



**Original Research Article**

## **Optimal Application of Pinch Power Analysis in Hybrid System Sizing and for electric vehicle charging stations**

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### **ABSTRACT**

This study proposes an optimisation framework dedicated to the optimal sizing of a hybrid renewable energy system composed of photovoltaic generation, wind power generation, and a battery energy storage system. The system is governed by an energy management system integrating the Pinch Power Analysis method, and the obtained results are validated using the Hybrid Optimization Model for Electric Renewables software. This framework is applied to a case study in the city of Oujda in Morocco, considering a residential electricity demand coupled with charging of electric vehicles. The results indicate that improving energy reliability requires higher installed generation and storage capacities. They show that the levelized cost of energy of the system composed of photovoltaic generation and battery energy storage (0.083 €/kWh) is lower than that of the configuration combining wind power generation, photovoltaic generation, and battery energy storage ( $\approx 0.10$  €/kWh) for a loss of power supply probability below two percent. However, the integration of wind power reveals favourable temporal complementarity with photovoltaic generation. This complementarity significantly reduces storage requirements, stabilises battery state of charge cycles, and limits the deep discharges observed in the configuration composed only of photovoltaic generation and battery energy storage. The analysis is further extended through a sensitivity assessment of the electricity demand associated with electric vehicle charging, corresponding to 737 charging sessions per year with one charging station and 484 sessions per year with two charging stations. This increase in electricity demand raises the overall load while inducing only a limited impact on economic and reliability indicators, thereby confirming the ability of the system to adapt dynamically to variations in demand. In addition, surplus electricity production is exported to the electrical grid, which improves the economic viability of the studied systems.

### **KEYWORDS**

*Energy Management System, Electric Vehicle, Levelized Cost of Energy, Loss of Power Supply*

### **I. INTRODUCTION:**

The sustained growth in electricity demand necessitates a transformation of energy systems to promote the integration of solar and wind power. However, the intermittency of these resources poses significant challenges to stability and reliability, making the deployment of hybrid renewable energy systems (HRES) coupled with storage technologies essential. Concurrently, the increasing integration of electric vehicles (EV) into microgrids introduces

new challenges related to the sizing and management of charging stations, requiring intelligent strategies to minimise costs and maximise energy efficiency.

From a systemic perspective, the literature highlights the diversity of hybrid configurations deployed to meet cost, reliability, and environmental assessment requirements, such as Life Cycle Assessment (LCA) within energy systems [1]. Techno-economic evaluation primarily relies on indicators such as the levelized cost of energy (LCOE) and the loss of power supply probability (LPSP), applied to both grid-connected (on-grid) and autonomous (off-grid) architectures. Recent studies employ various optimisation approaches.

In off-grid PV/ battery energy storage (BESS) configurations, particle swarm optimisation (PSO), applied to a smart photovoltaic (PV) microgrid, achieves an LPSP of 0.18%, an LCOE of 0.0187 USD/kWh, and a renewable energy penetration rate of 98%, reflecting optimised power-flow management and reduced annualised costs [2]. In another approach, integrating battery/hydrogen storage, a comparison at LPSP = 1% shows that the total solar panel capacity of the PV/BESS system is 44.8% lower than that of the PV/hydrogen system [3].

Hybrid systems incorporating thermal or hydraulic backup highlight additional trade-offs. Optimisation using the genetic algorithm (GA) for a PV/Diesel/PHS system results in an energy cost of 0.27 \$/kWh, which is lower than that of an optimised PV/Diesel/BESS reaching 0.34 \$/kWh [4].

The integration of wind turbine (WT) represents an additional leverage, as analysed in several studies. For example, in an off-grid context in Kenya, a PV/WT/BESS–flywheel hybrid system modelled using MATLAB/Simulink and optimised with Multi-Objective Particle Swarm Optimisation (MOPSO) achieves an LCOE of 0.519 USD/kWh and an energy independence ratio (EISR) of 99.7% [5]. A WT/PV/hydrogen configuration optimised using a modified Non-dominated Sorting Genetic Algorithm II (NSGA-II) coupled with CRITIC-TOPSIS achieves an LCOE of 0.226 \$/kWh and an LPSP of 4.01% [6].

In Bangladesh, a PV/WT/diesel/BESS optimised using GA-PSO with LPSP < 1% reaches a minimum LCOE of 0.234 \$/kWh, compared with 0.246 \$/kWh using PSO and 0.265 \$/kWh using GA. In addition, the valorisation of surplus energy reduces the total system cost by up to 11.8% and the electricity cost by 9.3% [7]. Consistently, the application of GA-PSO to a PV/WT/BESS system results in an LCOE of 0.502 \$/kWh for a maximum LPSP of 2%, corresponding to cost reductions of 42.17% compared with the WT/BESS system and 17.17% compared with the PV/BESS [8].

In the hyper-arid region of Tamanrasset (Algeria), a study using MOPSO for the optimisation of an off-grid HRES integrating PV, WT, batteries, and a diesel generator reports an LCOE of 0.05433 \$/kWh, an LPSP of 3.1%, and a renewable fraction of 98%, demonstrating a strong capability to meet energy demand while maintaining high renewable integration. In comparison, simulations with Hybrid Optimisation of Multiple Energy Resources (HOMER Pro) lead to an LCOE of 0.349 \$/kWh and a renewable fraction of 100%, illustrating that MOPSO provides a better trade-off between cost, reliability, and renewable integration [9].

A recent study employing the differential optimization multiagent (DOMA) algorithm, with comparison to the Salp Swarm Algorithm (SSA) and the Whale Optimisation Algorithm (WOA) for optimising a microgrid in Najran (Saudi Arabia), shows that the PV/BESS system achieves the lowest LCOE (0.041 USD/kWh) but with limited reliability (LPSP = 0.6723%), while the PV/WT/BESS configuration provides a better compromise between cost and reliability (LCOE = 0.098 USD/kWh, LPSP = 0.3129%) [10].

The distinction between off-grid and grid-connected systems is explicitly highlighted in the analysis of a commercial building optimised using HOMER Pro. In the first on-grid scenario, supplied by WT energy and the grid, the LCOE is 0.0976 \$/kWh, with renewable penetration and LPSP rates of 23.3% and 76.7%, respectively. The second scenario, based on solar energy and the grid, presents an LCOE of 0.111 \$/kWh, with a renewable penetration of 66.6% and an LPSP of 34%. The third scenario, combining PV/WT/grid, results in an LCOE of 0.1083 \$/kWh, with renewable penetration and LPSP values of 64.9% and 35.1%, respectively. These results show that WT energy, although presenting the lowest LCOE, is not sufficient to fully satisfy demand when used alone [11].

A study integrating real climatic and load data for grid-connected HRES, including PV, WT, and a BESS, shows that the reliability constraint (LPSP) strongly influences the LCOE depending on the optimisation methods applied (Moth-Flame Optimisation Algorithm (MFOA), Whale Optimisation Algorithm (WOA), Flower Pollination Algorithm (FPA), GA). For example, for an LPSP of 0.5%, the LCOE is 0.1443 \$/kWh, gradually decreasing to 0.1342 \$/kWh for an LPSP of 10%. Simulation results indicate that the PV/WT/BT configuration represents the most cost-effective and reliable option, with an LCOE of 0.1342 \$/kWh, corresponding to a cost reduction of 33% compared with an off-grid configuration [12].

Moreover, the Electric System Cascade Extended Analysis (ESCEA) tool enables the determination of the optimal sizes of renewable energy installations for both grid-connected and standalone configurations, assuming a reduced LPSP.

Results reported in the literature indicate that the LCOE varies depending on the system configuration. For standalone systems, an LCOE of 0.21 \$/kWh has been obtained for a PV/BESS system [13], while an LCOE of 0.196 \$/kWh has been reported for a CSP/TES system [14]. For grid-connected configurations, the reported LCOE values are 0.225 \$/kWh for WT, 0.110 \$/kWh for PV [15], and 0.210 \$/kWh for a CSP system without thermal storage [16]. Furthermore, for an isolated power supply system composed of PV/WT/BESS, previous studies have reported LCOE values of 0.3747 €/kWh [17]. In addition, the results presented in [18] indicate that it is possible to achieve an LCOE of 0.25 €/kWh under specific operating conditions.

In the context of EV integration, several studies have proposed optimisation approaches aimed at improving both the cost and reliability of energy systems. Study [19] employs a two-stage multi-objective stochastic programming approach for an isolated microgrid, showing that a trade-off between LPSP and cost can reduce expenses by 10–20%. Meanwhile, [20] applies a multi-objective whale optimisation algorithm (MOWOA) to optimally size PV, WT, BESS, and EV charging infrastructure, maximising energy efficiency and self-consumption while minimising total cost. In addition, [21] introduces an indicator to evaluate the balance between self-consumption and self-sufficiency.

Furthermore, studies such as [22] and [23] focus on the techno-economic modelling of charging stations under grid-connected or hybrid configurations. Study [22] proposes Python-based models for PV/grid and PV/grid/BESS systems and highlights the use of HOMER Grid to simulate and analyse load profiles. It particularly emphasises the flexibility of this tool in modelling a charging station of 150 EVs (maximum charging power of 85 kW, 7,253 charging sessions per year, 207,211 kWh/year), enabling the assessment of the impact of the number of chargers on system availability and techno-economic performance.

Similarly, [23] uses HOMER software with NASA-derived data to analyse two sites. For one site, the optimal energy configuration consists of a PV system, batteries, a wind turbine, and a converter, with an LCOE of \$0.450/kWh.

Finally, smart EV charging management is addressed in [24] and [25]. Study [24], based on the OCHRE tool integrated into a Home Energy Management System (HEMS),

demonstrates a 23% reduction in peak demand through optimised charging. Study [25] proposes a real-time energy management strategy coordinating grid-connected PV and BESS.

Overall, these approaches converge with recent research showing that optimising HRES integrating PV, biomass, and fuel cells in the presence of EVs significantly improves overall system performance. In a scenario without EV charging, the MCWOA achieves an LCOE of \$0.2273/kWh and an LPSP of 2.349%, whereas integrating EV charging demand reduces the LCOE to \$0.2203/kWh while maintaining a high level of reliability (LPSP = 2.209%) [26].

This study develops an optimisation framework aimed at the optimal sizing of a hybrid system combining PV, WT, and BESS, managed by an energy management system (EMS) integrating the Pinch Power Analysis method. The adopted methodology is structured into several complementary and sequential steps:

- Generation of EV charging profiles.
- Energy modelling of system components, including PV and WT generation, BESS, and residential load with EV charging. This step is organised into two steps:
  - Daily-based preliminary sizing and energy balance optimisation to establish a preliminary system configuration.
  - Hourly-based annual verification with operational constraints, enabling precise evaluation of the sizing over the full 8760h annual horizon with a one-hour timestep.
- Definition of technical constraints, such as the minimum and maximum BESS state-of-charge levels and power limits, along with the assessment of key economic and reliability performance indicators.
- Implementation of the Energy Management System (EMS) based on Pinch Power Analysis, to optimise energy flow management and reduce imbalances between production and demand.
- Sensitivity analysis on EV charging demand, performed after generating the charging profiles, to evaluate system robustness under varying usage patterns and progressively increasing energy requirements.
- Validation of results through comparison with HOMER software, in the context of a case study applied to the city of Oujda (Morocco), ensuring the consistency and reliability of the optimised configurations.

