currently set on the “Maximum self-consumption” option, which means it will prioritize using the power generated by the PV and the energy stored in the BESS to cover the electrical demand, only resorting to the grid when both these sources are insufficient. Also,

the excess power generated when the battery is at full charge is sent to the grid to simulate and, therefore, measure the curtailment rate, that would otherwise be impossible to determine. As anticipated, the power demand is provided by an ITECH IT-M3323 regenerative DC load emulator [185] with a capacity of 400 W, 150 V and 12 A. Given that the inverter output is AC, a Mean Well NDR-240-48 AC/DC converter [186] is installed between it and the load emulator. This element, with its 240 W, 48 V and 5 A capacity, defines the restriction the simulated electrical demand has to comply with. A CHINT DTSU666-H smart power sensor [187] is installed at the AC output of the inverter to correctly distribute the power between the load and the grid.

Figure 53 shows the schematic of the Infinity prototype plant, depicting the connections between the elements just described.

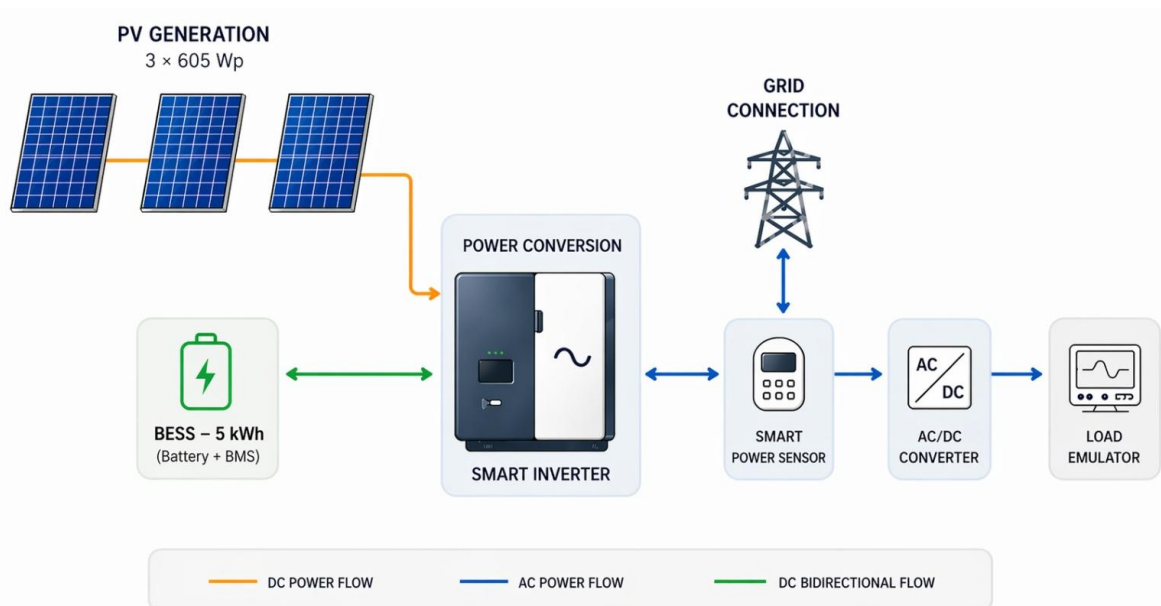


Figure 53 – Schematic of the Infinity prototype plant

5.3. Load emulation setup

The load profile chosen for the experiment is the electrical demand of the Engineering Macro-Area of Tor Vergata of the year 2019. The original table provided by the University contains hourly data. Other than reducing the values by a factor of 6185, it was decided to increase the time resolution to have smoother variations. Initially, a time resolution of 1 minute was chosen and the data was interpolated using the piecewise cubic hermite interpolating

polynomial (PCHIP) method, readily available in Matlab. This method was preferred for its ability to keep the curve smooth (unlike a linear interpolation) while avoiding overshooting and other artifacts typically associated with splines.

It was also decided to build a Matlab code that directly controls the power requested by the load emulator. This was deemed necessary as the control software recommended by the manufacturer only allows to input a limited number of data points, which does not suit long simulations like this one. On the other hand, Matlab is able to recognize the load emulator as a VISA (Virtual Instrument Software Architecture) object and directly interact with it using Standard Commands for Programmable Instruments (SCPI). The control program loads the electrical demand as a timetable directly from a .xlsx file containing the timestamps and the corresponding power request value. It then checks the date and time on the machine it's running on and, when the timestamp is hit, it updates the value on the load emulator. This effectively provides real-time management of the simulated power demand. Furthermore, the program provides the user with a "Stop" button, that immediately ends the simulation when clicked and resets the instrument. Every simulated power value with the corresponding timestamp is displayed on the Matlab command window as the simulation progresses, so as to allow the user to spot any errors or time misalignment. Each timestamp-power value pair is also progressively saved on a .csv file, useful in case of crashes or interruptions of the simulation not initiated by the user.

After testing the control program, the choice was made to lower the time resolution of the load to 5 minutes to match the highest available for the performance data from the inverter. The 1-minute update frequency would, therefore, not provide any benefit to the actual simulation, and a higher value reduces the likelihood of time misalignment caused by the code operation.

Figure 54a shows the load profile fed into the emulator for the whole year. The electrical demand is at its highest in the summer months (especially June and July), when the HVAC systems are most active, at times exceeding 200 W. Heating also plays a part in the winter, with peaks of around 120-140 W, while the load is at its lowest in spring and autumn, when air conditioning is disabled and energy consumption is mostly due to lighting and equipment. From a single-day standpoint (**Figure 54b**), given the function of the building, which is mainly active during the day, the power demand grows in the morning, stays stable in the central hours before decreasing in the evening. At night the power request is stable at what can be

5.3. Load emulation setup

105

considered a base load (30-50 W). The exceptions to this daily profile are Sundays and holidays, when the University is closed and only the base load is recorded (**Figure 54c**).

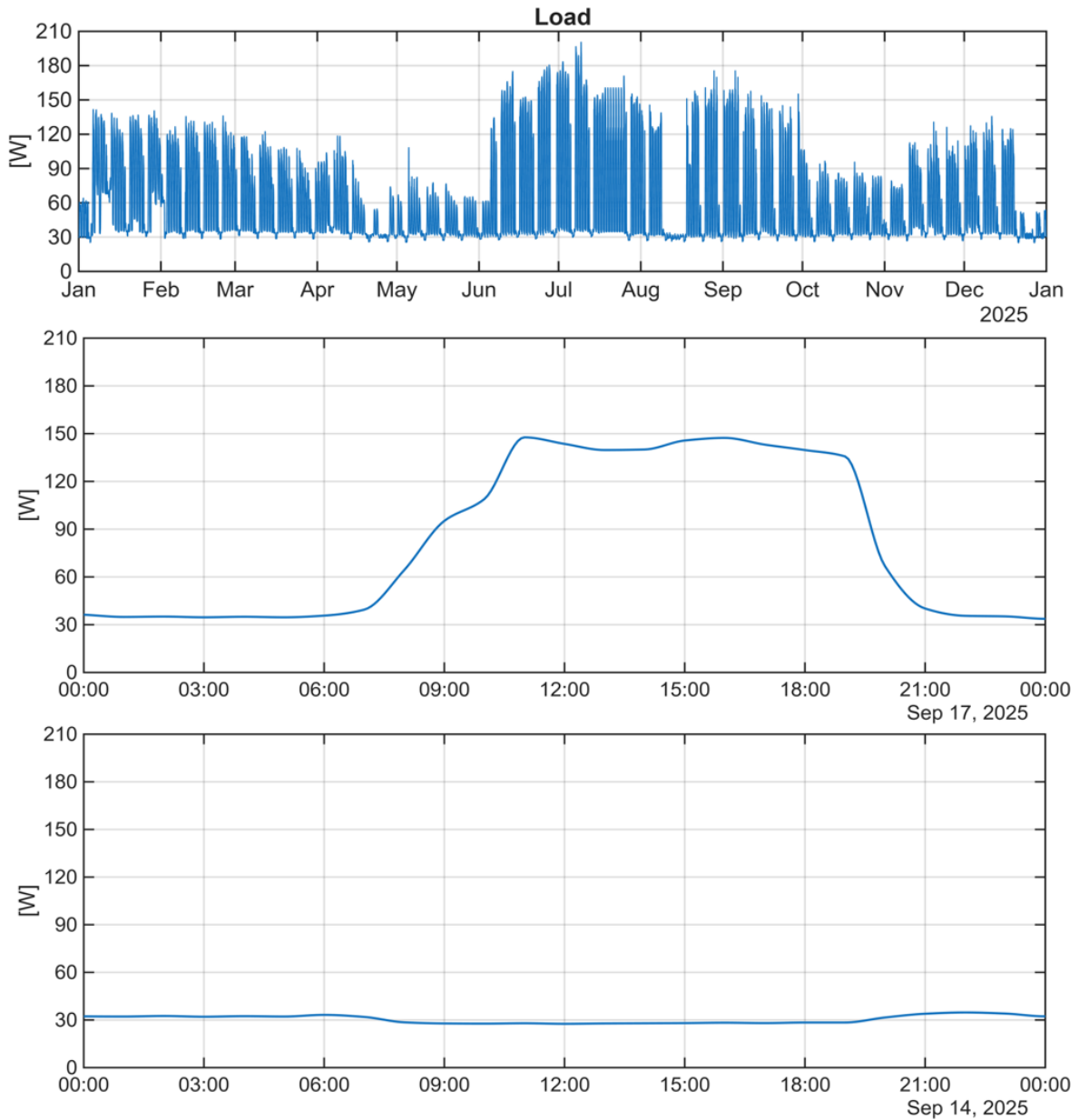


Figure 54 – Simulated load profile for the entire year (a) and detail for one weekday (b) and a Sunday (c)

Finally, it is worth mentioning that the simulated electrical demand is slightly different from the one that the plant actually sees, due to the presence of the AC/DC converter. This component introduces one additional element of power consumption that shifts the whole profile up and causes power spikes that reduce smoothness. This effect is evidenced in **Figure 55**, which compares the simulated load profile to the one that actually needs to be covered.

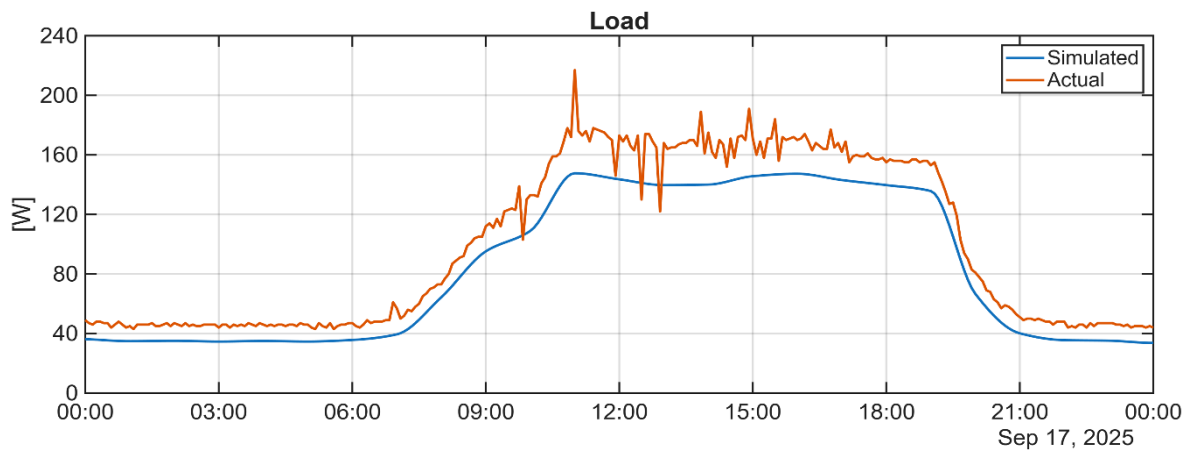


Figure 55 – Comparison between simulated load and actual load to meet.

5.4. Prototype fine-tuning and final settings

The installation of the prototype was finalized in November 2024. Before starting the experiments, though, the plant had to undergo some fine-tuning to determine the optimal operational settings for the single devices. It must be said that operating the system outside of the commercial boundaries set by the manufacturer was not an option, as they declared themselves unwilling to unlock any of the settings due to certification issues.

First and foremost, the SOC range of the battery had to be established. Initially, the idea was to set the SOC floor and ceiling so that only 2.5 kWh (50%) of storage capacity would be used, meeting the 1.55 NDY established by the preliminary simulations. However, as already discussed, the system would not allow a value higher than 20% for the SOC floor and lower than 90% for the SOC ceiling, so the choice was made to use these values, bringing the available capacity to 3 kWh, with a resulting NDY of 1.89. This configuration was ultimately changed again because testing showed that the system would, seemingly randomly, charge the battery up to 100% anyways once every few days. This made the value of the battery capacity uncontrollably variable within the experiment, which would complicate the data analysis process. The SOC ceiling was, thus, brought back to 100% for the final configuration, resulting in an available capacity of 4 kWh and in an NDY of 2.51.

Also in the battery settings, the charge/discharge mode was set to “Maximum self-consumption” and charging from the grid was disabled. The maximum charge and discharge power were left at their default values of 2500 and 2200 W respectively, the highest available.

For the inverter, the maximum active power was set to 2200 W, once again its default value and the highest available.

Table 20 summarizes the main settings of Infinity.

Table 20 – Main settings of the Infinity prototype

Setting	Value
Inverter maximum active power	2200 W
Battery maximum charge power	2500 W
Battery maximum discharge power	2200 W
Battery charge/discharge mode	Maximum self-consumption
Battery SOC ceiling	100%
Battery SOC floor	20%

5.5. Data acquisition, processing and analysis

This phase leverages Huawei's tool "FusionSolar" for acquisition and download of the plant's performance data, the EsterLab acquisition system for environmental quantities, and Matlab for filtering, gap filling and analysis.

5.5.1. Data acquisition

Data acquisition and download of the variables regarding the plant is performed via Huawei's proprietary tool FusionSolar, accessed through a dedicated web page. The tool gives access to a large number of variables, only some of which are selected to be analyzed.

Some of the relevant quantities (e.g. the electrical demand seen by the inverter) are not readily available and, thus, need to be obtained from a balance of power flows. Also, the choice was made to obtain some of the ones that are directly measured (e.g. the PV production) via power flows balance due to the direct measurement resulting less accurate. Example of these inaccuracies include negative PV production values (mostly -1) at night and unjustified imbalances between inverter input and output.

All the necessary calculations are performed in Matlab, and a .xlsx timetable is prepared, containing all the necessary data, and used from this point onwards for the next steps of processing.

Table 21 – Variables directly extracted from the FusionSolar tool.

Variable	Symbol	Variable information
Inverter active power	P_{active}^{inv}	Active power provided by the inverter at the AC output. Always ≥ 0 .
Power sensor active power	P_{active}^{sensor}	Active power measured by the sensor as grid exchange: >0 if exported to the grid <0 if imported from the grid $=0$ if no exchange is happening
Battery power	P_{batt}	Power exchange with the battery: 0 if the battery is charging <0 if the battery is discharging $=0$ if the battery is idle
Battery day charge	$E_{batt,chg}^{day}$	Total energy stored in the battery in the current day. Cumulative. Resets to 0 at midnight.
Battery total charge	$E_{batt,chg}^{tot}$	Total energy stored in the battery from plant commissioning. Cumulative.
Battery day discharge	$E_{batt,dchg}^{day}$	Total energy drawn from the battery in the current day. Cumulative. Resets to 0 at midnight.
Battery total discharge	$E_{batt,dchg}^{tot}$	Total energy drawn from the battery from plant commissioning. Cumulative.
Battery state of charge	SOC	Percentage of energy available in the battery compared to its full capacity of 5 kWh ($20\% \leq SOC \leq 100\%$).

Table 22 – Variables obtained indirectly through calculations using the directly extracted ones.

Variable	Symbol	Variable information	Formula
PV production	PV	Power produced by the PV array. Always ≥ 0 .	$PV = P_{active}^{inv} + P_{batt}$
Load	L	Power demand seen by the inverter (includes the AC/DC converter). $0\text{ W} \leq L \leq 240\text{ W}$	$L = P_{active}^{inv} - P_{active}^{sensor}$
Battery charge power	$P_{batt,chg}$	Power entering the battery. Always ≥ 0 .	≥ 0 values of P_{batt} .
Battery discharge power	$P_{batt,dchg}$	Power leaving the battery. Always ≥ 0 .	≤ 0 values of P_{batt} after sign change.
Curtailement	C	Power sent to the grid. Always ≥ 0 .	≥ 0 values of P_{active}^{sensor} .
Residual load	$L_{residual}$	Power drawn from the grid. Always ≥ 0 .	≤ 0 values of P_{active}^{sensor} after sign change.
PV to Load	L_{PV}	PV power directly sent to the load. Always ≥ 0 .	$L_{PV} = PV - P_{batt,chg} - C$

Table 21 presents the variables directly extracted from FusionSolar, while **Table 22** shows the ones obtained indirectly through calculations. In addition, data coming from the EsterLab weather monitoring system [6, 7, 8] is integrated into the timetable. This includes global horizontal irradiance (GHI), global tilted irradiance (GTI), rear tilted irradiance (RTI) and ambient temperature. To this, effective plane-of-array irradiance (G_E) is added, obtained as follows:

$$G_E = GTI + \varphi \cdot RTI \quad (19)$$

where $\varphi=0.8$ is the PV panels' bifaciality factor as stated on their datasheet. These quantities are integrated in the .xlsx timetable together with the plant's performance data. **Table 23** lists the variables included in the timetable with the respective units of measurement.

Table 23 – Variables included in the .xlsx timetable.

Variable	Unit of measurement	Variable	Unit of measurement
Timestamp	dd/mm/yyyy HH:MM	Battery day chg	kWh
Load	W	Battery total chg	kWh
PV production	W	Battery dchg power	W
Global Horiz. Irradiance	W/m ²	Battery day dchg	kWh
Global Tilted Irradiance	W/m ²	Battery total dchg	kWh
Rear tilted irradiance	W/m ²	Battery state of charge	%
Effective irradiance	W/m ²	Curtailment	W
Ambient temperature	°C	Residual load	W
Battery power	W	PV to Load	W
Battery chg power	W		

At this point the dataset still contains gaps and artifacts. These issues are mostly due to errors in data transmission from the plant to FusionSolar's servers, which happens via an internet connection. At first, the system was connected through Wi-Fi, the instability of which caused a number of data points to become lost. This problem was fixed in October 2025 by switching to a more stable ethernet connection, which practically eliminated data loss.

On the other hand, the acquisition from the EsterLab weather monitoring system proved very reliable and provided a very strong basis for the reconstruction of missing plant performance data.

5.5.2. *Data filtering*

Once the dataset was constructed, a number of filters are applied to eliminate potential unreasonable or inconsistent data points. It is worth pointing out that when filtering out a data point, all the variables coming from FusionSolar for that timestamp are deemed unreliable and are therefore erased. The variables registered by the EsterLab system are, instead, left untouched since they originate from a separate data stream. No filtering was applied to the EsterLab weather dataset, since it was deemed sufficiently solid.

First, the load is filtered to eliminate unreasonable power spikes and to make sure that all the values stay in the range between 0 and 240 W. The lower limit is dictated by the fact that a negative load is not feasible, while the upper limit is set by the limit of the AC/DC converter (section 5.2). Furthermore, a filter based on the moving median is applied to eliminate unreasonably steep peaks, even if they do not exceed these limits. The window size for the calculation of the moving median is set to 12 points (one hour) and the point is eliminated if it differs from the moving median by more than 60 W.

Then, the next filters are applied to PV production to eliminate any negative values, which are obvious measurement errors. It was noticed that these show up only at night, almost always as -1, and do not compromise the energy flows (i.e. the balance between load, battery and grid). Therefore, for these particular cases, the -1 value is simply overwritten with 0 in order to preserve the original data points. It was decided to also filter out any instances where the production exceeds the plant's installed PV power of 1815 W. Although in some specific conditions a plant might produce slightly above its capacity, it was noticed that values above 1600 W only presented themselves as isolated spikes that were not coherent with the measured GTI. This filter was also useful to catch some isolated data points showing a production greater than the maximum inverter active power of 2200 W.

Lastly, more filters are applied to eliminate situations that should either be impossible or not allowed by the system. These include instances where curtailment is greater than PV production (which is clearly impossible), points where curtailment happens while the battery is discharging (effectively sending energy from the battery to the grid, violating the "Maximum self consumption" setting), and cases where power is drawn from the grid even though the battery is not empty (which once again should be prevented by the "Maximum self consumption" setting).

All filters are applied in the order in which they have been described, so each filter acts on a progressively shrinking dataset. To give an idea of the number of data points erased, a distinction must be made between before and after the switch to ethernet connection, since the instability of the Wi-Fi is one of the main causes of data unreliability.

