D3.1 Concept WP3

Control of PV plants to optimise their performance.

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Deliverable Information Sheet

Version	1
Grant Agreement	101147000 (HE MGA)
Project Acronym	PVOP
Project Title	Digitalising the PV sector for the era of Terawatts
Call and topic	HORIZON-CL5-2023-D3-02 / HORIZON-CL5-2023-D3-02-13
Type of action	HORIZON Innovation Actions
Project Duration	36 months
Deliverable Number	3.1
Deliverable Title	Concept WP3
Deliverable Type	Document, report
Deliverable Dissemination Level	Public
Work Package	WP3
Lead Partner	Wattkraft
Contributing Partners	ASIC XXI, Qualifying Photovoltaics
Official Due Date	31/10/2024
Delivery Date	31/10/2024

List of Acronyms

AGR	Avoid Grid Reconstruction
AI	Artificial Intelligence
ARIMA	Auto Regressive Integrated Moving Average
BESS	Battery Energy Storage System
CM	Capacity Market
DT	Digital Twins
EMS	Energy Management System
FR	Frequency Regulation
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GRU	Gated Recurrent Unit
IoT	Internet of Things
LSTM	Long Short-Term Memory
ML	Machine Learning
MSC	Maximization of Self-Consumption
PS	Peak Shaving
RNN	Recurrent Neuronal Network
SARIMA	Seasonal ARIMA
TOU	Time of Use

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Keywords list

- Simulation
- Control
- Forecasting
- Sun tracking
- Batteries

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1. Executive summary

This document presents the concepts at the root of WP3 solutions, all of them about the Control of PV plants to optimise their performance. This WP3 is divided into two differentiated tasks:

- Task 3.1: Development and demonstration of a simulation tool and control system to maximize the performance of PV plants with sun tracking systems.

- Task 3.2: Development and demonstration of a control system to maximize the performance and energy trading of PV plants with batteries. In turn, this task is divided into two:

  - Chapter A: Battery control system
  - Chapter B: Electricity Market Forecast

The aim of T3.1 is to develop a smart tracking control algorithm and its corresponding simulation tool for large monofacial and bifacial single-axis tracking PV plants over terrain of arbitrary orientation and slope for the performance optimisation, taking into account diffuse irradiance conditions and extreme meteorological events. The concept behind these solutions is that considering terrains of arbitrary orientation and slope mainly requires modifications in the calculation of two different aspects: the backtracking geometry and the ground shading scenes needed to estimate the rear irradiance, G_{REAR}, in the case of bifacial generators. In addition, slopes affect the horizon which, in turn, affects the components of the front irradiance, G_{FRONT}. The 3D approach is likely to entail a significant increase in mathematical complexity, input information and computing time. This leads us to deal with sloping terrain while still relying on a 2D scene.

Once the models are in place, one way to better align the estimate with reality and to refine these models and assumptions is to use digital twins. Digital twins can be used to tune models for complex PV systems without repeated on-site measurement campaigns, provided that PV plants are adequately sensorised (which is an objective of WP2). This leads to a much more precise performance analysis and forecasting throughout the whole operational life of a PV plant.

For the validation, experiments at UPM facilities and at commercial PV plants are foreseen and specific KPIs are proposed.

Regarding T3.2, PVOP will develop a PV plant control system that will integrate a Smart Energy Management System (EMS) based on predictions of weather conditions (including extreme events) and an AI-based electricity market predictor. The concept at the root of this solution is the following: the EMS will receive inputs from sensors, electricity price databases, meteorological databases and Electricity Market Analysts predictor that will allow the EMS to select, in a hourly basis, the best strategy to maximize the profitability of the PV asset. Regarding, the forecast prices in the electricity market, a new concept will be implemented that is thought to be decisive: the stochastic analysis of the forecasts.

For the validation of these solutions, experiments and specific KPIs for both, the implementation of control strategies for batteries and for the electricity market forecast tool, have been proposed.

2. Introduction

This document presents the first deliverable of WP3 (Control of PV plants to optimize their performance), and it explains the main objectives to be reached, the techniques used for that and the KPIs defined for the validation of the different solutions.

This WP3 is divided into two differentiated tasks, and one of them is as well separated into two main lines of work. The deliverable is structured accordingly:

- Task 3.1: Development and demonstration of a simulation tool and control system to maximize the performance of PV plants with sun tracking systems.

- Task 3.2: Development and demonstration of a control system to maximize the performance and energy trading of PV plants with batteries.

    - Chapter A: Battery control system
    - Chapter B: Electricity Market Forecast

Sections T3.1 and chapters A and B from T3.2 are structured as independent parts, each of them with its own introduction, body and conclusions.

3. Task 3.1: Simulation tool and control system to maximise the performance of PV plants with sun tracking systems

3.1. Introduction

Current PV simulation software includes single-axis tracking and backtracking functionalities, typically assuming that the tracker axes lie within a horizontal plane (Kankiewicz, 2021). This assumption has generally been accurate for real-world systems until recently. However, with the growth of the PV market, single-axis trackers are now being deployed on sloped terrain. A recent solar financing report (kWh Analytics, 2021) indicates that, on average, solar projects underperform their target production (P50) estimates by 6.3%, noting that 'uneven terrain often causes losses for north-south aligned single-axis trackers on east-west slopes' as a significant factor contributing to the observed energy shortfall. Even on nearly flat terrain, actual tracking does not adhere to the ideal calculated values to avoid shading caused by slight terrain roughness.

PV simulation software carries out its computations with nominal parameters for system components, as given by their manufacturers. However, real equipment may have a performance which differs from nominal values due to manufacturing, handling, installation, operation, and aging factors. Typical practice is to make a campaign of on-site key measurements at the beginning of the life of a PV plant to tune model parameters, but this requires quite a significant effort, so that it is rarely repeated unless significant performance degradation is observed. As time goes on, there is a widening gap between expected and actual performance.

This drives the need to enhance PV software capabilities to **overcome the horizontal constraint** and to **improve performance forecasts as a PV plant evolves**.

Background on tracking software

Today's software for simulating tracking PV plants relies on two **simplifying assumptions**. Firstly, it assumes that the axis length is infinite (practically much longer than the tracker width) and that the axis height above the ground remains constant along its entire length. This leads to 2D modelling, reducing the geometric description to a projection onto a plane perpendicular to the tracker axes, i.e., the cross-axis plane. Secondly, it assumes an infinite number of axes (practically more than ten) arranged periodically so that they all lie in the same plane, parallel to the ground, and are evenly spaced. This approach neglects all edge effects and restricts the calculations to a single representative tracker row. This method is compatible with considering shading: mutual shading between adjacent tracker rows for backtracking algorithms and ground shading for estimating the rear global irradiance, GREAR. Together, these conditions—2D modelling and limiting calculations to one tracker row—significantly reduce the simulation load, both in terms of the number of input parameters needed to define the PV array configuration and the computation time. The simplifying assumptions and models of the tracking simulation software **apply equally to the tracker control**.

PV software is continually evolving, but it usually does not disclose internal model details or submit its procedures to peer-reviewed scientific journals. This opacity makes it challenging to determine the exact state-of-the-art. Nonetheless, it appears that most software currently used by the PV industry to simulate the energy yield of large PV plants employs such a 2D approach. Furthermore, software may have additional constraints. At present, much of the industry standard software is still limited by the horizontal constraint. PVsyst announced plans to overcome this limitation by using 3D modelling, but at least they decided to use a 2D model as well. DNV's Solar Farmer software claims to simulate complex terrain using both 2D and 3D modelling (Leung et al., 2022). We use SISIFO, open software developed by IES-UPM, available freely at https://www.sisifo.info, with its internal models thoroughly published (Lorenzo et al., 2011) (de la Parra et al., 2017) (Moretón et al., 2017) (Ledesma et al., 2020). For the purposes of this report, it is sufficient to know that, despite differences in detail, all these software are fundamentally compatible, leading to similar results when provided with the same input data and loss scenarios. Transitioning from 2D to 3D scenes likely involves a significant increase in mathematical complexity and simulation overhead. This motivates extending the capabilities of SISIFO to overcome the horizontal constraint while still relying on 2D modelling and a single representative tracker row. Interestingly, the authors of Solar Farmer also consider this approach viable. Indeed, (Leung et al., 2022) state that "… we observed that using a simple geometric shading approach for trackers provides sufficient accuracy for tracker shade, while 3D approach can be used for shade obstacle …".

Digital twins

Once the simplifying assumptions and models are in place, one way to better align the estimate with reality and to refine these models and assumptions is to use digital twins.

Digital twins (DT) are virtual replicas of physical entities or systems, integrating technologies such as the Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), and data analytics to simulate, analyse, and control their real-world counterparts. The primary components of digital twins include the physical entity, digital model, and connectivity infrastructure. The physical entity is the actual object or system being replicated. The digital model is a virtual representation constructed using data and algorithms, mainly through advanced analytic tools or machine learning, able to estimate outputs from given inputs. Real-time and historical data are collected from sensors and other sources to populate and update this digital model. Connectivity is required to enable continuous data exchange between the physical entity and its digital model. A human interface usually lets users interact with the digital twin, enabling them to monitor, analyse, and optimise the performance of the physical system.

Digital twins can be used to tune models for complex PV systems without repeated on-site measurement campaigns, provided that PV plants are adequately sensorised (which is an objective of WP2). This leads to a much more precise performance analysis and forecasting throughout the whole operational life of a PV plant.

3.2. PVOP simulation tool and control system proposal for solar trackers

3.2.1. Aim

To develop a **smart tracking control** algorithm **and its corresponding simulation tool** for large monofacial and bifacial single-axis tracking PV plants over **terrain of arbitrary orientation and slope** for the performance optimisation, taking into account diffuse irradiance conditions and extreme meteorological events.

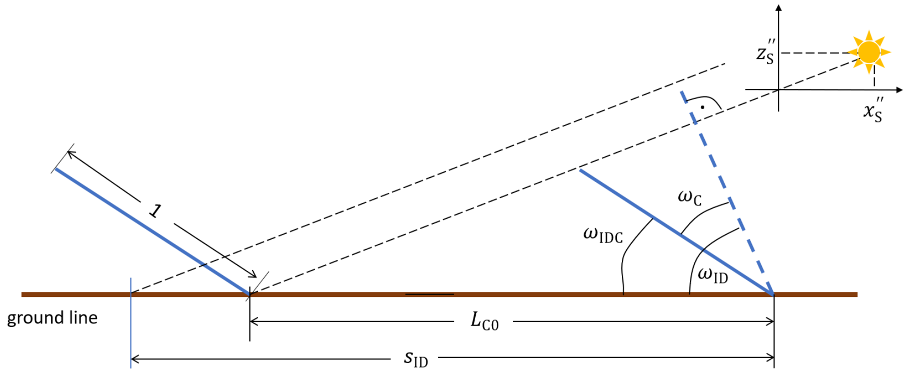
3.2.2. Conceptual aspects of PV simulation on uneven terrains

Considering terrains of arbitrary orientation and slope mainly requires modifications in the calculation of two different aspects:

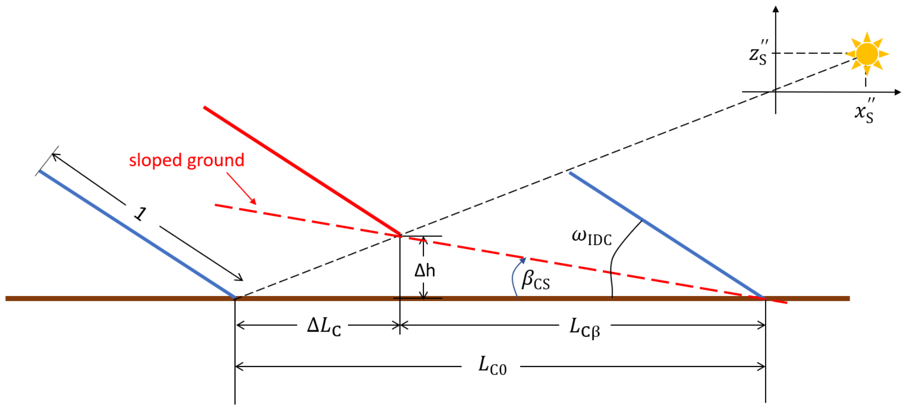
- the backtracking geometry and
- the ground shading scenes needed to estimate the rear irradiance, G_{REAR}, in the case of bifacial generators.

In addition, slopes affect the horizon which, in turn, affects the components of the front irradiance, G_{FRONT}. Slope-aware backtracking has been explored by (Schneider, 2012), (Nascimento et al., 2015), and (Anderson & Mikofski, 2020), so backtracking formulations that consider both horizontal and vertical row offsets are available. Current available PV energy yield simulation software has relied on 2D to define the shading scenes required for G_{REAR} calculations and seems to be moving towards 3D scenes to deal with complex terrains. The 3D approach is likely to entail a significant increase in mathematical complexity, input information and computing time. This leads us to deal with sloping terrain while still relying on a 2D scene. This is being implemented in SISIFO, an open software developed by the IES-UPM available at www.sisifo.info.