## II. System Modelling:

The HRES combines PV panels, WT turbines, and BESS to power residential loads and recharge EVs. The different components of this system are modelled as follows:

### 1) Photovoltaic panel model:

A PV model allows analysis of variations in efficiency and performance, which decrease as temperature increases, to maximise energy production.

The output power produced by PV system depends on the specific characteristics of the PV array and the solar irradiance received, and can be calculated using eq.(1):

$$P_{pv}(t) = P_{rated} \times \frac{G(t)}{G_{T,STC}} \times [1 - \beta \times (T_c(t) - T_{ref})] [KW] \quad (1)$$

Where:

$P_{rated}$ : the rated capacity of the PV array, meaning its power output under standard test conditions [KW]

$G(t)$ : the solar radiation incident on the PV array in the current time step [KW/m<sup>2</sup>]

$G_{T,STC}$ : the incident radiation at standard test conditions [1 KW/m<sup>2</sup>]

$\beta$  = the temperature coefficient of power [%/°C]

$T_c(t)$  = the PV cell temperature in the current time step [°C]

$T_{ref}$  = the PV cell temperature under standard test conditions [25°C]

## 2) Wind turbine model:

The wind turbine model converts wind energy into electrical power based on wind speed, which must be adjusted to the turbine hub height for accurate estimation.

Calculating Hub Height Wind Speed: is calculated from the wind speed measured at the anemometer height by applying the power law eq.(2):

$$V_{hub}(t) = V_{anem}(t) \times \left(\frac{H_{hub}}{H_{anem}}\right)^\alpha \quad [m/s] \quad (2)$$

Where:

$V_{hub}(t)$ : the wind speed at the hub height of the wind turbine [m/s]

$V_{anem}(t)$ : the wind speed at anemometer height [m/s]

$H_{hub}$ : the hub height of the wind turbine [m]

$H_{anem}$ : the anemometer height [m]

$\alpha$ : the power law exponent

Calculation of wind turbine electrical power: The electrical power produced ( $P_{WTG,STP}(t)$ ) is derived from the standardised wind power curve Figure 1:

If  $V_{hub}(t)$  is outside the operating range of the curve (below the minimum rated wind speed or above the cut-out wind speed), the power is zero:

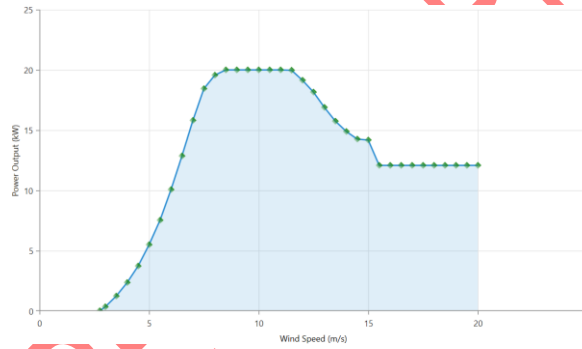


Figure 1. Wind turbine power curve

The actual power produced is adjusted according to the real air density relative to the standard air density (standard temperature and pressure conditions) eq.(3):

$$P_{WTG}(t) = \left(\frac{\rho}{\rho_0}\right) \cdot P_{WTG,STP}(t) \times \eta_{gearbox} \times \eta_{generator} \quad [KW] \quad (3)$$

Where:

$\rho$ : Real air density (kg/m<sup>3</sup>)

$\rho_0$ : Standard air density (1,225 kg/m<sup>3</sup>)

$\eta_{gearbox}$ : the efficiency of the multiplier (%)

$\eta_{generator}$ : The efficiency of the generator (%)

## 3) Energy Storage System Model:

The BESS is an essential component of the proposed energy system, ensuring operational flexibility and supply reliability. The EMS coordinates charging and discharging to enhance system reliability while maximising the utilisation of available energy resources.

To accurately represent the dynamic behaviour of the BESS, key parameters such as energy capacity and state of charge (SOC) are considered eq.(4), it is constrained within predefined lower and upper bounds, to ensure safe and efficient operation:

$$SOC_{BESS}(t) = \frac{E_{acc}(t)}{C_{BESS}} [\%] \quad (4)$$

Where:

$E_{acc}(t)$  is the energy stored at time  $t$

$C_{BESS}$  is the total BESS capacity, representing the maximum amount of energy it can store (KWh)

$SOC_{BESS}^{min}$ : Minimum allowable state of charge of the BESS (%)

$SOC_{BESS}^{max}$ : Maximum allowable state of charge of the BESS (%)

BESS sizing is performed by considering the depth of discharge (DOD), which limits the usable portion of  $C_{BESS}$  to prolong battery lifetime and maintain system stability. Accordingly, the effective or net storage capacity of the BESS is given by eq.(5):

$$C_{net} = \frac{(E_{acc}^{max} - E_{acc}^{min})}{DOD} [KWh] \quad (5)$$

Where:

$E_{acc}^{max}$ : the maximum accumulated energy in the BESS over the period  $T$ .

$E_{acc}^{min}$ : the minimum accumulated energy in the BESS over the period  $T$ .

Based on the required net capacity, the total number of batteries needed in the BESS is calculated as eq.(6):

$$N_{bat} = \frac{C_{net}}{C_{BESS}} \quad (6)$$

#### 4) Model of electric vehicle:

The EV modelling framework aims to simulate the energy needs for charging by incorporating user behaviours (arrival and departure times, distances travelled, parking habits) alongside vehicle characteristics, energy consumption, and charging strategies:

Number of electric vehicles: Number of EVs ( $N_{EV}$ ) is essential to specify the number of EVs present at the station.

Optimal number of chargers: The charging station is equipped with an optimal number of chargers  $N_{stat}$ , determined based on the cumulative charging demand and the total time required to serve planned charging events.

Energy consumption per kilometre: Energy consumption per kilometre ( $E_{Km}^{ID}$ ) value typically ranges between 0.15 and 0.18 kWh/km, depending on the vehicle model (Table 11).

Battery capacity of electric vehicle: Each vehicle has a specific battery capacity ( $C_{bat}^{ID}$ ) (in kWh) (Table 11).

Maximum charging power provided by the charger: Each charger delivers a maximum charging power ( $Charg_{pow}^{max}$ ) (in kW), corresponding, for example, 1.4 kW for Level 1 charging or 9 kW for Level 2 charging [22].

Maximum charging power accepted by EV: The maximum power ( $Charg_{pow\_EV}^{max}$ ) that the vehicle can accept during charging (Table 11).

Smart Charging control: At any time, the EV can be in one of three states:

- Connected and charging
- Connected but waiting for charger availability,
- Disconnected (no charging).

These states allow modelling charger occupancy, queuing effects, and waiting times without invoking control or optimisation logic.

The target state of charge: for each EV eq.(7) is defined based on the recovered driving range required after charging, and is expressed as:

$$SOC_{target}^{IDEV} = SOC_{min}^{IDEV} + \frac{RDR_{target}^{IDEV} \times E_{Km}^{IDEV}}{Cbat_{EV}^{IDEV}} \quad [\%] \quad (7)$$

Where:

$SOC_{min}^{IDEV}$ : minimum SOC of the EV battery [%]

$SOC_{target}^{IDEV}$ : Is the target SOC that the EV battery aims to reach [%]

$RDR_{target}^{IDEV}$ : Target recovered driving range, defined as the distance that the vehicle intends to cover after a recharge [Km] (Table 11)

The charging duration: depends on the requested energy and charger availability. Two charging modes are modelled:

- Partial (requested) charging: when full charging cannot be completed due to time or station constraints eq.(8) :

$$\Delta t_{partial} = \frac{(SOC_{target}^{IDEV} - SOC_{initial}^{IDEV,Day}) \times Cbat_{EV}^{IDEV} \times 60}{\min(Charg_{pow}^{max}, Charg_{pow, EV}^{max})} \quad [min] \quad (8)$$

- Full charging: when sufficient time and charger availability are ensured eq.(9):

$$\Delta t_{full} = \frac{(SOC_{max}^{IDEV} - SOC_{initial}^{IDEV,Day}) \times Cbat_{EV}^{IDEV} \times 60}{\min(Charg_{pow}^{max}, Charg_{pow, EV}^{max})} \quad [min] \quad (9)$$

Where:

$SOC_{max}^{IDEV}$ : maximum SOC of the EV battery [%]

Initial state of charge of EV batteries: The SOC upon arrival on the following day is updated depending on whether charging has occurred:

With charging eq.(10):

$$SOC_{initial}^{IDEV,Day+1} = \max\left\{ \left[ SOC_{initial}^{IDEV,Day} + \frac{\Delta t \times \min(Charg_{pow}^{max}, Charg_{pow, EV}^{max})}{60 \times Cbat_{EV}^{IDEV}} - (SOC_{target}^{IDEV} - SOC_{min}^{IDEV}) \right], SOC_{min}^{IDEV} \right\} \quad [\%] \quad (10)$$

Without charging eq. (11):

$$SOC_{initial}^{IDEV,Day+1} = \max\left\{ \left[ SOC_{initial}^{IDEV,Day} - (SOC_{target}^{IDEV} - SOC_{min}^{IDEV}) \right], SOC_{min}^{IDEV} \right\} \quad [\%] \quad (11)$$

### III. Materials and Methods:

This study proposes a methodology for generating EV load profiles in order to simulate the energy consumption of charging stations while optimising the available energy resources (Figure 2). The simulation process includes determining the optimal number of charging stations, generating the EV load profile, and using it to adjust energy resources through Pinch Power Analysis and EMS. This approach enables the resizing of renewable energy production (PV and WT) and BESS within an HRES, while relying on the techno-economic constraints that will be identified, to balance production and consumption, ensuring optimal resource management, thereby guaranteeing the performance and sustainability of the BESS.