In the month of July 2025, when Infinity was connected to the internet via Wi-Fi, considering one interval every 5 minutes, the total number of data points should be 8928. The number of points downloaded from FusionSolar is 7076, which means that 1852 are already missing due to connection difficulties. After filtering, 350 more data points are erased, leaving a dataset at 6726 with 2202 to be reconstructed.

In December 2025, after the switch to ethernet connection, all the 8928 intervals are available on FusionSolar, showing the improved reliability of the system. Of these, 139 are filtered out and are the only ones that need to be reconstructed to obtain a full dataset.

Table 24 details the effects of data filtering on the dataset, showing the number of points filtered out in every step of the process and the situation at the end of the filtering phase for July 2025, December 2025 and for the whole experiment period from April 2025 to March 2026.

Table 24 – Number of data points deleted in every step of the data filtering process.

	July 2025 (Wi-Fi)	December 2025 (Ethernet)	Full experiment
Expected data points	8928	8928	105120
Downloaded data points	7076	8928	95157
Filters on load	258	63	1843
Filters on PV	2	0	33
Curtailment greater than PV	11	7	153
Curtailment while discharging battery	15	5	62
Residual load with battery not empty	64	64	825
Total deleted data points	350	139	2916
Data points after filtering	6726	8789	92241
Data points to be reconstructed	2202	139	12879

5.5.3. *Data reconstruction and consistency verification*

Since a complete and physically consistent dataset is required for the subsequent energy analysis, a dedicated gap-filling procedure was developed to reconstruct missing and filtered-out values while preserving the operating logic of the system.

Since the objective is to evaluate the long-term operational behavior of the prototype and calculate monthly and yearly energy performance indicators, a reconstruction procedure was implemented to restore dataset continuity while preserving physical consistency among the system energy flows.

A hybrid reconstruction methodology combining physics-based constraints and data-driven interpolation techniques was implemented in Matlab. Specifically, multi-layer feed-forward neural networks trained via Bayesian regularization were employed as auxiliary tools. The procedure relied primarily on measured environmental variables, temporal operating patterns, and the physical constraints imposed by the system architecture and control logic. The reconstructed variables were required to satisfy the energy balance relationships among PV generation, battery charging/discharging, curtailment, load and residual load.

Matlab native fitting and neural-network-based regression tools were employed as auxiliary reconstruction instruments to estimate missing values from the available valid measurements. The reconstruction process exploited correlations among irradiance, PV power generation, battery state of charge, inverter operation, and electrical demand profiles observed during normal system operation.

The predictive performance of the models was quantitatively evaluated through the RMSE computed on the validation subsets, demonstrating high precision and reliability across the reconstructed profiles. The values of RMSE were 73.89 W for the PV, 9.11 W for the load and 22.77 W for the battery power. The reconstructed data were subsequently verified through consistency checks on the system energy balances and comparison against available measured operating conditions before being integrated into the final dataset used for the yearly analysis. This approach allowed continuity of the experimental campaign while maintaining coherence among the calculated energy indicators and operational energy flows of the prototype.

5.5.4. Data analysis

Infinity's performance was evaluated through a set of energy-based indicators derived from the reconstructed dataset. All power variables were converted into energy terms using the sampling time step (5 minutes), enabling a coherent energy balance across different time scales, namely daily, monthly, and yearly aggregation.

The photovoltaic performance was assessed in terms of final yield (Y_F), reference yield (Y_{Ref}) and performance ratio (PR), obtained through equations (8), (9) and (11). The reference yield was computed from the measured effective plane-of-array irradiance on the bifacial PV field (H_{POA} , obtained from G_E , presented in equation (19)), which includes both front- and rear-side contributions. This formulation ensures that the bifacial gain is consistently embedded in the irradiance term. At the same time, in this case, G_{STC} (1000 W/m^2) was used instead of G_{BSTC} since the modules' datasheet indicates that the P_n of 605 W was obtained at STC.

Beyond standard PV metrics, the analysis focused on system-level indicators directly related to the design objectives of the plant. In particular, the self-production rate (SP) was defined as the fraction of consumption covered by on-site generation (i.e. excluding grid imports).

$$SP = \frac{E_{load} - E_{residual\ load}}{E_{load}} \cdot 100 \quad (20)$$

The curtailment rate was evaluated as the fraction of PV energy not utilized. This metric is particularly relevant in assessing the effectiveness of the storage system and the overall energy management strategy.

$$Curtailment = \frac{E_{curtailed}}{E_{PV}} \cdot 100 \quad (21)$$

These indicators directly feed into the design philosophy of the prototype, as they were used in the Tor Vergata simulation and, thus, provide a direct comparison with it.

The energy exchange with the battery was analyzed through charge and discharge efficiencies, computed as the ratio between energy effectively stored or released and the total energy processed by the battery.

$$\eta_{chg} = \frac{E_{chg,stored}}{E_{chg,in}} \cdot 100 \quad (22)$$

$$\eta_{dchg} = \frac{E_{dchg,out}}{E_{dchg,released}} \cdot 100 \quad (23)$$

$E_{chg,stored}$ and $E_{dchg,released}$ are the difference in $E_{batt,chg}^{tot}$ and $E_{batt,dchg}^{tot}$, respectively, between the beginning and the end of each analyzed interval (day, month or year), while $E_{chg,in}$ and $E_{dchg,out}$ are obtained from converting $P_{batt,chg}$ and $P_{batt,dchg}$ into energy terms. This essentially means evaluating the share of energy dissipated as losses during battery charging and discharging.

Furthermore, round-trip efficiency was computed as the ratio between energy entering and exiting to quantify the overall effectiveness of the storage system. It is important to mention that this metric is not intended as a system-level round-trip efficiency, but rather as a measure of the battery's ability to release the energy it stores.

$$\eta_{RT} = \frac{E_{dchg,released}}{E_{chg,stored}} \cdot 100 \quad (24)$$

The efficiency analysis was carried out in collaboration with the CIEMAT institute in Madrid, Spain. During a research stay of 4 months between June and October 2025, a comparative analysis was conducted between Infinity and an equivalent plant installed at CIEMAT. Most of the components are exactly the same, with the two systems differing only in peak power installed (1815 W for Infinity and 1325 W for the CIEMAT plant) and in the load emulator. The Madrid system features a 3-kW AC emulator that was of critical importance to test the other components beyond the load limits of Infinity, stated in section 5.2.

This comprehensive set of indicators provides a full characterization of the Infinity prototype. While the PV-specific metrics (Y_F , Y_{Ref} and PR) allow for a standard assessment of the generation components, indices such as self-production and curtailment are crucial for evaluating the firmness of the power delivery. The analysis enables a direct comparison between experimental performance and the preliminary simulation benchmarks, ensuring, at the same time, that any deviations from the firm-PV behavior can be isolated and attributed to either environmental variability or specific component inefficiencies.

5.6. Prototype performance in the first year of operation

This section is dedicated to the presentation and discussion of the results achieved by the prototype after one year of operation. Representative experimental data cover the period from the beginning of April 2025 to the end of March 2026. The results will be presented in three sets of parameters: first the PV metrics (Y_F , Y_{Ref} and PR), then the firm-PV indicators (SP and curtailment rate), and finally the BESS efficiencies (η_{chg} , η_{dchg} and η_{RT}) will have their own section, to explain the joint analysis carried out during the research stay in Madrid in detail.

Before delving into the single sets of parameters, **Figure 56** provides an overall energy balance in terms of load coverage and allocation of PV-generated energy. 58% of the load was covered directly by the energy generated by the PV array, with 40% being covered by the battery. This leaves 1.4% residual load, which had to be covered by importing power from the grid. From the point of view of the energy produced by the PV, 12.8% was used directly to cover the electrical demand, 18.7% was used to charge the battery and the remaining 68.5% was curtailed (or, in this case, fed into the grid).

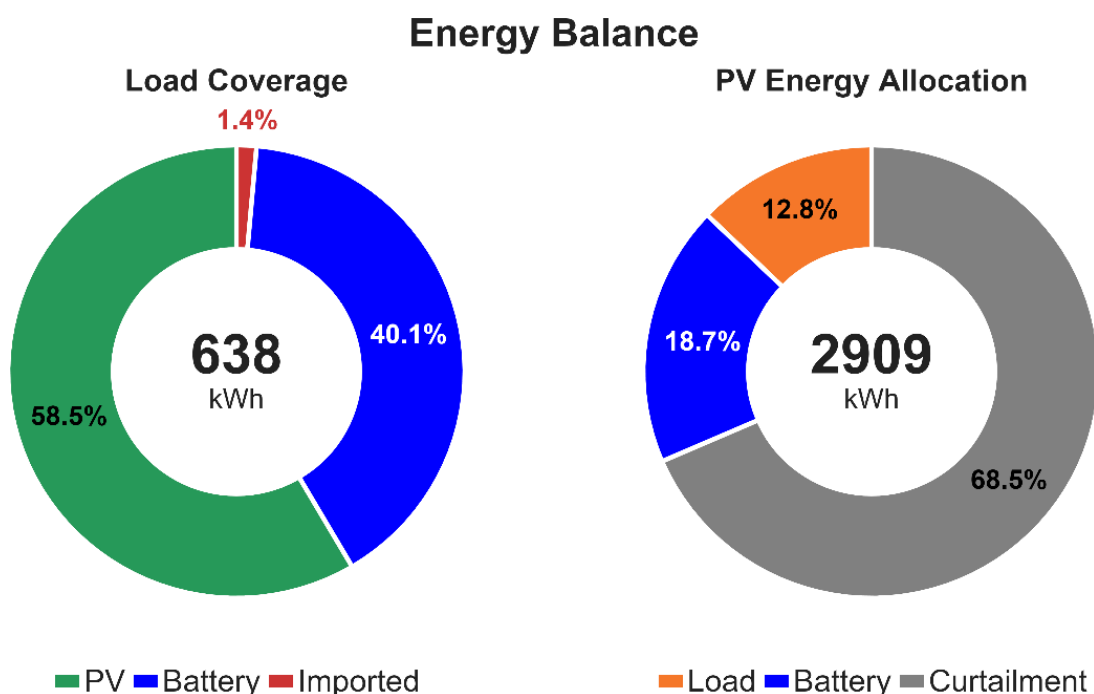


Figure 56 – Energy balance over one year in terms of load coverage and allocation of PV-generated energy.

5.6. Prototype performance in the first year of operation

116

5.6.1. PV metrics

The first set of parameters includes standard indicators used to evaluate the performance of PV systems, namely final yield (Y_F), reference yield (Y_{Ref}) and performance ratio (PR).

For final yield and reference yield, the analysis over one year suggested values of 1603 kWh/kW and 2013 kWh/kW, respectively. On a monthly basis, as shown in **Figure 57**, the highest figures were registered in July 2025, at 183 kWh/kW for Y_F and 243 kWh/kW for Y_{Ref} , while the lowest were experienced in January 2026, at 62 kWh/kW for Y_F and 69 kWh/kW for Y_{Ref} .

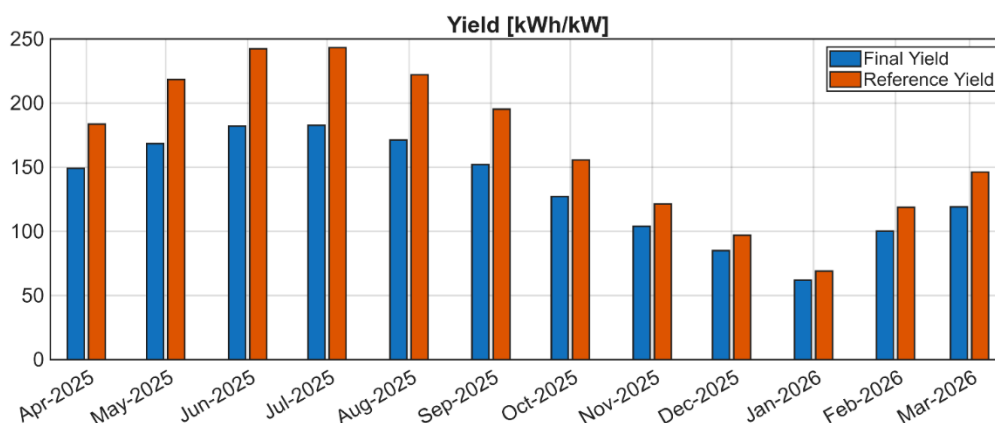


Figure 57 – Monthly values of final yield and reference yield for the Infinity prototype.

In terms of PR, the yield figures reported above produced an overall value of 0.796. Monthly results, available in **Figure 58**, suggest that this parameter varied, over the experiment period, between a minimum of 0.753 in July 2025 and a maximum of 0.898 in January 2026.

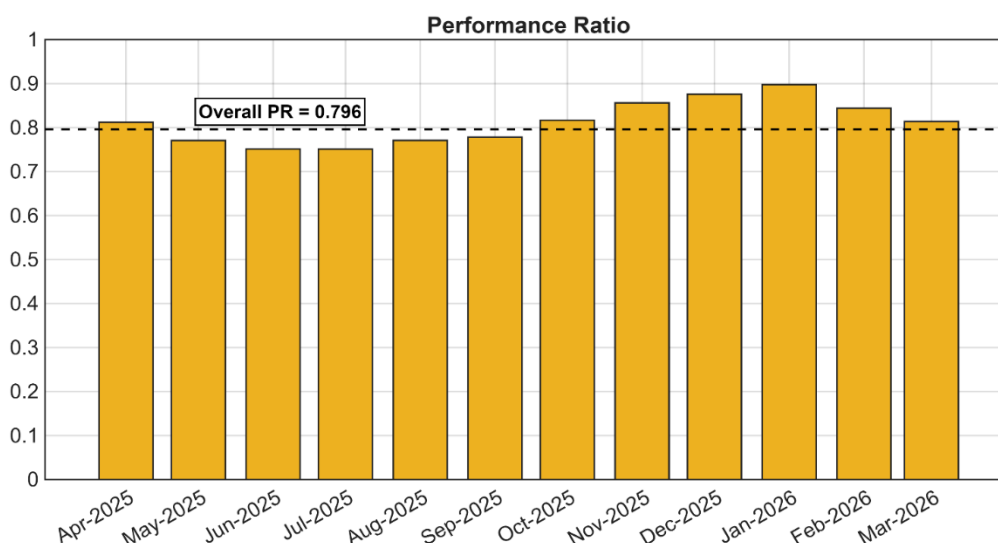


Figure 58 – Monthly figures and overall value of PR for the Infinity prototype.

5.6. Prototype performance in the first year of operation

117

The effects of seasonality are evident in both bar plots (**Figure 57** and **Figure 58**). In the summer, PR is generally lower, even with greater Y_F and Y_{Ref} , mostly due to warmer ambient temperature and, in turn, higher module temperature, which causes a decrease in efficiency. In the winter, conversely, even though Y_F and Y_{Ref} are much lower, the colder temperatures result in a higher performance ratio.

5.6.2. Firm-PV indicators

This set of parameters is particularly important to evaluate the prototype against its numerical simulation counterpart. As stated in section 5.2, the expected values for self-production and curtailment rate over one year with the current configuration were 100% and 78% respectively.

Figure 59 shows the monthly figures and an overall 98.6% self production during the experiment period. As we can see, the most critical month was January 2026, where the registered SP was 88.9%, meaning that the prototype needed grid support for more than 10% of the electrical demand. Conversely, in 8 out of the 12 months analyzed, Infinity was able to fully cover the power load with PV-generated and battery-stored energy. Furthermore, in 2 of the 4 remaining months, the SP rate exceeded 99% (November 2025 – SP = 99.2%, December 2025 – SP = 99.9%).

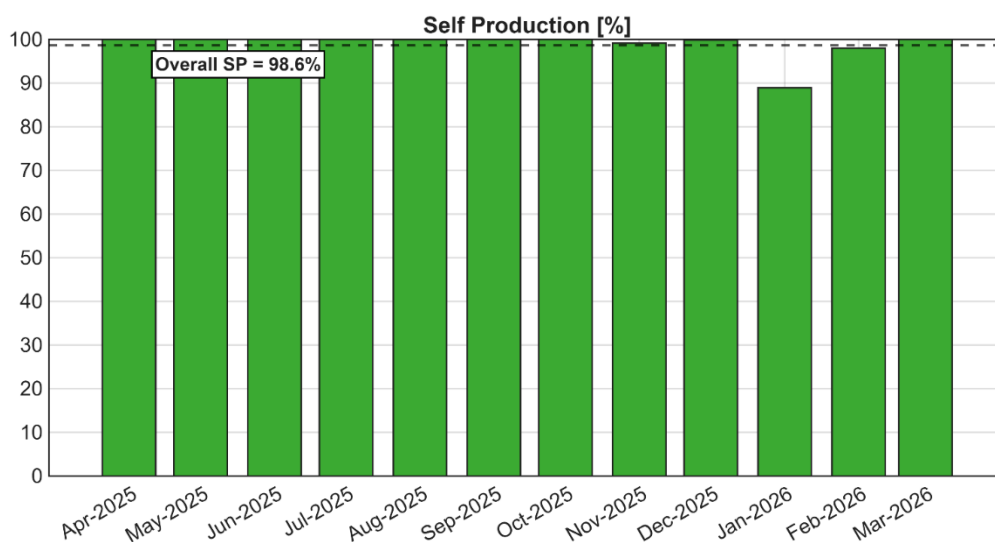


Figure 59 – Monthly figures and overall self production rate of the Infinity prototype.

In terms of curtailment, **Figure 60** shows the evolution month by month and an overall value of 68.5%, confirming the winter period as the bottleneck for the firm-PV generation

5.6. Prototype performance in the first year of operation

118

strategy. In this case, the minimum value was experienced in January 2026 at 27.0%. During the summer, Infinity reached a curtailed energy rate as high as 80.3% in June 2025.

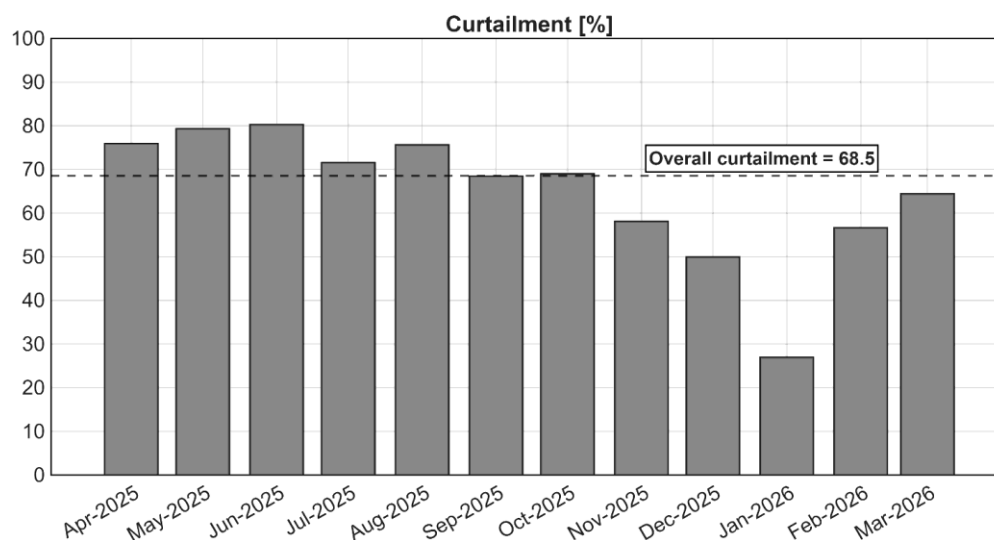


Figure 60 – Monthly figures and overall curtailment rate of the Infinity prototype.

Analyzing the overall figures against the initial guesses originating from the numerical simulations, some discrepancies can be detected both in terms of self-production and, especially, curtailment rate.

The experimental SP came out as 98.6% against the expected 100%. Although minimal percentage-wise, this difference is particularly significant conceptually, because it changes the prototype's perspective from a fully autonomous system to one that requires support, however minimal, to cover the electrical demand. This suggests that, with this configuration, some degree of redundancy in energy production is still necessary due to the inherent variability of the solar source.

On the other hand, the overall curtailment rate registered by Infinity (68.5%) was considerably lower than the 78% predicted by the simulations. This discrepancy mostly poses an economic problem in case of systems designed to inject the excess energy into the grid, since the actual remuneration would be lower than expected, resulting in a higher LCOE.

The unpredictability of weather conditions is probably the main reason for the observed differences between simulation and experimental results. The numerical model in use [141] relies on past solar and climate data (2013-2021), as seen in section 4.2.1, therefore deviations are to be expected on account of the solar source's variability. The 2025-2026 winter was an unusually cloudy and rainy one in Rome, and has surely had an impact on the prototype's

results. Another element is the non-ideality of the system in terms of BESS efficiencies, which will be discussed in further detail in the next section, and which causes losses that were not accounted for in the preliminary numerical analysis.