Figure 1-a shows the principle of the backtracking calculation under horizontal constraint for PV arrays consisting of many relatively long rows of PV trackers equally spaced across the ground plane. Figure 1-b depicts that in the case where the terrain has a cross-axis slope angle, β_{CS}. The point now is to note that this situation is equivalent to the previous one, that is, both lead to the same rotation angle ω_{IDC}, given the horizontal distance between the rows, $L_{\mathrm{C\beta}}$, by adjusting the distance considered for horizontal terrain tracking, $L_{\mathrm{C0},}$ to satisfy the condition $L_{\mathrm{C0}} = L_{\mathrm{C\beta}} + \Delta L_{\mathrm{C}}$



(a)



(b)

Figure 1. Geometry of backtracking for **(a)** horizontal and **(b)** sloping terrain. Both are equivalent, i.e. lead to the same rotation angle if $\Delta L_C = L_{C0} \tan(\omega_{ID}) \tan(\beta_{CS})$.

3.2.2.1. More in detail

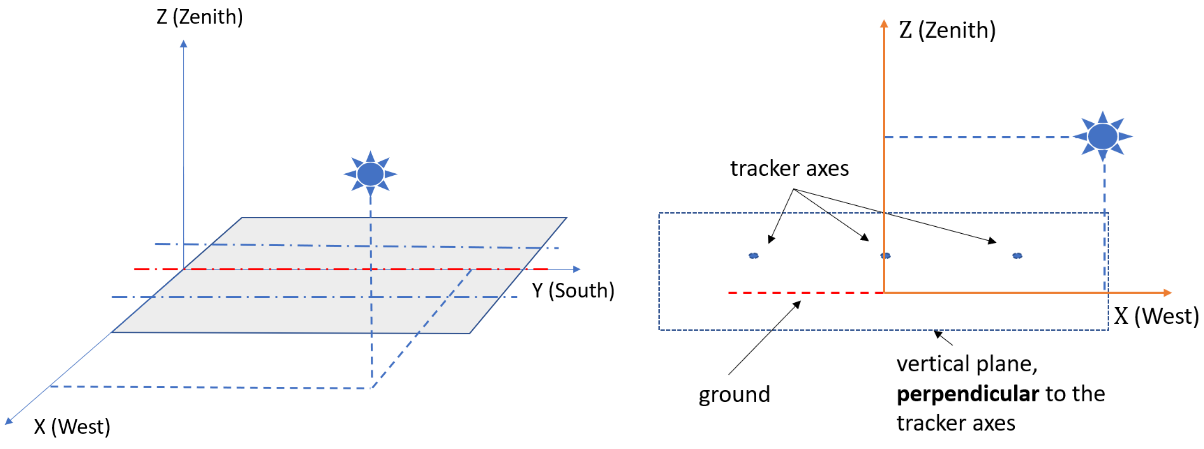
It is worth taking a moment to introduce the relevant reference frames and coordinate systems involved in the calculations of a tracked PV system. Figure 2 (left) shows the position of both the sun and the tracker in a site reference frame, using a right-handed three-dimensional Cartesian coordinate system with the X-axis pointing West, the Y-axis pointing South and the Z-axis pointing upwards. The tracker axes are shown as dotted and dashed lines. The coincidence with the Y axis, in red, is the representative row for which calculations are made. Figure 2 (right) shows the projection of both positions onto a cross-axis plane (a tracker reference frame) with a Cartesian coordinate system where the X axis contains the tracker axis points. Note the latter is a 2D scene. The depicted cases are:

(a) The traditional case of horizontal ground and north-south oriented axes, implemented in all the current PV software that we know of. The position of the sun in the global reference frame, i.e., the solar coordinate vector (x_S, y_S, z_S) is easily derived from the latitude and time. It should be noted that the position of the sun in the 2D scene, i.e. the vector (x_S, z_S) determines both the angle of rotation of the trackers and the shading scene cast on the ground by the tracker rows.

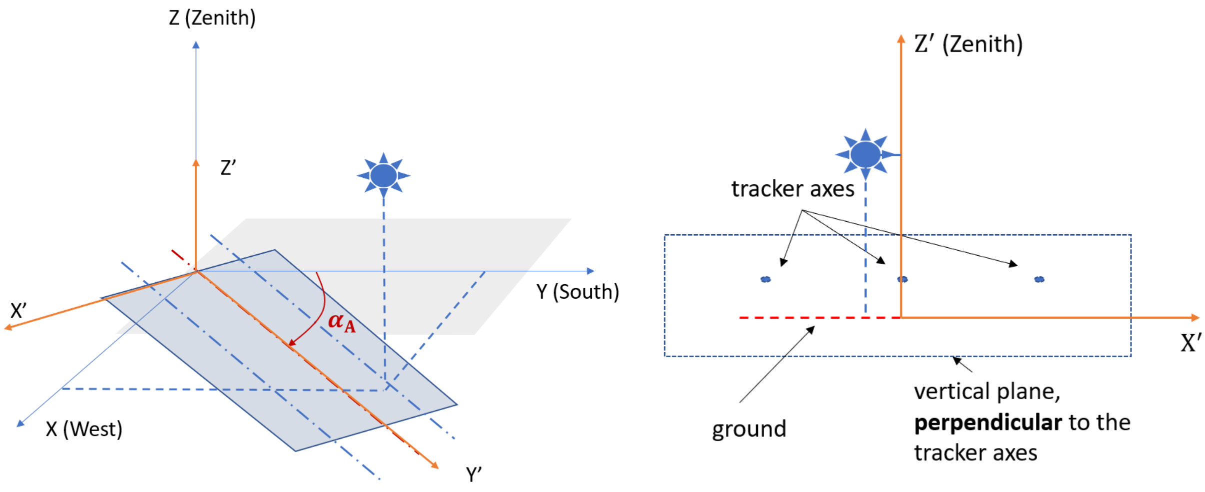
(b) The case of axes with given azimuth, α_A, on flat terrain. The relevant change from the previous case is the position of the sun in the cross-axis plane. The new sun position can be obtained from the former by applying a basic rotation matrix, rotating the sun position vector counter-clockwise by an angle α_A about the Z-axis.

(c) The case of both ground and axes with given azimuth and tilt. That is, here $\alpha_A = \alpha_G$ and $\beta_A = \beta_G$, where α and β are azimuth and tilt respectively, and the subscripts 'A' and 'G' denote axis and ground respectively. The new sun position is obtained by rotating the sun position vector counter-clockwise by an angle β_A about the X' axis. Note that although the ground plane is not horizontal, the intersection of the ground with the cross-axis plane is. Therefore, the axes line, the line that connects the axes crosswise, is also horizontal in the 2D-scene. This is why we say that in this case the horizontal constraint is still respected. SISIFO incorporates this feature from previous versions.

(d) The case for **sloping terrain** where the horizontal and the axes line have, irrespective of α and β, a non-zero cross-axis slope angle, β_{CS}. The axes are not parallel to the steepest line of the terrain and, therefore, $\alpha_A \neq \alpha_G$ and $\beta_A \neq \beta_G$. Again, this implies a change in the position of the sun in the cross-axis plane, and the new position can be obtained by rotating the sun vector counter-clockwise by an angle β_{CS} about the Y'' axis.

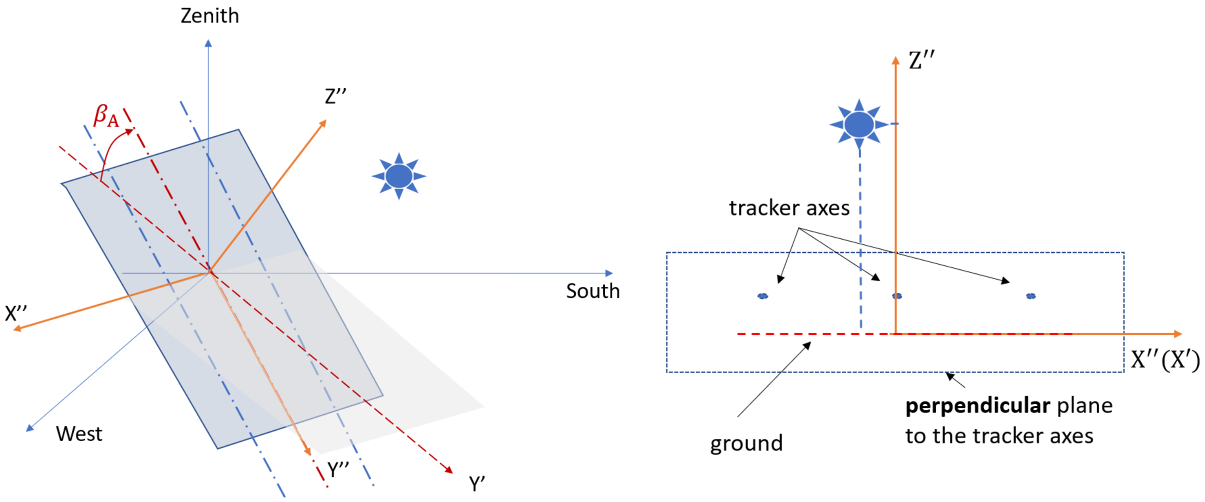


(a)



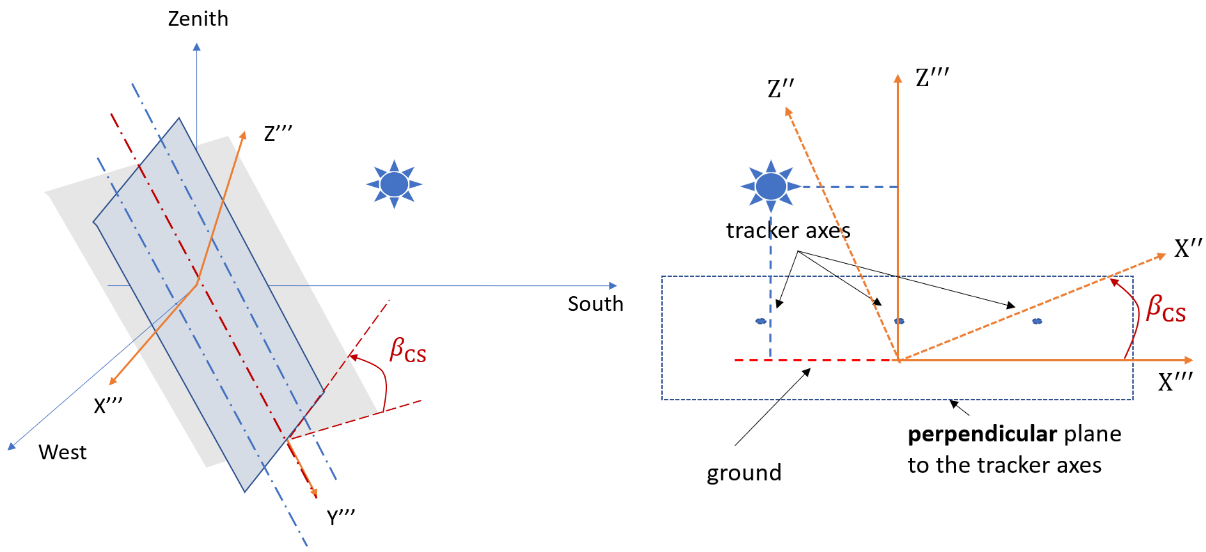
Z (Zenith)
Z'
X'
Y (South)
α_A
X (West)
Y'
Z′ (Zenith)
tracker axes
X′
ground
vertical plane,
perpendicular to the
tracker axes

(b)



Zenith
Z''
β_A
X''
South
West
Y''
Y'
Z′′
tracker axes
X′′(X′)
ground
perpendicular plane
to the tracker axes

(c)



(d)

Figure 2. Sun and tracker positions in site (left) and tracker (right) reference frames. Depicted cases are: **(a)** Horizontal ground and north-south oriented axes; **(b)** Axes with given azimuth, α_A, on flat terrain. **(c)** Ground and axes with given azimuth, $\alpha_A = \alpha_G$, and tilt, $\beta_A = \beta_G$; **(d)** Ground and axes with different azimuth, $\alpha_A \neq \alpha_G$, and tilt, $\beta_A \neq \beta_G$, leading to a non-zero cross-axis slope angle, β_{CS}, between horizontal and the axes line.

It should be stressed that the tracker axes must be parallel to the ground in order to preserve the 2D scenes. It is worth noting that this is the current state of the art for industrial single-axis tracker products. Furthermore, case (d) gives the principle for solving the mathematical problem of cross-axis sloping terrain, as it allows the system to be treated as if it were a simple north-south horizontal axis system, and this is the model that will be implemented in the SISIFO simulation tool. However, it will also be interesting to approach the problem in the framework of case (c), as this is the framework that most actual trackers may use for horizontal terrain, and it would allow them to be easily upgraded.