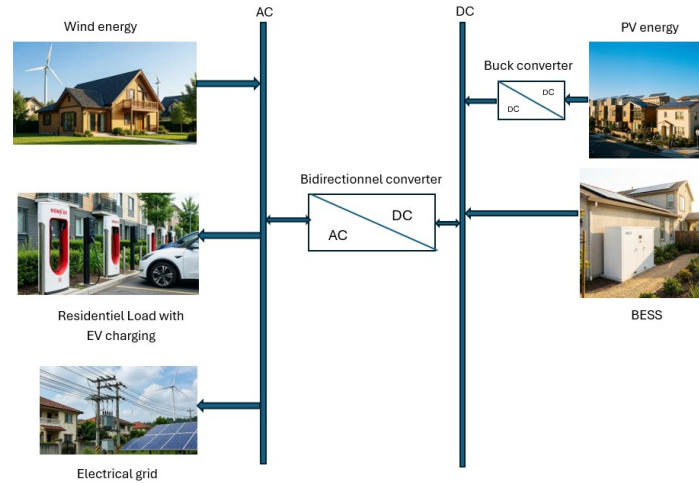


Figure 2. Flow Diagram between Renewable Sources, BESS, and Loads

### 1) Electric vehicle load profile generation:

Based on the previously defined EV modelling framework, a method is developed to determine the optimal number of charging stations and generate the EV charging load profile over an annual simulation horizon. The process follows the algorithm illustrated in (Figure 3) and operates on a day-by-day and vehicle-by-vehicle basis.

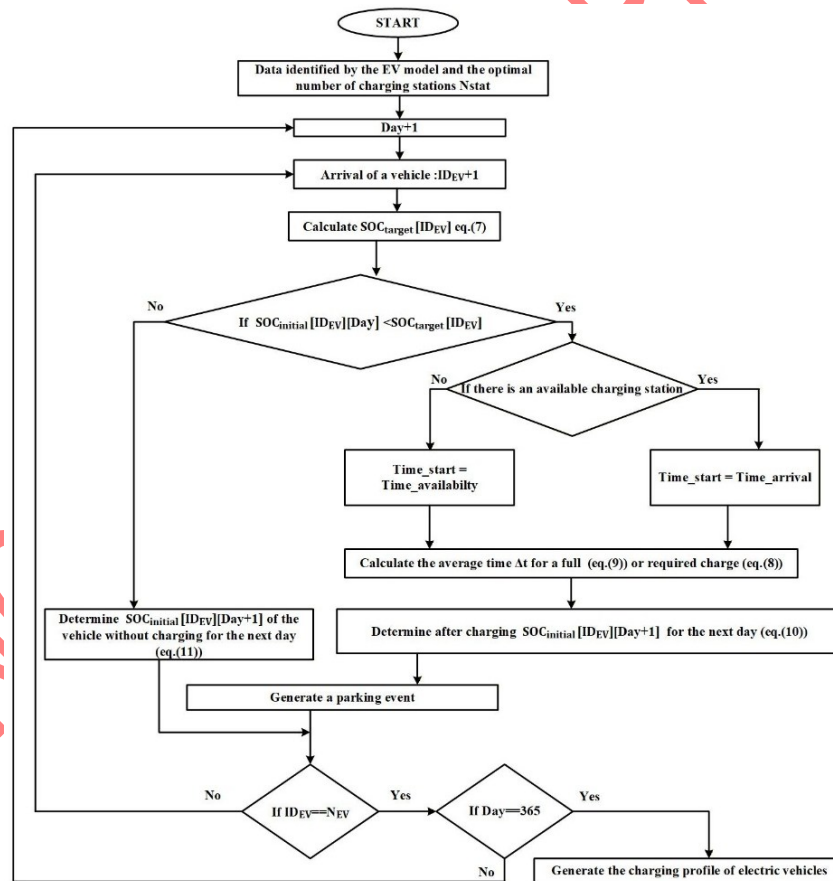


Figure 3. Flowchart of consumption profile generation for EV charging

When an EV arrives:

- Its  $SOC_{initial}^{ID,Day}$  is compared with  $SOC_{target}^{ID,Day}$
- If the  $SOC_{initial}^{ID,Day}$  is sufficient, no charging action is scheduled.
- Otherwise, charger availability is evaluated:

- If a charger is available, charging starts immediately:  $T_{start} = T_{arrival}$
- If no charger is available, charging is delayed until the first charger becomes available:  $T_{start} = T_{availability}$

A smart charging scheme is adopted, where charging does not necessarily start immediately upon connection, nor does it always operate at maximum power. Depending on station occupancy and remaining parking duration:

- Full charging is prioritised when feasible.
- Partial charging is applied when time constraints ( $T_{depart}$  : departure time) exist or when other EVs are waiting for a charging point to become available, thereby preventing full charging.

The average charging duration is determined using eqs. (8) and (9), ensuring compatibility with infrastructure and user requirements.

At the end of each charging session, a parking event is recorded, including:

- Arrival  $SOC_{initial}^{ID,Day}$ ,
- Charging Start/End time,
- Charging duration,
- Energy delivered.

The next EV arrival is then processed until all EVs of the day are served. This procedure is repeated daily until the end of the year (Day=365).

The aggregation of all recorded charging events results in the annual EV charging profile.

## 2) Optimisation Constraints:

The optimisation of HRES and BESS relies on constraints and key indicators that influence their performance, profitability, and management, particularly in the face of the intermittency of solar and WT sources. Among the main evaluation criteria considered in this study, the following have been identified:

Final Excess Energy: is the difference between the energy accumulated in the BESS at the end and the beginning of the analysis period. It represents the surplus energy in the system after meeting all demands, and is given by eq.(12):

$$FEE = SOC_{BESS}(T) - SOC_{BESS}(t = 0) [\%] \quad (12)$$

If  $FEE < 0$ , the BESS charging leads to failure.

If  $FEE > 0 \Rightarrow$  the charging of the BESS explains an over-sizing of the energy components.

Loss of Power Supply Probability: represents the ratio between the total of energy not satisfied eq.(26) and the total energy demand over the analysis period eq.(13):

$$LPSP = \frac{\sum_{t=0}^{t=8759} LPS(t) \times \eta_{DC/AC} \times \eta_{disch}}{\sum_{t=0}^{t=8759} E_{Load}(t)} [\%] \quad (13)$$

Excess power supply probability: is used to quantify the portion of renewable energy that remains unused due to generation exceeding both load demand eq. (23) and the total energy generated eq. (17) and eq. (18) over the analysis period. It reflects the effectiveness of the EMS in utilising available renewable resources, and is given by eq.(14):

$$EPSP = \frac{\sum_{t=0}^{t=8759} EPS(t)}{\sum_{t=0}^{t=8759} E_{pv\_wind}(t) \times \eta_{ch} \times \eta_{AC/DC}} [\%] \quad (14)$$

Levelized Cost of Energy: LCOE is an economic indicator used to evaluate the average cost of generating one unit of energy over the lifetime of a production system eq.(15):

$$LCOE = \frac{(cost_{comp} + cost_{installation} + cost_{BOS}) \times CRF + cost_{M\&O}}{\sum_{t=0}^{t=8759} E_{Load}(t)} \quad [€/KWh] \quad (15)$$

Where:

- $cost_{comp}$ : The purchase cost of all required equipment (€)
- $cost_{installation}(t)$ : the installation cost (€)
- $cost_{BOS}$ : the balance of system cost (€)
- $cost_{M\&O}$ : the operation and maintenance cost (€)
- CRF is the capital recovery factor and is computed as eq.(16):

$$CRF = \frac{r \times (1+r)^L}{(1+r)^L - 1} \quad (16)$$

Where:

- r: the interest rate
- L: the lifetime

**Energy Generation Ratio:** Energy Generation Ratio (EGR) represents the relative distribution of energy production between PV eq.(17) and WT sources (18) in HRES:

$$\sum_{t=0}^{t=24} E_{pv}(t) \times N_{pv} = \frac{EGR \times \sum_{t=0}^{t=24} E_{pv\_wind}(t)}{\eta_{DC/DC} \times \eta_{DC/AC}} \quad (17)$$

And:

$$\sum_{t=0}^{t=24} E_w(t) \times N_w = (1 - EGR) \times \sum_{t=0}^{t=24} E_{pv\_wind}(t) \quad (18)$$

Where:

- $E_{pv\_wind}(t)$ : The total energy produced by the renewable sources
- $E_{pv}(t)$ : The energy produced by a single PV
- $E_w(t)$ : The energy produced by a single WT
- $N_{pv}$ : The number of installed PV panels
- $N_w$ : The number of installed WT
- $\eta_{DC/DC}$ : correspond to the efficiencies of the DC/DC conversion stage.
- $\eta_{DC/AC}$ : correspond to the efficiencies of the AC/DC conversion stage.

**Battery Energy Charging Ratio:** Ratio of discharged to charged energy in the BESS over a given period (BECR) eq.(19):

$$BECR = \frac{\sum_{t=0}^{t=24} |E_{BESS}^{disch}(t)|}{\sum_{t=0}^{t=24} E_{BESS}^{ch}(t)} \quad [%] \quad (19)$$

### 3) Energy management strategy:

The Energy Management System (EMS) primary function is to coordinate energy generation, consumption, and BESS to ensure supply reliability, maximise renewable energy utilisation, and minimise dependency on the utility grid.

**Operational strategy for energy management:** The EMS implements a priority-based strategy to maximise renewable energy utilisation, maintain system reliability, and optimise battery operation. The operational strategy is structured as follows:

- Battery Charging Mode: ( $E_{pv\_wind}(t) > E_{Load}(t)$ ):
  - Case 1: Wind production covering the demand: If the wind production satisfies the demand ( $E_w(t) \geq E_{Load}(t)$ ):  
Then the residual energy is expressed as eq.(20):

$$Er(t) = (Ew(t) \times Nw - E_{Load}(t)) \times \eta_{AC/DC} + E_{pv}(t) \times N_{pv} \times \eta_{DC/DC} \quad (20)$$

- Case 2: PV + WT production covering the demand: If the wind production is insufficient but the combined PV and wind production meets the demand ( $Ew(t) < E_{Load}(t)$ ):  
Then the residual energy is eq.(21):

$$Er(t) = \frac{E_{pv\_wind}(t) - E_{Load}(t)}{\eta_{AC/DC}} \quad (21)$$

The battery charges if its SOC satisfies ( $SOC_{BESS}(t) < SOC_{BESS}^{max}$ ) with the charging power limited by eq.(22):

$$E_{BESS}^{ch}(t) = \min \{Er(t) \times \eta_{ch}, E_{acc}^{max} - E_{acc}(t-1)\} \quad (22)$$

When the battery reaches its maximum capacity  $SOC_{BESS}^{max}$ , it no longer charges. The excess energy is exported to the grid eq.(23) [7][26]:

$$EPS(t) = \max \left\{ \frac{E_{acc}(t) - E_{acc}^{max}}{\eta_{AC/DC} \times \eta_{ch}}, 0 \right\} \quad (23)$$

➤ Battery Discharging Mode:

- Cas 3: Renewable production below demand: If renewable production is less than the demand ( $E_{pv\_wind}(t) < E_{Load}(t)$ ) and the  $SOC_{BESS}$  is below the minimum allowed level  $SOC_{BESS}(t) < SOC_{BESS}^{min}$ , the battery discharges to compensate the energy deficit according to eq.(24):

$$E_{BESS}^{disch}(t) = \min \left\{ \frac{Er(t)}{\eta_{disch}}, E_{acc}^{min} - E_{acc}(t-1) \right\} \quad (24)$$

with residual energy calculated by eq.(25):

$$Er(t) = \frac{E_{pv\_wind}(t) - E_{Load}(t)}{\eta_{DC/AC}} \quad (25)$$

If the battery reaches the minimum threshold  $SOC_{BESS}^{min}$ , it ceases discharging and the uncovered deficit is expressed by (26):

$$LPS(t) = \max \left\{ \frac{E_{acc}^{min} - E_{acc}(t)}{\eta_{DC/AC} \times \eta_{disch}}, 0 \right\} \quad (26)$$

Battery Energy Update: The energy stored in the BESS is updated at each time step according to the net charging or discharging action determined by the EMS eq.(27):

$$E_{acc}(t) = E_{acc}(t-1) + E_{BESS}^{ch}(t) + E_{BESS}^{disch}(t) \quad (27)$$

#### 4) Pinch Power Analysis and Energy Management:

This study proposes a structured, multi-stage optimisation framework developed in Python to determine the optimal configuration of a HRES composed of PV units, WT, and BESS, operated under an integrated EMS. The primary objective of the proposed optimisation framework is to identify the most suitable system sizing that minimises grid dependency while enhancing techno-economic and reliability performance indicators.