5.7. BESS efficiency analysis

The analysis of the BESS charge and discharge efficiencies (η_{chg} , η_{dchg}) allows to quantify energy losses during battery charging and discharging, while the round-trip efficiency (η_{RT}) is used to evaluate the overall effectiveness in deploying the energy stored. These parameters are generally expected and assumed at around 90-95% [38, 39].

The results over one year (**Figure 61**) suggest that the charge and round-trip efficiencies meet expectations at 90.0% and 95.4% respectively. For the discharge efficiency, however, the results show a value as low as 54.8%.

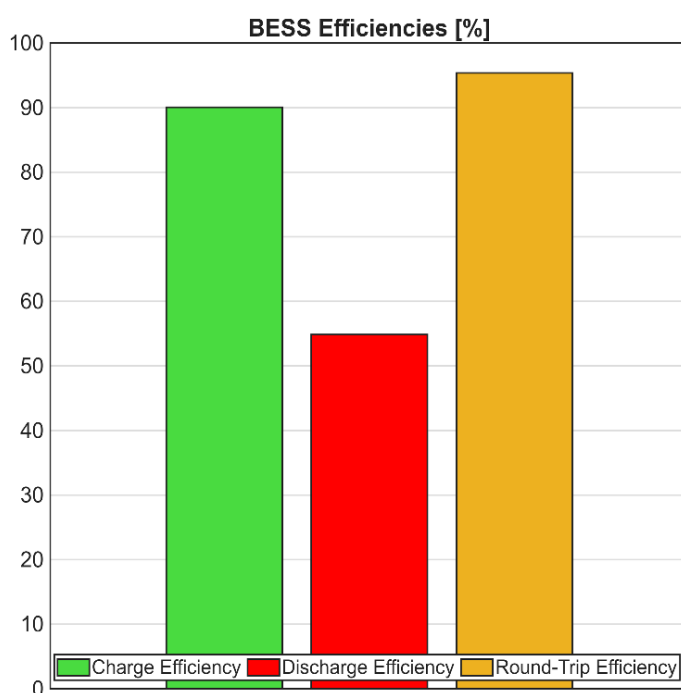


Figure 61 – Charge, discharge and round trip efficiency overall values in the experiment period.

Since this anomaly was already becoming apparent during the early stages of the plant's operation, a targeted investigation was undertaken to study this parameter. Preliminary speculation pointed to the low power demand and, as a result, to the system not working in a proper operating window as the reason for the inefficiency.

Tests were carried out fixating the load at different values inside the AC/DC converter limits (0-240 W) for a full 24 hours and studying the effects on battery discharge efficiency. At the same time, similar experiments at higher power load values were performed at the CIEMAT plant, leveraging its 3-kW emulator.

The points were plotted (**Figure 62**) and the trend seems to confirm the initial hypothesis, showing a clear tendency of the discharge efficiency to increase as the power demand grows. In particular, at base load (30-50 W), normally registered at night, the efficiency stands at about 50% at both Infinity and the CIEMAT plant. This is significant, since nights are when most of the battery discharge happens, and thus, the base load constitutes the most important contribution to the discharge efficiency. As the power demand reaches values of 180-240 W (the limit for Infinity), the resulting discharge efficiency exceeds 80%. Points beyond this limit (up to 600 W), obtained from the CIEMAT plant follow the same trend, showing a discharge efficiency close to 90%. Although CIEMAT's load emulator and the inverter would, in theory, allow for tests at higher power load, this was avoided to prevent stressing the system beyond what was deemed safe.

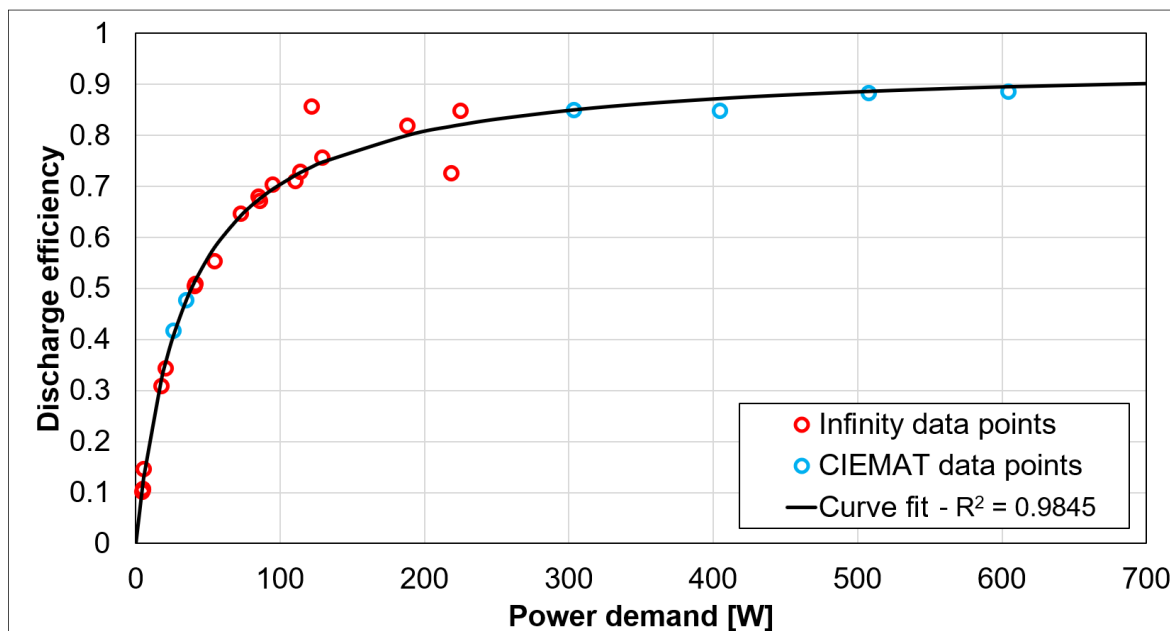


Figure 62 – Results of battery discharge efficiency tests at different power demand values and curve fit.

A fitting process was performed on the available data points to obtain the following mathematical equation to represent the observed trend:

$$\eta_{dchg} = \frac{AL}{L + B} \quad (25)$$

with

$$A = 0.9457$$

$$B = 34.3175$$

where L is the power load. This curve is also shown by the black line in **Figure 62** and was useful to estimate η_{dchg} at higher power demand values. According to the fit, with a load of 1 kW, the discharge efficiency would be 91.4%, while at 2 kW it would reach 93.0%.

To isolate the baseline losses causing the low discharge efficiency at low loads, operating intervals where the battery was fully depleted and no solar irradiance was available were investigated. Under these conditions, the system relies entirely on grid import (residual load) to meet the demand. A primary source of inefficiency is the power internally consumed by the inverter and the BMS, which is excluded from the inverter's power balance metrics. However, this internal consumption can be quantified through the external smart power sensor. While power exported to the grid is measured downstream of the conversion stage, grid power imported during non-productive hours is measured upstream of the inverter. Theoretically, this imported power should exceed the active load by an amount equal to the system's internal overhead losses.

To validate this hypothesis, a dedicated experiment was set up, where a constant load was imposed to intentionally drain the battery prior to sunrise. This caused the system to draw power from the grid, and allowed to compare the quantity registered as residual load with the power demand. The CIEMAT plant was the only feasible option for this test, since the limitations of Infinity's load emulator and AC/DC converter would not allow to set a power value high enough to drain the battery.

The results from this experiment, exemplified in **Figure 63**, confirm that the registered residual load does, indeed, exceed the power demand by a relatively constant value of about 35 W. This figure is critical, since it is comparable with the base load of 30-50 W, which, as previously stated, constitutes the most important contribution to the discharge efficiency.

This test seems to confirm that, when operating under low loads, the internal consumption becomes equal in magnitude to the useful load, effectively halving the discharge efficiency. As

the load changes, these losses stay constant, which is coherent with the trend depicted in **Figure 62**.

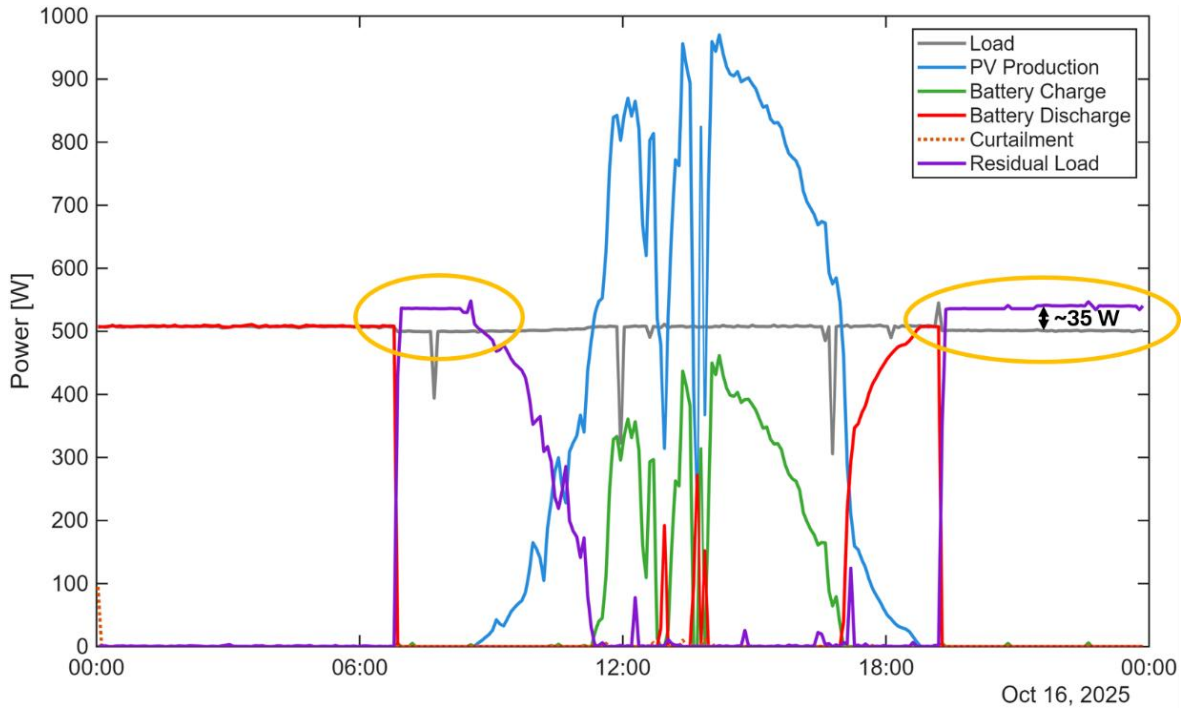


Figure 63 – Results of the experiment to assess the internal losses of the plant.

In conclusion, the unexpectedly low discharge efficiency, as anticipated, can be considered one of the reasons for the discrepancies in SP and curtailment rate compared to the simulation results. Due to losses unaccounted for in the numerical study, Infinity needs more energy to cover the electrical demand, which explains the higher residual load and lower curtailment.

5.8. Analysis of the battery's state of charge

As said in section 5.2, limitations in the single components did not allow to exactly replicate the design parameters, namely 3.9 OVS and 1.55 NDY. For the latter, however, a good indication of how the system would fare comes from analyzing the battery's state of charge (SOC) trace for the whole year (**Figure 64**).

The initial design battery capacity to meet the aforementioned NDY was 2.5 kWh, or 50% of the total available on Infinity. It is, therefore, useful to evaluate how often the SOC went

below 50% to detect the time frames where residual load would appear with a battery capacity of 2.5 kWh.

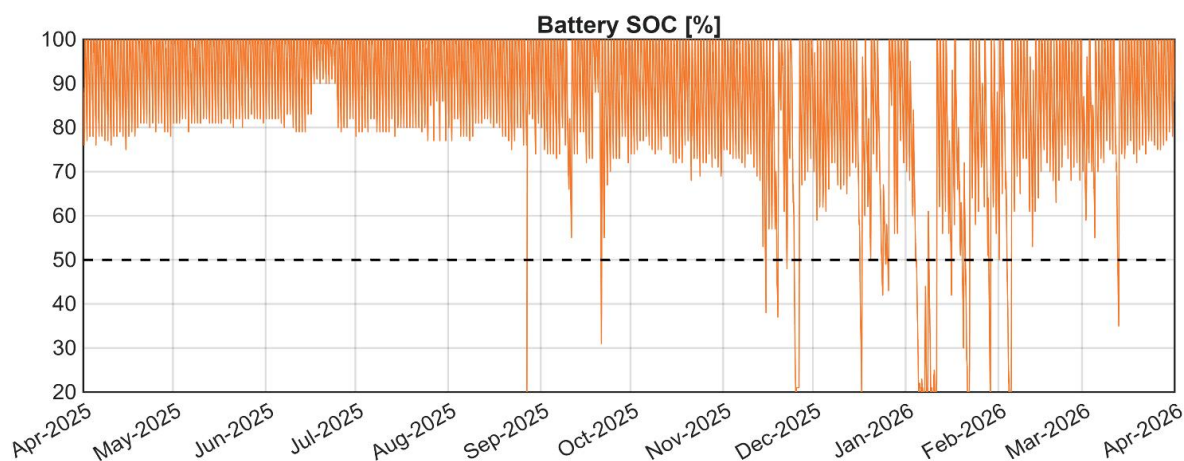


Figure 64 – Plot of the battery's state of charge (SOC) over the duration of the experiment.

Figure 64 shows that the 50% threshold was crossed mostly during the winter. In line with the previously presented data, January 2026 was the most critical month, since it was characterized by very low insolation, bad weather and high precipitation. Instances were recorded also in December 2025, early February and, very briefly, March 2026. The plot shows high battery consumption also in September and November 2025, however, this can be attributed to battery efficiency tests being performed in these months. Power demand values during these tests, at times, surpassed 200 W for a full 24 hours, considerably altering the energy flows and putting the battery under much higher stress than it otherwise would be. Finally, the one instance in August where battery SOC went all the way to 20% was due to a communication error with the inverter, which caused the battery to send all the available charge to the grid and required a full system reset.

This analysis is not conclusive, since the battery, in our case, does not actually stop providing energy when it reaches 50%. If this was the case, energy flows localized in these time frames would be considerably different. However, it allows us to assess that, even if the battery capacity was to be reduced from the current 4 kWh to 2.5 kWh, Infinity would still be able to provide complete coverage of the electrical demand for most of the year.

5.9. Matlab energy flows simulation model

The experimental data presented in the previous sections of this chapter were used to calibrate a pre-existing simulation model, developed in Matlab by EsterLab researchers, which allows to fully reproduce the behavior of a PV+BESS system in terms of energy flows. This model, once correctly calibrated, is useful to evaluate the potential of any application of the firm-PV generation strategy prior to implementation, since it takes the PV generation and the power demand as inputs, and simulates the resulting energy flows for the selected time period.

The data from Infinity's first year of operation were used to validate this simulation model by comparing its output with the actual energy flows recorded by the prototype.

5.9.1. Description of the model

The Matlab simulation model is designed to recreate the energy flows of a PV plant and assess the self-production and curtailment rates. It does so by taking the system's design parameters (PV power installed and BESS capacity), the battery's charge and discharge efficiencies, the PV production and the load profile as inputs.

Figure 65 shows a flowchart of the model's operation. For every timestamp, the algorithm checks the load, the availability of PV generated energy and the presence of battery charge and progressively constructs the energy flows. If no PV generation is available, the system draws from the battery and, if the charge is not sufficient, it updates the residual load. When the PV array produces power, the model checks whether it is sufficient to cover the load. If that is the case, it then evaluates if the surplus must be used to charge the battery or curtailed, otherwise it integrates it with battery-stored energy and updates the residual load if necessary. Whenever energy is sent to or drawn from the battery, the charge and discharge efficiencies, respectively, are considered in the calculations, to accurately reproduce the real plant's non-idealities.

The model, as anticipated, can be used for design purposes. By inputting the desired PV power and BESS capacity, using provisional PV production data and efficiency values, and implementing a typical load profile, the algorithm outputs a detailed prediction of all energy flows and main variables' trends, as well as the expected self-production and curtailment rates.

5.9. Matlab energy flows simulation model

125

For the validation, the results of which will be discussed in the next subsection, the simulation output resulting from feeding the actual PV production and load profiles of Infinity into the model was compared to the experimental data recorded directly by the prototype.

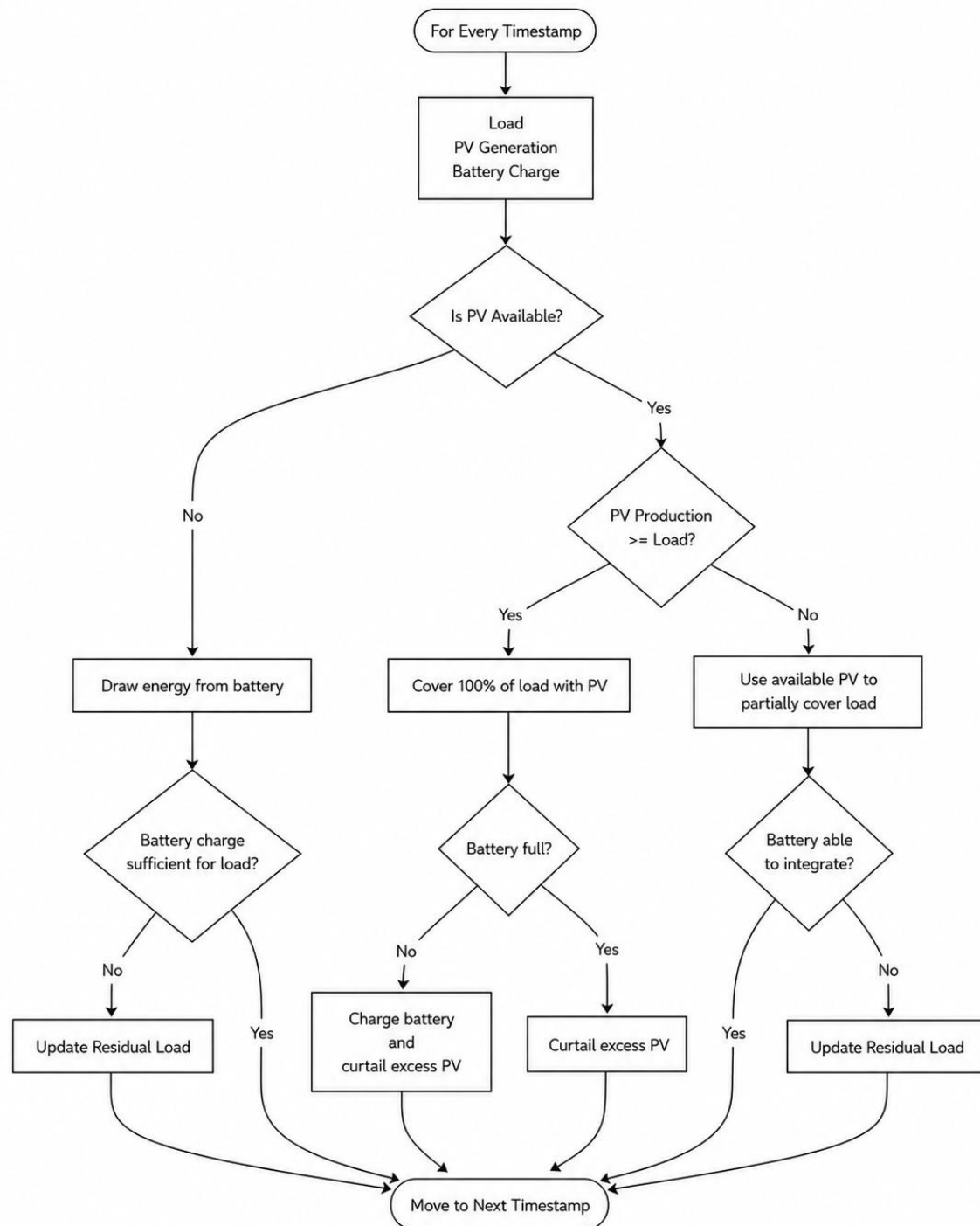


Figure 65 – Flowchart of the Matlab simulation model algorithm.

5.9.2. Validation of the model

The energy flows simulation model was tested by setting the parameters to the values characterizing Infinity, meaning a PV power of 1815 W, a BESS capacity of 4 kWh, a charge efficiency of 0.9 and a discharge efficiency of 0.548. For the PV production and load profiles, the values directly measured by the plant were used, thus including the AC/DC converter in the power demand. It is also worth pointing out that, when comparing the battery's state of charge (SOC), the experimental data were corrected according to the total effective capacity of 4 kWh, so that the values would range from 0 to 100%, not from 20 to 100% like they originally do based on the battery settings.

The simulation results for self-production and curtailment rate show good agreement with the experimental values. The model achieved 98.3% SP, only slightly lower than the 98.6% reached by the prototype, and suggested that 69.5% of the energy generated would be curtailed, compared to the 68.5% recorded by Infinity.