This algorithm will be transferred to some control hardware for validation with real trackers. In order not to be dependent on the tracker manufacturer's control algorithm in real installations, a processing and control hardware will be designed to replace the one currently supplied by the manufacturer. This will be done in a non-invasive way, so that it will be possible to revert to the original manufacturer's control if necessary, or to compare results. To this end, this alternative control hardware will take control of the existing tracker motor and gearbox system when tested on real plants.

3.2.2.2. Irradiance components

Typically, software authors tend to model as many details as possible, regardless of their weight in the results. We are no exception. SISIFO will take into account the seven irradiance components listed in Table 1, despite four of them: G^{RG}_{FRONT}, G^{B}_{REAR}, G^{DS}_{REAR} and G^{RG}_{REAR} are almost irrelevant to the annual radiation in most practical cases. The table includes comments on how β_{CS} affects each component.

G_{FRONT}	G_{REAR}
Beam, G^{B}_{FRONT} β_{CS} affects the skyline.	**Beam, G^{B}_{REAR}** This component is zero for trackers.
Diffuse from the sky, G^{DS}_{FRONT} β_{CS} entails a vertical offset between the rows. This in turn affects the amount of sky covered by the adjacent frontal row.	**Diffuse from the sky, G^{DS}_{REAR}** β_{CS} entails a vertical offset between the rows. This in turns affects the amount of sky covered by the adjacent rear row.
	Reflected by the rear row, G^{RR}_{REAR} β_{CS} entails a vertical offset between rows. This in turn affects the view factor from the adjacent rear row.
Reflected by the ground, G^{RG}_{FRONT} β_{CS} affects the view factor from the shaded and unshaded areas of the ground.	**Reflected by the ground, G^{RG}_{REAR}** β_{CS} affects the view factor from the shaded and unshaded areas of the ground.

Table 1. Influence of β_{CS} on the different irradiance components.

3.2.3. Tracking control under conditions of diffuse irradiance and extreme meteorological events

Under conditions of high diffuse irradiance, or in the presence of certain extreme weather events, the most optimal position of the tracker may not be the astronomical position calculated by the previous model. These cases will also be taken into account in the simulation tool.

For instance, when diffuse irradiance is high, a horizontal angle in the tracker may produce a better yield. Also, heavy snow or hail may lead to a steeper tracker angle, and strong winds may lead to a protection angle to avoid damage in the components.

3.3. PVOP simulation tool and digital twins proposal

3.3.1. Aim

To develop a **free-access tool for the energy yield forecasting with digital twins** adjusted with sensor data.

3.3.2. Conceptual aspects

Digital twins for utility-scale PV plants will be built as a system of interconnected models, each focusing on a specific component: the PV generator, the inverter, and the high-voltage transformation stage. Figure 3 shows this modular approach which allows for precise tuning of each digital twin within its respective subsystem, enhancing the accuracy of the simulation of the overall performance of the PV plant.

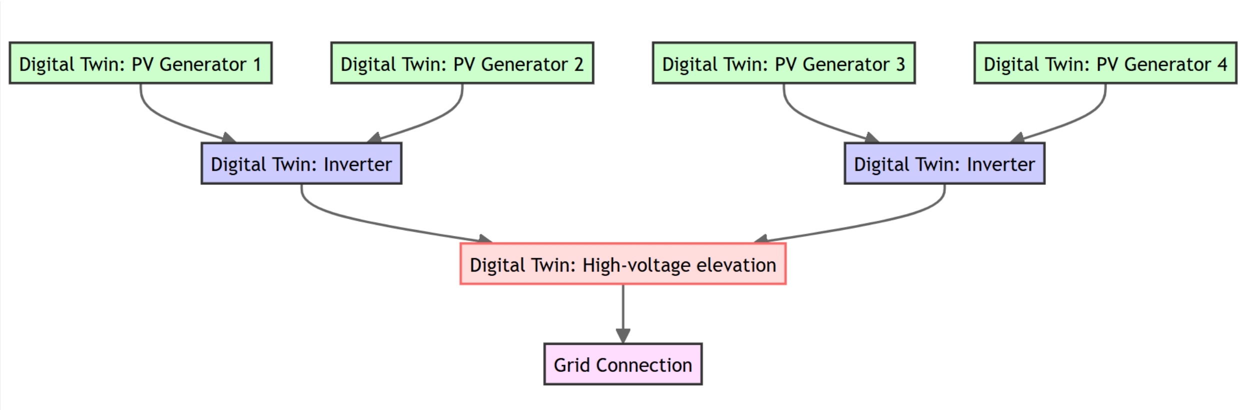


Figure 3. Digital twins.

In addition, this approach makes it possible to better cover the current reality of installations where different types of PV generators or inverters are used in the same PV installation (different models of PV modules or inverters, different power ratios of PV generator to inverter, ...). And in the long term, once the data is available, it will be possible to compare the in-situ performance of similar PV generators or inverters in different locations through their digital twins.

For the PV generator digital twin, analytical models based on mathematical equations will be first applied and evaluated. These models, which are well-established in simulation software, estimate energy production for bifacial and monofacial PV generators by considering factors such as irradiance, temperature, and angle of incidence. With the actual data from the PV generators, it will be possible to adjust and improve these models. In addition, having data from different PV generators will make it possible to analyse the deviations between them. The aim will always be to extract knowledge from these deviations and actual data in order to improve these analytical models, to provide better estimates for the PV plant and also for other future PV plants under study.

The inverter digital twin will also mainly include analytical models tuned to real inverter data to monitor and optimise inverter performance. The analytical models will simulate the electrical behaviour of the inverters under different operating conditions.

The digital twin for the high-voltage transformation stage will also utilize analytical models fitted to the actual data. The analytical models will simulate the electrical characteristics of the transformation process.

In addition, in some cases, the use of machine learning techniques could be considered to implement a second version of the digital twin taking advantage of historical and real-time data to optimise its accuracy and predictive capacity.

The digital twins could also be used to develop what-if scenarios, which would allow plant owners and operators to make better-informed decisions about possible upgrades or configuration changes in the plant operation or characteristics, or to test the plant's resilience or behaviour under extreme and rare events.

3.4. Experiments and KPIs

3.4.1. At the IES-UPM outdoor facilities

A scale model of a single axis tracker PV generator will be designed and built. This will be used to test the control of the tracker on sloping terrain and under conditions of diffuse irradiance. Using a scale model makes sense because with a proper design and construction all relevant effects scale and consequently the results are extrapolable to real generators.

The scale model we are planning to build could be made of 156-millimetre PERC bifacial cells to simulate scaled trackers. A total of 14 cells can simulate a typical tracker carrying a string of 28 modules. Better still, we will investigate the feasibility of laser cutting commercial PV modules to obtain the scaled down strings of modules, as this would better match the properties of the scale trackers to the real properties of commercial PV modules. A scale model made of five rows, each with several scaled trackers in a line would be sufficient to do representative experiments.

The scale model will have a flexible floor that allows to set up several arbitrary terrain slopes of up to 35 degrees, to vary the spacing between rows of trackers (ground cover ratio), and to use different substrates (with different albedos). This would be sufficient to set different tracking angles in each row and to simulate different terrain configurations.

These scaled PV generators would also allow testing and verification of the associated digital twin.

3.4.2. At a commercial PV plant

In order to test the control of solar trackers on real tilted terrain systems and to feed the associated digital twins, a non-invasive alternative will be chosen on real PV plant trackers. To this end, an alternative hardware device to the current tracker controller will be designed, based on the experience gained with the previous scale systems, which will generate the necessary signals to set the tilt angles using the real tracker motor. The current tracker control provided by the manufacturer will be disconnected from the actual tracker motor and switched to control the actual tracker motor resulting from the proposed new model. This allows the change to be undone, if necessary, without affecting the current infrastructure.

A continuous data feed is required between each real plant and its digital twin. It is envisaged that this data can be collected from the SCADA deployed in the actual PV plant. This data can be supplemented with data from some additional sensors deployed in WP2. If, for some reason, these cannot be integrated into the SCADA, the necessary communication system to obtain them will be analysed and designed.

3.4.3. Targets for KPI

- Deviation of the Real angle vs the Optimum Angle on Arbitrarily Oriented Sloping Terrain, which should be < 2°
- Validation of the model based on 2D view factors for the estimation of the irradiance on the back side of a PV system on a sloping site by comparison with the real scaled system. Error (Estimated - Actual) / Estimated < 10% after excluding the effects of inhomogeneity due to shading of the structure itself.
- Correlation of real system and digital twin > 94% (for each of the three twins and for 1-2 key variables in each) under normal operating conditions and without failures.

3.5. Conclusions

The concept of the simulation and control solutions is based on some relevant assumptions that standard PV software relies on to simplify the energy yield simulation, and pinpoints the horizontal constraint, which does not necessarily require the ground to be horizontal, only that its cross-axis slope angle be zero. The mathematical basis for modifications to overcome the horizontal constraint while preserving these assumptions will be established. Therefore, the sensitivity of the annual energy yield to the slope of the terrain could be analysed in the light of simulation exercises performed with SISIFO for commercial PV plants.

Evaluating the use of scale models to test tracker control on sloping terrain is a promising approach. This method involves simulating different configurations and measuring parameters such as front and rear irradiance on both edge and interior scaled trackers. The experimental setup should allow for adjustable ground slope and albedo to accurately assess the effects of sloping and uneven terrain, including potential shading effects. This would enable the application of proposed tracker controls and the validation of associated digital twin models, providing valuable insights into tracker performance in varying real-world conditions.

In short, the goal is to get a good representation of reality under normal operating conditions and without failures. Some KPIs are established to quantify the goodness of this representation. Once this is achieved, the deviation of the digital twin output from the sensed data will act as a trigger to initiate the specific fault classification mechanisms that are likely to trigger more advanced and specific fault-finding processing. These fault classification mechanisms will be addressed in WP4.

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4. Task 3.2: Control system to maximise the performance and energy trading of PV plants with batteries

The second task of WP3 focuses on the development and validation of an advanced control system that permits to optimise the performance of PV plants with batteries. There are two differentiated lines of work involved in this task that will be explained in two separate chapters:

- The development of the solutions for a smart Energy Management System (EMS) that will include different strategies for battery management (Chapter A)

- The development of an AI-based electricity market predictor that will be an input for the smart EMS in some of the control strategies (Chapter B)

4.1. Chapter A: Smart Energy Management System

4.1.1. Introduction

Background

Photovoltaics has been remarkably successful in integrating into the electricity mix and reducing electricity prices during solar hours. To continue this progress, various stakeholders are keen on advancing **Battery Energy Storage Systems (BESS)**:

- **Consumers** are benefiting from the electricity low-price scenario during sunny hours, but to save money at night, they must implement load management strategies (adjusting consumption patterns to shift electricity use from high-price periods to low-price periods) or adopt Behind the Meter (BtM) storage solutions.

- **Photovoltaic Developers** are also interested in promoting Front the Meter (FtM) storage. In a saturated photovoltaic (PV) market, the low price of electricity is reducing profits and hindering new investments in PV plants. Standalone and hybrid Battery Energy Storage Systems (BESS) projects will facilitate the integration of additional PV power into the grid by balancing supply and demand, improving grid stability, and enhancing the economic efficiency of electricity markets.

- **Grid operators** would significantly benefit from energy storage solutions. As PV power generation drops off rapidly in the evening while electricity demand remains high, this creates a sharp increase in net demand, known as the "ramp-up" period, requiring fast and flexible power sources. Storing excess PV power generated during the day and releasing it in the evening will mitigate the "Duck Curve," reducing the challenge for grid operators to bring other power sources online quickly.

BESS is a mature technology with a promising trend of decreasing costs. The state of the art of battery integration is dominated by batteries in PV self-consumption installations. Although the integration of batteries in utility-scale PV plants is starting to be a trend in several European countries, its use is limited due to a lack of regulation and incentives beyond electricity arbitrage. This is expected to change with the approval of capacity markets and other incentives by European governments. Once these measures are established, a massive introduction of BESS into the market is anticipated.

PVOP objectives

This report constitutes the first deliverable of the WP 3 of PVOP project. This work package is entitled “Control of PV plants to optimize their performance”. WP 3 is divided in two main tasks, T3.1 and T3.2. This part is devoted to T3.2 which is entitled **“Development and demonstration of control systems to maximize the performance and energy trading of PV plants with batteries”** and aims to develop the results R3 and R5 of the project.

The **main objectives** of T3.2 are:

1) To develop and demonstrate technical solutions for the control of PV plants to **maximize their performance**.

2) To **optimize the energy trading** of PV plants with batteries.