The methodology integrates meteorological inputs (solar irradiation, ambient temperature, and wind speed), residential load profiles, and EV charging demand over a one-year horizon (8760 h). The overall optimisation process is depicted as a step-by-step flowchart and follows a two-level sizing and verification strategy, inspired by Pinch Power Analysis concepts applied to EMS (Figure 4).

Step 1: Daily-Based Preliminary Sizing and Energy Balance Optimisation: In the first stage, all input data are aggregated into 24h daily average profiles to reduce computational

complexity and enable a preliminary sizing of the generation and storage components. The optimisation process is initialised by setting the number of PV panels and WT to unity ( $N_{pv}=N_w=1$ ). At this stage, the EMS is executed without enforcing the  $SOC_{BESS}^{min}$  and  $SOC_{BESS}^{max}$ , as the objective is to determine these suitable bounds for the BESS, which will be implemented in the second stage of the process.

The system performance (Figure 4), is evaluated through objective indicators, particularly BECR and FEE. Based on the BECR value, three resizing scenarios are considered to adjust the total amount of renewable energy to be produced:

- **Scenario 1 (BECR > 1):** When discharged energy exceeds charged energy, an additional amount of renewable energy is supplied to compensate for the deficit eq.(28):

$$\sum_{t=0}^{t=24} E_{pv\_wind}(t) = \sum_{t=0}^{t=24} E_{pv\_wind}(t) + (|\sum_{t=0}^{t=24} E_{BESS}^{disch}(t)| - \sum_{t=0}^{t=24} E_{BESS}^{ch}(t)) \times \eta_{disch} \quad (28)$$

- **Scenario 2 (BECR < 1):** When charged energy exceeds discharged energy, the renewable generation capacity is curtailed accordingly eq.(29):

$$\sum_{t=0}^{t=24} E_{pv\_wind}(t) = \sum_{t=0}^{t=24} E_{pv\_wind}(t) - \frac{(\sum_{t=0}^{t=24} E_{BESS}^{ch}(t) - |\sum_{t=0}^{t=24} E_{BESS}^{disch}(t)|)}{\eta_{ch} \times \eta_{AC/DC}} \quad (29)$$

- **Scenario 3 (BECR = 1):** Energy balance is achieved, and the sizing is considered optimal.

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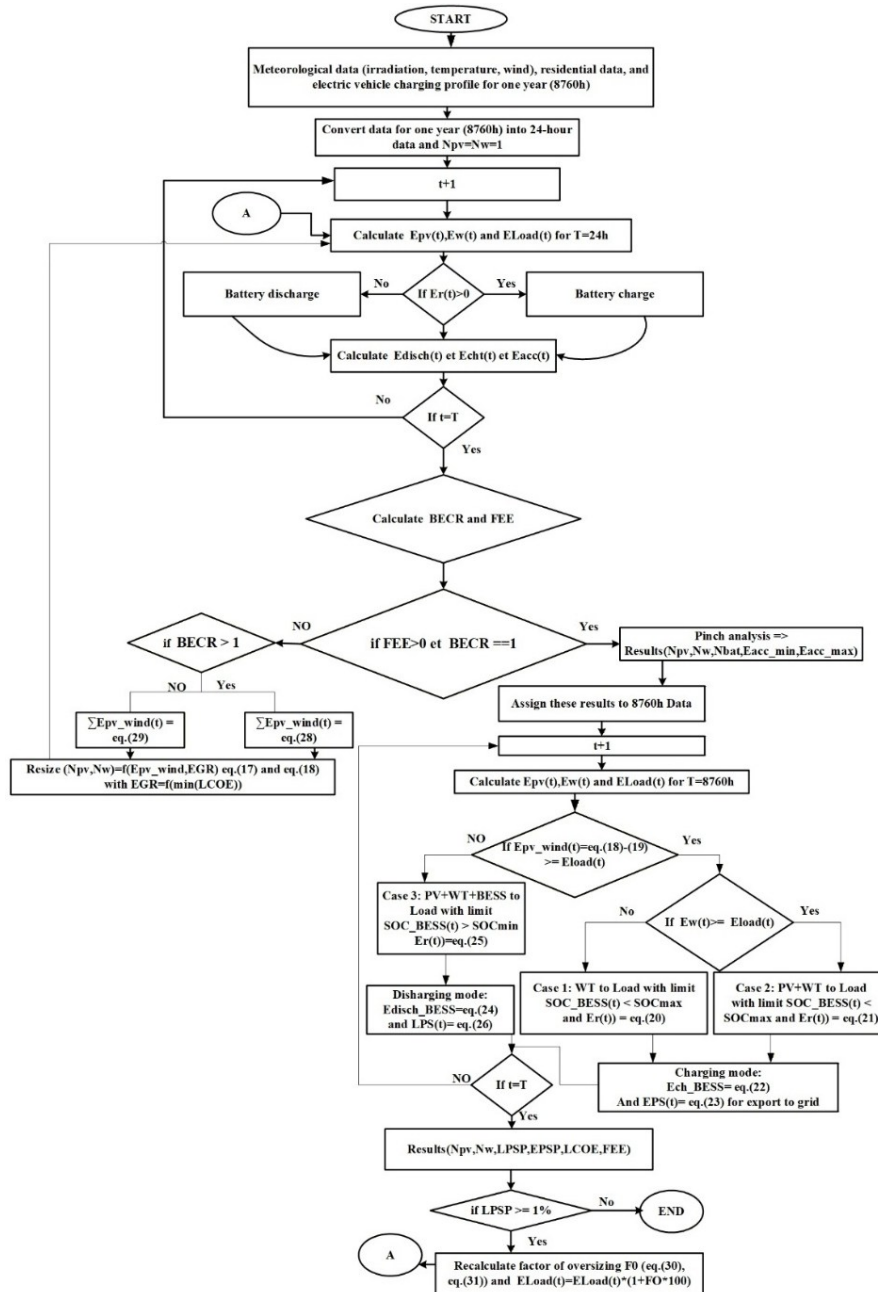


Figure 4. Flowchart of Pinch Power Analysis and EMS

Once equilibrium is achieved, pinch analysis is applied by imposing  $E_{acc}^{initial}$  to ensure strictly positive energy values throughout the analysis, which allows for the determination of the  $E_{BESS}^{min}$  and  $E_{BESS}^{max}$  to maintain the exploitable storage range, defined as eq.(5), which directly correspond to the operational limits of the  $SOC_{BESS}$ , set at 10% for discharge and 90% for charge, and the optimal allocation between PV and wind generation is established through the EGR, chosen to minimise LCOE.

**Step 2: Hourly-Based Annual Verification with Operational Constraints:** The second stage performs a detailed verification of the sizing results obtained in Step 1 using the full 8760 h dataset with a one-hour timestep. During this phase, the integrated EMS is executed under strict operational constraints, including the previously defined  $SOC_{BESS}^{min}$  and  $SOC_{BESS}^{max}$ , enabling the evaluation of key reliability indicators such as LPSP and the EPSP.

However, the use of daily average profiles in Step 1 may underestimate peak demand variations, potentially leading to an elevated LPSP during the annual assessment. To overcome this limitation, a load oversizing factor is iteratively applied only to the 24h aggregated load

profiles during Step 1, while the annual 8760 h dataset used in Step 2 remains unaltered to ensure realistic operational validation (Figure 4):

The oversizing factor is computed using a linear formulation when LPSP is high eq.(30):

$$FO = \frac{LPSP}{1-LPSP} [\%] \quad (30)$$

and a logarithmic formulation when LPSP is below 5% eq.(31):

$$FO = \frac{\ln(LPSP - 1\%)}{\ln(LPSP)} - 1 [\%] \quad (31)$$

The two-step procedure is repeated iteratively by adjusting the oversizing factor until the  $LPSP > 1\%$ , resulting in a more conservative and robust system sizing that significantly reduces LPSP during long-term operation.

#### IV. Results and Discussion:

This section presents all the results obtained within the framework of the case study conducted in the city of Oujda (Morocco), it is based on the collection and utilisation of data to provide a solid foundation for establishing demand scenarios intended for the optimal sizing of two hybrid energy production and storage configurations:

- **Configuration I:** PV and BESS
- **Configuration II:** PV, WT, and BESS

Local meteorological data (solar irradiation, temperature Figure 5, and wind speed Figure 6) were collected to characterise the climatic conditions specific to the region, and in addition, a charging profile for a fleet of 15 EVs was simulated and integrated into the existing residential load profiles, thus generating a comprehensive dataset that combines domestic consumption with specific mobility-related energy needs.

