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Matching Industry 5.0 and Renewable Energy Integration: an optimization approach for robotic warehouses

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Abstract

This paper presents a methodology to embed Industry 5.0 principles in the preliminary design of the photovoltaic (PV) system with battery energy storage (BESS) in robotic warehouses. The desired sustainability and resilience performances are translated into optimisation constraints on self-consumption, self-sufficiency, and net-zero. The PV-BESS system is sized at minimum cost using an untapped approach which combines Constraint Programming and procedural computation to speed up the process. The multi-dimensional performance mapping of current and alternative solutions allows to study the trade-off of economic, sustainability, and resilience indicators. Energy demand of material handling equipment is then redistributed adopting micro-charges to enhance self-consumption, assessing further potential gains of the candidate solution. The methodology was validated with a case study, where PV size was aligned to the upper bound of net zero ratio, while BESS was kept to the minimum to satisfy 40% of self-consumption, improvable to 56% by demand response.

Keywords: sustainable logistics; energy resilience; photovoltaic system; demand response

1. Introduction

Climate change, energy supply disruptions, and geopolitical instability have exposed significant vulnerabilities in contemporary industrial systems, highly dependent on conventional energy resources. This is particularly pronounced within the European context, where energy cost has been identified as a critical obstacle to industrial development in a recent analysis of competitiveness [1]. According to this assessment, approximately half of European enterprises consider escalating and volatile energy costs to be a substantial barrier to investment and growth, underscoring the urgent need for enhanced energy independence and decarbonization strategies. These challenges align directly with

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the United Nations Sustainable Development Goals (SDGs), particularly with SDG 7 (Affordable and Clean Energy), as well as the 2030 Agenda and 2050 climate neutrality targets.

Industry 5.0 is emerging as a direct response to these issues. This new paradigm shifts from Industry 4.0's efficiency focus toward a more balanced framework incorporating human-centricity, sustainability, and resilience [2, 3]. While human-centricity refers to the use of technology to improve human well-being, sustainability means reducing energy consumption and greenhouse emissions, avoiding depletion and degradation of natural resources, ensuring the needs of today generations without jeopardizing the needs of future generations [2]. Resilience refers to the capability of supply chains to withstand, adapt, and recover from disruptions to meet customer demand and ensure performance [4].

Among solutions addressing both the sustainability and resilience, photovoltaic (PV) technology emerges as particularly impactful [5]. The integration of photovoltaic systems fundamentally transforms facilities from passive energy consumers into active "prosumers", that both produce and consume energy [6]. The prosumer model creates the foundation for achieving Net-Zero Energy status, a concept which aims to balance energy production and consumption on an annual basis. However, various interpretations exist in recent literature [7], from a broader definition including externally acquired renewable energy [8], to stricter production-consumption equilibrium requirement [9].

Two other concepts translate the sustainability and resilience pillars of Industry 5.0 into quantifiable energy metrics that characterize PV energy systems: self-consumption and self-sufficiency [10]. The former measures to what extent locally produced renewable energy is utilized on-site. As demonstrated in [11], improving self-consumption not only reduces operational costs but also yields significant environmental benefits. From a complementary point of view, self-sufficiency is defined as the portion of energy demand covered by own PV production. It quantifies energy independence, which has been shown to strengthen organizational resilience against external disruptions and improving operational efficiency [12].

While this energy supply transformation could benefit various industrial sectors, their application must be prioritized in domains with significant energy consumption, substantial growth trajectories, and strategic importance to global supply networks. The vulnerabilities of logistics operations to supply chain disruptions [13], coupled with the dramatic expansion of storage infrastructure driven by e-commerce growth [14], have intensified warehousing environmental footprint and created significant opportunities for sustainability interventions. Despite this potential, sustainable warehousing strategies have emerged as research topics only in the last decade [15]. The concept of Green Warehousing, which aims to minimize energy consumption, costs, and emissions, was systematically categorized by [16] into three main research streams: warehouse management practices, building characteristics, and energy efficiency in storage and material handling systems. While the initial approaches primarily focused on reducing consumption within the traditional paradigm of warehouses as passive energy consumers, a more transformative direction has begun to emerge, that fundamentally redefines warehouses as energy prosumers through photovoltaic integration. This approach leverages rooftop solar panels as a particularly promising solution due to their proximity to end-users, adaptability to specific needs, maintainability, and favorable economic profile [17]. Thus, PV integration has been identified as a green strategy within the utility intervention area for environmental sustainability at logistics sites in the conceptual framework proposed in [18].