The PV scenario integrating batteries is very diverse. Here we propose to develop the solutions for a smart EMS that will include different strategies for battery management. This will be accompanied by **AI-based electricity marked predictor** (developed ad-hoc by the PVOP team, according to the plan detailed in **chapter B**) and **weather event forecast** (which will be bought from one of the available databases in the market). These two inputs are the key to develop an advanced control system and to truly optimize the battery integration.

The following sections of this chapter detail the **PVOP proposal** (how will the smart EMS operate, and what battery control strategies will be implemented) and the **Key Performance Indicators (KPIs)** that are believed to better quantify the benefits of this innovative solution.

4.1.2. PVOP proposal: concept

PVOP will develop a PV plant **control system** that will **integrate a Smart Energy Management System (EMS)** based on **predictions of weather conditions** (including extreme events) and an **AI-based electricity market predictor**. The EMS will be able to **manage the battery according to the most suitable control strategy** (among several strategies that will be described further in this document), receiving as input the data from weather and electricity market forecasters. By considering the weather forecasts (and the associated estimated PV productions) and the expected market prices, the Smart EMS will evaluate and implement the most appropriate management strategy for each hour.

Additionally, the EMS and the business model will also be developed **for centralized storage (**not attached to a specific PV plant). This storage would be installed at some point in the low or medium voltage rings, allowing the battery to be charged directly from the grid or from any PV plant in the ring through bilateral contracts. This would have **several advantages**: cost reduction due to economies of scale, greater access to PV generation, a greater number of charge and discharge cycles with the corresponding increase in profitability, and access to secondary regulation markets that have a higher average price.

Regarding the battery control strategies that will be developed and implemented, they have been selected because of their usefulness for some of the most interesting **applications for batteries** nowadays:

1) **PV plants for electricity generation.** They represent the biggest share in the PV market and are the most mature in technology and regulation. Batteries can help to improve the energetic and economic performance of PV plants (i.e. storing electricity when the selling price is low, when the evacuation point is overloaded…), but advanced control algorithms are necessary to guarantee the economic feasibility.

2) **Large self-consumption installations** (>1MW$_p$). Installed typically in industrial facilities or in very large neighbourhoods. Batteries are essential to optimize the energy flows between different consumers, optimizing the self-consumption and the self-sufficiency of the system.

3) **New niches:** less explored and with bigger room for innovation. The project partners believe that there are two applications in particular that will become relevant in the near future:

   - **Mining:** it is worth noting that the mining industry consumes a staggering amount of energy, around 11% of the world's total energy consumption. A considerable part of this energy currently comes from fossil fuels and mines are responsible for 4-7% of global greenhouse gas emissions. In this sense, renewable energies not only help to avoid the rising costs of fossil fuels, but also significantly reduce greenhouse gas (GHG) emissions. By adding PV generators without batteries, 20% of the diesel consumption during the day can be saved, but to go beyond this limit it is necessary to have them. In addition, PV generators allow to turn most of the diesel generators off. However, precautions must be taken regarding PV power fluctuations: diesel generators take some minutes to be turned on, so batteries are fundamental to guarantee the stability of the system during these critical periods.

   - **Energetic communities:** similar to shared self-consumptions in many aspects of, but different from a regulatory point of view. Mainly, the energetic community can be registered as an actor of the electricity market, being allowed to distribute, share, accumulate or sell the electricity produced.

There are different operating modes contributing to generating revenue for a Battery Energy Storage System (BESS) and enable a quicker return on investment. In fact, considering the actual cost of BESS a “revenue stacking” strategy is needed to assure an acceptable return on investment. Revenue stacking refers to the strategic utilization of multiple revenue streams and cost-saving opportunities to maximize the financial returns of a BESS. Table 2 shows how different operating strategies contribute to revenue stacking and facilitate a swift amortization of the investment:

Operating modes	Revenue Generation	Return on Investment
Time of Use (TOU) Arbitrage	TOU arbitrage involves charging the battery during off-peak hours when electricity prices are low and discharging during peak hours when prices are high.	Consistently leveraging daily market fluctuations generates regular income, contributing to the overall revenue stack and

	This process allows the BESS to capitalize on price differentials by buying low and selling high	shortening the payback period.
Peak Shaving (PS)	Peak shaving reduces the demand charges on electricity bills by lowering the peak demand during high-consumption periods. By discharging the battery during peak times, businesses can avoid the highest tariff rates associated with their peak usage.	A significant reduction in demand charges, which can constitute a large portion of industrial and commercial electricity bills, directly improves net income. This cost-saving measure adds to the revenue stack, accelerating the return on investment. This operation mode can avoid Grid reconstruction (AGR).
Maximization of Self-Consumption (MSC)	This mode ensures that energy generated by a PV system is used as much as possible on-site rather than being exported to the grid at lower rates. The BESS stores excess solar energy during the day for use during the night or periods of low generation.	Maximizing self-consumption reduces dependency on grid electricity, leading to substantial savings on energy bills. These savings contribute to the revenue stack, resulting in a faster recovery of the BESS investment.
Frequency Regulation (FR) and Ancillary Services	Providing grid services such as frequency regulation, voltage support, and spinning reserve can generate additional income. Utilities and grid operators often pay for these ancillary services to maintain grid stability and reliability.	Participating in these markets provides a steady revenue stream, adding to the revenue stack and ensuring a quicker payback period.

Capacity Market (CM)	Capacity markets allow BESS owners to receive payments for being available to supply energy during high-demand periods, ensuring sufficient capacity for grid stability.	By participating in these markets, the BESS earns additional income simply by being available, which adds to the revenue stack and contributes to faster investment recovery.

Table 2. Description and benefits of the different operating modes (i.e. control strategies) that will be implemented in the Smart EMS.

By leveraging revenue stacking, a BESS can strategically utilize multiple revenue streams and cost-saving opportunities. Each operating mode enhances the economic performance of the BESS by either increasing revenue or reducing costs. This diversified approach ensures that the system consistently generates financial returns from various sources. The combination of cost savings through reduced peak demand and energy bills, revenue from market arbitrage, ancillary services, and other value-added applications means that the system could pay for itself in a relatively short timeframe. It is also worth noting that the right combination of several control strategies might **Avoid Grid Reconstruction (AGR)** which is also translated into to cost savings**.** Thus, a well-implemented BESS with versatile operating modes and a revenue stacking strategy justifies the initial investment through its quick amortization.

The starting point of the system for PVOP project, resulting from the first cycle of WATT incremental development strategy, already integrates several of the operation modes described in the table above, such as: Time of Use, Peak Shaving, a quite premature Network Arbitrage, Self-consumption Maximization and the first specification of the Smart Predictive mode.

Not only are grid ancillary services and grid demands strategies still to be implemented, but there is also room for improvement of existing strategies. For the system to coordinate with the grid and its requirements, it needs to evolve to a higher level, in which it acquires the ability to control other energy terms, such as reactive power. Regarding the improvement of the existing operating modes, control engineering methods are being studied to stabilize the system response and guarantee the best behaviour, which could involve, for example, methods in states space or in the frequency domain. The aim is also to improve the inference capabilities of the system to anticipate future behaviours. While electricity prices or some solar incidence parameters are currently consulted through the cloud and used for small-term prediction, many others can be integrated, such as the behavioural patterns of the installation, other meteorological factors and even neural networks that learn from the performance of the controller to give it feedback or that model the transfer function of the entire set. Among all the improvements, those that are viable within the scope of the project and that align with its objectives will be chosen.

Regarding all these strategies, WATT EMS will receive inputs from sensors, electricity price databases, meteorological databases and Electricity Market Analysts as ASIC XXI (this last one described in chapter B). In relation to this last point, WATT and ASIC will agree on an **Application Program Interface**, **API**, to interchange information. WATT will provide actual technical restrictions of the BESS system (such as SOC, Maximum Power…) and ASIC XXI will provide instructions for charging and discharging depending on market opportunities for additional revenue.

4.1.3. Control strategies, algorithms and KPIs

The KPIs defined in this deliverable are divided into two categories: first, the KPIs necessary to evaluate if a certain control strategy was correctly implemented; second, the KPIs that quantify the impact of the battery integration for a certain application. The KPIs for the impact are strongly dependent on the system where the battery is integrated, and are affected by external factors like the size of the system, the consumption profiles, the electricity prices… Hence, such KPIs will be defined but not quantified, as there is not enough information available.

4.1.3.1. KPIs for the implementation of the control strategies

Figure 4 shows the schematic of a system with the following components:

- PV generator: it generates DC power (P_{PV})
- Li-ion battery: it exchanges DC power when it is charging ($P_{ch,B}$) or discharging ($P_{dis,B}$)
- Consumer: it consumes AC power (P_{cons})
- Electric grid: it permits to import AC power ($P_{imp,G}$) or to export it ($P_{exp,G}$)

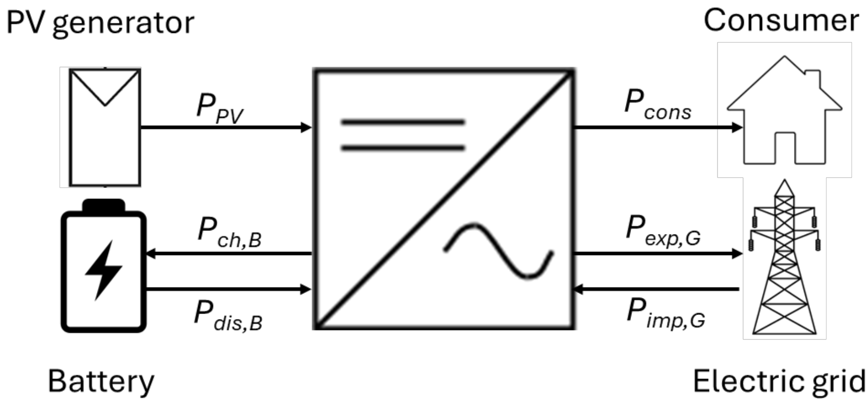

Figure 4. Schematic of a system with a battery integrated, showing the different power exchanges.

The battery permits to implement different control strategies with different objectives. In this section, it is explained how to evaluate the correct implementation of such strategies, attending to two different levels:

1. **Algorithm implementation:** first, it is necessary to evaluate if the battery responds to what the controller orders it to do, depending on the different control logics. The Root Mean Squared Error (RMSE) will be used as a metric to evaluate the accuracy of the performance of the battery's power output. In this case, the RMSE measures the discrepancy between the predicted power output of the battery and the actual power output, based on a given set of power set points under specific State of Charge (SOC) conditions.

   The equation for RMSE is expressed as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_{\mathrm{predicted},i} - P_{\mathrm{actual},i})^2}$$

Where:

- $P_{predicted,i}$ represents the predicted power output of the battery at time i, calculated based on the power set points and SOC conditions.
- $P_{actual,i}$ represents the actual measured power output of the battery at time i. It can be $P_{ch,B}$ or $P_{dis,B}$ depending if battery is charging or discharging
- n is the total number of observations.

In this context, the set points for power define the desired power output levels, and the SOC represents the current charge level of the battery, which can influence its ability to deliver or absorb power. The RMSE quantifies the precision of the battery model by summarizing how closely the predicted power output matches the actual output across various conditions. A lower RMSE value indicates higher accuracy, meaning the model more accurately reflects the battery's real-world behaviour.

Note that this KPI is independent of external factors, like solar irradiance or electricity consumption, and do not consider whether the size of the battery is optimized or not.

Note that this RMSE threshold is defined under the nominal standard operating conditions of the system, excluding from this value the boundary conditions under which the system exhibits responses not studied at this point of the project, that could affect the RMSE calculation. The previous includes factors, among others, such as the battery cell and ambient temperatures and the SOC status of the system, since this value approaching its upper end implies that some battery packs will be full of charge while others will not, causing the maximum instantaneous charging power to decrease. Similarly, low SOC percentages produce the same not yet studied effect on power setpoint performance. The nominal conditions will then be defined together with their corresponding thresholds for the proposed KPIs.

2. **Algorithm impact (functionality of the strategy):** once that it is guaranteed that the implementation of the algorithms is validated as correct, i.e., the battery operates at the set point that corresponds to each strategy in any operating situation, it is necessary to evaluate if the control strategy implemented has the expected impact on the system. For this, different KPIs will be required for each control strategy, attending to their ultimate objective. These KPIs are dependent on external factors, like solar irradiance or the electricity consumption, and on the sizing of the battery. However, at this point of the project it is almost impossible to estimate which values could be expected for these KPIs, so in this deliverable they will be only qualitatively defined, and their quantification will be the objective of future work.

The following section lists and describes all the control strategies that will be implemented, explaining how the code calculates the set point of the battery (**set point variables are highlighted in green**, indicating that it is necessary to guarantee that the RMSE between the calculated and the measured values is lower than OJO%) and defining the KPIs to evaluate the impact on the system. Note that there will be situations when the battery is not capable of fulfilling the strategy objective (when it is completely charged or discharged). These situations will be indicated with a **warning message highlighted in red**.