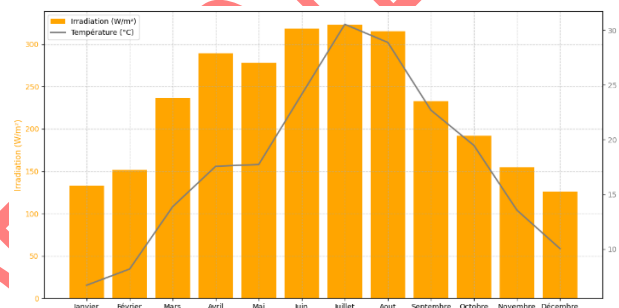


Figure 5. Monthly Variation of Solar Irradiance and Average Temperature (°C)

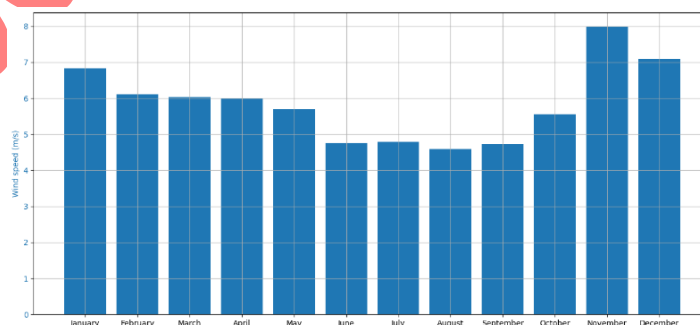


Figure 6. Monthly Average Wind Speed Variation (m/s) Throughout the Year

##### 1) Electric vehicle charging Profile:

The EV charging profile was established from data collected on 15 vehicles using Level 2 charging with  $Charg_{pow}^{max} = 11KW$ , and an analysis of charging habits reveals that the majority of

vehicles are connected for charging in the late afternoon and evening, specifically between 16:00 and 23:30 (Appendix: Table 11), moreover, the batteries of the studied EVs have capacities ranging from 32.3 kWh to 64.8 kWh, with accepted charging powers generally between 7.2 kW and 7.4 kW. Furthermore, a simulation over a full year enabled the evaluation of the total number of charging sessions together with the associated satisfaction rate. In addition, the charging management analysis indicated that using either one or two chargers was feasible, which consequently led to the study of two cases: the first corresponds to the operation of a single charging station, while the second considers two stations operating simultaneously; these configurations represent the optimal solutions identified to meet the charging needs. With this in mind, three performance indicators were selected, namely Maximum Satisfaction (vehicles fully charged), Required Satisfaction (vehicles reaching a minimum acceptable charge level), and the case where vehicles remain uncharged. As a result, the findings demonstrate that with two charging stations, overall satisfaction increases significantly, thereby reducing the number of undercharged vehicles. Finally, over the course of the year, 737 charging sessions were recorded for the first case (Figure 7) compared to 484 for the second case (Figure 8), suggesting that the choice between these two options ultimately depends on the trade-off between investment cost and the level of service provided.

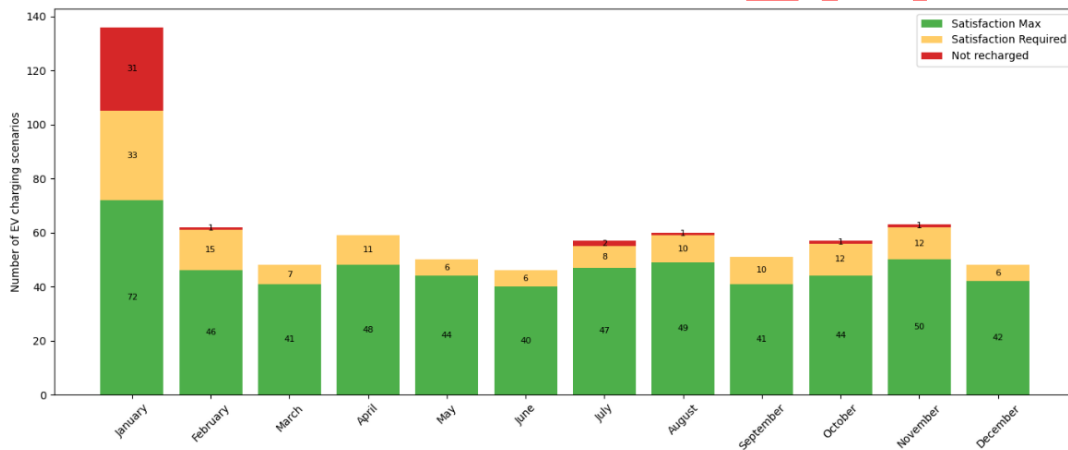


Figure 7. Charging sessions of EVs with the satisfaction rate for a single charging station

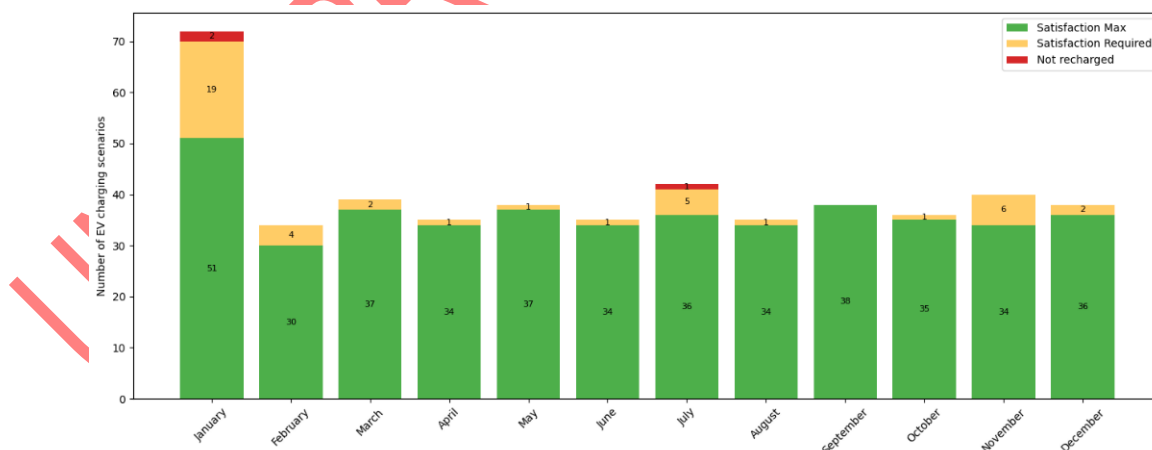


Figure 8. Charging scenarios of EVs with the satisfaction rate for two charging stations

## 2) Results of Pinch Power Analysis:

The monthly profiles show a seasonal variability of residential load, higher in winter and lower during spring–summer, while the charging demand of EVs remains relatively stable. The integration of one or two charging stations adds a constant load, whose impact becomes significant in the sizing of HRES (Figure 9).

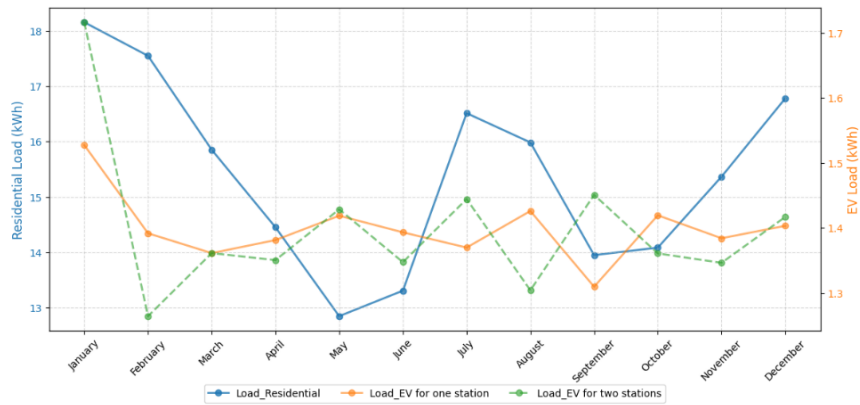


Figure 9. Residential and EV charging Load

The Pinch Power Analysis and strategy of EMS method is applied while respecting operational constraints to compare three energy consumption scenarios:

- **Scenario 1:** residential load only
- **Scenario 2:** residential load combined with EV charging
- **Scenario 3:** residential load combined with EV charging using two chargers

Step 1: Results of Daily-Based Preliminary Sizing and Energy Balance Optimisation:

Figure 10 illustrates the average 24h evolution, calculated over one year, of  $E_{acc}(t)$  in the BESS before and after applying the Pinch Power Analysis approach

The purpose is to determine the optimal sizing of energy systems ( $N_{pv}$ ,  $N_w$ ,  $N_{bat}$ ) and the operational constraints ( $E_{acc}^{min}$  and  $E_{acc}^{max}$ ) for two energy configurations under these scenarios.

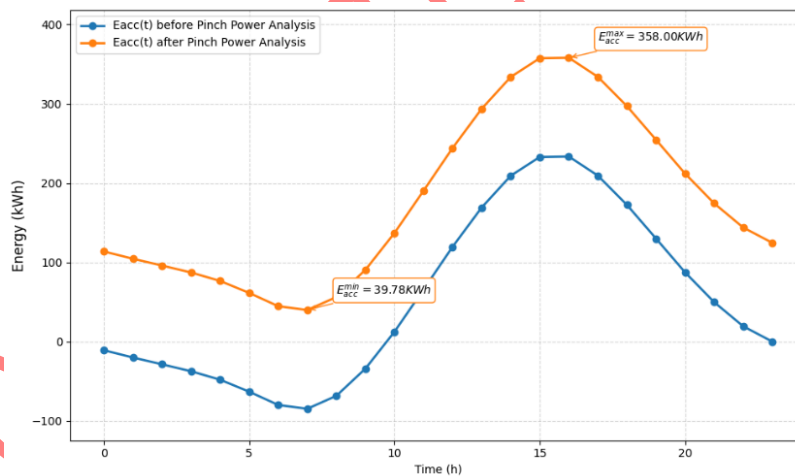


Figure 10.  $E_{acc}(t)$  in the BESS, averaged over a year on a 24-hour basis, for Configuration II under Scenario 2 for LPSP=1.54%

The evolution of  $E_{acc}(t)$  over the 24-hour average (Figure 11-Figure 12) shows that the two curves corresponding to the scenarios overlap at the beginning of the day, which indicates that the  $E_{acc}^{initial}$  is identical in both cases, since the residential load is active only.

EV charging begins in the evening, from 16 :00 onward, causing a gradual divergence between the two curves, this results in an increase of approximately 15% in peak demand, reflected in both the  $E_{acc}^{min}$  and  $E_{acc}^{max}$  values of the accumulated energy in BESS. After the charging period, the two curves converge again, indicating that the impact of EV charging is concentrated exclusively in the evening time window.