To draw an overall comparison between simulation and experimental energy flows, **Figure 66** shows a representative sample of 5 days between the 17th and 21st of September 2025. This sample contains instances where the load follows the profile of the Macro-area as well as days where the power demand is fixed at a low (close to 0 W) and high (about 220 W) value. These constant-load instances correspond to the tests for the battery's discharge efficiency discussed in section 5.7. This sample provides sufficient variety to analyze the alignment in diverse conditions.

Figure 66a shows the comparison of the two datasets for the battery's charge and discharge power (P_{batt} in **Table 21**). Positive values indicate that the battery is charging, while negative values mean that the battery is providing power. This quantity is useful when analyzed in conjunction with the battery's state of charge (**Figure 66b**), also evaluating the possible consequences on the curtailed power (**Figure 66c**) and residual load (**Figure 66d**).

Focusing on the days where the load follows the Macro-area's profile (17th and 18th September) a good alignment can be noticed at night and also during the charging phase. A difference can be observed in the peak charge power, which is lower for the simulated data, and also in the timestamp when 100% SOC is reached, that happens 10-15 minutes earlier for the prototype.

5.9. Matlab energy flows simulation model

127

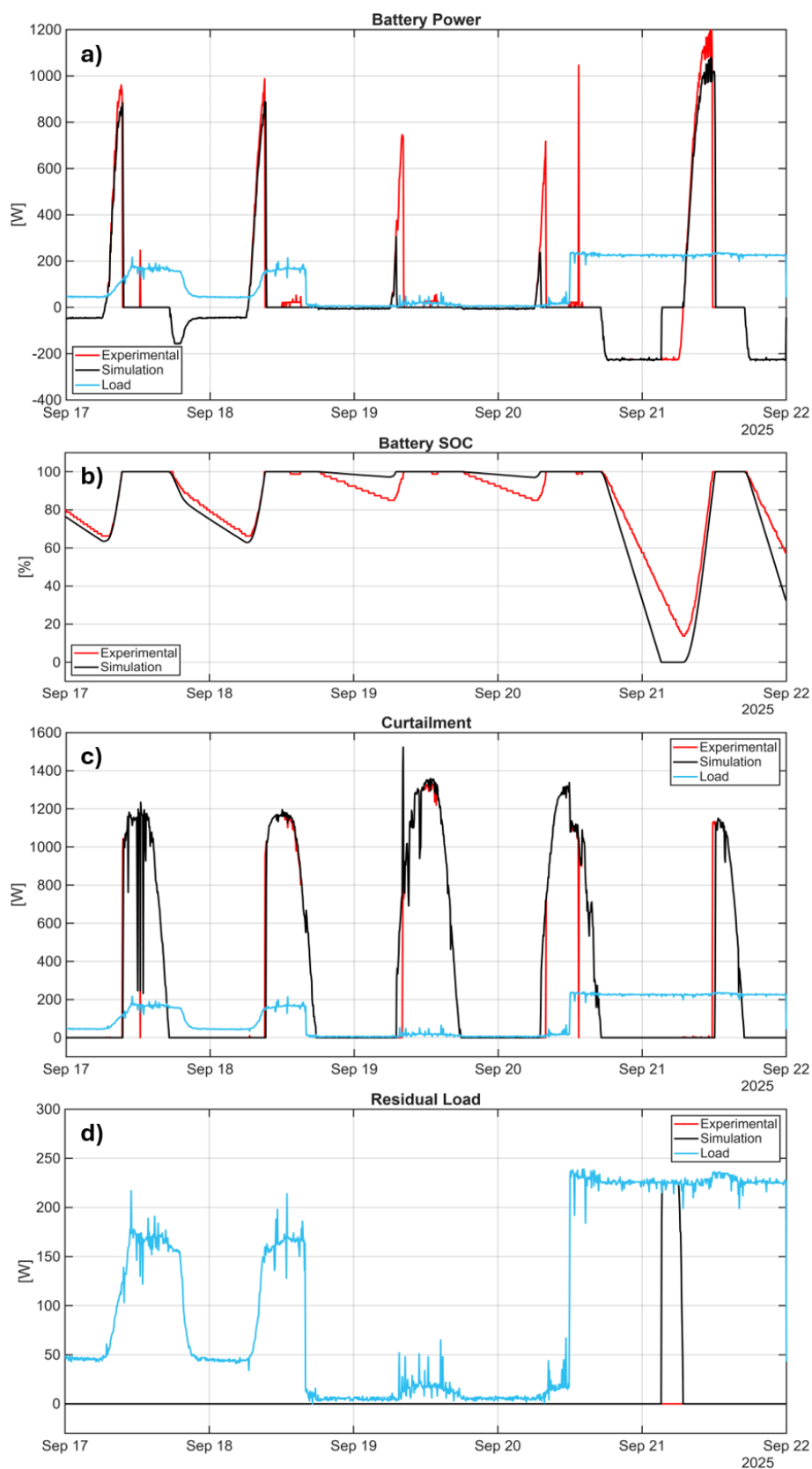


Figure 66 – Comparison between experimental data and simulation model results in terms of battery power (a), battery SOC (b), curtailment (c) and residual load (d).

The slope of the SOC during charge is comparable, while during discharge, the model seems to slightly overestimate the descent rate, particularly in the first hours, when the load is still high. This causes an underestimation of the minimum SOC, which is compatible with the slight delay in reaching maximum charge the following morning. Curtailment is generally well aligned, excluding instances when Infinity's battery needed some charging in the afternoon, most likely to compensate for standby losses, and residual load is zero for both datasets.

Analyzing the central part of the plots (from the 18th of September afternoon to the 20th in the morning), the SOC slope at night appears much lower for the simulated data, where the battery only drops to about 97%, as opposed to 85% for the experimental data. This is reflected in the battery charge power the following morning, when the model reaches 100% SOC more than one hour earlier.

Finally, examining the final part of **Figure 66** (from the 20th of September afternoon onwards) reveals the differences between the two datasets at high load. As could already be guessed by the analysis of the first sample days, the simulation overestimates the SOC slope during discharge when the power demand is high. In this case, the model has the system run out of battery charge in the morning of the 21st of September, before sunrise, whereas the experimental data suggests that Infinity only got down to 14% of the available 4kWh. This causes the residual load of the simulation to jump up to cover the power demand and brings the delay in reaching 100% battery charge the following day to almost 30 minutes.

Table 25 shows some statistical performance indicators for the model, namely bias, MAE and RMSE. The model's global reliability is confirmed by the near-zero bias and low MAE values across all evaluated variables.

Table 25 – Statistical performance indicators of the model.

Variable	Bias	MAE	RMSE
Battery Power	- 0.74 Wh	1.20 Wh	6.66 Wh
Battery SOC	+ 0.01%	2.47%	5.36%
Curtailment	+ 0.27 Wh	0.73 Wh	6.65 Wh
Residual Load	+ 0.02 Wh	0.03 Wh	0.56 Wh

These results suggest that, at surface level, the model is able to effectively reproduce the prototype's behavior, given the SP and curtailment rates. However, a deeper analysis of the

energy flows compared to the ones observed experimentally, proves that further calibration is needed. The instances of misalignment point towards the necessity of a more advanced implementation of the charge and discharge efficiencies, currently set as flat values.

As discussed, the slope of the SOC during discharge is underestimated at low loads, overestimated at high loads, and almost perfectly accurate when the power demand is around 30-50 W. This is perfectly compatible with the behavior observed when testing the discharge efficiency. **Figure 62** suggests that the flat value of 0.548, used for the validation, is only accurate in the 30-50 W load region. At lower loads, this value is much higher than the actual efficiency, which explains why the model underestimates the battery discharge. Conversely, when the power demand grows beyond this region, the actual discharge efficiency is higher, resulting in the observed overestimation.

For what concerns the charge efficiency, the need for a dynamically adjusted value is less evident, because the charge power is generally high, in a region where the efficiency curve is supposedly already flat. This is also the reason why the analysis performed on η_{dchg} (section 5.7) was not repeated for η_{chg} . However, the battery power plot in **Figure 66** shows slight misalignments even in the charging phase, namely the peak charge power value and a difference in the timestamp when full charge is reached. These deviations suggest that a dynamic η_{chg} could improve the overall performance of the model.

To try and improve on these results, the dynamic discharge efficiency described by equation (25) was implemented into the model. The outcome of this new comparison is shown in **Figure 67**, showing the same plots as those analyzed for the constant efficiency case.

It is immediately apparent that with the updated model the simulated SOC slope is much better aligned with the experimental one when the battery is discharging (**Figure 67b**). The accuracy is remarkable when the system follows the Macro-area's load profile, while still improvable in more extreme situations of very high or very low power demand. This is attributable to the fact that the data points fitted to obtain equation (25) were mostly concentrated in the 20-120 W region and the function is, therefore, better optimized for these values. It is also worth mentioning that, due to hardware limitations, no data points are available beyond 650 W.

5.9. Matlab energy flows simulation model

130

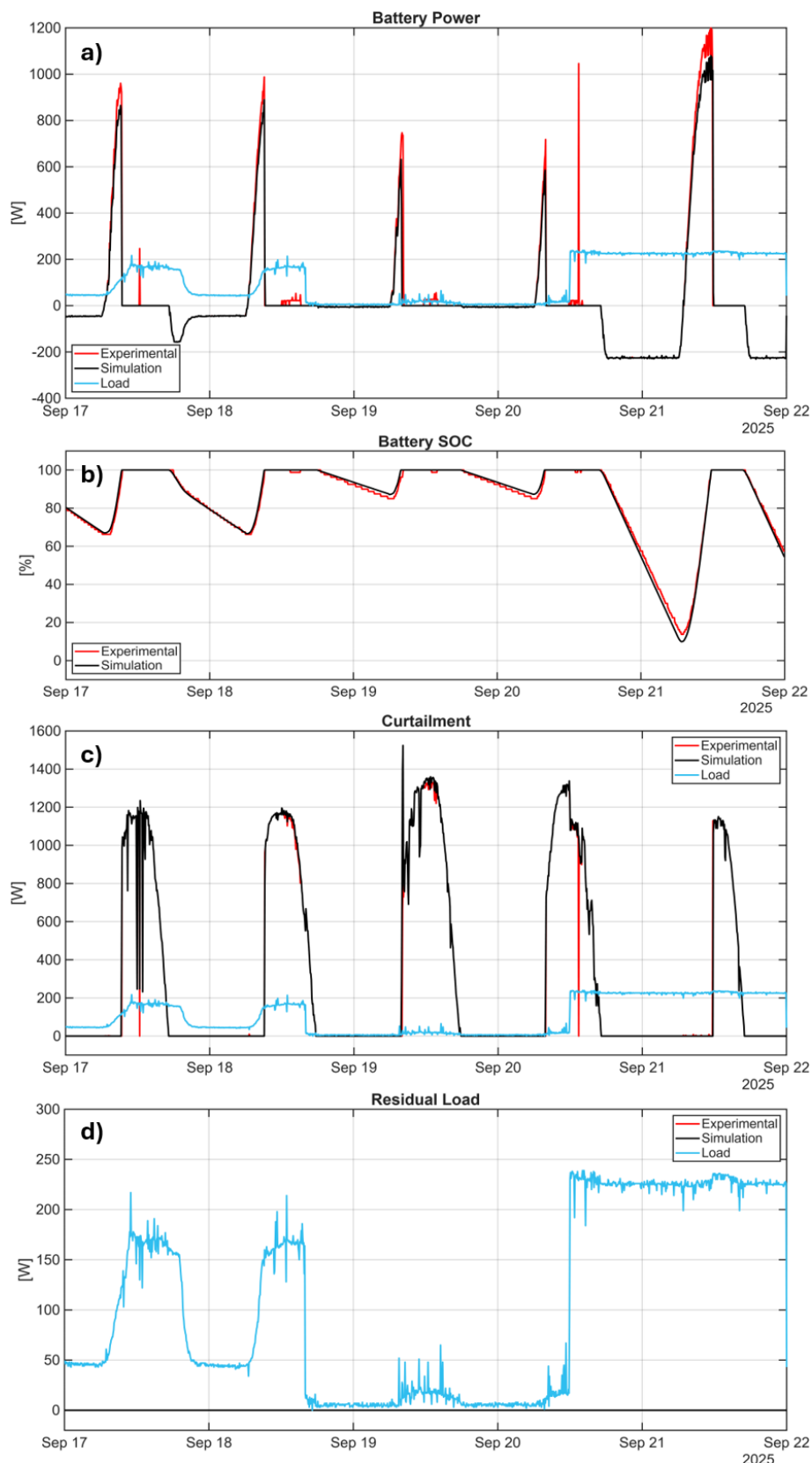


Figure 67 – Comparison between experimental data and simulation model results in terms of battery power (a), battery SOC (b), curtailment (c) and residual load (d) with dynamic discharge efficiency.

Nevertheless, the better accuracy in the SOC simulation directly translates in a higher fidelity of the other variables. Most notably, the battery depletion seen in the model on the 21st of September, which contrasted with the experimental data, was substituted by a much more realistic slope. This also fixed the consequent discrepancies in the battery power (**Figure 67a**), curtailment (**Figure 67c**) and residual load (**Figure 67d**) plots.

Focusing the attention on the charging phase, although the charge efficiency is unchanged compared to the original version, we can notice some changes due to the increased accuracy in discharge. Particularly, the difference in the timestamp at which 100% SOC is reached was almost completely removed. On the other hand, the difference in peak charge power is still noticeable and confirms that the implementation of a dynamic charge efficiency would further improve the model's performance.

Table 26 shows the updated statistics for the model after the implementation of the dynamic efficiency. It is immediately evident how the Battery SOC tracking shows a substantial enhancement, with the MAE dropping from 2.47% to 1.35% and the RMSE improving from 5.36% to 3.36%. However, the +1.18% bias highlights a slight tendency to overestimation, confirming that the mathematical model still has room for improvement.

Table 26 – Statistical performance indicators of the updated version of the model

Variable	Bias	MAE	RMSE
Battery Power	- 0.89 Wh	0.97 Wh	5.36 Wh
Battery SOC	+ 1.18%	1.35%	3.36%
Curtailment	+ 0.39 Wh	0.48 Wh	5.08 Wh
Residual Load	- 0.02 Wh	0.02 Wh	0.41 Wh

Concerning the overall results for self-production and curtailment rate, the updated model retained the accuracy of the first version, achieving 98.9% SP and showing 69.9% curtailment compared to the 98.6% and 68.5%, respectively, recorded experimentally. This confirms that the ability of the model to predict the overall behavior of the system, irrespective of whether a flat value or a dynamic efficiency is used, is still remarkable.

In conclusion, the Matlab energy flows simulation model proved its potential through effective prediction of the self-production and curtailment rates and, with the implementation of a dynamic discharge efficiency, even as a tool to simulate point-by-point energy flows.

Further fine-tuning steps, however, are necessary to make it an effective and accurate design tool, particularly refining the dynamic efficiency function to more accurately reproduce the system behavior at very high and very low loads, and implementing a demand-dependent value also for η_{chg} .

6

Final remarks

This final chapter synthesizes the main scientific contributions and findings achieved throughout this Ph.D. program. By following a transitional path from individual component, through numerical simulation and cost optimization, to small-scale field prototyping, this dissertation addresses the primary barriers to transforming variable solar generation into a dispatchable, firm energy asset.

The conclusions are presented according to the two main pillars of this research: bifacial photovoltaic characterization and the practical implementation of the firm-PV generation strategy. Furthermore, the limitations of the current findings are explicitly acknowledged, the research questions are answered, and future research directions are outlined.

6.1. Bifacial PV characterization and testing

6.1.1. Conclusions

The characterization of bifacial PV modules under real operating conditions is essential for bridging the gap between laboratory studies and field performance. This thesis developed and experimentally validated a three-phase full outdoor testing protocol designed for facilities lacking specialized indoor solar simulators or climate-controlled chambers. The protocol covers electrical parameter determination through I-V curves translated to STC and BSTC using Anderson's method, temperature coefficient extraction via natural temperature ramps on a sun-tracker, and rear-irradiance-driven power gain yield (BiFi) determination.

Validation across 13 custom-made agrivoltaic Mono-PERC samples demonstrated high alignment with nominal manufacturer datasheets, yielding an average P_{MAX} deviation of -3.95% and a bifaciality (ϕ) range of 77-80%. Thermographic inspections confirmed uniform thermal behavior across module surfaces during data acquisition. Phase two successfully extracted the normalized temperature coefficients for V_{OC} , I_{SC} and P_{MAX} by monitoring continuous sun-induced temperature ramps (35-50°C) under stable-irradiance clear-sky conditions. While the resulting average values for V_{OC} and P_{MAX} coefficients showed strong agreement and low variability compared to datasheet figures, the I_{SC} coefficient exhibited higher dispersion due to its low absolute magnitude and its inherent sensitivity to minor outdoor fluctuations. Furthermore, phase three evaluated the rear-irradiance-driven power gain yield (BiFi) under natural field conditions, suggesting a linear dependence of the normalized parameter (BiFi/ ϕ)

on both rated module power and rear active surface area. To further validate this trend, the experimental outdoor dataset was compared with indoor characterization data provided by CIEMAT, which showed remarkable alignment with the outdoor measurements, significantly strengthening the linear correlation ($R^2 > 0.99$) and suggesting BiFi as a promising descriptor for estimating rear-side contributions across different module classes.

Complementing the characterization protocol, a 7-month long-term outdoor testing campaign (February to August 2025) provided valuable insights into seasonal operational dynamics. Bifacial modules demonstrated a distinct yield advantage, generating between 9 and 11.8% more energy per kWp compared to equivalent monofacial setups, driven by a 16.8% higher reference yield. The performance ratio (PR) of bifacial units appeared slightly lower (0.949-0.957 against 0.990-0.992 for monofacial), and exhibited the expected temperature-driven reduction during the summer months. In terms of monthly degradation, analysis showed high stability of the translated I-V curves, with no observable descending trend in P_{MAX} over the testing period.

6.1.2. *Limitations*

Outdoor characterization is inherently sensitive to environmental variability. The extraction of the I_{SC} temperature coefficient, as anticipated, is a clear example of this, exhibiting significant statistical dispersion (with a standard deviation comparable in magnitude to the mean value), as low-magnitude current variations under natural sunlight remain highly sensitive to irradiance fluctuations and spectral shifts. Additionally, the BiFi analysis relied on naturally available reflected irradiance rather than ground-cloth conditioning, acting as an operational descriptor of field behavior rather than a strict alternative to indoor certification standards.

Furthermore, the overall validation was conducted on a relatively restricted population of 13 custom-made modules, necessitating a broader experimental campaign across different module sizes and cell architectures to fully generalize the procedural accuracy and the observed BiFi scaling trends.

Practical handling considerations must also be acknowledged: while the lightweight and compact design of the custom agrivoltaic samples allowed rapid manual flipping and sensor installation within approximately 10 minutes, testing heavier commercial utility modules may prove more challenging. For larger modules, these handling steps could extend operational

times, potentially challenging the execution within the optimal 11:40-12:20 solar noon time window required to maintain near-normal incidence conditions.

Lastly, the long-term testing span of 7 months, while sufficient to capture spring and summer behavior, remains a preliminary window for full lifecycle degradation assessment.

6.2. Contribution to the firm PV landscape

6.2.1. Conclusions

The transition toward high renewable penetration requires evolving from passive energy harvesting to active, firm power delivery. Through the numerical simulation of the Engineering Macro-area at Tor Vergata University, acting as a representative case for the Rome Technopole campus, this research demonstrated that achieving high targets of energy self-production (SP) without storage is physically impossible, capping at an SP of 49% even with massive PV overbuilding. Conversely, achieving 100% self-production without oversizing (OVS = 1) requires an economically unfeasible storage capacity (NDY = 350 days, LCOE $\approx$ 4.2 €/kWh).

By applying a brute-force optimization algorithm targeting LCOE minimization, this thesis confirmed the effectiveness of pairing photovoltaic oversizing (implicit storage) with battery energy storage and proactive curtailment. A clear dual pattern emerged: for self-production levels up to 86-87%, the LCOE curve remains virtually flat, allowing SP to grow significantly with minimal economic penalties. Beyond 90%, the LCOE escalates sharply.

These outputs produced a strategic roadmap for the progressive implementation of the firm PV strategy in the Macro-area. By projecting technology learning curves across four key milestones, the roadmap targets self-production rates of 65% in 2023, 80% in 2030, 90% in 2040, and 100% in 2050. When compared against the 2023 average Italian National Unique Price (PUN) benchmark, the first three milestones prove to be cost-effective, whereas a maximum competitive threshold of 95.5% SP can be achieved under 2050 technology cost scenarios.

A comprehensive land occupation analysis identified approximately 65000 m² of suitable, shade-free surfaces. In particular, equipping the primary student parking lots with solar canopies offers sufficient capacity (4.5 MWp) to fulfill the 90% SP milestone, whereas reaching

100% self-production (9.8 MWp) would require an almost complete, intensive exploitation of all available rooftop and ground-level areas.