1) **Time of Use Arbitrage (TOU):** typically, TOU arbitrage involves charging the battery during off-peak hours when electricity prices are low and discharging during peak hours when prices are high. This process allows the BESS

to capitalize on price differentials by buying low and selling high. However, TOU can also refer to a strategy that defines periods when it is convenient to import/export electricity from the grid, attending to criteria that are not necessarily economic. In this case, there are two factors to consider: when are the import/export periods, and what is the power that should be exchanged with the electric grid. The set point of the battery will be a consequence of both factors and of the State of Charge (SOC).

Algorithm implementation

0% < SOC < 100%:

- Import period (charging the battery): $\mathbf{P_{ch,B}} = P_{imp,G} + P_{PV} – P_{cons}$
- Export period (discharging the battery): $\mathbf{P_{dis,B}} = P_{exp,G} - P_{PV} + P_{cons}$

SOC = 100%:

- Import period (charging the battery): **WARNING**
- Export period (discharging the battery): $\mathbf{P_{dis,B}} = P_{exp,G} - P_{PV} + P_{cons}$

SOC = 0%:

- Import period (charging the battery): $\mathbf{P_{ch,B}} = P_{imp,G} + P_{PV} – P_{cons}$
- Export period (discharging the battery): **WARNING**

The KPIs for the correct implementation of the algorithm is:

- KPI1$_{TOU}$: RMSE ($P_{dis/ch,B}$ - $P_{dis/ch,B\ measured}$) < 2%. It evaluates the goodness of the algorithm to establish the setpoint of the power of the battery. NOTE: the operational conditions for which the upper KPI1$_{TOU}$ value is proposed are 20%<=SOC<=80% @ 0º-40º.

- KPI2$_{TOU}$: $t_{transition}$ < 2s. It evaluates the time of the transition between the import and export periods.

Algorithm impact

- KPI3$_{TOU}$: it evaluates if the power imported or exported from the grid is the one stablished for every period. It is the RMSE between the calculated import/export power values and the measured values of $P_{imp,G}$ and $P_{exp,G}$.

- KPI4$_{TOU}$: it evaluates if energy is imported/exported from the grid when it should. For a certain period, it is calculated as follows:

$$KPI4TOU = \frac{Energy\ exchanged\ with\ the\ grid\ during\ TOU\ hours}{Energy\ exchanged\ with\ the\ grid}$$

- KPI5$_{TOU}$: for the specific case when the TOU hours are defined attending to the electricity tariffs, the power exchanged with the grid is limited to the contract power with the electric company ($P_{max,G}$). The electricity company does not measure the power in real time but measures the energy consumption every 15 minutes. So, it is important to assure the following:

$$\int_{t1}^{t2} P_{imp/exp,G} \leq P_{max,G} \times (t_2 - t_1)$$

where $(t_2 - t_1)$ corresponds to periods of 15 minutes and $P_{imp/exp,G}$ can be the imported or exported energy from the grid in that period of time.

2) **Peak shaving (PS):** Peak shaving reduces the demand charges on electricity bills by lowering the peak demand during high-consumption periods. By discharging the battery during peak times, businesses can avoid the highest tariff rates associated with their peak usage. For this control strategy, the main parameter is the maximum power that can be exchanged from the grid ($P_{max,G}$), whether it is imported or exported.

Algorithm implementation

0% < SOC < 100%:

- If $P_{PV} > (P_{max,G} + P_{cons})$ then charge the battery: $\mathbf{P_{ch,B}} = P_{PV} – P_{max.G} - P_{cons}$
- If $P_{cons} > (P_{max,G} + P_{PV})$ then discharge the battery: $\mathbf{P_{dis,B}} = P_{cons} – P_{max.G} – P_{PV}$

SOC = 100%:

- If $P_{PV} > (P_{max,G} + P_{cons})$ then charge the battery: **WARNING**
- If $P_{cons} > (P_{max,G} + P_{PV})$ then discharge the battery: $\mathbf{P_{dis,B}} = P_{cons} – P_{max.G} – P_{PV}$

SOC = 0%:

- If $P_{PV} > (P_{max,G} + P_{cons})$ then charge the battery: $\mathbf{P_{ch,B}} = P_{PV} – P_{max.G} - P_{cons}$
- If $P_{cons} > (P_{max,G} + P_{PV})$ then discharge the battery: **WARNING**

The KPIs for the correct implementation of the algorithm is:

- KPI1$_{PS}$: RMSE ($P_{dis/ch,B}$ - $P_{dis/ch,B\ measured}$) < 2%. It evaluates the goodness of the algorithm to establish the setpoint of the power of the battery. NOTE: the operational conditions for which the upper KPI1$_{PS}$ value is proposed are 20%<=SOC<=80% @ 0º-40º.

- KPI2$_{PS}$: $t_{transition}$ < 2s. Evaluates the transition time from one power setpoint to another when sudden setpoint changes occur.

Algorithm impact

- KPI3$_{PS}$: RMSE ($P_{imp/exp,G}$ - $P_{max,G}$). It evaluates if the power imported or exported from the grid does not exceed the maximum permitted value. It is the RMSE between $P_{max,G}$ and the measured values of $P_{imp,G}$ and $P_{exp,G}$, considering only the periods when the battery should actually peak shave.

- KPI4$_{PS}$: it evaluates if the electricity company would penalize the user of the battery for exceeding $P_{max,G}$. Considering that the electricity company does not measure the power in real time, but only measures the energy consumption every 15 minutes, it is important to assure the following:

$$\int_{t1}^{t2} P_{imp/exp,G} \leq P_{max,G} \times (t_2 - t_1)$$

where $(t_2 - t_1)$ corresponds to periods of 15 minutes and $P_{imp/exp,G}$ can be the imported or exported energy from the grid in that period of time.

3) **Maximization of self-consumption (MSC):** This mode ensures that energy generated by a solar PV system is used as much as possible on-site rather than being exported to the grid at lower rates. The BESS stores excess solar energy during the day for use during the night or periods of low generation. This objective can also be understood as minimizing the energy exported to the grid.

Algorithm implementation

0% < SOC < 100%:

- If $P_{PV} > P_{cons}$ then charge the battery: $\mathbf{P_{ch,B}} = P_{PV} - P_{cons}$
- If $P_{cons} > P_{PV}$ then discharge the battery: $\mathbf{P_{dis,B}} = P_{cons} – P_{PV}$

SOC = 100%:

- If $P_{PV} > P_{cons}$ then **export to the grid**: $\mathbf{P_{exp,G}} = P_{PV} - P_{cons}$
- If $P_{cons} > P_{PV}$ then discharge the battery: $\mathbf{P_{dis,B}} = P_{cons} – P_{PV}$

SOC = 0%:

- If $P_{PV} > P_{cons}$ then charge the battery: $\mathbf{P_{ch,B}} = P_{PV} - P_{cons}$
- If $P_{cons} > P_{PV}$ then import from the grid: $\mathbf{P_{imp,G}} = P_{cons} – P_{PV}$

The KPIs for the correct implementation of the algorithm is:

- $KPI1_{MSC}$: RMSE ($P_{dis/ch,B}$ - $P_{dis/ch,B\ measured}$) < 2%. It evaluates the goodness of the algorithm to establish the setpoint of the power of the battery. NOTE: the operational conditions for which the upper $KPI1_{MSC}$ value is proposed are 20%<=SOC<=80% @ 0º-40º.

- $KPI2_{MSC}$: $t_{transition}$ < 2s. Evaluates the transition time from one power setpoint to another when sudden setpoint changes occur.

Algorithm impact

- $KPI3_{MSC}$: Self-Consumption Rate (SCR): it is the portion of the total PV energy that is consumed in the system, whether directly or previously storing it in the battery.

$$SCR = \frac{E_{PV}^{C} + E_{B}^{C}}{E_{PV}}$$

  Where E_{PV}^{C} is the PV energy that is directly consumed, E_{B}^{C} is the energy consumed from the battery and E_{PV} is the total energy produced.

- $KPI4_{MSC}$: Surplus Energy Rate (SER): it is the portion of the total PV energy that is exported to the grid.

$$SER = 1 - \frac{E_{PV}^{C} + E_{PV}^{S}}{E_{PV}}$$

  Where E_{PV}^{S} is the PV energy that is stored in the battery.

4) **Frequency Regulation (FR):** Providing grid services such as frequency regulation, voltage support, and spinning reserve can generate additional income. Utilities and grid operators often pay for these ancillary services to maintain grid stability and reliability. From the different types of grid regulation, batteries can contribute to frequency regulation, as they are capable of delivering or absorbing active power (reactive power, on the other hand, is how the grid voltage is regulated).

* The standard frequency in Europe's electricity grid is 50 Hz. In North America and parts of Japan, on the other hand, a standard frequency of 60 Hz is used. In any case, there is always a tolerance for this value. For general purposes, we will call $freq_{SP}$ to the stablished frequency in each grid and consider a ±Tolerance.

*For this control strategy, the frequency regulation will be translated into the power that might be demanded from the grid according to the setpoint established by the grid operator, whether it is imported or exported for grid stabilization (so, here $P_{imp,G}$ and $P_{exp,G}$ means the setpoints established by the grid operator). There is also a maximum time of response, established by the electric grid operator ($t_{max,FR}$), that is crucial for this strategy.

Algorithm implementation

0% < SOC < 100%:

- If frequency > ($freq_{SP}$ + Tolerance) then import from the grid (charging the battery): $\mathbf{P_{ch,B}} = P_{imp,G} + P_{PV} - P_{cons}$
- If frequency < ($freq_{SP}$ - Tolerance) then export to the grid (discharge the battery): $\mathbf{P_{dis,B}} = P_{exp,G} - P_{PV} + P_{cons}$

SOC = 100%:

- If frequency > ($freq_{SP}$ + Tolerance) then import from the grid (charging the battery): **WARNING**
- If frequency < ($freq_{SP}$ - Tolerance) then export to the grid (discharge the battery): $\mathbf{P_{dis,B}} = P_{exp,G} - P_{PV} + P_{cons}$

SOC = 0%:

- If frequency > ($freq_{SP}$ + Tolerance) then import from the grid (charging the battery): $\mathbf{P_{ch,B}} = P_{imp,G} + P_{PV} - P_{cons}$
- If frequency < ($freq_{SP}$ - Tolerance) then export to the grid (discharge the battery):
  If $P_{PV} > P_{cons} + P_{exp,G}$ then $P_{exp,G}$ imported to the grid is dispatched from P_{PV}
  If $P_{PV} < P_{cons} + P_{exp,G}$ then discharge battery: **WARNING**

The KPIs for the correct implementation of the algorithm is:

- $KPI1_{FR}$: RMSE ($P_{dis/ch,B}$ - $P_{dis/ch,B\ measured}$) < 1%. It evaluates the goodness of the algorithm to establish the setpoint of the power of the battery. NOTE: the operational conditions for which the upper $KPI1_{FR}$ value is proposed are 20%<=SOC<=80% @ 0º-40º.

- $KPI2_{FR}$: $t_{transition}$ < 2s. Evaluates the transition time from one power setpoint to another when sudden setpoint changes occur.

Algorithm impact

- $KPI3_{FR}$: RMSE ($P_{imp/exp,G}$ - $P_{imp/exp,G\ measured}$). It evaluates if the power imported or exported from the grid is the one stablished for every demand period. It is the RMSE between the calculated import/export power values and the measured values of $P_{imp,G}$ and $P_{exp,G}$.

- KPI4$_{FR}$: it is the percentage of $t_{max,FR}$ that the battery took to react. It is defined as follows:

$$KPI2_{FR} = \frac{t_{max,FR} - t_{react}}{t_{max,FR}} x100$$

5) **Capacity markets (CM):** allow BESS owners to receive payments for being available to supply energy during high-demand periods, or absorbing energy during high-production periods, ensuring sufficient capacity for grid stability. For this strategy we will consider that capacity markets may demand support for both the supply of power to the grid (export period) or the reduction of power from the grid (import period). So, here $P_{imp,G}$ and $P_{exp,G}$ means the setpoints established by the capacity markets. There is also a maximum time of response, established by the electric grid operator ($t_{max,CM}$), that is crucial for this strategy.