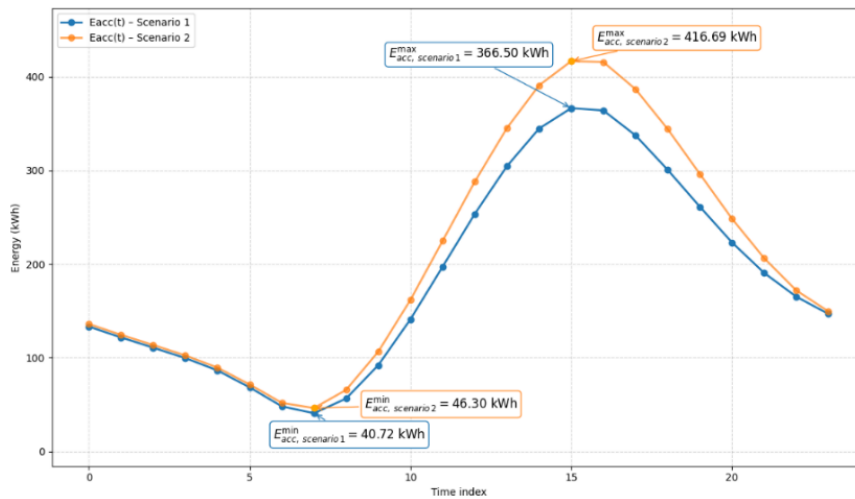


Figure 11. Eacc(t) in the BESS averaged over a year on a 24h basis, for Configuration I (scenario 1 and 2) after Pinch power analysis with  $1\% < LPSP < 2\%$

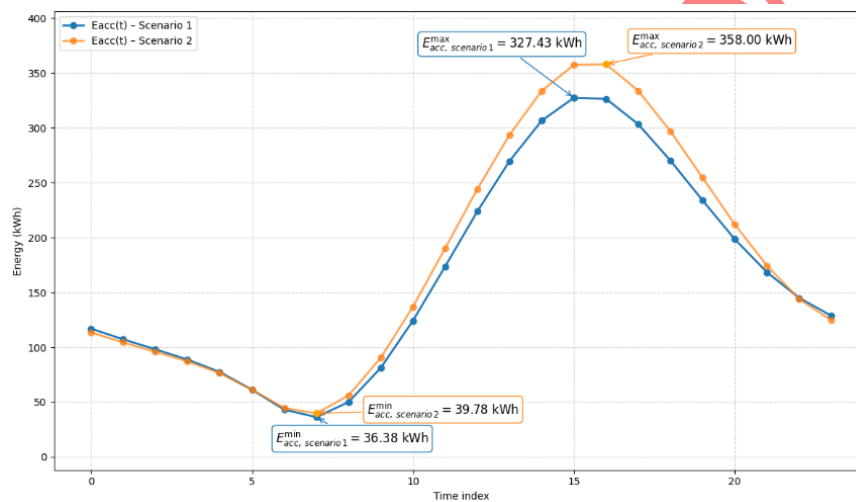


Figure 12. Eacc(t) in the BESS averaged over a year on a 24h basis, for Configuration II (scenario 1 and 2) after Pinch power analysis with  $1\% < LPSP < 2\%$

**Step 2: Results of Hourly-Based Annual Verification with Operational Constraints:**

The tables below present the results obtained after validation, under operational constraints, of the sizing determined in Step 1, highlighting several fundamental relationships between sizing and the performance of hybrid systems. During this stage, the objective functions LPSP, FEE, and EPSP can be evaluated.

A significant reduction in LPSP reflects improved energy availability, inevitably requiring an increase in the capacity of PV panels and BESS.

For instance, in Configuration I, the decrease in LPSP from 11.85% to 1.95% in Scenario 1 (Table 1) is accompanied by an increase in the number of batteries from 19 to 28 units, and PV panels from 211 to 316.

This system expansion leads to a rise in the LCOE from 0.057€/KWh to 0.083€/KWh (Table 5), illustrating the economic trade-off associated with improved reliability.

Table 1. Optimal sizing results for Configuration I

Configuration I		
Scenario 1	Scenario 2	Scenario 3

LPSP (%)	Npv	Nbat	LPSP (%)	Npv	Nbat	LPSP (%)	Npv	Nbat
11.85	211	19	11.5	230	22	11.78	231	22
7.67	239	21	7.58	260	24	7.87	261	24
5.33	259	23	5.33	282	26	5.16	284	27
3.86	274	25	3.94	298	28	4.17	299	28
3.19	285	26	3.23	310	29	2.77	325	30
1.95	316	28	1.86	343	32	1.37	365	34

Table 2. Optimal Power Converter Sizing Results for Configuration I

Configuration I					
Scenario 1		Scenario 2		Scenario 3	
Inverter Power Input(KW)	Rectifier Power Input(KW)	Inverter Power Input(KW)	Rectifier Power Input(KW)	Inverter Power Input(KW)	Rectifier Power Input(KW)
39.49	0	44.89	0	47.55	0
39.49	0	44.89	0	47.55	0
39.49	0	44.89	0	47.55	0
39.49	0	44.89	0	47.55	0
39.49	0	44.89	0	47.55	0
39.49	0	44.89	0	47.55	0

In Configuration II, a similar trend is observed (Table 3): in Scenario 1, the reduction of LPSP from 9.9% to 1.21% corresponds to an increase in the number of batteries from 18 to 25 units, while the LCOE remains stable at approximately 0.10€/kWh (Table 6). The integration of WT enables the achievement of comparable reliability levels with a less heavily utilised energy storage capacity, reflecting the temporal complementarity effect between PV and WT.

Table 3. Optimal sizing results for Configuration II

Configuration II											
Scenario 1				Scenario 2				Scenario 3			
LPSP (%)	Npv	Nw	Nbat	LPSP (%)	Npv	Nw	Nbat	LPSP (%)	Npv	Nw	Nbat
9.9	136	1	18	9.9	155	1	20	9.99	155	1	20
6.02	159	1	20	6.03	180	1	22	6.15	181	1	22
4.34	174	1	21	4.08	197	1	24	4.24	197	1	24
3.28	185	1	22	3.14	208	1	25	3.28	209	1	25
2.75	194	1	22	--	--	--	--	--	--	--	--
1.21	227	1	25	1.54	239	1	28	1.69	240	1	28

Table 4. Optimal Power Converter Sizing Results for Configuration II

Configuration II					
Scenario 1		Scenario 2		Scenario 3	
Inverter Power Input(KW)	Rectifier Power Input(KW)	Inverter Power Input(KW)	Rectifier Power Input(KW)	Inverter Power Input(KW)	Rectifier Power Input(KW)
36.43	13.6	40.5	13.6	47.45	13.6
36.43	13.6	40.5	13.6	47.45	13.6
36.43	13.6	40.5	13.6	47.45	13.6
36.43	13.6	40.5	13.6	47.45	13.6
36.43	13.6	--	--	--	--
36.43	13.6	40.5	13.6	47.45	13.6

Furthermore, EGR (Table 6) increases as the LPSP decreases in Configuration II, rising from 64.39% to 75.12% (Scenario 1), indicating a growing share of PV production within a generally more reliable configuration.

The addition of wind power reveals a beneficial temporal complementarity that significantly reduces storage requirements: at an LPSP of 1.21% in Configuration II, the number of batteries needed is almost equivalent to that required at a higher LPSP of 3.86% in Configuration I (approximately 25 batteries, see Table 1 and Table 3). This equivalence confirms the favourable effect of wind power in limiting storage needs for a given reliability level.

This complementarity is also reflected by FEE value, close to zero, corresponding to LPSP values between 5% and 10% in Configuration II, whereas it remains high in Configuration I (Table 6).

Moreover, the hybrid system in Configuration II achieves a better balance between production and demand, reducing unused energy surplus (EPSP) (Table 6), However, EPSP shows a slight decrease compared to Configuration I (Table 5), which is mainly explained by the high penetration rate of solar renewable energy (EGR) in Configuration II. In other words, the strong solar contribution in this configuration helps stabilise overall system performance despite changes induced by integrating other resources or loads, thereby limiting reductions in EPSP.

Table 5. Techno-economic results for the configuration I

Configuration I								
Scenario 1			Scenario 2			Scenario 3		
FEE(%)	LCOE(€/KWh)	EPSP(%)	FEE(%)	LCOE(€/kWh)	EPSP(%)	FEE(%)	LCOE(€/kWh)	EPSP(%)
3.01	0.057	12.66	0	0.059	12.11	1.22	0.059	12.75
14.61	0.063	19.48	9.85	0.065	19.06	11.9	0.065	19.61
20.55	0.069	24	15.49	0.07	23.75	19.71	0.072	24.13
25.48	0.074	27.19	20.26	0.075	26.93	22.02	0.075	27.34
27.7	0.077	29.64	22.44	0.078	29.36	26.14	0.081	32.43
31.75	0.083	36.08	28.14	0.086	35.58	32.82	0.091	39.35

Table 6. Techno-economic results for configuration II

Configuration II											
Scenario 1				Scenario 2				Scenario 3			
FEE(%)	LCOE(€/KW)	EPSP(%)	EGR(%)	FEE(%)	LCOE(€/kW h)	EPSP(%)	EGR(%)	FEE(%)	LCOE(€/kWh)	EPSP(%)	EGR(%)
0	0.094	10.99	64.39	0	0.091	10.78	67.34	0	0.091	10.83	67.34
0	0.1	16.47	67.89	0	0.097	16.25	70.54	0	0.097	16.67	70.65
0	0.1	20.25	69.83	0	0.1	20.01	72.38	0	0.10	20.11	72.38
1.39	0.1	22.9	71.1	0	0.1	22.48	73.45	1.91	0.10	22.84	73.54
6.24	0.1	25.17	72.07	--	--	--	--	--	--	--	--
21.15	0.11	32.65	75.12	12.66	0.11	29.28	76.07	14.84	0.11	29.59	76.14

The integration of EV results in a notable increase in energy and storage requirements, but its overall impact remains controlled and limited, with EPSP varying moderately between -0.55% and +3.37% depending on the configuration, reflecting the system's stability in response to this new demand (Table 5 and Table 6).

The robust sizing of the BESS and the implemented management strategies help maintain EPSP levels close to those of scenarios without EVs. Furthermore, variations in the LCOE remain low after the integration of EV charging, in Configuration II (Table 6), and in Configuration I (Table 5), demonstrating the effectiveness of the EMS in economically adapting the system.

Thus, the system accommodates this additional load without significantly compromising its performance in terms of reliability and cost.

On an hourly daily dynamic, both configurations show charging predominantly concentrated during daylight hours when solar production is optimal, typically between 9 a.m. and 5–6 p.m.

For Configuration II, the charging peaks  $E_{BESS}^{ch}(t)$  reach high levels, sometimes exceeding 40 to 70 kWh/h around midday during seasons with strong sunlight (spring/summer), whereas Configuration I exhibit a slightly wider range, varying from 20 to 80 kWh/h, indicating greater variability in solar load. However, when demand persists and solar production wanes, significant discharges  $E_{BESS}^{disch}(t)$  occur, reaching -30 to -40 kW/h in both Configurations II and I, mainly in autumn and winter, reflecting substantial reliance on batteries (Figure 13 and Figure 14).