This numerical modeling framework served as the foundation for designing the real-world Infinity prototype, the largest empirical contribution of this thesis. Over a full year of operation (April 2025 to March 2026), under an OVS of 4.56 and an NDY of 2.51, Infinity achieved an annual self-production rate of 98.6% and an annual curtailment rate of 68.5%, covering an annual load of 638 kWh almost completely from solar and stored energy.

However, the experimental campaign uncovered critical field non-idealities that had not been evidenced by the preliminary simulations. A joint experimental investigation conducted with CIEMAT revealed that while BESS charge efficiency (90.0%) and round-trip efficiency (95.4%) met theoretical expectations, the actual battery discharge efficiency dropped to an overall average of 54.8%. Preliminary investigations suggest that this behavior is tied to low-power operating conditions during nighttime baseloads (30-50 W). Under these reduced power levels, the internal consumption of the inverter and BMS (≈ 35 W) appears to become comparable in magnitude to the active load itself, offering a plausible explanation for the observed efficiency drop. This hypothesis is supported by dedicated tests under higher active loads (> 500 W), where the discharge efficiency recovered toward expected values at about 90%. These tests also led to the definition of a mathematical model representing the evolution of the discharge efficiency as a function of the plant's operating conditions in terms of load.

These real-world non-idealities were further corroborated through the validation of a Matlab energy flow simulation model against the prototype's full-year experimental dataset. While the model demonstrated strong macro-level results, reproducing annual performance indicators with remarkable accuracy in terms of SP (98.3% simulated vs. 98.6% measured) and curtailment (69.5% simulated vs. 68.5% measured), the granular comparison of power flows highlighted key areas for model refinement. In particular, assuming static efficiency caused the model to underestimate State of Charge (SOC) depletion rate under low load and overestimate it under high demand. Implementing the aforementioned dynamic efficiency mathematical model allowed to retain the observed accuracy in overall SP (98.9% simulated vs. 98.6% measured) and curtailment (69.9% simulated vs. 68.5% measured) while significantly improving the point-by-point energy flow prediction. Nevertheless, these findings remain preliminary, and further research is required to fully isolate and quantify the specific physical mechanisms driving low-load system losses.

6.2.2. *Limitations*

Regarding the firm-PV generation framework, the primary limitation lies in the physical scale of the experimental prototype relative to real-world utility installations. While Infinity successfully validated the operational feasibility of firm PV generation at a laboratory scale, questions remain regarding how these findings translate to larger systems featuring complex multi-inverter and multi-string architectures as well as central storage assets.

In particular, it is critical to determine whether field non-idealities scale linearly with system capacity or if large-scale equipment follows different operational dynamics. Similarly, the mathematical model developed to describe the discharge efficiency was derived specifically from a single small-scale system. Its direct applicability to utility-scale applications and industrial BESS units, which may require completely different management, definitely calls for further experimental verification.

Furthermore, limitations can also be identified within the numerical modeling framework itself. The optimization process relied on historical meteorological datasets (2013–2021) and an extrapolated electrical demand profile, which, despite thorough statistical validation, cannot fully capture future climate anomalies, long-term PV/BESS aging dynamics, or structural shifts in load profile. Additionally, given the rapid pace of technological innovation and the fast-evolving market dynamics, component prices and cost learning curves change rapidly, requiring the optimization process to be periodically updated to reflect the latest market conditions and ensure the continued accuracy of the LCOE minimization.

Finally, while the Matlab energy flow model effectively matched global annual performance metrics and, with dynamic discharge efficiency, even provided good granular energy-flows prediction, broader and more detailed studies remain necessary to define more accurate and generalized efficiency functions both for the discharge and discharge phases.

6.3. Answer to the research questions

In light of the results obtained in this dissertation, the research questions formulated in section 1.4 can be answered:

RQ1: What are the techno-economic trade-offs between battery storage capacity (BESS), implicit storage achieved through photovoltaic oversizing (OVS) and proactive curtailment when aiming for high energy self-production targets while minimizing energy costs (LCOE)?

PV oversizing essentially acts as implicit storage, drastically suppressing the required BESS capacity. Up to an SP target of 86-87%, oversizing predominantly boosts useful generation during winter and low-irradiance periods, keeping the LCOE nearly constant. Pushing SP beyond 90% toward 100% requires non-linear increases in both BESS size (NDY jumps from 0.6 to 1.55 days) and PV overbuilding (OVS grows from 2.0 to 3.9), resulting in severe summer curtailment (> 70%) and an LCOE increase of over 140%. From an economic feasibility standpoint, reaching 65% SP could already be profitable today, based on comparison of the LCOE with the Italian National Price (PUN). Furthermore, projections show the feasibility of 80% SP in 2030 and 90% in 2040, while the 100% target still appears out of reach even for 2050.

RQ2: To what extent can a properly designed PV system utilizing commercial components effectively guarantee continuous power demand coverage (firm power generation) under real, highly dynamic operating conditions?

A real-world small-scale firm-PV architecture utilizing commercial components has proven able to deliver near-complete load coverage. The Infinity prototype, designed based on the results of the firm-PV simulation targeted at covering 100% of the energy demand for the Engineering Macro-area of Tor Vergata, demonstrated a self-production rate of 98.6% over a full operational year. The prototype fully covered the load for 8 out of 12 months and exceeding 99% coverage in two additional months. This outcome was achieved while curtailing 68.5% of the energy generated by the PV array and grid support was required almost exclusively during prolonged, severe winter weather events. The result, while remarkable for the near-full coverage of the electrical demand, exposes the vulnerability of the strategy to the unpredictability of weather conditions, underscoring the importance of maintaining some degree of redundancy in energy production.

RQ3: What are the primary operational deviations that emerge when transitioning from simulations to actual hardware performance, and how can these field non-idealities be addressed to calibrate predictive sizing tools?

The primary operational deviations stem from non-linear, load-dependent component inefficiencies. Specifically, operating inverters and storage systems under low-load conditions causes fixed standby consumption (quantified in about 35 W in the case of Infinity) to dominate the energy balance, reducing the overall average discharge efficiency to about 55%. Predictive simulation tools must, therefore, be calibrated by replacing static efficiency values with dynamic, load-dependent ones to accurately track energy flows and prevent deviation from the actual system behavior. Furthermore, the effects of field non-idealities must be confirmed and studied on larger-scale case studies to determine effective countermeasures upon system commissioning.

RQ4: At component level, in light of their growing prevalence, is it possible to reliably assess the performance and electrical parameters of advanced bifacial photovoltaic modules directly under real, highly variable outdoor operating conditions?

A full outdoor characterization procedure was established by structuring testing into three sequential phases: acceptance reproducing standard conditions to assess the electrical parameters, continuous temperature-ramp testing under stable-irradiance clear-sky conditions to determine temperature coefficients, and P_{MAX} monitoring under naturally varying rear-irradiance to evaluate BiFi. Integrating these tests into a single workflow allows to paint a full picture of bifacial modules, providing results largely comparable to those stated in datasheets or obtained through standard indoor testing. The three phases build upon the well-established indoor characterization normative framework, providing an accurate, low-cost alternative to indoor testing for facilities lacking solar simulators or climate-controlled environments. Furthermore, coupling this protocol with long-term testing can integrate the characterization with insight about the modules' performance and degradation over time.

6.4. Directions for future research

To build upon the contributions of this dissertation and push towards further advancements, several key research lines should be further explored.

Regarding bifacial PV outdoor characterization, future efforts should prioritize establishing a more rigorous, standardized benchmark campaign to directly cross-compare the proposed outdoor protocol against high-precision indoor measurements performed under controlled laboratory conditions. While the present work validated the procedure on custom-made, lightweight agrivoltaic modules, evaluating the adaptability and operational feasibility of the protocol on full-scale commercial units represents a critical next step. Larger commercial modules, characterized by increased weight, alternative cell architectures, and different dimensions, will test the practical boundaries of manual handling and module flipping within the restricted solar-noon time window, providing essential insights for refining outdoor testing guidelines. Further experimental work will also be required to definitively assess the dependence of parameters like BiFi on module characteristics, possibly confirming the preliminary trends observed in this work.

On the topic of firm PV generation and prototype operational validation, research must necessarily expand from small-scale demonstrators toward utility-scale systems, investigating how physical non-idealities and control dynamics scale across multi-inverter and multi-string configurations. Concurrently, the experimental capabilities of the Infinity prototype should be leveraged to test system responses under different demand profiles. While the current investigation focused on an office-like load characterized by daytime consumption peaks, testing other profiles, such as residential loads featuring morning and evening peaks, will reveal how different load shapes influence operational energy flows, system sizing metrics, and LCOE minimization. Evaluating these load-specific behaviors will offer valuable criteria to determine whether firm PV systems should be designed around centralized production hubs or distributed energy generation facilities.

Furthermore, a comprehensive economic evaluation and a Life Cycle Assessment (LCA) based on the real-world operational data of the prototype should be conducted. Since the final physical parameters (OVS and NDY) implemented in Infinity slightly deviated from initial simulation-based sizing due to commercial hardware constraints, grounded techno-

economic and environmental assessments derived from empirical field data will carry significantly greater weight in establishing the true economic feasibility and sustainability of firm PV systems.

Finally, the Matlab energy flow simulation model must be further refined by transitioning from static to dynamic, power-dependent efficiency formulations. Incorporating dynamic battery charge and discharge efficiency functions and, potentially, active inverter loss curves will ultimately contribute to deliver a highly accurate, fully calibrated design tool for future firm renewable infrastructure.

Appendix A

In this section, the equivalents to **Table 4** for each of the modules that underwent Phase 1 of the characterization protocol are reported.

Table A1 – Acceptance results for module E002, tested on 01/10/2024 between 11:53 and 12:01

E002	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	55.00	55.27 ± 0.17	0.5	50.38 ± 0.04	40.04 ± 0.08	N/A
V_{OC} [V]	17.25	16.53 ± 0.02	-4.2	16.54 ± 0.02	16.43 ± 0.02	N/A
V_{MAX} [V]	13.14	13.13 ± 0.05	-0.1	13.24 ± 0.03	13.28 ± 0.05	N/A
I_{SC} [A]	4.710	4.542 ± 0.012	-3.6	4.088 ± 0.003	3.252 ± 0.003	N/A
I_{MAX} [A]	4.290	4.208 ± 0.015	-1.9	3.807 ± 0.007	3.016 ± 0.013	N/A
FF	0.677	0.736 ± 0.0005	8.7	0.745 ± 0.0006	0.750 ± 0.0007	N/A
$\phi(V_{OC})$			0.9934			
$\phi(I_{SC})$			0.7955			
$\phi(P_{MAX})$			0.7947			

Table A2 – Acceptance results for module B075, tested on 06/06/2025 between 11:52 and 12:04

B075	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	75.00	72.40 ± 0.23	-3.5	67.01 ± 0.05	54.09 ± 0.08	77.44
V_{OC} [V]	23.00	22.17 ± 0.02	-3.6	22.15 ± 0.01	21.85 ± 0.04	21.84
V_{MAX} [V]	17.51	17.23 ± 0.06	-1.6	17.52 ± 0.03	17.83 ± 0.07	18.25
I_{SC} [A]	4.710	4.530 ± 0.002	-3.8	4.092 ± 0.002	3.223 ± 0.003	4.423
I_{MAX} [A]	4.290	4.202 ± 0.010	-2.1	3.826 ± 0.007	3.033 ± 0.008	4.244
FF	0.692	0.721 ± 0.0019	4.2	0.739 ± 0.0007	0.767 ± 0.0004	0.802
$\phi(V_{OC})$			0.9867			
$\phi(I_{SC})$			0.7883			
$\phi(P_{MAX})$			0.8071			

Table A3 – Acceptance results for module B106, tested on 11/07/2024 between 11:55 and 12:09

B106	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	75.00	71.79 ± 0.17	-4.3	66.31 ± 0.10	52.46 ± 0.07	75.64
V_{OC} [V]	23.00	21.80 ± 0.03	-5.2	21.95 ± 0.01	21.70 ± 0.01	21.32
V_{MAX} [V]	17.51	17.14 ± 0.07	-2.1	17.34 ± 0.01	17.51 ± 0.03	17.80
I_{SC} [A]	4.710	4.490 ± 0.009	-4.7	4.097 ± 0.007	3.194 ± 0.007	4.406
I_{MAX} [A]	4.290	4.188 ± 0.012	-2.4	3.823 ± 0.007	2.996 ± 0.008	4.249
FF	0.692	0.733 ± 0.0009	5.9	0.737 ± 0.0006	0.757 ± 0.0007	0.805
$\phi(V_{OC})$			0.9887			
$\phi(I_{SC})$			0.7796			
$\phi(P_{MAX})$			0.7912			

Table A4 – Acceptance results for module B109, tested on 12/07/2024 between 12:10 and 12:20

B109	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	75.00	72.65 ± 0.13	-3.1	67.07 ± 0.15	53.29 ± 0.43	75.87
V_{OC} [V]	23.00	22.04 ± 0.01	-4.2	22.04 ± 0.01	21.77 ± 0.02	21.32
V_{MAX} [V]	17.51	17.36 ± 0.09	-0.9	17.60 ± 0.07	17.70 ± 0.07	17.82
I_{SC} [A]	4.710	4.491 ± 0.002	-4.6	4.090 ± 0.009	3.189 ± 0.027	4.423
I_{MAX} [A]	4.290	4.185 ± 0.025	-2.4	3.811 ± 0.020	3.011 ± 0.020	4.259
FF	0.692	0.734 ± 0.0013	6.1	0.744 ± 0.0008	0.768 ± 0.0012	0.805
$\phi(V_{OC})$			0.9876			
$\phi(I_{SC})$			0.7797			
$\phi(P_{MAX})$			0.7945			

Table A5 – Acceptance results for module B130, tested on 06/06/2025 between 12:09 and 12:20

B130	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	75.00	74.83 ± 0.08	-0.2	68.38 ± 0.09	53.85 ± 0.13	77.33
V_{OC} [V]	23.00	22.04 ± 0.02	-4.2	22.06 ± 0.01	21.82 ± 0.01	21.91
V_{MAX} [V]	17.51	17.64 ± 0.04	0.7	17.77 ± 0.05	17.88 ± 0.08	18.28
I_{SC} [A]	4.710	4.569 ± 0.004	-3.0	4.109 ± 0.003	3.187 ± 0.005	4.403
I_{MAX} [A]	4.290	4.242 ± 0.008	-1.1	3.849 ± 0.012	3.012 ± 0.015	4.231
FF	0.692	0.743 ± 0.0007	7.4	0.754 ± 0.0013	0.775 ± 0.0006	0.802
$\phi(V_{OC})$			0.9888			
$\phi(I_{SC})$			0.7755			
$\phi(P_{MAX})$			0.7876			

Table A6 – Acceptance results for module A007, tested on 15/07/2024 between 12:00 and 12:10

A007	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	105.00	100.05 ± 0.07	-4.7	91.60 ± 0.04	72.23 ± 0.17	108.71
V_{OC} [V]	29.20	30.16 ± 0.04	3.3	30.18 ± 0.02	29.79 ± 0.01	30.09
V_{MAX} [V]	24.75	24.01 ± 0.06	-3.0	24.18 ± 0.05	24.19 ± 0.05	25.27
I_{SC} [A]	4.710	4.455 ± 0.003	-5.4	4.061 ± 0.004	3.184 ± 0.006	4.459
I_{MAX} [A]	4.290	4.167 ± 0.011	-2.9	3.789 ± 0.007	2.986 ± 0.009	4.301
FF	0.763	0.745 ± 0.0005	-2.4	0.747 ± 0.0010	0.761 ± 0.0007	0.810
$\phi(V_{OC})$			0.9869			
$\phi(I_{SC})$			0.7842			
$\phi(P_{MAX})$			0.7886			

Table A7 – Acceptance results for module A027, tested on 15/07/2024 between 11:44 and 11:55

A027	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	105.00	98.73 ± 0.20	-6.0	90.53 ± 0.21	72.02 ± 0.06	107.85
V_{OC} [V]	29.20	30.20 ± 0.01	3.4	30.13 ± 0.01	29.78 ± 0.02	30.11
V_{MAX} [V]	24.75	23.92 ± 0.07	-3.4	24.12 ± 0.06	24.14 ± 0.12	25.22
I_{SC} [A]	4.710	4.461 ± 0.012	-5.3	4.070 ± 0.010	3.181 ± 0.003	4.450
I_{MAX} [A]	4.290	4.127 ± 0.011	-3.8	3.754 ± 0.015	2.983 ± 0.013	4.276
FF	0.763	0.733 ± 0.0007	-3.9	0.738 ± 0.0008	0.760 ± 0.0006	0.805
$\phi(V_{OC})$			0.9882			
$\phi(I_{SC})$			0.7816			
$\phi(P_{MAX})$			0.7955			

Table A8 – Acceptance results for module D013, tested on 24/07/2024 between 12:10 and 12:20

D013	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	105.00	94.77 ± 0.31	-9.7	86.26 ± 0.95	67.56 ± 0.12	107.22
V_{OC} [V]	27.88	28.70 ± 0.01	2.9	28.77 ± 0.02	28.23 ± 0.06	30.08
V_{MAX} [V]	24.48	22.92 ± 0.02	-6.4	23.03 ± 0.08	22.94 ± 0.09	25.24
I_{SC} [A]	4.710	4.435 ± 0.015	-5.8	4.027 ± 0.043	3.132 ± 0.004	4.421
I_{MAX} [A]	4.290	4.134 ± 0.012	-3.6	3.746 ± 0.039	2.945 ± 0.009	4.248
FF	0.800	0.745 ± 0.0003	-6.9	0.745 ± 0.0008	0.764 ± 0.0010	0.806
$\phi(V_{OC})$			0.9814			
$\phi(I_{SC})$			0.7778			
$\phi(P_{MAX})$			0.7832			

Table A9 – Acceptance results for module D047, tested on 01/10/2024 between 11:41 and 11:49

D047	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	105.00	99.18 ± 0.07	-5.5	89.61 ± 0.07	70.57 ± 0.05	107.21
V_{OC} [V]	27.88	29.18 ± 0.01	4.7	29.00 ± 0.01	28.64 ± 0.02	30.11
V_{MAX} [V]	24.48	23.50 ± 0.01	-4.0	23.49 ± 0.03	23.48 ± 0.05	25.26
I_{SC} [A]	4.710	4.512 ± 0.003	-4.2	4.075 ± 0.002	3.175 ± 0.003	4.434
I_{MAX} [A]	4.290	4.220 ± 0.012	-1.6	3.814 ± 0.039	2.006 ± 0.009	4.244
FF	0.800	0.753 ± 0.0003	-5.9	0.758 ± 0.0008	0.776 ± 0.0007	0.803
$\phi(V_{OC})$			0.9879			
$\phi(I_{SC})$			0.7792			
$\phi(P_{MAX})$			0.7876			

Table A10 – Acceptance results for module C121, tested on 23/07/2024 between 11:43 and 12:01

C121	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	125.00	117.79 ± 0.21	-5.8	109.32 ± 0.09	86.84 ± 0.02	128.13
V_{OC} [V]	34.52	35.62 ± 0.01	3.2	35.82 ± 0.01	35.27 ± 0.03	35.51
V_{MAX} [V]	29.14	28.09 ± 0.13	-3.6	28.55 ± 0.05	28.57 ± 0.06	30.20
I_{SC} [A]	4.710	4.496 ± 0.002	-4.5	4.103 ± 0.003	3.245 ± 0.002	4.439
I_{MAX} [A]	4.290	4.193 ± 0.013	-2.3	3.829 ± 0.008	3.039 ± 0.006	4.243
FF	0.769	0.735 ± 0.0003	-4.4	0.744 ± 0.0008	0.759 ± 0.0010	0.813
$\phi(V_{OC})$			0.9846			
$\phi(I_{SC})$			0.7908			
$\phi(P_{MAX})$			0.7944			

Table A11 – Acceptance results for module C145, tested on 23/07/2024 between 12:06 and 12:19

C145	Datasheet	Bifacial	Δ (%)	Front	Rear	Indoor
P_{MAX} [W]	125.00	117.47 ± 0.33	-6.0	108.93 ± 0.12	85.20 ± 0.06	N/A
V_{OC} [V]	34.52	35.43 ± 0.02	2.6	35.65 ± 0.05	35.29 ± 0.01	N/A
V_{MAX} [V]	29.14	28.06 ± 0.08	-3.7	28.52 ± 0.05	28.42 ± 0.04	N/A
I_{SC} [A]	4.710	4.494 ± 0.008	-4.6	4.115 ± 0.002	3.201 ± 0.002	N/A
I_{MAX} [A]	4.290	4.186 ± 0.005	-2.4	3.819 ± 0.008	2.998 ± 0.006	N/A
FF	0.769	0.738 ± 0.0005	-4.0	0.742 ± 0.0006	0.754 ± 0.0004	N/A
$\phi(V_{OC})$			0.9898			
$\phi(I_{SC})$			0.7779			
$\phi(P_{MAX})$			0.7822			

Appendix B

In this appendix, the calculated temperature coefficient values for the 55, 75, and 105 W modules are reported.