Algorithm implementation

0% < SOC < 100%:

- Import period (charging the battery): **$P_{ch,B}$** = $P_{imp,G}$ + P_{PV} – P_{cons}
- Export period (discharging the battery): **$P_{dis,B}$** = $P_{exp,G}$ - P_{PV} + P_{cons}

SOC = 100%:

- Import period (charging the battery): **WARNING**
- Export period (discharging the battery): **$P_{dis,B}$** = $P_{exp,G}$ - P_{PV} + P_{cons}

SOC = 0%:

- Import period (charging the battery): **$P_{ch,B}$** = $P_{imp,G}$ + P_{PV} – P_{cons}
- Export period (discharging the battery):
  If P_{PV} > P_{cons} + $P_{exp,G}$ then $P_{exp,G}$ exported from grid is dispatched from P_{PV}
  If P_{PV} < P_{cons} + $P_{exp,G}$ then discharge battery: **WARNING**

The KPIs for the correct implementation of the algorithm is:

- KPI1$_{CM}$: RMSE ($P_{dis/ch,B}$ - $P_{dis/ch,B\ measured}$) < 2%. It evaluates the goodness of the algorithm to establish the setpoint of the power of the battery. NOTE: the operational conditions for which the upper KPI1$_{CM}$ value is proposed are 20%<=SOC<=80% @ 0º-40º.

- KPI2$_{CM}$: $t_{transition}$ < 2s. Evaluates the transition time from one power setpoint to another when sudden setpoint changes occur.

Algorithm impact

- KPI3$_{CM}$: RMSE ($P_{imp/exp,G}$ - $P_{imp/exp,G\ measured}$). It evaluates if the power imported or exported from the grid is the one stablished for every period. It is the RMSE between the calculated import/export power values and the measured values of $P_{imp,G}$ and $P_{exp,G}$.

- KPI4$_{CM}$: it is the percentage of $t_{max,CM}$ that the battery took to react. It is defined as follows:

$$KPI4_{CM} = \frac{t_{max,CM} - t_{react}}{t_{max,CM}} x100$$

6) **Demand management (DM):** aim to manage and balance the supply and demand of electricity in real-time, responding to fluctuations in consumption and energy generation. Both energy providers (generators) and consumers who can reduce their demand in response to signals from the system operator participate in these markets.

   * The algorithm implementation of this strategy is very similar to the one developed for peak shaving except that in this case the max power from the grid is not a fixed value and can vary according to real time demand. So, the same strategy and PIs will be used.

4.1.3.2. KPIs for the impact of battery integration

The **impact of implementing the Smart EMS in the control system** of a PV installation needs to be somehow quantified, to determine whether it is beneficial or not. This section details the KPIs proposed to evaluate different aspects of the innovations implemented. These KPIs are structured in three levels:

1. **General KPIs**: related to the general objectives of T3.2, which are maximizing the performance and the energy trading of the PV installation. They will be obtained by comparing a certain PV installation with and without batteries, in terms of performance and economic profitability. This way, the KPIs will quantify the benefits of including the Smart EMS developed at PVOP. We will simulate both plants using digital twins: first, we will replicate the production of a given installation without battery; second, we will simulate its production with the battery and the advanced control system. We expect approximate increments of the annual energy yield of 5% (based on avoidance of technical curtailments at the point of injection by means of deviating the excess of instantaneous solar production to the battery) and a minimum reduction of the LCOE of 10% (based on correct energy arbitrage strategies) both calculated for a 30-year span.

Calculation of the Levelized Cost of Storage (**LCOS**) of a BESS installation is a measure of the average cost per unit of electricity that is stored and then discharged by an energy storage system over its lifetime. It is used to evaluate the economic performance and cost-effectiveness of different energy storage technologies, such as batteries. To give real LCOS numbers we need to study the performance of the system for approximately one year. The WATT EMS system has not been deployed for that long, so it is not yet possible to give very accurate data on this. But it is expected that over the course of the PVOP project this figure will not only be known but can be reduced based on different implementations and improvements of the battery energy strategies.

2. **Specific KPIs**: specific to the application. In this case, the outcome of the system depends on too many external factors, so these KPIs will be conceptually defined, but not quantified for now.

- PV plants: the performance of grid-connected PV plants is typically evaluated through the **Performance Ratio (PR)**, which is the ratio between the AC energy delivered to the grid and the DC energy that could have been ideally produced, for a certain period of time. Including a battery could delay in time the AC energy injection but should reduce it because the battery efficiency losses. The **battery integration** generally results in a lower PR compared to a system without a battery, but it adds value by allowing stored energy to be used at optimal times for the grid, improving overall energy management.

- Large self-consumption: these installations are typically evaluated thorough the **Self-Consumption Rate (SCR)** -the fraction of PV energy that is consumed in situ from the total PV energy produced- and the **Self-Sufficiency Rate (SSR)** -the fraction of energy that comes from the PV generator from the total energy consumption-. Incorporating **a battery in a self-consumption installation can increase both rates, specially the SSR**; the SCR is highly dependent on the consumption profiles, and if they are too decompensated from the PV generation, the battery needed to increase the SCR would be too big to be economically feasible.

- New niches:

    - **Energy communities:** can be characterized by the same KPIs as self-consumption installations: **the SCR and the SSR**. However, it should be noted that the SCR is strongly affected by the proportion between the members of the community that install PV generators and the members who are only consumers. If few generators provide electricity for many consumers, the energetic surplus must increase to the detriment of the SCR.

    - **Mining:** batteries in mining installations are crucial for **reducing the consumption of diesel fuel**, that is both pollutant and expensive (and the prices are expected to keep increasing). The idea is to use diesel generators only as back-up for the periods when the PV power is reduced or the consumption increases. For guaranteeing the stability of the system, **it is critical that batteries can power the whole mine, self-sufficiently, during the 10 minutes that take diesel generators to be turned on**. For this, meteorological forecasting will be fundamental.

3. **Fundamental KPIs:** to reach the objective values for the general KPIs, it is necessary to guarantee the technical quality of the different solutions implemented. It is difficult to imagine all the relevant technical KPIs that will be involved, but at least the following must be considered:

    - Accuracy in the estimation of the SOC: To increase the operational and financial reliability of all BESS systems it is necessary to have accurate state of charge estimations which are essential for reliable operation by increasing the accuracy of the estimated energy available for discharge. A recent report alerts that conventional SOC measurements can result in average errors of 7% when the EMS estimates the energy available in the battery. An independent assessment of the SOC will be carried out. We will monitor the current flows in and out of the battery with very accurate sensors (quantifying any possible offset) and will account for the internal architecture connecting cells (advanced EMS use more complex strategies, with a significant impact on the energy availability). With this, we intend to reduce **average errors to 3% in the estimation of the energy available**.

    - Accuracy in the estimation of the SOH: The battery degrades not only because of the aging that it suffers due to the fact of being stopped only and exclusively by the passage of time, but also because of the number of cycles it has throughout its life (cycling aging). We will develop and implement aging models for the different control strategies in the advanced EMS. This way, the degradation induced by a certain cycling of the battery will be considered when selecting one control strategy or another. Also, we will perform regular tests for **comparing the estimated SOH, according to the implemented models, and the real one: the difference should be less than 7%** at the end of the project, after the aging models have been correctly tuned.

4.1.3.3. Implementation of the Smart EMS

A. Implementation at the IES-UPM outdoor testing facilities

The solutions will be developed, and a first validation (during the first 18 months of PVOP project) will be carried out **at prototype-alpha level in controlled environments (at IES-UPM battery)**. It is planned to be installed a 15 kWp PV System prototype with an integrated 100 kW battery and 97 kWh capacity at UPM facilities by WATT at the beginning of the project. At this stage (during month 6 of the project), an alpha version of API interface between Wattkfrat and ASIC XXI will be provided. This API version will continue to develop over the next months of the project. The following planification of the battery installation is briefly explained:

- Battery Selection: DONE (Manufacturer & Model: Huawei LUNA2000 97KWh)
- Emplacement validation based on technical and safety restrictions evaluation: DONE (internal yard at the ETSIT campus has been selected in agreement with the University)
- Procuring and Delivering (lead time > 22 weeks -> Critical path): ETA October 2024.
- Contract for executing Civil works and installation: IN PROGRESS
- Battery Commissioning and Field Acceptance Tests: Planned During November 2024 after installation

Figure 5. Battery selected for the PVOP project

B. Implementation at a commercial PV plant

On a second period of the project, the technical solutions will be implemented and validated **in real PV plants.** WATT EMS development process will follow an engineering and empirical approach: incremental integration of functionalities to be promptly tested on real batteries. This approach will yield a time to market functional product.

Figure 6 shows one of the pilot sites for testing beta EMS version, already in operation since March 2024.

Figure 6. One of the pilot sites for testing beta EMS version in operation since March 2024

Site 1: Installation of 12.6MWn PV + 10MWh/5MW BESS

- FV: 12.6MWn (64xHuawei SUN2000-215KTL-H0 inverters)
- BESS: 10MWh/5MW
- COD: March 2024
- Control: Power Plant Controller + EMS integrated in the factory SCADA

4.1.4. Conclusions

This chapter is intended to evaluate the **control of PV plants with storage systems**, what control strategies are most interesting and how they could be combined and optimized by a smart EMS. The following innovations are proposed:

- AI-based electricity market predictions (detailed in chapter B), that will be an input for the EMS.

- Weather conditions predictor will be used as input for the EMS.

- The EMS will decide every hour what the most suitable battery control strategy is and implement it, instead of only operating according to one strategy.

- SOC estimations will be performed in parallel to the EMS, to reduce the error.

- Aging models will be implemented for a more accurate estimation of the SOH.

This report paves the way for the next PVOP experimental steps, that must lead to developing an advanced control system for PV systems with batteries. For that, the validation experiments will be implemented in two phases: at the

IES-UPM outdoor testing facilities and at a few commercial PV installations. Corresponding KPIs, based on the **maximization of the performance and the energy trading** of the PV installation, are proposed.

4.2. Chapter B: Electricity Market Forecast

4.2.1. Introduction

Background

As previously mentioned in the document, the objective of this project is to maximize the potential of photovoltaic installations in combination with Battery Energy Storage Systems (BESS). One of the main factors influencing this optimization is economic profitability, as without it, no project can be feasible. Therefore, the correct operation of the plants, maximizing the value of their generation and the charge-discharge cycles of the battery systems, is key.

To ensure this operation is carried out correctly, it is necessary to evaluate the different operational scenarios that are viable for the specific plant. For this, predicting the different selling prices of the energy, whether produced or fed into the system from the batteries, is crucial. For this reason, PVOP includes among its development objectives the creation of forecasting models, based on various existing tools, to enable the most efficient and profitable operation of the plants.

In recent years, the modelling and forecasting of electricity prices have seen significant advances, largely driven by the emergence of artificial intelligence (AI) and self-learning regression models. Traditionally, electricity price forecasting relied on statistical and econometric models that used historical data and exogenous variables such as demand, supply, and weather conditions. However, these models often faced limitations in their ability to capture the complexity and dynamics of the electricity market.

With the advent of AI, more sophisticated models have been developed that can handle large volumes of data and learn complex patterns. Machine learning algorithms, such as neural networks and decision trees, have proven particularly effective in forecasting electricity prices. These models can adapt and continuously improve as they are fed with new data, allowing them to anticipate market changes with greater accuracy. Models like ARIMA (AutoRegressive Integrated Moving Average) and LSTM (Long Short-Term Memory) are capable of capturing both long-term trends and short-term fluctuations in electricity prices. Additionally, they can incorporate a wide range of variables, from weather data to information on renewable energy generation, further enhancing their accuracy.

Nevertheless, there is still much progress to be made in this field. Modelling and influencing chaotic events (unpredictable a priori), as well as rare or infrequent events that affect prices, remain challenges and are foundational aspects of this part of the PVOP project. The goal is not so much to obtain a fixed price, which is almost impossible to achieve from a technical standpoint, for each hour or day for the next 10-15 years, but to generate models that provide price ranges to facilitate decisions regarding productive operation, maintenance, or predictive measures.

Generic characteristics of initial models

Regarding the most commonly used models, the objective of this document is not to provide detailed information on each one, but it is necessary to give an overview to understand the uses, weaknesses, and strengths of each chosen as a first option from those available.

ARIMA

The ARIMA (AutoRegressive Integrated Moving Average) model is a statistical technique used for time series analysis and forecasting. It consists of three components: autoregressive (AR), moving average (MA), and differencing (I). The AR component uses dependencies between past observations, the MA component models the prediction error as a linear combination of past errors, and differencing is used to make the time series stationary.

- Technical characteristics:
    - AR(p): Number of autoregressive terms.
    - I(d): Number of differences needed to make the series stationary.
    - MA(q): Number of moving average terms.
- Use cases:
    - Best: Time series without seasonality.
    - Worst: Series with strong seasonal components.
- Computational complexity: Moderate, as it requires the estimation of several parameters and can be computationally intensive for long series.

Neural Networks (LSTM and GRU)

Recurrent neural networks (RNN) such as LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) are advanced deep learning techniques designed to handle sequential data.

- Technical characteristics:
    - LSTM: Uses memory cells and three gates (input, output, and forget) to maintain and update information over time.
    - GRU: Similar to LSTM but with a simpler architecture, using only two gates (update and reset).
- Use cases:
    - Best: Time series with long-term dependencies and complex patterns.
    - Worst: Series with few data points or without clear patterns.
- Computational complexity: Very high, due to the need to train multiple layers and parameters, requiring significant computational resources.