The literature on PV-integrated warehouses is limited and has developed along two distinct but complementary trajectories: system design optimization and demand response management strategies. System design research has predominantly focused on refrigerated warehouses, leveraging the natural alignment between PV power generation patterns and refrigeration requirements, both peaking during warmer daylight periods and declining during colder ones. A cold store for frozen fish in India was designed for complete self-sufficiency by supplying the vapor compression refrigeration system with PV energy in [19]. In [20] a refrigerated warehouse equipped with PV panels was analysed in a smart grid setting maximizing profits under different electricity tariff structures. In [21] the configuration of a refrigerated automated storage and retrieval system was optimized at minimum cost with the integration of a PV system without energy storage or sales to the grid, to partially cover the high energy requirements at frozen food temperatures. Comparing different energy storage options for PV-powered cooling for a refrigerated warehouse in Singapore, lithium-ion batteries were proven to achieve better self-sufficiency despite higher levelized costs compared to thermal storage alternatives [22]. In contrast, non-refrigerated warehouses have received less attention, with [23] being one of the few examples, which proposes a grid-tied PV system for a military warehouse that could cover approximately 71% of energy consumption, using PV*SOL software for the 3D design and simulation of the system. Demand response management research explores how to modify energy consumption patterns to align with renewable energy availability. In material handling applications, a Mixed-Integer Programming model was developed to schedule battery charging operations for electric stackers, minimizing energy costs by leveraging periods of PV energy availability [24]. Similarly, task sequencing and scheduling were optimized for shuttle-based storage systems supplied by rooftop PV panels and battery storage, implementing power-load management to avoid consumption peaks and favor PV energy utilization [25]. In [11] electrification of the heating system and an opportunity charging strategy for forklift trucks have been evaluated to enhance PV self-consumption of a logistics facility by simulation.

Concerning optimization methodologies, Linear Programming (LP), Mixed Integer Linear Programming (MILP), Mixed Integer Non-Linear Programming (MINLP), and Dynamic Programming, represent the predominant modeling approaches for complex PV system design and energy management problems [26]. They are often complemented with meta-heuristic algorithms like Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) when dealing with non-linear aspects of PV system performance [27]. As mentioned in [28], most of the sizing techniques are time-consuming, and evaluating the proper size of the PV system can take a long time, especially when considering a battery energy storage system (BESS).

From the above literature review, it emerges that: 1) Industry 5.0 sustainability and resilience dimensions should be considered from the early stages of PV system sizing; 2) the feasibility study of PV integration can be limited by computational effort; 3) the benefits of potential demand response strategies are currently considered separately after PV system installation, while related benefits can strengthen the decision about PV system adoption just in the design phase. This paper proposes a five-step methodology and a two-phase optimization approach for rapid assessment of renewable energy integration in robotic warehouses. Our approach enables industrial practitioners to efficiently evaluate hybrid PV-BESS configurations while considering Industry 5.0 key performance indicators, without requiring extensive computational resources. The methodology incorporates a multi-dimensional analysis involving self-consumption, self-sufficiency, and economic performances, that facilitates the understanding of the trade-offs beyond purely mathematical optima. Additionally, it addresses the critical challenge of temporal misalignment between renewable generation and consumption through a load redistribution strategy. By providing quantitative insights, this framework offers an accessible pathway for logistics facilities to enhance sustainability and resilience from the preliminary planning stages.

The paper is organized as follows: in section 2 is described the proposed methodology for evaluating PV system integration, with the related mathematical models and implementation; section 3 is about its application to a real-world case study; section 4 draws conclusions and outlines future research directions.

2. Methodology

The proposed methodology focuses on the early sizing of a PV-BESS system, to be integrated on the rooftop, with particular attention to robotic warehouses. Its five-step optimization process is illustrated in Fig. 1. In the first stage, the desired Industry 5.0 sustainability and resilience performance are translated into strategic constraints through self-consumption (SC), self-sufficiency (SS), and net-zero range (NZ) thresholds, directly affecting PV system sizing. In the second step, system sizing optimization determines the PV panels and battery storage configuration that minimizes

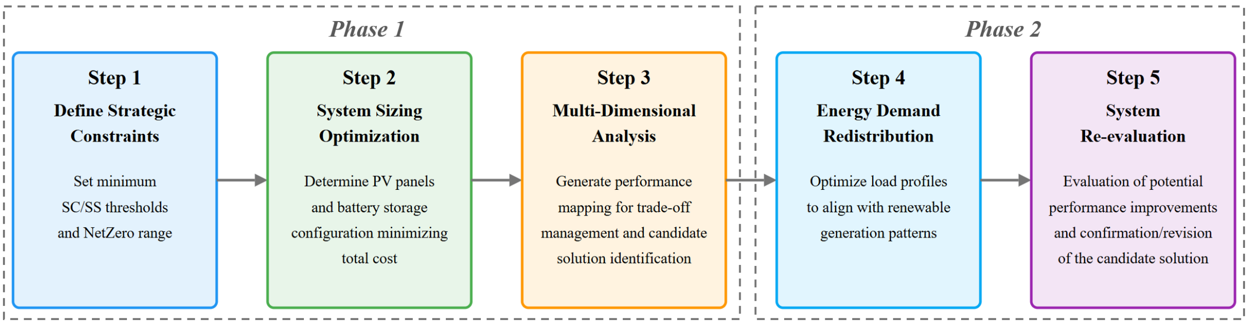

Fig. 1. Optimization process of renewable energy integration from Industry 5.0 perspective.