Table B1 – Temperature coefficient for the 55W modules

	V_{oc} (V/°C)	I_{sc} (A/°C)	P_{MAX} (W/°C)
E002 - Front	-0.046328±0.000534	0.000902±0.000283	-0.196087±0.004613
E002 - Rear	-0.039011±0.000346	0.001735±0.000423	-0.116552±0.004852
E010 - Front	-0.041515±0.000277	0.003952±0.000106	-0.154254±0.001863
E010 - Rear	-0.041119±0.000300	0.002196±0.000428	-0.124949±0.005074

Table B2 - Temperature coefficient or 75W panel

	V_{oc} (V/°C)	I_{sc} (A/°C)	P_{MAX} (W/°C)
B109 - Front	-0.064880±0.000574	0.005950±0.000314	-0.220612±0.004445
B109 - Rear	-0.061243±0.001148	0.003710±0.000207	-0.178049±0.002976
B106 - Front	-0.053653±0.001028	0.003608±0.000189	-0.195782±0.004584
B106 - Rear	-0.060339±0.000620	0.003548±0.000185	-0.171469±0.002938

Table B3 - Temperature coefficient or 105W panel

	V_{oc} (V/°C)	I_{sc} (A/°C)	P_{MAX} (W/°C)
A007 - Front	-0.092100±0.000488	0.001349±0.000591	-0.406568±0.011303
A007 - Rear	-0.079987±0.000418	0.001300±0.000346	-0.271831±0.007667
A027 - Front	-0.083495±0.000636	0.000874±0.000547	-0.373460±0.011287
A027 - Rear	-0.082101±0.000345	-0.003844±0.000496	-0.383470±0.009176

Appendix C

A quantitative uncertainty assessment was performed using all the experimental datasets reported in the manuscript and in the supplementary tables. The analysis combines Type A (experimental repeatability and regression statistics) and Type B (instrumental) uncertainty, according to ISO/IEC Guide 98-3 (GUM) .

Phase 1 – Acceptance test uncertainty analysis

During Phase 1, the electrical parameters V_{OC} , I_{SC} , P_{MAX} , I_{MAX} , V_{MAX} and FF were determined from five I-V curves for each module translated to bifacial standard test conditions (BSTC) using the Anderson procedure. The electrical parameters reported in the bifacial column of **Table 4** and **Table A1 – Table A11**(Appendix A), correspond to the mean values obtained from the translated curves, while the associated “ $\pm$ ” values represent the standard deviation of the five repetitions. Since each individual I-V curve was translated prior to averaging, the observed standard deviation already captures the repeatability of the measurement chain together with part of the variability induced by small fluctuations in irradiance, module temperature, and residual differences among translated curves. To avoid double counting, irradiance and temperature were therefore not introduced as separate uncertainty terms.

Accordingly, the Type A contribution was estimated as the standard error of the mean (SEM) of the five translated curves:

$$u_A(x) = \frac{STD}{\sqrt{5}} \quad (C1)$$

where x is the corresponding electrical parameter.

For each electrical parameter x , the combined standard uncertainty was evaluated as:

$$u_c(x) = \sqrt{u_A^2(x) + u_B^2(x)} \quad (C2)$$

The expanded uncertainty was then obtained using a coverage factor $k=2$, corresponding approximately to a 95% confidence level:

$$U(x) = 2u_c(x) \quad (C3)$$

For direct comparison among modules with different nominal ratings, the expanded uncertainties were expressed as relative values normalized to the corresponding bifacial parameter:

$$U_r(x) = 100 \frac{U(x)}{x} \quad (C4)$$

Expressing the uncertainty in relative terms facilitates direct comparison among modules belonging to different nominal power classes. The resulting expanded uncertainties are summarized in **Table C1**.

For P_{MAX} , the relative expanded uncertainty ranged from approximately 1.0% to 1.4% across the full dataset. Voltage-related quantities exhibited lower relative uncertainty, generally between about 0.7% and 1.0%, whereas current-related quantities remained comparatively stable, with typical values close to 1.3–1.5%. The fill factor showed remarkable consistency among all tested modules, with relative expanded uncertainties close to 1.6%.

Table C1 – Relative expanded uncertainty of the bifacial electrical parameters measured in Phase 1

Module	$U(P_{MAX})$ [%]	$U(V_{OC})$ [%]	$U(V_{MAX})$ [%]	$U(I_{SC})$ [%]	$U(I_{MAX})$ [%]	$U(FF)$ [%]
E002	1.23	0.85	0.84	1.32	1.43	1.63
E010	1.21	0.85	0.69	1.32	1.42	1.62
B075	1.16	0.81	0.81	1.32	1.43	1.66
B106	1.06	0.83	0.93	1.34	1.43	1.64
B109	1.02	0.82	1.04	1.34	1.67	1.63
B130	1.00	0.82	0.74	1.31	1.41	1.62
A007	1.24	0.83	0.75	1.35	1.44	1.61
A027	1.27	0.83	0.84	1.35	1.45	1.64
D013	1.41	0.80	0.83	1.35	1.45	1.61
D047	1.24	0.82	0.77	1.33	1.42	1.59
C121	1.27	0.81	0.85	1.33	1.43	1.63
C145	1.37	0.82	0.75	1.34	1.19	1.63

Overall, the results indicate that the uncertainty budget is mainly governed by residual instrumental and model-related Type B contributions associated with electrical measurement accuracy and residual translation-model uncertainty, while the contribution arising from experimental repeatability of the five translated I-V curves remains comparatively small. The relatively narrow spread of the relative expanded uncertainties among the different module families confirms the robustness of the adopted methodology and indicates that the proposed approach provides a consistent and physically realistic estimate of the total uncertainty associated with the acceptance-stage bifacial electrical characterization.

Phase 2 – Temperature coefficient uncertainty analysis

During Phase 2, the temperature coefficients of V_{oc} , I_{sc} , and P_{max} were determined for the selected 55 W, 75 W, and 105 W modules by linear regression of the measured electrical parameters as a function of module temperature. For each module side (front and rear), the temperature coefficient was identified as the slope of the corresponding linear fit.

The values reported in Appendix B (

Table B3) are expressed in dimensional form (V/°C, A/°C and W/°C).

In order to allow comparison among modules of different nominal power classes, the coefficients were normalized using the corresponding front- and rear-side reference values obtained during Phase 1. The normalized temperature coefficient was therefore calculated as:

$$\gamma_x = 100 \cdot \frac{1}{x_{ref}} \frac{dx}{dT} \quad (C5)$$

where x_{ref} denotes the corresponding front- or rear-side electrical parameter measured during Phase 1.

The uncertainty analysis was based on two independent contributions. The first one corresponds to the estimated standard uncertainty (1σ) of the slope coefficient obtained from the linear regression. Since this quantity directly represents the uncertainty of the fitted slope, no additional scaling by the number of observations was applied.

The second contribution arises from the uncertainty associated with the normalization parameter x_{ref} . Consistently with the procedure adopted in Phase 1, the standard uncertainty

of the normalization parameter was evaluated from the standard error of the mean of the five translated I–V curves with eq. (C1).

The combined relative standard uncertainty of the normalized temperature coefficient was then obtained by propagation of independent uncertainty contributions according to

$$u_r(\gamma_x) = \sqrt{\left(\frac{u(\text{slope})}{\text{slope}}\right)^2 + \left(\frac{u(x_{\text{ref}})}{x_{\text{ref}}}\right)^2} \quad (\text{C6})$$

The expanded uncertainty was finally calculated using a coverage factor $k=2$, corresponding approximately to a 95% confidence level.

The resulting expanded uncertainties are summarized in **Table C2**. The uncertainty associated with the normalized V_{OC} temperature coefficient remained generally low, with values ranging from approximately 0.0023 to 0.0105 %/°C. For I_{SC} , a wider spread, ranging from approximately 0.0052 to 0.0312 %/°C was observed, reflecting the comparatively smaller absolute magnitude of the current temperature coefficient and its greater sensitivity to experimental variability. The expanded uncertainty of the normalized P_{MAX} temperature coefficient was comparatively stable across the investigated modules, typically ranging between approximately 0.0074 and 0.0255 %/°C.

Table C2 – Expanded uncertainty of the normalized temperature coefficients determined in Phase 2.

Module	$U(\gamma_{V_{OC}})$ [%/°C]	$U(\gamma_{I_{SC}})$ [%/°C]	$U(\gamma_{P_{MAX}})$ [%/°C]
A007 – Front	0.0032	0.0291	0.0247
A007 – Rear	0.0028	0.0217	0.0212
A027 – Front	0.0042	0.0269	0.0250
A027 – Rear	0.0023	0.0312	0.0255
B109 – Front	0.0052	0.0154	0.0133
B109 – Rear	0.0105	0.0130	0.0114
B106 – Front	0.0094	0.0092	0.0138
B106 – Rear	0.0057	0.0116	0.0112
E002 – Front	0.0065	0.0138	0.0183
E002 – Rear	0.0042	0.0260	0.0242
E010 – Front	0.0034	0.0052	0.0074
E010 – Rear	0.0037	0.0267	0.0252
Mean* (all modules)	0.0051	0.0192	0.0184

*Mean values were calculated as simple arithmetic averages across all front- and rear-side module measurements

Overall, the uncertainty budget of the temperature coefficients was primarily governed by the uncertainty of the slope estimated by linear regression, while the contribution associated with normalization to the Phase 1 reference values remained secondary. The relatively limited spread of the expanded uncertainties among module technologies and module sides confirms the consistency of the adopted methodology and supports the robustness of the temperature-coefficient characterization under outdoor operating conditions.

Phase 3 – BiFi coefficient uncertainty analysis

During Phase 3, the bifaciality factor (BiFi) was determined by linear regression of the bifacial maximum power P_{MAX} (bifacial) as a function of rear-side transmitted irradiance (RTI). For each module, the regression was performed with the intercept constrained to the corresponding front-side maximum power measured during Phase 1. Under this formulation, the bifaciality factor corresponds to the slope of the linear relationship between power gain and rear irradiance.

The values reported in Table 6 are expressed as the estimated slope coefficients of the linear fit. The associated uncertainty analysis considered two independent contributions. The first contribution corresponds to the estimated standard uncertainty (1σ) of the fitted slope coefficient obtained directly from the linear regression. Since this quantity already represents the standard uncertainty of the regression parameter, no additional scaling by the number of observations was applied.

The second contribution arises from the uncertainty associated with the fixed intercept P_{MAX} (front), which was derived from the Phase 1 acceptance measurements. Consistently with the procedure adopted in Phase 1, the standard uncertainty of the front-side reference power was evaluated from the standard error of the mean of the five translated I-V curves, Eq. C1.

The uncertainty of the constrained intercept was propagated to the slope estimate using the experimental distribution of RTI values employed in each regression. For a given module, the corresponding contribution was evaluated as a function of the dispersion of the irradiance dataset around its mean value.

For modules for which repeated measurements were available (E002 and C145), the individual BiFi estimates were combined by inverse-variance weighted averaging. The

combined standard uncertainty was then obtained from the inverse of the summed statistical weights.

The expanded uncertainty was finally calculated using a coverage factor $k=2$, corresponding approximately to a 95% confidence level.

The resulting expanded uncertainties are summarized in **Table C3**.

Table C3 – Expanded uncertainty of the bifaciality factor determined in Phase 3

Module	BiFi	Expanded uncertainty
E002	0.0266	0.0011
E010	0.0293	0.0008
B075	0.0497	0.0014
B130	0.0387	0.0028
B274	0.0346	0.0010
D013	0.0723	0.0175
D047	0.0643	0.0020
C121	0.0813	0.0021
C145	0.0803	0.0019

For most modules, the expanded uncertainty remained limited, generally below 0.003. The largest uncertainty was observed for module D013, for which the broader dispersion of the experimental dataset and the larger uncertainty of the front-side reference power resulted in a more pronounced propagated contribution. Overall, the uncertainty budget was primarily governed by the statistical uncertainty of the fitted slope, while the contribution associated with the constrained intercept remained secondary for the majority of modules.

The relatively low uncertainty levels obtained across the investigated module classes support the robustness of the adopted regression-based methodology for estimating bifaciality under outdoor operating conditions.

References

- [1] Energy Institute, “Statistical Review of World Energy,” 2026. Accessed: Jul. 07, 2026. [Online]. Available: <https://www.energyinst.org/statistical-review>
- [2] International Energy Agency, “Global Energy Review 2026,” 2026. Accessed: Jul. 07, 2026. [Online]. Available: <https://www.iea.org/reports/global-energy-review-2026>
- [3] International Energy Agency, “World Energy Outlook 2025,” 2025. Accessed: Jul. 07, 2026. [Online]. Available: <https://www.iea.org/reports/world-energy-outlook-2025>
- [4] Oxford Institute for Energy Studies, “Unpacking the Hormuz Crisis: Implications for energy markets and the energy transition,” 2026. Accessed: Jul. 07, 2026. [Online]. Available: <https://www.oxfordenergy.org/publications/unpacking-the-hormuz-crisis-implications-for-energy-markets-and-the-energy-transition-issue-149/>
- [5] United Nations, “COP28.” Accessed: Jul. 08, 2026. [Online]. Available: <https://www.un.org/en/climatechange/cop28>
- [6] European Commission, “The European Green Deal - Striving to be the first climate-neutral continent.” Accessed: Jul. 07, 2026. [Online]. Available: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en
- [7] European Council, “Fit for 55.” Accessed: Jul. 08, 2026. [Online]. Available: <https://www.consilium.europa.eu/en/policies/fit-for-55/>
- [8] European Commission, “Clean Industrial Deal.” Accessed: Jul. 08, 2026. [Online]. Available: https://commission.europa.eu/topics/competitiveness/clean-industrial-deal_en
- [9] International Energy Agency, “Renewables 2025,” 2025.
- [10] Rome Technopole Foundation, “Rome Technopole.” Accessed: Jul. 07, 2026. [Online]. Available: <https://www.rometechnopole.it/>
- [11] Italian Government, “Piano Nazionale di Ripresa e Resilienza.” Accessed: Jul. 07, 2026. [Online]. Available: <https://www.governo.it/sites/governo.it/files/PNRR.pdf>

-
- [12] S. Ahmed, A. Ali, J. Ahmed Ansari, S. Abdul Qadir, and L. Kumar, "A Comprehensive Review of Solar Photovoltaic Systems: Scope, Technologies, Applications, Progress, Challenges, and Recommendations," 2025, *Institute of Electrical and Electronics Engineers Inc.* doi: 10.1109/ACCESS.2025.3558539.
- [13] M. Yamaguchi, "Current Status and Future Direction of Photovoltaics," Sep. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/app15179416.
- [14] A. O. Ali *et al.*, "Advancements in photovoltaic technology: A comprehensive review of recent advances and future prospects," Apr. 01, 2025, *Elsevier Ltd.* doi: 10.1016/j.ecmx.2025.100952.
- [15] S. Al-Ali, A. G. Olabi, and M. Mahmoud, "A review of solar photovoltaic technologies: developments, challenges, and future perspectives," Jul. 01, 2025, *Elsevier Ltd.* doi: 10.1016/j.ecmx.2025.101057.
- [16] Fraunhofer Institute, "Photovoltaics Report," 2025.
- [17] REN21, "Renewables 2025 Global Status Report - Global Overview," 2025.
- [18] Y. Wang, G. Luo, and Y. Guo, "Why is there overcapacity in China's PV industry in its early growth stage?," *Renew. Energy*, vol. 72, pp. 188–194, Dec. 2014, doi: 10.1016/j.renene.2014.07.008.
- [19] International Renewable Energy Agency, *Renewable power generation costs in 2024*. IRENA, 2025.
- [20] P. Denholm, M. O'connell, G. Brinkman, and J. Jorgenson, "Overgeneration from Solar Energy in California: A Field Guide to the Duck Chart," 2013. [Online]. Available: www.nlr.gov/publications.
- [21] R. Bowers, E. Fasching, and K. Antonio, "As solar capacity grows, duck curves are getting deeper in California," Energy Information Administration. Accessed: Jul. 14, 2026. [Online]. Available: <https://www.eia.gov/todayinenergy/detail.php?id=56880>
- [22] G. M. Pitra and K. S. S. Musti, "Impact Analysis of Duck Curve Phenomena with Renewable Energies and Storage Technologies," *Journal of Engineering Research and Sciences*, vol. 1, no. 5, pp. 52–60, May 2022, doi: 10.55708/js0105006.

-
- [23] B. Krietemeyer, J. Dedrick, E. Sabaghian, and T. Rakha, "Managing the duck curve: Energy culture and participation in local energy management programs in the United States," *Energy Res. Soc. Sci.*, vol. 79, Sep. 2021, doi: 10.1016/j.erss.2021.102055.
- [24] J. Pastuszak and P. Węgierek, "Photovoltaic Cell Generations and Current Research Directions for Their Development," *Materials*, vol. 15, no. 16, p. 5542, Aug. 2022, doi: 10.3390/ma15165542.
- [25] A. Mdallal, A. Yasin, M. Mahmoud, M. A. Abdelkareem, A. H. Alami, and A. G. Olabi, "A comprehensive review on solar photovoltaics: Navigating generational shifts, innovations, and sustainability," *Sustainable Horizons*, vol. 13, p. 100137, Mar. 2025, doi: 10.1016/j.horiz.2025.100137.
- [26] T. Kirchartz, G. Yan, Y. Yuan, B. K. Patel, D. Cahen, and P. K. Nayak, "The state of the art in photovoltaic materials and device research," *Nat. Rev. Mater.*, vol. 10, no. 5, pp. 335–354, Mar. 2025, doi: 10.1038/s41578-025-00784-4.
- [27] National Laboratory of the Rockies, "Best Research-Cell Efficiency," 2026.
- [28] B. Liang *et al.*, "Progress in crystalline silicon heterojunction solar cells," *J. Mater. Chem. A Mater.*, vol. 13, no. 4, pp. 2441–2477, 2025, doi: 10.1039/D4TA06224H.
- [29] E. T. Efaz *et al.*, "A review of primary technologies of thin-film solar cells," *Engineering Research Express*, vol. 3, no. 3, p. 032001, Sep. 2021, doi: 10.1088/2631-8695/ac2353.
- [30] O. Almora *et al.*, "Device Performance of Emerging Photovoltaic Materials (Version 5)," Mar. 25, 2025, *John Wiley and Sons Inc.* doi: 10.1002/aenm.202404386.
- [31] Y. Zhang, H. Xia, J. Yu, Y. Yang, and G. Li, "Materials and Device Engineering Perspective: Recent Advances in Organic Photovoltaics," *Advanced Materials*, vol. 37, no. 48, Dec. 2025, doi: 10.1002/adma.202504063.
- [32] M. Ashrafuzzaman, A. Kalam, A. G. Al-Sehemi, P. Yadav, and M. Dubey, "A review of photoanode materials, challenges, and outlook of dye-sensitized solar cells," *J. Power Sources*, vol. 638, p. 236636, May 2025, doi: 10.1016/j.jpowsour.2025.236636.
- [33] M. N. Rahman Antu, M. W. Hasan, M. Hasanuzzaman, and M. M. Islam, "Challenges and prospects of semi transparent dye-sensitized solar cells for real-world applications: A review," *Curr. Opin. Colloid Interface Sci.*, vol. 77, p. 101907, Jun. 2025, doi: 10.1016/j.cocis.2025.101907.