GARCH

The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model is primarily used to model and forecast volatility in financial time series. This model assumes that the variance of the error is autocorrelated and follows an autoregressive moving average process.

- Technical characteristics:
    - GARCH(p, q): p is the number of autoregressive terms and q is the number of moving average terms in the variance.

- Use cases:
  - Best: Financial time series with variable volatility.
  - Worst: Series with constant variance or without heteroscedasticity.
- Computational complexity: Moderate to high, depending on the number of terms included in the model.

Model	Strength	Weakness	Computational Complexity
ARIMA	Time series without seasonality	Series with strong seasonal components	Moderate
SARIMA	Time series with clear seasonal patterns	Series without seasonality or with irregular seasonality	High
LSTM and GRU	Time series with long-term dependencies and complex patterns	Series with few data points or without clear patterns	Very high
GARCH	Financial time series with variable volatility	Series with constant variance or without heteroscedasticity	Moderate to high

Table 3. Summary of forecasting models in terms of their strengths and weaknesses.

These models offer different approaches and levels of complexity for time series forecasting, and their choice depends on the specific characteristics of the data and the objectives of the analysis.

Regarding the temporal use of the aforementioned models, we must consider that not all models will be equally accurate, a priori, for all simulation scopes. Based on the three simulation ranges to be used in the project (hourly, monthly, and annual), we can conduct an initial analysis to indicate which of these previously mentioned models may be a priori, more suitable for each of them.

Hourly forecasting

- Time series models: ARIMA (AutoRegressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models are widely used to predict hourly prices. These models consider seasonal patterns and historical trends.

- Neural networks: Neural networks, such as LSTM (Long Short-Term Memory), have proven to be effective in forecasting electricity prices. These networks can capture nonlinear relationships and complex patterns in the data.

Monthly forecasting

- Seasonal analysis: The monthly forecast is based on seasonal patterns and climatic factors. Variables such as demand, availability of renewable sources and special events (holidays, vacations, etc.) are considered. So, models such as ARIMA and SARIMA are appropriate.

- Econometric models: Models such as the multiple linear regression model are used to relate prices to explanatory variables such as demand, supply and fuel prices.

Annual forecast

- Macroeconomic scenarios: The annual forecast involves considering long-term economic, political and technological factors. Scenarios such as economic growth, infrastructure investment and the transition to clean energy are evaluated based, among others, on government strategic plans. Structural models (SSM) could be the most accurate for this work.

Hybrid models

Combined approaches, such as the integration of econometric models with neural networks (LSTM), allow for more accurate and robust forecasting.

All of the above allows us to outline a starting scenario from which to begin the necessary work to achieve the project's objectives.

4.2.2. PVOP proposal: concept

4.2.2.1. Conceptual aspects

The purpose of this PVOP project is clear: to push PV generation to the next level of efficiency, safety and profitability to reach the level of excellence that will allow this technology to lead the energy revolution in the coming years. To optimize profitability to the maximum, it is necessary to be able to operate these installations, and more specifically, those with storage that discharge energy into the system.

To achieve this goal, it is necessary to be able to create energy management strategies that maximize the economic return on each MWh generated. When to store, when to feed the associated facilities in self-consumption or when to discharge to the grid, and how much, will be one of the keys to the success of these systems. And for this, it is necessary to know as accurately as possible the grid energy prices in the necessary time frames as well as the foreseeable balance of generation and demand with the necessary anticipation. It is important to keep in mind that the forecast domains depend very much on the purpose of the forecast. We can reduce these forecast blocks to 4 scenarios:

- **Pluriannual model**: The objective of these models is to forecast over a period of 5 - 10 - 15 years both the expected average prices and the possible fluctuations of these prices. Their objective is the realization of the business plan of each facility, as well as the analysis of its payback period and profitability. As it is logical, these forecasts cannot pretend to be of a high accuracy and must be more oriented to create scenarios of not exceeding or lowering the price, giving a range of prices that allow, with the necessary reliability, to create business scenarios that facilitate the financing of the facilities. Although their calculation should include price weightings according to each hour, to be able to adjust the data correctly to PV installations, which have a large component of seasonality both monthly and hourly, they should be based on global annual data.

- **Annual model**: This pricing model should be able to, with greater predictability than the multi-year model, present price scenarios with tighter reliability. With the objective of planning a year ahead from the operational point of view of the plant (looking for maintenance windows, knowing the expected monthly cash flows, foreseeing advanced amortizations or other actions of a more operational or financial nature), this model should present better results on a monthly basis than the previous one, and should be able to be weighted by generation hours, although the hourly nature is not its main objective.

- **Monthly model**: For this model, the temporal scope should be of several months, being the chosen term discussed later during the PVOP project with the objective of adjusting more to the needs of the plants from the point of view of technical shutdowns, maintenance operations or revenue optimization. Its character is more operative than the previous ones, since it will allow making decisions not so much in terms of plant financing, but more in terms of its technical effectiveness, minimizing the energy losses in usual operations. Its hourly forecast must be more adjusted, and the seminal scope should be the basic calculation unit from which to start. It should allow a more global planning of the load/discharge cycles of the installations, which will then be optimized in the following model.

- **Daily model:** the daily model is the one that should be the basis for the short-term operation of each facility. With a horizon of several days (maximum 10 days), it must reach high efficiency quotas in the hourly forecast, since it will be the basis for short-term sales/storage strategies. Starting from the daily forecasting unit, which must have very high reliability values in the forecast price, it must perform an efficient hourly price forecast in all the days of analysis, and especially in the short period of time of 5 days ahead. In addition to this hourly forecast, this daily model has to be able to reach a quarter-hourly forecast resolution on the shortest time horizon (from a few hours, to act intraday up to 1 or 2 days), to allow the efficient operation of the asset in regulation, secondary, adjustment markets, etc.

As mentioned in the previous point, there are several methodologies in use, with better or worse results, for each area of analysis of the above models. Moreover, the objective is not the same for all of them, and therefore, their approach to the calculation cannot be similar. To simplify the understanding of the objective, scope and characteristics of each model, Table 4 is attached.

MODEL	Multi-year	Annual	Monthly	Daily
Time scope	5 to 15 years	12 months	3 or 4 months	10 days
Base forecasting unity	Annual	Monthly	Monthly	Daily
Accuracy required	High	High	Very high	Very high

Maximum granularity	Hourly	Hourly	Hourly	Quarter Hour
Accuracy required	Medium	High	High	Very high
Model objective	Financial	Financial/operative	Operative/Financial	Operative
Reliability interval	High	High	Very high	Very high
Sensitivity to stochastic analysis	Very high	High	High	Medium

Table 4. Summary of forecasting models in terms of their scope and characteristics.

The selection of the mathematical forecasting model will be carried out throughout the experimentation process, starting for each block from the most suitable ones according to the scope of analysis. This process does not differ much from the standard analyses that are already being carried out, but in PVOP project, a new concept will be implemented that is thought to be decisive: the stochastic analysis of the forecasts.

4.2.2.2. Stochastic analysis of forecasts

Stochastic analysis is a statistical technique, widely used in the financial sector, which aims to determine **the strength and trend of a price based on external events**. In this way, it is possible to try to anticipate trading operations to sudden changes or price caps/lows.

In more specific terms, the stochastic indicator compares the current closing price with previous closing prices over a chosen period. It was created by George Lane in the 1950s and is popular in Forex, indices and stock trading. Some common uses of this indicator are as follows:

- Divergences: It can help to identify divergences between the indicator and the price, which can signal possible trend changes.
- Day trading and scalping: Intraday traders can use it to make quick decisions.
- Buy and sell confirmations: Provides signals to enter or exit the market.
- Overbought and oversold: Helps to identify extreme price levels.

Currently, most electricity market price analyses are based on technical criteria such as the degree of penetration of renewable energies in the market or the overall demand forecast for a given period. Under stable conditions, being these data well known, this type of analysis gives good results, especially in the short term. But experience and observation allow us to confirm that external events not directly associated with actual consumption affect the price in a critical way. As an example:

- We can appreciate slight price increases in the electricity market in the order of 2-3 months before an electoral process, not being this increase related to objective parameters.
- The world pandemic, and more specifically its confinement, produced a critical drop in prices. In this case, it is related to the drop in demand, but previous analyses indicate that this drop was not correlated and had an indeterminate component related more to bearish market expectations than to fundamentals.
- The Ukrainian war generated a price increase that, although it can be attributed to the gas price increase, should not have responded abruptly given the level of storage filling or supply conditions.

These examples are just a sample of how external processes, or "black swans", which often do not have a direct effect on supply or do not affect price formation parameters with the weight that justifies the price change they produce, generate critical impacts on these prices.

The analysis, modelling and implementation of these external elements is defined as key to understand and forecast the price in the medium and long term, mainly. In the short term, only major events can affect these forecasts, which, as indicated above, respond more to technical parameters, but in a monthly or longer-term analysis, their presence is critical.

That is why in PVOP project, the stochastic analysis of external events and their effect on the market price is defined as one of the mainstays of the work to be developed.

4.2.3. MODELING, ANALYSIS AND KEY PERFORMANCE INDICATORS (KPIs)

The objective of the modelling and analysis processes of this project will be to determine which mixed models (data-driven and stochastic) respond best to the analysis in each time domain, and to select their priority for use in the implementation, development and calculation of PV plant operation strategies. These models will be able to exploit their full potential in installations that have a certain level of management when hybridized with associated BESS, but for some applications, especially for issues of participation in regulation and secondary markets, this does not necessarily have to be the case.

First, we must define what we consider as success. It must be considered that, as in any practical project, the objectives must be feasible from the theoretical point of view and achievable from the technical point of view. The objective, therefore, cannot be to determine with high precision the outcome in each time range of a given strategy. Except for very short-term predictions (from quarter-hourly to a couple of days), accurately predicting the outcome of such a strategy by thinking of a closed value of € is impossible, and pursuing such a goal would be unrealistic.

The objective, therefore, should be that the chosen models achieve a range of results for each of the strategies as close to the real one as possible, with sufficient reliability to allow them to:

- Develop firm facility business plans that improve their bankability and facilitate their actual execution.

- Allow medium-term operational decisions to be made, such as in which month it is more appropriate to stop for corrective work or similar actions.

- Allow to define short-term strategies for plant operation. These strategies will have as main objective the maximization of plant revenues, considering, in addition, where appropriate, the possible technical restrictions of the associated storage.

On the other hand, the general management strategies of the BESS associated to the PV plant will be defined and agreed jointly with WATT partner, initially proposing those already mentioned in Chapter A of this deliverable.

4.2.3.1. Modelling and experimentation process

To perform this analysis, the following actions should be carried out:

A) First, some models should be chosen for each temporal scope of analysis, as indicated in Table 5 of this document (Chapter B). The state of the art at the time of initiating this work will determine which mathematical models are most appropriate.

The models initially proposed based on the application time horizon are the following

MODEL	Pluriannual	Annual	Monthly	Daily
Time scope	5 to 15 years	12 months	3 or 4 months	10 days
Proposed Models	• ARIMA • Structural models SSM • Neural Networks LSTM • Econometric models (VAR/VECM)	• SARIMA (Seasonal ARIMA) • Neural Networks (LSTM o GRU) • GARCH Models	• ARIMA y SARIMA • Neural Networks (LSTM o GRU) • Machine learning models (random forest, gradient boosting)	• ARIMA y SARIMA • Neural Networks (LSTM o GRU) • Machine learning models (random forest, gradient boosting) GARCH models

Table 5. Summary of the forecasting models depending on the application time horizon.

In this phase, it will be necessary to collect data that is known to directly affect the price of the electricity market, such as the degree of penetration of renewable energy sources, weather forecasts, the availability of hydroelectric power, economic indicators, the price of natural gas or the price of emission rights.

Data	Description	Granularity	Data Source
Electricity Price	Hourly electricity price in the wholesale market.	Hourly	Electricity market operators (e.g., OMIE in Spain)

Electricity Demand	Hourly electricity consumption.	Hourly	System operators (e.g., REE in Spain)
Renewable Production	Electricity generation from renewable sources (wind, solar, hydro).	Hourly	System operators, energy agencies
Non-renewable Production	Electricity generation from non-renewable sources (coal, gas, nuclear).	Hourly	System operators, energy agencies
Temperature	Ambient temperature, which affects electricity demand.	Hourly	Meteorological services (e.g., AEMET in Spain)
Natural Gas Price	Natural gas price, influencing electricity generation costs.	Daily	Commodity markets (e.g., Henry Hub)
CO2 Price	Price of CO2 emission allowances.	Daily	Carbon markets (e.g., EU ETS)
International Exchanges	Electricity imports and exports.	Hourly	System operators, energy agencies

Table 6. Proposal for data to collect

B) Secondly, we will proceed to determine a base set of stochastic parameters to be implemented in the model. At this point, we must define what they are and how much they affect the price in relative terms, what is their time cycle (time in which they surely occur), their probability of occurrence in time...... If, for example, we think of an electoral process, the probability of occurrence in 5 years is 100%, and as time passes since the last process, the probability of repetition increases (the quarter after the electoral process, the probability of repetition is close to zero, but after 3 years it is much higher).