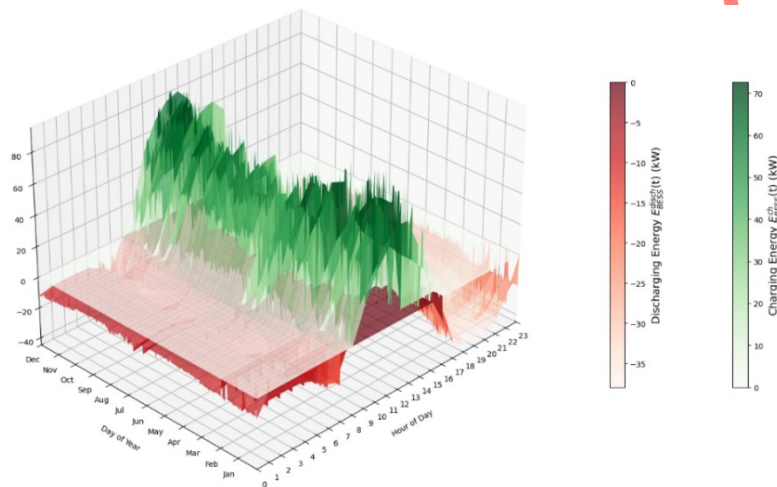


Figure 13. Yearly discharge profiles  $E_{BESS}^{disch}(t)$  and charge profiles  $E_{BESS}^{ch}(t)$  of the BESS in Configuration I under Scenario 2

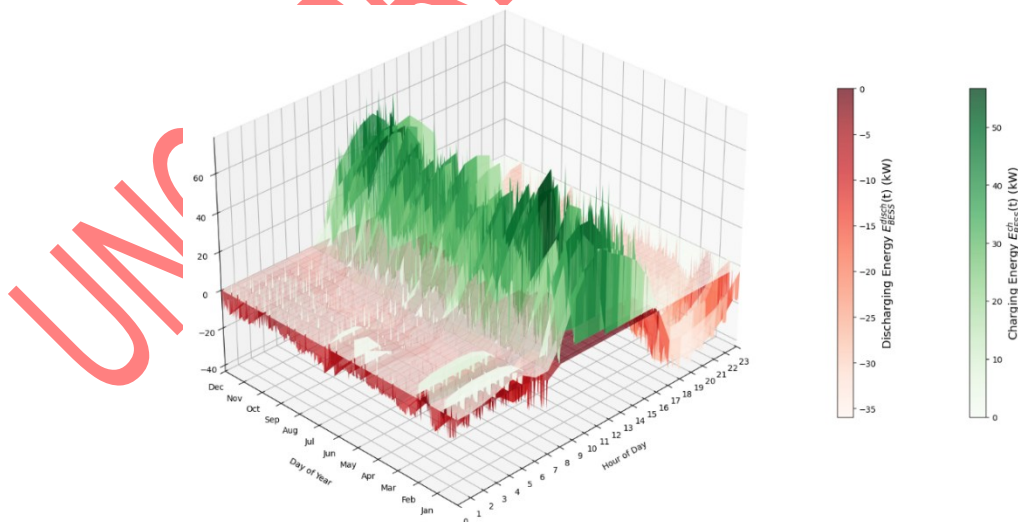


Figure 14. Yearly discharge profiles  $E_{BESS}^{disch}(t)$  and charge profiles  $E_{BESS}^{ch}(t)$  of the BESS in Configuration II under Scenario 2

During spring and summer, the system operates optimally, with overall demand generally lower (Figure 9) (around 15 to 17 kW/h), meanwhile, Configuration II benefits from a solar

production average that increases significantly, reaching 465 to 536 KWh/day (Figure 15) and wind power generation in Configuration II remains low and consistent (on average ~140 KWh/day), sometimes dropping below 90 KWh/day, and contributes only moderately to recharging (Figure 16).

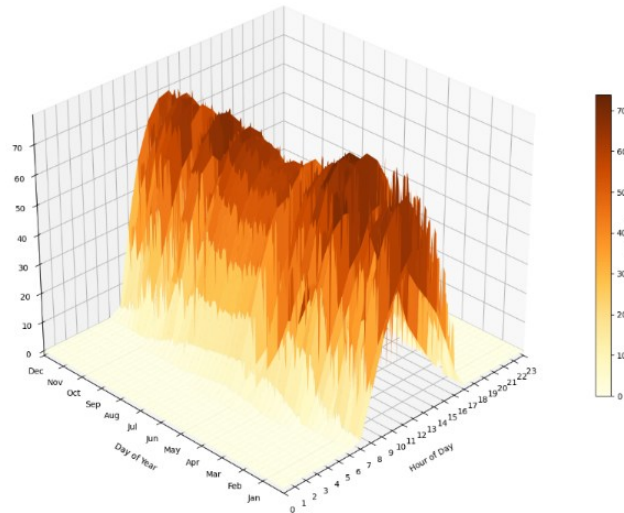


Figure 15. Yearly profiles of  $E_{pv}(t)$ , representing the solar energy generated in Configuration II under Scenario 2

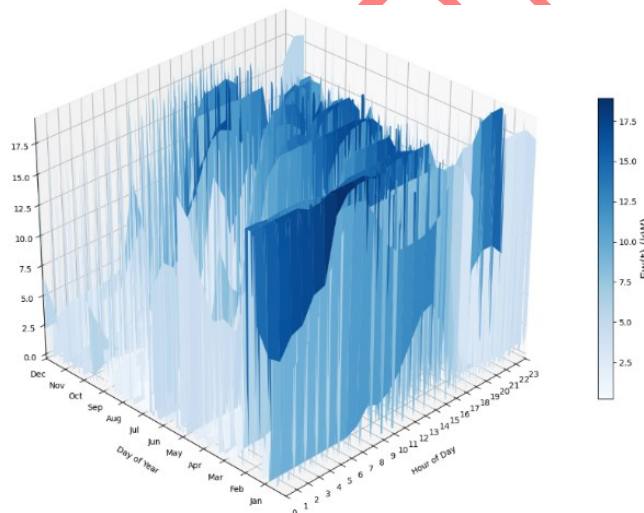


Figure 16. Yearly profiles of  $E_w(t)$ , representing the wind energy generated in Configuration II under Scenario 2

Consequently, the  $SOC_{BESS}$  in Configuration II (Figure 18) mainly fluctuates between 40% and 80%, indicating that the batteries are often highly charged, with limited discharges. This results in higher charging levels of the BESS, close to but often below the demand, with more regular (~175 kWh/day on average) and elevated yet shallow discharge cycles generally ranging between -247 and -164 kWh/day (Figure 14), reflecting a cautious management strategy aimed at prolonging battery life. On days with exceptionally high solar production, excess energy may even occur if demand is low and the  $SOC_{BESS}$  approaches its maximum limit.

In Configuration I, the  $SOC_{BESS}$  also remains high (Figure 17), frequently above 45–70%, with fewer deep cycles, thereby limiting deep discharges (Figure 13). However, the more

pronounced presence of solar peaks allows for fuller BESS charging and a more stable maximum SOC above 70%, reflecting a good match with variable summer demand.

In autumn and winter, with average demand (Figure 9) gradually increasing to approximately 15–18 kW/h and generally settling in winter—often above 18 kW/h, reaching up to 21 Kw/h and solar production in Configuration II decreases (Figure 15) to an average level of around 372–490 kWh/day, partially offset by wind production (Figure 16) which rises to 104–334 kWh/day and remains relatively high in winter with notable peaks up to 356 kWh/day on windy days. This complementarity allows the  $SOC_{BESS}$  (Figure 18) to fluctuate between 30% and 80%, occasionally dropping to 10%, with significant discharge dynamics regularly reaching -314 and -187 kWh/day (Figure 14), particularly on days when reduced solar output is not compensated by wind (<100Kwh/day) and with charging energy of BESS sometimes (~260 kWh/day on average) close to or slightly below the demand. This indicates that solar production alone cannot cover consumption, resulting in increased reliance on discharges, while generally avoiding reaching the critical low threshold ( $SOC_{BESS}$  is often below 30%). However, in Configuration I, despite the high variability of solar production (peaks of >700 kWh/day on some days but also days with lower solar energy between 540 and 650 kWh/day), combined with relatively stable energy needs, the batteries undergo deep and frequent discharge cycles (Figure 13), et The  $SOC_{BESS}$  can then frequently drop to between 10% and 15% (Figure 17), with the daily maximum limited to 35–50%, imposing increased stress on the battery and posing a potential risk to its durability, particularly due to prolonged and frequent discharges.

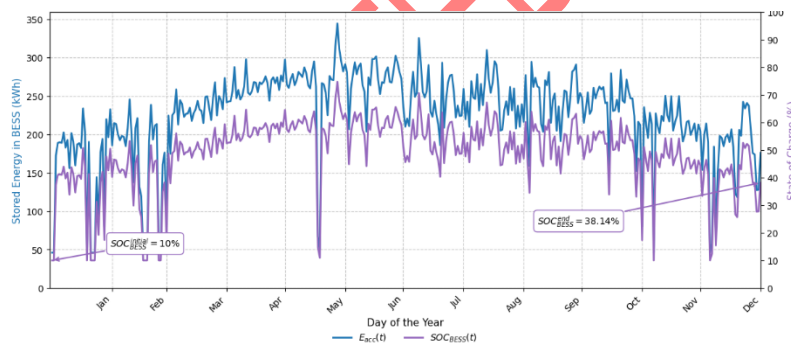


Figure 17. Yearly profiles of  $E_{acc}(t)$  and  $SOC_{BESS}(t)$  for the BESS in Configuration I under Scenario 2

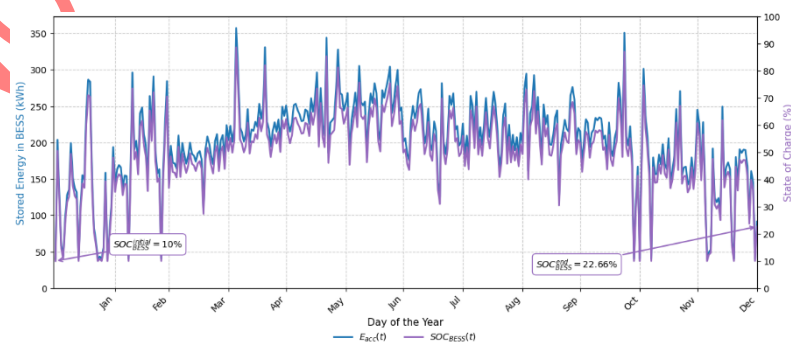


Figure 18. Yearly profiles of  $E_{acc}(t)$  and  $SOC_{BESS}(t)$  for the BESS in Configuration II under Scenario 2

Thus, Configuration II offers better regulation of energy dynamics, thanks to the moderating contribution of wind power in winter and more balanced battery cycles, promoting

the long-term health of the batteries. Although Configuration I performs well in summer with higher solar production, it presents an increased risk of deep discharges and taxing battery cycles during the cold season, due to lesser wind energy complementarity and greater solar variability.

The integration of the sale of 20% of excess energy eq.(23) (in accordance with Law 82-21 on self-production of electricity applied in Morocco) at prices equivalent to %SALE = 40%, 50%, and 60% of the reference LCOE (Table 5 and Table 6) results in a significant reduction of LCOE for all studied systems, giving the LCOE<sub>SALE</sub> values shown in Table 7 and

Table 8. This decrease is proportional to the applied sale price: the higher the price, the greater the reduction.