-
- [34] J. Han *et al.*, “Perovskite solar cells,” *Nature Reviews Methods Primers*, vol. 5, no. 1, p. 3, Jan. 2025, doi: 10.1038/s43586-024-00373-9.
- [35] L. Zhang *et al.*, “Diverse Perovskite Solar Cells: Progress, Challenges, and Perspectives,” *Advanced Materials*, vol. 38, no. 1, Jan. 2026, doi: 10.1002/adma.202512221.
- [36] S. Wang *et al.*, “Flexible perovskite/silicon tandem solar cells with 33.6% efficiency,” *Nature*, vol. 649, no. 8095, pp. 59–64, Jan. 2026, doi: 10.1038/s41586-025-09849-4.
- [37] J. Lim, N.-G. Park, S. Il Seok, and M. Saliba, “All-perovskite tandem solar cells: from fundamentals to technological progress,” *Energy Environ. Sci.*, vol. 17, no. 13, pp. 4390–4425, 2024, doi: 10.1039/D3EE03638C.
- [38] Y. Shi, J. J. Berry, and F. Zhang, “Perovskite/Silicon Tandem Solar Cells: Insights and Outlooks,” *ACS Energy Lett.*, vol. 9, no. 3, pp. 1305–1330, Mar. 2024, doi: 10.1021/acsenergylett.4c00172.
- [39] L. Duan *et al.*, “Stability challenges for the commercialization of perovskite–silicon tandem solar cells,” *Nat. Rev. Mater.*, vol. 8, no. 4, pp. 261–281, Jan. 2023, doi: 10.1038/s41578-022-00521-1.
- [40] T. Seyisi *et al.*, “Major challenges for commercialization of perovskite solar cells: A critical review,” *Energy Reports*, vol. 13, pp. 1400–1415, Jun. 2025, doi: 10.1016/j.egy.2025.01.019.
- [41] G. Bovesecchi *et al.*, “Outdoor Performance Monitoring Method for Degradation Studies of Perovskite Modules,” *Progress in Photovoltaics: Research and Applications*, vol. 33, no. 3, pp. 445–461, Mar. 2025, doi: 10.1002/pip.3860.
- [42] F. Batista, A. S. Guimarães, and A. I. Palmero-Marrero, “Building Integrated Photovoltaics: a multi-level design review for optimized implementation,” *Renewable and Sustainable Energy Reviews*, vol. 220, p. 115837, Sep. 2025, doi: 10.1016/j.rser.2025.115837.
- [43] P. Ni *et al.*, “Building integrated photovoltaics that move beyond rooftops,” *Cell Rep. Phys. Sci.*, vol. 6, no. 8, p. 102725, Aug. 2025, doi: 10.1016/j.xcrp.2025.102725.
- [44] A. Faes *et al.*, “Building-integrated photovoltaics,” *Nature Reviews Clean Technology*, vol. 1, no. 5, pp. 333–350, May 2025, doi: 10.1038/s44359-025-00059-9.

-
- [45] S. Aguacil, S. Duque, S. Lufkin, and E. Rey, “Designing with building-integrated photovoltaics (BIPV): A pathway to decarbonize residential buildings,” *Journal of Building Engineering*, vol. 96, Nov. 2024, doi: 10.1016/j.jobbe.2024.110486.
- [46] E. Belloni *et al.*, “An overview on building-integrated photovoltaics: technological solutions, modeling, and control,” *Energy Build.*, vol. 324, Dec. 2024, doi: 10.1016/j.enbuild.2024.114867.
- [47] M. K. Basher, M. Nur-E-Alam, M. M. Rahman, K. Alameh, and S. Hinckley, “Aesthetically Appealing Building Integrated Photovoltaic Systems for Net-Zero Energy Buildings. Current Status, Challenges, and Future Developments—A Review,” Apr. 01, 2023, *MDPI*. doi: 10.3390/buildings13040863.
- [48] Y. Li, X. Huang, H. K. M. Sheriff, and S. R. Forrest, “Semitransparent organic photovoltaics for building-integrated photovoltaic applications,” *Nat. Rev. Mater.*, vol. 8, no. 3, pp. 186–201, Dec. 2022, doi: 10.1038/s41578-022-00514-0.
- [49] B. Sharma and S. Satapathi, “Semi-Transparent Perovskite Solar Cells for Building Integrated Photovoltaics Application,” Aug. 21, 2025, *John Wiley and Sons Inc.* doi: 10.1002/admt.202500434.
- [50] M. H. Oeishee and Md. M. Rahman, “A Review of Floating Photovoltaic Systems: Prospects, Challenges, and Sustainability Considerations,” *Global Challenges*, vol. 10, no. 2, Feb. 2026, doi: 10.1002/gch2.202500581.
- [51] S. Fan, Z. Ma, T. Liu, C. Zheng, and H. Wang, “Innovations and development trends in offshore floating photovoltaic systems: A comprehensive review,” *Energy Reports*, vol. 13, pp. 1950–1958, Jun. 2025, doi: 10.1016/j.egy.2025.01.053.
- [52] A. Mahmoudi Aznaveh, H. Yousefi, and F. Razi Astaraei, “Mitigating water evaporation and enhancing renewable energy with floating photovoltaic systems: An integrated approach to resource sustainability,” *Energy Nexus*, vol. 21, Mar. 2026, doi: 10.1016/j.nexus.2026.100683.
- [53] P. M. B. Oliveira, R. M. Almeida, and S. J. Cardoso, “Effects of floating photovoltaics on aquatic organisms: a review,” Jul. 01, 2025, *Springer Science and Business Media Deutschland GmbH*. doi: 10.1007/s10750-024-05686-0.

-
- [54] i-Pergola, “FloatingPV Tech.” Accessed: Jul. 15, 2026. [Online]. Available: <https://i-pergola.it/it/soluzioni-pv/floating-pv.php>
- [55] L. Micheli, “The temperature of floating photovoltaics: Case studies, models and recent findings,” Aug. 01, 2022, *Elsevier Ltd.* doi: 10.1016/j.solener.2022.06.039.
- [56] C. J. Ramanan, K. H. Lim, and J. C. Kurnia, “Thermal behavior of floating photovoltaics: A comparison of performance at varying heights and benchmarking against land-based photovoltaics,” *Appl. Energy*, vol. 388, Jun. 2025, doi: 10.1016/j.apenergy.2025.125642.
- [57] V. S. Nysted *et al.*, “Modelling wave-induced losses for floating photovoltaics: Impact of design parameters and environmental conditions,” *Solar Energy*, vol. 293, Jun. 2025, doi: 10.1016/j.solener.2025.113439.
- [58] L. Micheli, D. L. Talavera, G. Marco Tina, F. Almonacid, and E. F. Fernández, “Techno-economic potential and perspectives of floating photovoltaics in Europe,” *Solar Energy*, vol. 243, pp. 203–214, Sep. 2022, doi: 10.1016/j.solener.2022.07.042.
- [59] S. Z. Golroodbari, A. W. A. Ayyad, and W. van Sark, “Offshore floating photovoltaics system assessment in worldwide perspective,” *Progress in Photovoltaics: Research and Applications*, vol. 31, no. 11, pp. 1061–1077, Nov. 2023, doi: 10.1002/pip.3723.
- [60] A. Ghosh, “Nexus between agriculture and photovoltaics (agrivoltaics, agriphotovoltaics) for sustainable development goal: A review,” *Solar Energy*, vol. 266, p. 112146, Dec. 2023, doi: 10.1016/j.solener.2023.112146.
- [61] E. B. Agyekum, “A comprehensive review of two decades of research on agrivoltaics, a promising new method for electricity and food production,” *Sustainable Energy Technologies and Assessments*, vol. 72, p. 104055, Dec. 2024, doi: 10.1016/j.seta.2024.104055.
- [62] S. Zainali *et al.*, “Modelling, simulation, and optimisation of agrivoltaic systems: a comprehensive review,” *Appl. Energy*, vol. 386, p. 125558, May 2025, doi: 10.1016/j.apenergy.2025.125558.
- [63] TSE, “Agricultural canopy.” Accessed: Jul. 15, 2026. [Online]. Available: <https://www.tse.energy/en/agrivoltaic/agricultural-canopy>

-
- [64] M. Birchall, S. N. Hussain, and A. Ghosh, "Review of agrivoltaic demonstration site studies with comparable configurations for a UK-based application," *Solar Compass*, vol. 15, p. 100135, Sep. 2025, doi: 10.1016/j.solcom.2025.100135.
- [65] Á. Fernández Solas *et al.*, "Monitoring and assessment of elevated agrivoltaic systems in southern Spain," *Solar Energy*, vol. 316, p. 114845, Sep. 2026, doi: 10.1016/j.solener.2026.114845.
- [66] M. H. Riaz, H. Imran, H. Alam, M. A. Alam, and N. Z. Butt, "Crop-Specific Optimization of Bifacial PV Arrays for Agrivoltaic Food-Energy Production: The Light-Productivity-Factor Approach," *IEEE J. Photovolt.*, vol. 12, no. 2, pp. 572–580, Mar. 2022, doi: 10.1109/JPHOTOV.2021.3136158.
- [67] Ö. E. Özdemir *et al.*, "Design, simulation, and experimental evaluation of an agrivoltaic greenhouse in Turkey," *Results in Engineering*, vol. 26, Jun. 2025, doi: 10.1016/j.rineng.2025.105278.
- [68] G. Bovesecchi, L. Rosati, F. Biso, A. Sohani, M. Berardo Di Stefano, and C. Cornaro, "Design and implementation of an integrated microclimate, irrigation, and photovoltaic monitoring system for a pilot agrivoltaic greenhouse," *Journal of Building Engineering*, p. 116854, Jul. 2026, doi: 10.1016/j.jobbe.2026.116854.
- [69] S. Y. Kim, N. Rayes, A. R. Kemanian, E. D. Gomez, and N. Y. Doumon, "Semitransparent organic and perovskite photovoltaics for agrivoltaic applications," Nov. 08, 2024, *Royal Society of Chemistry*. doi: 10.1039/d4ya00492b.
- [70] REGACE, "Using CO₂ for Green Energy." Accessed: Feb. 20, 2026. [Online]. Available: <https://regaceproject.com/>
- [71] C. H. Thum, K. Okada, Y. Yamasaki, and Y. Kato, "Impacts of agrivoltaic systems on microclimate, grain yield, and quality of lowland rice under a temperate climate," *Field Crops Res.*, vol. 326, May 2025, doi: 10.1016/j.fcr.2025.109877.
- [72] E. H. Adeh, J. S. Selker, and C. W. Higgins, "Remarkable agrivoltaic influence on soil moisture, micrometeorology and water-use efficiency," *PLoS One*, vol. 13, no. 11, Nov. 2018, doi: 10.1371/journal.pone.0203256.
- [73] T. Krexner, A. Bauer, A. Gronauer, C. Mikovits, J. Schmidt, and I. Kral, "Environmental life cycle assessment of a stilted and vertical bifacial crop-based agrivoltaic multi land-use

- system and comparison with a mono land-use of agricultural land,” *Renewable and Sustainable Energy Reviews*, vol. 196, p. 114321, May 2024, doi: 10.1016/j.rser.2024.114321.
- [74] Z. Liu and Y. Du, “Evolution towards dispatchable PV using forecasting, storage, and curtailment: A review,” Oct. 01, 2023, *Elsevier Ltd.* doi: 10.1016/j.epsr.2023.109554.
- [75] L. A. Wong, V. K. Ramachandaramurthy, S. L. Walker, and J. B. Ekanayake, “Optimal Placement and Sizing of Battery Energy Storage System Considering the Duck Curve Phenomenon,” *IEEE Access*, vol. 8, pp. 197236–197248, 2020, doi: 10.1109/ACCESS.2020.3034349.
- [76] A. and P. A. Harisankar A. H. and Nandan, “Energy Storage Sizing and Management Using Optimization for an Anticipated Duck Curve in Mumbai,” in *Advances in Multidisciplinary Design, Analysis and Optimization*, S. S. and M. T. K. and S. U. K. Sharma Deepak and Gautam, Ed., Singapore: Springer Nature Singapore, 2025, pp. 253–261.
- [77] P. Kaledio and O. Favour, “Integration of Solar Energy with Energy Storage Systems,” *SSRN Electronic Journal*, 2024, doi: 10.2139/ssrn.4888883.
- [78] M. Kurtoğlu and F. Eroğlu, “Current trends and challenges in solar PV-integrated battery energy storage technology: Key components, methods, and future prospects,” Apr. 15, 2026, *Elsevier Ltd.* doi: 10.1016/j.apenergy.2026.127461.
- [79] P. Boonluk, A. Siritaratiwat, P. Fuangfoo, and S. Khunkitti, “Optimal siting and sizing of battery energy storage systems for distribution network of distribution system operators,” *Batteries*, vol. 6, no. 4, pp. 1–16, Dec. 2020, doi: 10.3390/batteries6040056.
- [80] N. Pompern, S. Premrudeepreechacharn, A. Siritaratiwat, and S. Khunkitti, “Optimal Placement and Capacity of Battery Energy Storage System in Distribution Networks Integrated With PV and EVs Using Metaheuristic Algorithms,” *IEEE Access*, vol. 11, pp. 68379–68394, 2023, doi: 10.1109/ACCESS.2023.3291590.
- [81] K. Wichitkrailat, S. Premrudeepreechacharn, A. Siritaratiwat, and S. Khunkitti, “Optimal Sizing and Locations of Multiple BESSs in Distribution Systems Using Crayfish Optimization Algorithm,” *IEEE Access*, vol. 12, pp. 94733–94752, 2024, doi: 10.1109/ACCESS.2024.3425963.

-
- [82] J. A. Tejero-Gómez and Á. A. Bayod-Rújula, "Analysis of Photovoltaic Plants with Battery Energy Storage Systems (PV-BESS) for Monthly Constant Power Operation," *Energies (Basel)*, vol. 16, no. 13, Jul. 2023, doi: 10.3390/en16134909.
- [83] T. F. Agajie *et al.*, "A Comprehensive Review on Techno-Economic Analysis and Optimal Sizing of Hybrid Renewable Energy Sources with Energy Storage Systems," *Energies (Basel)*, vol. 16, no. 2, p. 642, Jan. 2023, doi: 10.3390/en16020642.
- [84] A. Emrani and A. Berrada, "A comprehensive review on techno-economic assessment of hybrid energy storage systems integrated with renewable energy," *J. Energy Storage*, vol. 84, p. 111010, Apr. 2024, doi: 10.1016/j.est.2024.111010.
- [85] E. Gul *et al.*, "A techno-economic analysis of a solar PV and DC battery storage system for a community energy sharing," *Energy*, vol. 244, p. 123191, Apr. 2022, doi: 10.1016/j.energy.2022.123191.
- [86] C. Budischak, D. Sewell, H. Thomson, L. Mach, D. E. Veron, and W. Kempton, "Cost-minimized combinations of wind power, solar power and electrochemical storage, powering the grid up to 99.9% of the time," *J. Power Sources*, vol. 225, pp. 60–74, Mar. 2013, doi: 10.1016/j.jpowsour.2012.09.054.
- [87] International Energy Agency, "Bifacial Photovoltaic Modules and Systems: Experience and Results from International Research and Pilot Applications," 2021. [Online]. Available: www.iea-pvps.org
- [88] R. Guerrero-Lemus, R. Vega, T. Kim, A. Kimm, and L. E. Shephard, "Bifacial solar photovoltaics – A technology review," *Renewable and Sustainable Energy Reviews*, vol. 60, pp. 1533–1549, Jul. 2016, doi: 10.1016/j.rser.2016.03.041.
- [89] E. Muñoz-Cerón, S. Moreno-Buesa, J. Leloux, J. Aguilera, and D. Moser, "Evaluation of the bifaciality coefficient of bifacial photovoltaic modules under real operating conditions," *J. Clean. Prod.*, vol. 434, p. 139807, Jan. 2024, doi: 10.1016/j.jclepro.2023.139807.
- [90] J. P. Singh, A. G. Aberle, and T. M. Walsh, "Electrical characterization method for bifacial photovoltaic modules," *Solar Energy Materials and Solar Cells*, vol. 127, pp. 136–142, Aug. 2014, doi: 10.1016/j.solmat.2014.04.017.

-
- [91] C. Deline, S. MacAlpine, B. Marion, F. Toor, A. Asgharzadeh, and J. S. Stein, "Evaluation and field assessment of bifacial photovoltaic module power rating methodologies," in *2017 IEEE 44th Photovoltaic Specialist Conference (PVSC)*, IEEE, Jun. 2017, pp. 1–6. doi: 10.1109/PVSC.2017.8366887.
- [92] T. S. Liang, D. Poh, and M. Pravettoni, "Challenges in the pre-normative characterization of bifacial photovoltaic modules," *Energy Procedia*, vol. 150, pp. 66–73, Sep. 2018, doi: 10.1016/j.egypro.2018.09.006.
- [93] T. S. Liang *et al.*, "A review of crystalline silicon bifacial photovoltaic performance characterisation and simulation," *Energy Environ. Sci.*, vol. 12, no. 1, pp. 116–148, Jan. 2019, doi: 10.1039/C8EE02184H.
- [94] IEC, "TS 60904-1-2," 2019.
- [95] J. Lopez-Garcia *et al.*, "Implementation of the IEC TS 60904-1-2 Measurement Methods for Bifacial Silicon PV Devices," *IEEE J. Photovolt.*, vol. 12, no. 3, pp. 787–797, May 2022, doi: 10.1109/JPHOTOV.2022.3161186.
- [96] M. Rauer, A. Schmid, F. Guo, F. Neuberger, P. Gebhardt, and J. Hohl-Ebinger, "Comprehensive evaluation of IEC measurement procedures for bifacial solar cells and modules," in *Proceedings of the 37th European PV Solar Energy Conference and Exhibition*, Sep. 2020.
- [97] VDMA, "International Technology Roadmap for Photovoltaics (IRTPV) - 17th edition," 2026.
- [98] IndustryARC, "Bifacial Solar Panel/Bifacial Solar Module Market." Accessed: Jul. 17, 2026. [Online]. Available: <https://www.industryarc.com/report/19375/bifacial-solar-panel-bifacial-solar-module-market.html>
- [99] Fortune Business Insights, "Bifacial Solar Market Size, Share & Industry Analysis, By Panel (Glass-Glass Panel and Glass Transparent Backsheet Panel), By Cell Technology (Bifacial PERC, Bifacial TOPCon, and Others), By Application (Utility, Commercial & Industrial, and Residential), and Regional Forecast, 2026-2034," Jan. 2026. Accessed: Feb. 24, 2026. [Online]. Available: <https://www.fortunebusinessinsights.com/industry-reports/bifacial-solar-panels-market-100291>

-
- [100] R. Kopecek, I. Shoukry, and J. Libal, “Cost/kWh thinking and bifaciality: Two allies for low-cost PV of the future,” *Photovoltaics Int.*, vol. 30, pp. 88–97, 2015.
- [101] P. K. Sahu, C. Chakraborty, and J. N. Roy, “Comparative Economic Analysis of Bifacial Roof-top PV Systems,” *Energy for Sustainable Development*, vol. 83, p. 101593, Dec. 2024, doi: 10.1016/j.esd.2024.101593.
- [102] S. Pilaniya, S. Sharma, and S. Sinha, “Techno-economic comparative evaluation of Monofacial and Bifacial PV Modules,” in *2025 IEEE 5th International Conference on Sustainable Energy and Future Electric Transportation (SEFET)*, IEEE, Jul. 2025, pp. 1–6. doi: 10.1109/SEFET65155.2025.11255527.
- [103] R. O. Yakubu, L. D. Mensah, D. A. Quansah, and M. S. Adaramola, “A systematic literature review of the bifacial photovoltaic module and its applications,” *The Journal of Engineering*, vol. 2024, no. 8, Aug. 2024, doi: 10.1049/tje2.12421.
- [104] N. Ishikawa and S. Nishiyama, “Photovoltaic Technical Solutions - World First Large Scale 1.25MW Bifacial PV Power Plant on Snowy Area in Japan,” PVG Solutions, 2016. [Online]. Available: <http://www.pvgs.jp>
- [105] L. Stocker, “Europe Round-up: Denmark’s first bifacial solar farm is sold, RWE to pocket French solar,” PVTech. Accessed: Jul. 17, 2026. [Online]. Available: <https://www.pv-tech.org/europe-round-up-denmarks-first-bifacial-solar-farm-is-sold-rwe-to-pocket-fr/>
- [106] Sunpreme Inc., “Sunpreme deploys the World’s Largest Bifacial PV Installation for a 12.8 MW Utility Project in Eastern US,” PR Newswire. Accessed: Jul. 17, 2026. [Online]. Available: <https://www.prnewswire.com/news-releases/sunpreme-deploys-the-worlds-largest-bifacial-pv-installation-for-a-128-mw-utility-project-in-eastern-us-300325989.html>
- [107] E. Bellini, “LONGi supplies 101 MW bifacial modules for an ultra-large power plant in Chile,” PV Magazine. Accessed: Jul. 17, 2026. [Online]. Available: <https://www.pv-magazine.com/press-releases/longi-supplies-101-mw-bifacial-modules-for-an-ultra-large-power-plant-in-chile/>