total cost while respecting strategic constraints. In the third stage, a multi-dimensional analysis reveals trade-offs between economic indicators and energy metrics, enabling informed decisions beyond pure mathematical optima. This allows a company to identify the final solution that better fits the desired economic performance and Industry 5.0 targets. The fourth step focuses on energy demand redistribution of material handling equipment (MHE) and implements load management strategies to enhance self-consumption of renewable energy. Finally, the PV system is re-evaluated with the modified load profile, to assess further potential gains of the current solution or new sizing optimization opportunities. From a modeling and solving perspective, the proposed approach involves a two-phase optimization, mainly ascribed to system sizing (phase 1) and demand management (phase 2). The following subsections present the main equations about the energy system behavior, optimization objectives, and constraints. Then, the implementation approach is described, highlighting the computational architecture supporting each optimization phase.

2.1. Optimization models

The PV-BESS system is modeled in terms of number of PV panels to be installed on rooftops (n_{PV}), and BESS modular units (n_{BESS}). The energy system integrates photovoltaic arrays as the primary renewable source, with battery storage providing temporal flexibility by storing excess production and releasing it when needed. A power conversion system manages DC/AC transformation between components and industrial loads. The system is completed by a bidirectional grid connection that supplies backup power during insufficient renewable generation and accepts surplus energy during excess production periods.

The system behavior is described by a multiperiod model, where index t represents hourly intervals, and aligns with the temporal resolution of data from the European PVGIS (Photovoltaic Geographical Information System) tool [29]. This hourly discretization is particularly valuable for economic optimization, as the model incorporates time-of-use tariffs, accounting for differentiated electricity prices when purchasing from or selling to the grid across various periods of the day. The main parameters and variables is provided in Table 1.

The energy flows of the system are governed by the following fundamental equations:

$$E_{load}(t) = E_{PV}(t) + E_{BESS}(t) + E_{grid}(t) \tag{1}$$

$$E_{PV}(t) = \eta_{PV}(t) \cdot n_{PV} \cdot P_{PV} \tag{2}$$

$$E_{BESS}(t) = \gamma_{dch}(t) \cdot E_{dch}(t) - \gamma_{ch}(t) \cdot E_{ch}(t) \qquad s.t. \quad \gamma_{ch}(t) + \gamma_{dch}(t) \leq 1 \tag{3}$$

$$SOC(t) = \left(SOC(t-1) + \gamma_{ch}(t) \cdot \frac{E_{ch}(t) \cdot \eta_{ch}}{Cap_{BESS} \cdot n_{BESS}} - \gamma_{dch}(t) \cdot \frac{E_{dch}(t)}{Cap_{BESS} \cdot n_{BESS} \cdot \eta_{dch}} \right) \cdot (1 - \lambda_{loss}) \tag{4}$$

Eq. (1) requires that the industrial demand $E_{load}(t)$ is met in each time slot through a combination of photovoltaic production, storage utilization, and grid interaction. Eq. (2) calculates the energy produced by the PV system, where the energy conversion efficiency $\eta_{PV}(t)$ is related mainly to the temperature of the PV module, which in turn depends on the hourly outdoor temperature, the solar in-plane irradiance and the local wind speed of the region and can be derived directly from PVGIS database [29]. The battery storage system operation is defined by Eq. (3), where the binary variables $\gamma_{ch}(t)$ and $\gamma_{dch}(t)$ are used to prevent simultaneous charging and discharging. The state of charge evolution is tracked through Eq. (4), and accounts for charging and discharging efficiency, and the natural self-discharge rate (λ_{loss}).

Grid interactions are valued through time-differentiated selling prices and supply costs (time-of-use tariff):

$$C_{buy}(t) = \max\left[0, E_{grid}(t)\right] \cdot p_{buy}(t) = E_{buy}(t) \cdot p_{buy}(t) \tag{5}$$

$$R_{sell}(t) = \max\left[0, -E_{grid}(t)\right] \cdot p_{sell}(t) = E_{sell}(t) \cdot p_{sell}(t) \tag{6}$$

The objective function guides the PV-BESS system sizing in terms of n_{PV} and n_{BESS} (see Eq. 7). It is defined as the minimization of the total annual cost, and includes annualized investment costs, maintenance costs, energy supply costs from the grid whenever the PV system cannot cover energy requirements, and the revenues from sales of the exceeding renewable energy to the grid. The related equation is as follows:

$$\min_{n_{PV},\, n_{BESS}} \left(C_{invPV} + C_{invBESS} + C_{OM} + C_{buyTOT} - R_{sellTOT} \right) \tag{7}$$

where the subscript TOT with any variable indicates its annual aggregated value.