Table 7. Results of the new LCOE values after selling excess energy for Configuration I

LPSP (%)	Configuration I								
	Scenario 1			Scenario 2			Scenario 3		
	%SALE=40%	%SALE=50%	%SALE=60%	%SALE=40%	%SALE=50%	%SALE=60%	%SALE=40%	%SALE=50%	%SALE=60%
11.85	0.0522	0.051	0.0498	0.0542	0.053	0.0518	0.0543	0.0531	0.0519
7.67	0.0574	0.0559	0.0544	0.0591	0.0576	0.0561	0.0592	0.0577	0.0561
5.33	0.0606	0.0585	0.0564	0.0621	0.06	0.0579	0.0636	0.0614	0.0592
3.86	0.0634	0.0607	0.058	0.0646	0.0619	0.0592	0.0645	0.0617	0.059
3.19	0.0644	0.0612	0.0581	0.0655	0.0623	0.0591	0.0659	0.0621	0.0583
1.95	0.0652	0.0606	0.0559	0.0674	0.0628	0.0581	0.0682	0.0623	0.0564

Table 8. Results of the new LCOE values after selling excess energy for Configuration II

LPSP (%)	Configuration II								
	Scenario 1			Scenario 2			Scenario 3		
	%SALE=40%	%SALE=50%	%SALE=60%	%SALE=40%	%SALE=50%	%SALE=60%	%SALE=40%	%SALE=50%	%SALE=60%
9.9	0.0865	0.0846	0.0827	0.0841	0.0822	0.0804	0.0842	0.0823	0.0805
6.02	0.0911	0.0888	0.0866	0.0884	0.0862	0.0840	0.0886	0.0863	0.0841
4.34	0.0934	0.0909	0.0883	0.0923	0.0898	0.0873	0.0923	0.0898	0.0874
3.28	0.0942	0.0911	0.088	0.093	0.09	0.087	0.0929	0.0899	0.0869
2.75	0.0932	0.0897	0.0861	--	--	--	--	--	--
1.21	0.0939	0.0883	0.0827	0.0943	0.0897	0.0851	0.0942	0.0895	0.0848

The analysis indicates that the economic impact of valorising excess energy depends on the LPSP level. For low LPSP, the sale of surplus energy allows a further reduction in cost, as initial values of LCOEs remain high compared to systems with high LPSP. Moreover, for the same sale price, LCOE<sub>SALE</sub> remains very close regardless of LPSP, suggesting that valorisation of excess energy reduces the cost gap between systems with low and high LPSP, thereby mitigating the impact of oversizing and enhancing the economic viability of renewable systems. Finally, as the percentage of energy sold increases, this convergence of LCOE<sub>SALE</sub> values becomes even more pronounced, strongly reducing the relative effect of LPSP on the final cost.

*Validation by Homer Pro software:* The results obtained with Homer Pro (Table 9 and Table 10), using the equipment sizing derived from des Table 1 and Table 3 initially corresponding to an LPSP of approximately 1%, generally confirms the reliability and consistency of the modelled systems. Although the LPSP calculated by Homer Pro shows some variation, ranging from 0.9% to 1.74%, these values remain low and close to the initial target, thus ensuring satisfactory energy continuity.

Furthermore, other key indicators such as EPSP, LCOE, and FEE present results consistent with those in Table 5 and Table 6, reflecting effective energy production management,

maintained reliability, and solid economic control. The stable numbers of PV panels, WT, and batteries between the two sets of results further reinforce this validation, demonstrating that the initial sizing meets the system requirements within Homer Pro.

Table 9. Optimal sizing and techno-economic results for configuration I and scenario 2 were obtained using Homer Pro software

	Configuration I							
	LPSP (%)	Npv	Nbat	FEE(%)	LCOE(€/KWh)	EPSP(%)	Inverter Power Input(KW)	Rectifier Power Input(KW)
Scenario 1	1.74	315	28	28.53	0.085	36.5	38.7	0
Scenario 2	1.6	342	32	24.51	0.087	36.1	44	0

Table 10. Optimal sizing and techno-economic results for configuration II and scenario 2 were obtained using Homer Pro software

	Configuration II									
	LPSP (%)	Npv	Nw	Nbat	FEE(%)	LCOE(€/KWh)	EPSP(%)	EGR(%)	Inverter Power Input(KW)	Rectifier Power Input(KW)
Scenario 1	0.9	227	1	25	22.41	0.11	33	75.9	35.7	13.3
Scenario 2	1.24	239	1	28	16.15	0.11	29.9	76.8	39.7	13.3

## V. CONCLUSION

This study demonstrates that a structured two-step optimisation framework, combining Pinch Power Analysis and integrated EMS, enables a robust sizing of a HRES incorporating EV charging, while generating EV charging profiles and managing techno-economic trade-offs.

The main scientific contribution lies in the integration of a simplified daily pre-sizing (24 h) with an annual hourly validation, reducing computational complexity while ensuring system reliability over 8760 hours.

From a practical perspective, these results provide a decision-making framework for the design of hybrid systems. Improving reliability (reducing LPSP) incurs measurable costs, and the integration of wind power allows achieving a lower LPSP (1.21 %) with a stable LCOE of approximately €0.10/kWh for LPSP > 10 %, requiring only 25 batteries. This number is nearly equivalent to that required for a higher LPSP of 3.86 % in the PV/BESS configuration, highlighting the role of WT–PV complementarity in reducing storage requirements for a given reliability level.

This complementarity is also reflected in the FEE value, which remains close to zero for LPSP between 5 % and 10 %, whereas it is higher in the PV/BESS configuration. Moreover, the  $SOC_{BESS}$  predominantly remains between 40 % and 80 % in the WT/PV/BESS configuration, while deeper discharges reaching 10–15 % are observed in the PV/BESS configuration, particularly during winter. Thus, although the PV/BESS configuration exhibits a slightly lower cost of energy, the addition of wind power improves seasonal stability and reduces storage stress.

The integration of EVs increases energy and storage requirements, but its impact remains controlled: reliability and cost indicators vary only slightly, demonstrating the effectiveness of the EMS in the economic and operational adaptation of the system. Validation with HOMER confirms the consistency of the sizing and the stability of the achieved performance.

Certain limitations should be noted: the analysis relies on deterministic annual climate profiles. Future research could incorporate stochastic scenarios for renewable generation and charging behaviour, as well as a more detailed economic sensitivity analysis, including investment costs (residential, commercial, utility scale) and a wider diversity of energy resources (hydrogen, hydropower).

In continuation of this work, several perspectives can be considered, in particular, a detailed techno-economic analysis could be carried out to evaluate the actual integration capacity of renewable energies into medium-voltage (MV) and low-voltage (LV) networks, taking into account power flow constraints, power quality, and dynamic load management. In addition, the implementation of advanced strategies for optimal energy dispatch within the network appears essential to adjust production, minimise overall costs, and ensure supply security.

## Appendix:

Table 11. EV parking behaviour and characteristics

$ID_{EV}$	$Cbat_{EV}^{ID_{EV}}$	$RDR_{max}^{ID_{EV}}$	$Charg_{pow_{EV}}^{max}$	$RDR_{target}^{ID_{EV}}$	$T_{arrival}(h)$	$T_{arrival}(min)$	$T_{depart}(h)$	$T_{depart}(min)$
1	38,4	270	6,6	15	16	20	23	30
2	37,9	305	7,4	20	16	40	23	30
3	64,8	460	7,4	16	17	20	23	30
4	50	357	7,4	17	17	30	23	30
5	32,3	260	7,2	12	17	30	23	30
6	46	359	7,4	19	18	10	23	30
7	64,8	460	7,4	25	18	30	23	30
8	38,4	270	6,6	12	18	30	23	30
9	52	395	7,4	13	18	40	23	30
10	54	406	7,4	15,6	19	0	23	30
11	37,9	305	7,4	18	19	30	23	30
12	32,3	260	7,2	13	19	40	23	30
13	50	357	7,4	14,5	19	40	23	30
14	52	395	7,4	19,5	20	0	23	30
15	46	359	7,4	20	20	0	23	30

Table 12. Characteristics of HRES

PV module DATA	
Peak power rating	327 W
Maximum Power Point Voltage	54,7 V
Maximum Power Point Current	5,98 A
Open-Circuit Voltage	64,9 V
Short-circuit current	6,46 A
Area	1,63 m <sup>2</sup>
Module efficiency ( $\eta_{ref}$ )	20,4 %
Normal operating cell temperature ( $T_{NOCT}$ )	45 C
Temperature coefficient of efficiency ( $\beta$ )	-0,04 %/ K
Temperature at rated efficiency ( $T_{ref}$ )	25 C
Solar radiation at $T_{NOCT}$ ( $I_{NOCT}$ )	800 W/m <sup>2</sup>
Cost per unit	124 €
BOS cost	35 % of PV system costs
Installation cost	10% of the overall project cost
O&M cost	1% of the initial cost of the installation
Wind energy system	
Rated power ( $P_n$ )	20 KW
Cut in speed ( $v_{cut.in}$ )	2,75 m/s
Cut out speed ( $v_{cut.out}$ )	20 m/s
Rated speed ( $v_{nom}$ )	12 m/s
Rotor diameter (r)	12 m
gearbox efficiency ( $\eta_{gearbox}$ )	98 %
generator efficiency ( $\eta_{generator}$ )	98 %
Cost per unity	49 680 €
BOS cost	40 % of the WT system cost
O&M cost (\$/kW-yr)	1% of the initial cost of the installation
Battery Energy Storage System (BESS)	
Battery capacity ( $Cbat$ )	300 Ah

Battery voltage	48 V
Courant de Charge Max.	200 A
Courant de Décharge Max.	200 A
Depth of discharge (DOD)	90 %
Maximum state of charge (SOC max)	90 %
Cost per unity	1902€
Cost of bidirectional inverter	169 €
BOS cost	35 % of BESS cost
O&M cost (\$/kW-yr)	1% of the initial cost of the installation

## Abbreviations

**BECR** : Battery Energy Charging Ratio

**BESS** : Battery Energy Storage System

**EMS** : Energy Management System

**EGR** : Energy Generation Ratio

**EPSP** : Excess Power Supply Probability

**ESCEA** : Energy System Configuration and Economic Assessment

**EV** : Electric Vehicle

**FEE** : Final Excess Energy

**GA** : Genetic Algorithm

**GA-PSO** : Hybrid Genetic Algorithm–Particle Swarm Optimization

**HOMER Pro** : Hybrid Optimization of Multiple Energy Resources (Professional version)

**HRES** : Hybrid Renewable Energy Systems

**LCA** : Life Cycle Assessment

**LCOE** : Levelized Cost of Energy

**LPSP** : Loss of Power Supply Probability

**MOPSO** : Multi-Objective Particle Swarm Optimization

**NREL** : National Renewable Energy Laboratory

**PSO** : Particle Swarm Optimization

**PV** : Photovoltaic

**WT** : Wind Turbine

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