-
- [108] LONGi, “LONGi supplies 800MW of bifacial modules for the first solar power plant in Qatar,” LONGi News. Accessed: Jul. 17, 2026. [Online]. Available: <https://www.longi.com/en/news/first-solar-power-plant-in-qatar/>
- [109] B. Willockx, C. Lavaert, and J. Cappelle, “Performance evaluation of vertical bifacial and single-axis tracked agrivoltaic systems on arable land,” *Renew. Energy*, vol. 217, Nov. 2023, doi: 10.1016/j.renene.2023.119181.
- [110] G. M. Tina, F. Bontempo Scavo, L. Merlo, and F. Bizzarri, “Comparative analysis of monofacial and bifacial photovoltaic modules for floating power plants,” *Appl. Energy*, vol. 281, Jan. 2021, doi: 10.1016/j.apenergy.2020.116084.
- [111] E. Mouhib, L. Micheli, F. M. Almonacid, and E. F. Fernández, “Overview of the Fundamentals and Applications of Bifacial Photovoltaic Technology: Agrivoltaics and Aquavoltaics,” Dec. 01, 2022, *MDPI*. doi: 10.3390/en15238777.
- [112] Z. R. K. Abojela, M. K. M. Desa, and A. H. Sabry, “Current prospects of building-integrated solar PV systems and the application of bifacial PVs,” 2023, *Frontiers Media S.A.* doi: 10.3389/fenrg.2023.1164494.
- [113] H. Kim, K. Shin, H. S. Lim, S. R. Lee, and C. K. Lee, “Development and application of photovoltaic noise barrier system for sustainable transportation infrastructures from a life cycle carbon perspective,” *Energy Reports*, vol. 15, Jun. 2026, doi: 10.1016/j.egyr.2026.109086.
- [114] G. J. Faturrochman, M. M. de Jong, R. Santbergen, W. Folkerts, M. Zeman, and A. H. M. Smets, “Maximizing annual yield of bifacial photovoltaic noise barriers,” *Solar Energy*, vol. 162, pp. 300–305, Mar. 2018, doi: 10.1016/j.solener.2018.01.001.
- [115] SoliTek, “Photovoltaic Noise Barriers (PVNBs): A Sustainable Solution.” Accessed: Jul. 17, 2026. [Online]. Available: <https://www.solitek.eu/en/solutions/photovoltaic-noise-barrier>
- [116] M. Perez, R. Perez, K. R. Rábago, and M. Putnam, “Overbuilding & curtailment: The cost-effective enablers of firm PV generation,” *Solar Energy*, vol. 180, pp. 412–422, Mar. 2019, doi: 10.1016/j.solener.2018.12.074.
- [117] C. Budischak, D. Sewell, H. Thomson, L. Mach, D. E. Veron, and W. Kempton, “Cost-minimized combinations of wind power, solar power and electrochemical storage,

- powering the grid up to 99.9% of the time,” *J. Power Sources*, vol. 225, pp. 60–74, Mar. 2013, doi: 10.1016/j.jpowsour.2012.09.054.
- [118] M. Perez, R. Perez, and T. Hoff, “Implicit Storage - Optimally Achieving Lowest-Cost 100% Renewable Power Generation,” in *Proceedings of the ISES Solar World Congress 2021*, Freiburg, Germany: International Solar Energy Society, 2021, pp. 1–5. doi: 10.18086/swc.2021.01.02.
- [119] G. Yang, D. Yang, C. Lyu, and J. Kleissl, “Firm Photovoltaic Generation through Battery Storage, Overbuilding, and Proactive Curtailment,” in *2022 4th International Conference on Smart Power & Internet Energy Systems (SPIES)*, IEEE, Dec. 2022, pp. 1997–2002. doi: 10.1109/SPIES55999.2022.10082605.
- [120] J. Remund, R. Perez, M. Perez, M. Pierro, and D. Yang, “Firm Photovoltaic Power Generation: Overview and Economic Outlook,” *Solar RRL*, vol. 7, no. 23, Dec. 2023, doi: 10.1002/solr.202300497.
- [121] J. Remund, M. Perez, R. Perez, J. Schlemmer, and M. Pierro, “Localized, cost-effective, 100% renewable firm power generation,” *IET Conference Proceedings*, vol. 2025, no. 45, pp. 276–281, Mar. 2026, doi: 10.1049/icp.2025.4313.
- [122] International Energy Agency, “Task 16 - Solar Resource for High Penetration and Large Scale Applications.” Accessed: Jul. 23, 2026. [Online]. Available: <https://iea-pvps.org/research-tasks/solar-resource-for-high-penetration-and-large-scale-applications/>
- [123] M. Pierro, C. Cornaro, D. Moser, R. Perez, J. Remund, and G. Barchi, “A pathway for firm and dispatchable solar/wind supply through generation and markets splitting,” *Energy Convers. Manag.*, vol. 348, p. 120662, Jan. 2026, doi: 10.1016/j.enconman.2025.120662.
- [124] International Renewable Energy Agency, “24/7 renewables: The economics of firm solar and wind,” 2026. [Online]. Available: www.irena.org
- [125] M. Pierro, R. Perez, M. Perez, D. Moser, and C. Cornaro, “Italian protocol for massive solar integration: Imbalance mitigation strategies,” *Renew. Energy*, vol. 153, pp. 725–739, Jun. 2020, doi: 10.1016/j.renene.2020.01.145.

-
- [126] M. Pierro, R. Perez, M. Perez, D. Moser, and C. Cornaro, “Imbalance mitigation strategy via flexible PV ancillary services: The Italian case study,” *Renew. Energy*, vol. 179, pp. 1694–1705, Dec. 2021, doi: 10.1016/j.renene.2021.07.074.
- [127] M. Pierro *et al.*, “Impact of PV/Wind Forecast Accuracy and National Transmission Grid Reinforcement on the Italian Electric System,” *Energies (Basel)*, vol. 15, no. 23, p. 9086, Nov. 2022, doi: 10.3390/en15239086.
- [128] R. Perez *et al.*, “Perfect Operational Solar Forecasts: A Scalable Strategy Toward Firm Power Generation,” in *Proceedings of the ISES Solar World Congress 2019*, Freiburg, Germany: International Solar Energy Society, 2019, pp. 1–11. doi: 10.18086/swc.2019.45.07.
- [129] M. Pierro, D. Moser, R. Perez, and C. Cornaro, “The Value of PV Power Forecast and the Paradox of the ‘Single Pricing’ Scheme: The Italian Case Study,” *Energies (Basel)*, vol. 13, no. 15, p. 3945, Aug. 2020, doi: 10.3390/en13153945.
- [130] L. Micheli, A. Soria-Moya, D. L. Talavera, B. Abbasi, and E. F. Fernández, “Energy and economic implications of photovoltaic curtailment: current status and future scenarios,” *Sustainable Energy Technologies and Assessments*, vol. 81, p. 104414, Sep. 2025, doi: 10.1016/j.seta.2025.104414.
- [131] E. O’Shaughnessy, J. Cruce, and K. Xu, “Solar PV Curtailment in Changing Grid and Technological Contexts,” in *2019 CIGRE Grid of the Future Symposium*, Atlanta (Georgia), USA, Nov. 2019.
- [132] E. O’Shaughnessy, J. R. Cruce, and K. Xu, “Too much of a good thing? Global trends in the curtailment of solar PV,” *Solar Energy*, vol. 208, pp. 1068–1077, Sep. 2020, doi: 10.1016/j.solener.2020.08.075.
- [133] F. Odoi-Yorke, B. Baah, R. Kissi-Boateng, R. Opoku, and F. B. Effah, “Unlocking the potential of redundant energy from solar photovoltaic systems: Navigating global research trends, innovations, and future directions,” Jun. 01, 2025, *Elsevier Ltd.* doi: 10.1016/j.egy.2025.05.072.
- [134] R. Perez *et al.*, “From Firm Solar Power Forecasts to Firm Solar Power Generation an Effective Path to Ultra-High Renewable Penetration a New York Case Study,” *Energies (Basel)*, vol. 13, no. 17, p. 4489, Aug. 2020, doi: 10.3390/en13174489.

-
- [135] M. Perez, “Solar Potential Analysis -MISO Region: Pathways to 100% Renewables across the MISO Region,” 2020. Accessed: Mar. 26, 2024. [Online]. Available: <https://www.osti.gov/servlets/purl/1668266>
- [136] M. Perez, R. Perez, C. McNevin, R. Djebbar, R. Kilpatrick, and L. Whelan, “Firm VRE Power generation in an All-Electric Grid The Case of Nova Scotia, Canada,” in *2025 IEEE 53rd Photovoltaic Specialists Conference (PVSC)*, IEEE, Jun. 2025, pp. 0460–0462. doi: 10.1109/PVSC59419.2025.11132500.
- [137] R. van Eldik and W. van Sark, “Firm wind and solar photovoltaic power with proactive curtailment: A European analysis,” *Energy Convers. Manag.*, vol. 347, p. 120399, Jan. 2026, doi: 10.1016/j.enconman.2025.120399.
- [138] J. Remund, M. Perez, and R. Perez, “Firm PV Power Generation in Switzerland,” in *2022 IEEE 49th Photovoltaics Specialists Conference (PVSC)*, IEEE, Jun. 2022, pp. 0661–0666. doi: 10.1109/PVSC48317.2022.9938518.
- [139] M. Pierro, R. Perez, M. Perez, M. G. Prina, D. Moser, and C. Cornaro, “Italian protocol for massive solar integration: From solar imbalance regulation to firm 24/365 solar generation,” *Renew. Energy*, vol. 169, pp. 425–436, May 2021, doi: 10.1016/j.renene.2021.01.023.
- [140] G. Bovesecchi, M. Pierro, M. Petitta, and C. Cornaro, “Flexible photovoltaic systems for renewable energy integration in Lazio region, Italy,” *Energy Reports*, vol. 12, pp. 1221–1234, Dec. 2024, doi: 10.1016/j.egy.2024.07.029.
- [141] G. Bovesecchi, F. Andreozzi, M. Petitta, M. Pierro, R. Perez, and C. Cornaro, “Flexible photovoltaic generation strategy for Rome Technopole,” *Energy Conversion and Management: X*, vol. 27, p. 101204, Jul. 2025, doi: 10.1016/J.ECMX.2025.101204.
- [142] Q. Gao *et al.*, “Firm Solar Power Forecasting With Photovoltaic Overbuilding and Battery Storage in Northeastern China,” *IEEE Trans. Ind. Appl.*, pp. 1–11, 2025, doi: 10.1109/TIA.2025.3584293.
- [143] C. Cheng, A. Blakers, M. Stocks, and B. Lu, “100% renewable energy in Japan,” *Energy Convers. Manag.*, vol. 255, Mar. 2022, doi: 10.1016/j.enconman.2022.115299.
- [144] E. Tapachès, M. David, P. Lauret, M. Perez, and R. Perez, “100% electricity generation from PV in Reunion Island,” 2023. Accessed: Mar. 24, 2024. [Online]. Available:

- <https://iea-pvps.org/wp-content/uploads/2023/01/Report-IEA-PVPS-T16-04-2023-Firm-Power-generation.pdf>
- [145] E. Rey-Costa, B. Elliston, D. Green, and G. Abramowitz, “Firming 100% renewable power: Costs and opportunities in Australia’s National Electricity Market,” *Renew. Energy*, vol. 219, p. 119416, Dec. 2023, doi: 10.1016/j.renene.2023.119416.
- [146] L. Debruyne, C. Lavaert, and J. Cappelle, “Feasibility of Firm PV Power Generation for Residential Consumers,” in *2025 IEEE Electrical Power and Energy Conference (EPEC)*, IEEE, Oct. 2025, pp. 63–67. doi: 10.1109/EPEC65543.2025.11230391.
- [147] J. Lopez Lorente, “Demonstrating the principles of firm PV generation with inverter controls,” Freiburg, Germany, Sep. 2022.
- [148] G. Barchi, G. Miori, D. Moser, and S. Papantoniou, “A Small-Scale Prototype for the Optimization of PV Generation and Battery Storage through the Use of a Building Energy Management System,” in *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, IEEE, Jun. 2018, pp. 1–5. doi: 10.1109/EEEIC.2018.8494012.
- [149] N. Orth et al., “Efficiency characterization of 26 residential photovoltaic battery storage systems,” *J. Energy Storage*, vol. 65, Aug. 2023, doi: 10.1016/j.est.2023.107299.
- [150] F. J. Sepúlveda, I. Montero, F. Barrena, M. A. Domínguez, and M. T. Miranda, “Efficiency evaluation of photovoltaic systems with batteries considering different voltage levels,” *J. Energy Storage*, vol. 63, Jul. 2023, doi: 10.1016/j.est.2023.106971.
- [151] F. Andreozzi, G. Bovesecchi, M. Pierro, M. Neglia, and C. Cornaro, “Full outdoor characterization procedure for bifacial PV modules,” *Energy Convers. Manag.*, vol. 365, p. 121779, Oct. 2026, doi: 10.1016/j.enconman.2026.121779.
- [152] IEC, “TS 60891,” 2022.
- [153] IEC, “International standard 61215-1-2,” 2021.
- [154] M. A. García et al., “Outdoor I-V characterization of tilted and vertical bifacial PV modules,” *J. Phys. Conf. Ser.*, vol. 2538, no. 1, p. 012002, Jun. 2023, doi: 10.1088/1742-6596/2538/1/012002.

-
- [155] D. L. Dias, G. A. Rampinelli, G. N. Garrido, J. A. Tejero, M. S. de Cardona Ortín, and L. E. Bremermann, "Performance assessment of bifacial and monofacial PV systems on different types of soils in a low-latitude site," *Renew. Energy*, vol. 246, p. 122868, Jun. 2025, doi: 10.1016/j.renene.2025.122868.
- [156] Tor Vergata University of Rome, "EsterLab Facility." Accessed: Jul. 07, 2026. [Online]. Available: <http://ester.uniroma2.it/index.php>
- [157] A. Spena, C. Cornaro, and S. Serafini, "Outdoor ESTER test facility for advanced technologies PV modules," in *2008 33rd IEEE Photovoltaic Specialists Conference*, IEEE, May 2008, pp. 1–5. doi: 10.1109/PVSC.2008.4922594.
- [158] A. Spena, C. Cornaro, G. Intreccialagli, and D. Chianese, "Data validation and uncertainty evaluation of the ESTER outdoor facility for testing of PV modules," in *Proceedings of the 24th European photovoltaic solar energy conference and exhibition / eds. W. Sinke, H. Ossenbrink, P. Helm, W. Sinke, H. Ossenbrink, and P. Helm, Eds., Hamburg (Germany), 2009*, pp. 3586–3590.
- [159] M. Mittag, A. Grünzweig, M. Wiese, N. Mahmoud, A. Schmid, and M. Heinrich, "ANALYSIS OF BACKSHEET AND REAR COVER REFLECTION GAINS FOR BIFACIAL SOLAR CELLS," in *Proceedings of the 33rd European PV Solar Energy Conference and Exhibition*, 2017.
- [160] T. S. Liang, M. Pravettoni, J. P. Singh, and Y. S. Khoo, "Meeting the requirements of IEC TS 60904-1-2 for single light source bifacial photovoltaic characterisation: evaluation of different back panel materials," *Engineering Research Express*, vol. 2, no. 1, p. 015048, Mar. 2020, doi: 10.1088/2631-8695/ab7ee5.
- [161] A. Singh, "Monitoring the Performance of Bifacial Solar PV Panels: Challenges and Opportunity." Accessed: Jan. 21, 2026. [Online]. Available: <https://www.campbellsci.eu/blog/bifacial-solar-pv-panels>
- [162] A. J. Anderson, "Photovoltaic translation equations: A new approach. Final subcontract report," Golden, CO (United States), Jan. 1996. doi: 10.2172/177401.
- [163] M. A. García *et al.*, "Outdoor I-V characterization of tilted and vertical bifacial PV modules," *J. Phys. Conf. Ser.*, vol. 2538, no. 1, p. 012002, Jun. 2023, doi: 10.1088/1742-6596/2538/1/012002.

-
- [164] J. Lopez-Garcia, D. Pavanello, and T. Sample, "Analysis of Temperature Coefficients of Bifacial Crystalline Silicon PV Modules," *IEEE J. Photovolt.*, vol. 8, no. 4, pp. 960–968, Jul. 2018, doi: 10.1109/JPHOTOV.2018.2834625.
- [165] A. Schmid, G. Dülger, G. Baraah, and U. Kräling, "IV Measurement of Bifacial Modules: Bifacial vs. Monofacial Illumination," in *Proceedings of the 33rd European PV Solar Energy Conference and Exhibition*, 2017.
- [166] N. Leon-Rodriguez, A. Sanchez-Juarez, J. Ortega-Cruz, C. A. Arancibia Bulnes, and H. Leon-Rodriguez, "Bifacial Solar Modules Under Real Operating Conditions: Insights into Rear Irradiance, Installation Type and Model Accuracy," *Eng*, vol. 6, no. 9, Sep. 2025, doi: 10.3390/eng6090233.
- [167] N. Belhaouas *et al.*, "Comprehensive analysis and insights into the relationship between temperature coefficients, PV failures, and investigating their correlation with other PV parameters," *Solar Energy*, vol. 301, Nov. 2025, doi: 10.1016/j.solener.2025.113891.
- [168] N. Belhaouas *et al.*, "Analysis of the Relationship Between Photovoltaic Temperature Coefficients and Varying Solar Irradiance Levels," *Journal of Renewable Energies*, vol. 2025, pp. 103–111, Nov. 2025, doi: 10.54966/jreen.v1i1.1548.
- [169] IEC, "TS 60904-1-2," 2019.
- [170] J. Polo, M. Alonso-Abella, A. Marcos, C. Sanz-Saiz, and N. Martín-Chivelet, "On the use of reference modules in characterizing the performance of bifacial modules for rooftop canopy applications," *Renew. Energy*, vol. 220, p. 119672, Jan. 2024, doi: 10.1016/j.renene.2023.119672.
- [171] ISO/IEC, "Guide to the expression of uncertainty in measurement," 2024. doi: ISO/IECGUIDE98-1:2024(en).
- [172] IEC, "International standard 61724-1," 2021.
- [173] Gestore dei Mercati Energetici, "Markets: Electricity." Accessed: Jul. 07, 2026. [Online]. Available: <https://www.mercatoelettrico.org/en/>
- [174] Copernicus, "Atmosphere Monitoring System." Accessed: Jul. 07, 2026. [Online]. Available: <https://atmosphere.copernicus.eu/>

-
- [175] J. S. Stein, R. Perez, and A. Parkins, "Validation of PV performance models using satellite-based irradiance measurements: A case study," in *39th ASES National Solar Conference 2010, SOLAR 2010*, May 2010, pp. 265–290.
- [176] ARPA Lazio, "Scheda Tecnica - Stazione di rilevamento AL001." Accessed: Jul. 07, 2026. [Online]. Available: <https://www.arpalazio.it/documents/20124/67746/AL001.pdf>
- [177] Hanjie Chen, Yijun Du, and J. N. Jiang, "Weather sensitive short-term load forecasting using knowledge-based ARX models," in *IEEE Power Engineering Society General Meeting, 2005*, IEEE, 2005, pp. 92–98. doi: 10.1109/PES.2005.1489086.
- [178] Q. Zeng *et al.*, "An optimum regression approach for analyzing weather influence on the energy consumption," in *2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, IEEE, Oct. 2016, pp. 1–6. doi: 10.1109/PMAPS.2016.7764178.
- [179] National Laboratory of the Rockies, "2023 Electricity ATB Technologies and Data Overview." Accessed: Jul. 07, 2026. [Online]. Available: <https://atb.nlr.gov/electricity/2023/technologies>
- [180] E. Veronese, G. Manzolini, and D. Moser, "Improving the traditional levelized cost of electricity approach by including the integration costs in the <scp>techno-economic</scp> evaluation of future photovoltaic plants," *Int. J. Energy Res.*, vol. 45, no. 6, pp. 9252–9269, May 2021, doi: 10.1002/er.6456.
- [181] O. Schmidt, S. Melchior, A. Hawkes, and I. Staffell, "Projecting the Future Levelized Cost of Electricity Storage Technologies," *Joule*, vol. 3, no. 1, pp. 81–100, Jan. 2019, doi: 10.1016/j.joule.2018.12.008.
- [182] JA Solar, "JAM72D40 MB Datasheet".
- [183] Huawei, "Smart String Energy Storage System Datasheet."
- [184] Huawei, "SUN2000-(2KTL-6KTL)-L1 Datasheet."
- [185] ITECH, "IT-M3300 Regenerative DC Electronic Load Datasheet." [Online]. Available: www.itechate.com
- [186] Mean Well, "NDR-240-SPEC."
- [187] CHINT, "DTSU666-H Smart Power Sensor Datasheet."

List of publications

- Potenza, M., **Andreozzi, F.**, Donati, S., Petracci, I., & Corasaniti, S. (2024). Scale-Effect on energy performance of a Reduced-Scale Trombe–Michel solar system. *Applied Thermal Engineering*, 250. <https://doi.org/10.1016/j.applthermaleng.2024.123557>
- Bovesecchi, G., **Andreozzi, F.**, Petitta, M., Pierro, M., Perez, R., & Cornaro, C. (2025). Flexible photovoltaic generation strategy for Rome Technopole. *Energy Conversion and Management: X*, 27, 101204. <https://doi.org/10.1016/J.ECMX.2025.101204>
- **Andreozzi, F.**, Bovesecchi, G., Pierro, M., Neglia, M., & Cornaro, C. (2026). Full outdoor characterization procedure for bifacial PV modules. *Energy Conversion and Management*, 365, 121779. <https://doi.org/10.1016/j.enconman.2026.121779>

In preparation:

- **Andreozzi, F.**, Bovesecchi, G., Pierro, M., Perez, R., Cornaro, C. (2026). Experimental validation of firm-PV generation through a PV-BESS prototype: real-world operation and comparison with simulation-based design.