A starting proposal for the stochastic parameters to be considered in these models would be the following:

Stochastic parameters
Extreme heat events
Extreme cold events
Droughts
Natural disasters (earthquakes, hurricanes of extreme magnitude)
Elections
Events affecting demand (World Cups, Olympics, etc)

Epidemics
Economics crises
Military Conflicts / Terrorist Attacks / Cyber Attacks
Disruptions / supply reductions Gas / Oil
Legislative changes

Table 7. Proposal for stochastic parameters

After these first two points, the mixed mathematical models that combine both analysis philosophies will be generated. Specifically, the initial idea is that stochastic analysis will be applied to technical analysis, modifying its forecast as effects may or may not appear.

C) Finally, the validity of the models determined will be analysed by choosing past time periods and determining whether those models are appropriate based on the chosen KPIs.

The data to be used for the validation of the different models, and for their subsequent training, will be extracted from the different European NEMOS (Nominated Electricity Market Operator) on the one hand and from the TSOs (Transmission System Operators) on the other hand. Both NEMOS and TSOs are subject to the different European directives that establish the need to publish information related to electricity generation, consumption, capacity, balancing energies etc.

It is important to keep in mind that in these experiments, the boundary conditions will be very important. It is difficult to know a priori how the weather will behave or if there will be a global pandemic in the next five years. Therefore, in order to launch the models and validate the results, Monte Carlo simulations will be applied.

Also known as the Monte Carlo method or multiple probability simulation, this technique is used to predict outcomes in uncertain situations. It was invented by John von Neumann and Stanislaw Ulam during World War II to improve decision making under uncertainty. Unlike a normal forecasting model, Monte Carlo simulation predicts a set of outcomes based on an estimated range of values rather than fixed input values. It uses probability distributions (such as uniform or normal) to model uncertain variables. It then calculates the results repeatedly using different random numbers between the minimum and maximum values. This process is repeated thousands of times to generate many probable outcomes.

This simulation allows sensitivity analyses to be performed and correlations between inputs to be calculated. In addition, it is accurate over the long term, projecting results with greater accuracy as the number of inputs increases.

Taking as inputs all our variables, stochastic or technical, determined as a normal distribution or more complex ones, but allowing us to generate random scenarios in a given time frame, we can simulate different scenarios that generate different expected market prices, and determine which models are in the desired ranges.

It is important to indicate that the analyses will be carried out on past dates, in order to be able to validate the model. It is unfeasible in the early stages of the project to validate the modelling without reference prices as a result, so we will proceed to model past price scenarios, starting with more stable periods and ending in periods of great changes, to study how the model acts against these imponderables. Future forecasts will only be studied in the final stages of the project, once the possible final candidates have been chosen, to carry out real tests in the second period of the project.

Finally, it is important to consider that market prices behave mostly as an elastic system: when an event takes them out of their equilibrium point, they oscillate until they reach that equilibrium again. The amplitude of the wave, the transition period and the distance from that point of equilibrium to the previous one is variable, but what seems clear is that after large declines appears a large rise, which chains lower and lower rises until stabilizing at a point not far from the previous one, and that can be estimated with technical parameters.

4.2.3.2. KPIs definition

The objective of the work previously described is twofold:

- Determine with simulations the minimum and maximum prices for a period of time that are reached with a given reliability interval.
- Determine which models extract results with the above conditions, dispersing those minimum and maximum values at the shortest possible distance from the actual price of the analysis period.

These objectives directly lead to the definition of two fundamental KPIs to evaluate the quality of the results:

1. **Confidence interval:** Probability that the price is in a range of maximum and minimum prices.
2. **Maximum percentage dispersion:** Percentage deviation of the real final price with the minimum and maximum values that comply with the confidence intervals indicated for each model layer. For this, the indicated simulations will be carried out, obtaining the prices that each forecast model generates for each period of analysis, and determining its maximum dispersion with respect to the average price of the period to be analysed.

Table 8 shows the target values for the two KPIs, for each Base Forecasting Unit (BFU), for the Maximum granularity (MG) and for the actual prediction models. Note that the pluriannual analysis is the one where more uncertainty is accepted in the predictions, while the daily analysis must be very precise to be considered valid.

MODEL	Pluriannual	Annual	Monthly	Daily
BFU	Annual	Monthly	Monthly	Diary
Confidence Interval BFU	80 %	80 %	90 %	95 %

Maximum percentage dispersion BFU	20%	15%	10%	5%
MG	Hourly	Hourly	Hourly	Quarter-Hourly
Confidence Interval MG	50%	80%	90%	95%
Maximum percentage dispersion MG	50%	25%	15%	5%
Confidence Interval Model	80%	85%	90%	95%
Maximum percentage dispersion Model	15 %	7,5 %	5 %	2,50 %

Table 8. Summary of the target values for the KPIs described.

The Maximum Granularity (MG) is a forecast control group considered essential for evaluating the model's performance. In other words, an annual model is of no use if, despite meeting its annual average objectives, it generates monthly prices that deviate significantly from the average.

For example, and following the previous table, an annual model should:

- Obtain an annual forecast where the hourly dispersion does not exceed 25% and the confidence interval is 80%.
- Obtain average monthly prices with a confidence interval of 80% and a dispersion of 15%.
- Obtain an overall model with a confidence interval of 85% and a dispersion of 7.5%.

So, it should not only be a model that provides a correct annual result, but the different granularities should also meet these criteria.

4.2.3.3. Integration with the BESS System

The main objective of obtaining models with reliable price predictions in the different markets is the calculation of the potential revenues obtained by the PV plant according to the different possible operating models for a given time horizon.

As mentioned in Chapter A of this document, the results obtained by these models will serve for each moment as input for the calculation of these different operating modes for the BESS EMS, which in turn will take into account technical operating restrictions, both of the PV plant itself, such as generation forecasts based on the weather, as well as restrictions of the BESS system itself (for example, maximum discharge depth allowed).

Development plan

In order to outline an initial roadmap for the development of this solution, a basic plan of the tasks to be carried out is included. The phases indicated for the development of each model are as follows:

Phase 1, Model Use Validation: For each model, the first step will be to perform an analysis of the different calculation options for the model in question. To do this, working with past data, the necessary set of simulations will be carried out to recognize which forecasting models and against which parameters the desired results are obtained. Once this phase is completed, the model or models that will be the basis of the development will be chosen.

Phase 2, Simple Modelling: In this phase, and after selecting the best possible methods in the previous phase, the future forecast will be made for the periods and granularities indicated in each model. The objective will be to obtain a future forecast that is recognized as validatable, eliminating from the analysis the stochastic processes that may negatively affect pure mathematical modelling.

Phase 3, Stochastic Modelling: Once the base forecast model from the previous point has been validated for each analysis model, the previously indicated stochastic events will be introduced into this model. Starting from past data and modelling these events in specific periods where non-estimable events appear in the calculation, the application of the effect of these unpredictable events in the model will be validated.

Phase 4, Monte Carlo Implementation: With the final model that includes the validated and defined stochastic models, the Monte Carlo analysis will be introduced into these models. In the first phase, work will be done with past values, and then with future values. Both processes must be validated.

Each phase of each model will be validated when the work of the same yield deviation and dispersion data, both for the model in general and for the maximum granularities indicated, within the ranges presented in Table 4 of this chapter.

The development plan will be defined under two axes: On the one hand, each phase of the development within its own model cannot be started until the previous one has been completed, for obvious reasons. Each part of it is built on the results of the previous step, so the strength of each phase of the project must be maximum.

As a second axe, it should be noted that the 4 models will be developed in parallel, with the first starting the hourly modelling and the last the multi-annual modelling, although the phases of the different models cannot be started until that same phase of the previous one is completed. That is, the Validation phase of the use model or Phase 1 of the monthly modelling cannot be started until Phase 1 of the previous modelling or hourly modelling is completed. This is done in this way due to three reasons:

- The complexity of checking and implementing the models increases with the future time horizon being analysed. In this way, it is easier to define a good model for 2 days than for 5 years. This development format enhances continuous learning and makes it so that once the multi-annual modelling is reached, the experience acquired in a repetitive process of increasing complexity simplifies these tasks in the more complex models.
- Minimizes the time to market the most required products in other parts of the project, with more direct application.
- Avoids possible model blockages due to eventual problems in others.

The period from November 1, 2024, to October 31, 2025, will be dedicated to the development of solutions and their validation in controlled environments (e.g., using historical data in a laboratory). Subsequently, from November 1, 2025, to October 31, 2026, the focus will shift to improving the solutions and validating them under real operating conditions in one or more photovoltaic (PV) plants or in laboratory but using real time predictions, due to the work characteristics.

Definition of Validation Environments

- Controlled Environment: This refers to the analysis of historical prices, where both the boundary conditions (events, meteorological data, sector consumption, etc.) and the final results are known. The objective is to obtain results consistent with historical prices based on previous data, simulating price modelling as if it were conducted just before the evaluated dates.

- Real Conditions: In this environment, work will be conducted in real-time, validating the results obtained afterward. This means future modelling will be performed, and subsequently, the accuracy of the forecast modelling will be analysed by comparing it with actual prices. Although ideally, this process would be extended as long as possible, it will be necessary to limit the analysis period to avoid unnecessarily prolonging the project.

Regarding the previous phases, the validation environments for each phase will be as follows:

Phases 1 and 3: Evaluation of models in Controlled Environments, as their objective is to generate the appropriate models.

Phases 2 and 4: Evaluation under Real Conditions, as the objective is to test these models in real use.

It is very likely that some iteration of the verification in Phase 3 will be conducted under real conditions in its final stages, depending on the results obtained.

4.2.4. Conclusions

This document corresponds to Chapter B of the first PVOP deliverable of T3.2 of WP3 which is intended to develop and optimize the AI-based electricity marked predictor for the development of an advanced control system and to truly optimize the battery integration. With the proposed innovations it can be determined that the PVOP project:

- Will implement concepts that are not currently included in forecasting systems, such as the inclusion of stochastic analysis in combination with technical analysis or the modelling of the price as an elastic system.

- The reliability and dispersion objectives indicated will be a clear improvement in the current situation, especially in terms of making financial or operational decisions.

- The price forecast will be launched for several types of markets simultaneously and for several time horizons. The immediate and simultaneous linking of these price signals with the different operating modes of the PV plant and its associated BESS will allow not only to maximize the monetization of the asset but also to establish sufficiently in advance medium- and long-term operating strategies that contribute to a better maintenance and performance of the asset

5. Conclusions

This document presents the first deliverable of WP3 (Control of PV plants to optimize their performance), which is divided into two separate tasks:

- Task 3.1: Development and demonstration of a simulation tool and control system to maximize the performance of PV plants with sun tracking systems. The concept of this task is based on some relevant assumptions that standard PV software relies on to simplify the energy yield simulation, and pinpoints the horizontal constraint, which does not necessarily require the ground to be horizontal, only that its cross-axis slope angle be zero. Evaluating the use of scale models to test tracker control on sloping terrain is a promising approach. This method involves simulating different configurations to get a good representation of reality under normal operating conditions and without failures. Once this is achieved, the deviation of the digital twin output from the sensed data will act as a trigger to initiate the specific fault classification mechanisms that will be addressed in WP4

- Task 3.2: Development and demonstration of a control system to maximize the performance and energy trading of PV plants with batteries. This task is as well divided into two lines of work:

    - **Chapter A:** Battery control system. This line of work is intended to evaluate the control of PV plants with storage systems, what control strategies are most interesting and how they could be combined and optimized by a smart EMS. The EMS will decide every hour what the most suitable battery control strategy is and implement it, instead of only operating according to one strategy. For taking such decisions, the Smart EMS will receive AI-based electricity market predictions and weather conditions predictor as inputs. The validation experiments will be implemented in two phases: at the IES-UPM outdoor testing facilities and at a few commercial PV installations.

    - **Chapter B:** Electricity Market Forecast. This line of work is intended to develop and optimize the AI-based electricity marked predictor for the development of an advanced control system and to truly optimize the battery integration. The methodology used will implement concepts that are not currently included in forecasting systems, such as the inclusion of stochastic analysis in combination with technical analysis or the modelling of the price as an elastic system. The price forecast will be launched for several types of markets simultaneously and for several time horizons, with the objective of linking them with the different operating modes of the Smart EMS (developed in Chapter A).