Table 1. Mathematical model parameters and variables.

Symbol	Type	Description	Value of the Case Study
$C_{invBESS}, C_{invPV}$	Variable	BESS/PV & PCS system annualized investment cost	-
C_{OM}	Variable	System operation and maintenance cost	-
Cap_{BESS}	Parameter	Capacity of a single BESS module	5.12 kWh
$E_{BESS}(t)$	Variable	Net energy exchanged with the BESS at time t	-
$E_{buy}(t),\ C_{buy}(t)$	Variable	Energy/Cost of energy purchased at time t	-
$E_{ch}(t),\ E_{dch}(t)$	Variable	Energy used to charge/discharge the battery at time t	-
$E_{grid}(t)$	Variable	Energy exchanged with the grid at time t	-
$E_{load}(t)$	Parameter	Original energy demand at time t	Load profile
$E'_{load}(t)$	Variable	Redistributed energy consumption at time t	-
E_{min}	Parameter	Minimum operational power requirement	2,000 W
$E_{PV}(t)$	Variable	Energy produced by the PV system at time t	-
E_{robot}	Parameter	Energy required for a micro-charge cycle	70 Wh
$E_{sell}(t),\ R_{sell}(t)$	Variable	Energy/Revenue from energy sold at time t	-
$E'_{surplus}(t)$	Variable	Energy surplus after load redistribution	-
$n_{BESS},\ n_{PV}$	Variable	Number of battery storage modules / photovoltaic panels	-
N_{cs}	Parameter	Number of available charging stations	53
N_{mch}	Parameter	Hourly allowed microcharges	12
N_{robot}	Parameter	Total number of robots in the system	53
$n_{robot}(t)$	Variable	Number of robots charging at time t	-
P_{PV}	Parameter	Nominal power of a single PV module	450 Wp
$p_{buy}(t), p_{sell}(t)$	Parameter	Grid energy purchase/sell price at time t	Company time-of-use tariff, GSE [30]
$SOC(t)$	Variable	Battery state of charge at time t	-
T_{fav}	Set	Time periods with favorable tariff rates	Evening/night hours
T_{flex}	Set	Time periods when flexible charging is permitted	Daytime hours
T_{start}	Set	Time periods when charging is prohibited	Early shift hours
α_{min}	Parameter	Minimum MHE availability requirement	90%
$\gamma_{ch}(t), \gamma_{dch}(t)$	Binary var	Charging/Discharging of BESS at time t	-
$\eta_{ch},\ \eta_{dch}$	Parameter	Battery charging/discharging efficiency	95%, 95%
$\eta_{PV}(t)$	Parameter	Time-dependent PV efficiency coefficient	PVGIS [29]
λ_{loss}	Parameter	Battery self-discharge rate	0.1%/day

The optimization is subject to three strategic constraints translating the company's attitude towards the sustainability and resilience dimensions of Industry 5.0:

$$SC = \frac{E_{loadTOT} - E_{buyTOT}}{E_{PVTOT}} \qquad s.t. \quad SC \geq SC_{min} \tag{8}$$

$$SS = \frac{E_{loadTOT} - E_{buyTOT}}{E_{loadTOT}} \qquad s.t. \quad SS \geq SS_{min} \tag{9}$$

$$NZ = \frac{E_{PVTOT}}{E_{loadTOT}} \qquad s.t. \quad NZ_{min} \leq NZ \leq NZ_{max} \tag{10}$$

These constraints enforce minimum self-consumption (SC) and self-sufficiency (SS) thresholds while maintaining an appropriate net-zero energy ratio (NZ), preventing oversized systems that would prioritize grid energy trading over operational resilience. They represent the novelty of the sizing model with respect to current literature.

The temporal redistribution of energy loads (phase 2), to enhance self-consumption of renewable energy in each day of the year, is modeled by the following main constraints:

$$\sum_{t=1}^{24} E'_{load}(t) = \sum_{t=1}^{24} E_{load}(t) \tag{11}$$

$$E'_{surplus}(t) = \max(0, E_{PV}(t) - E'_{load}(t)) \quad \forall t \in [1, 24] \tag{12}$$

Eq. (11) ensures that the total daily energy demand remains unchanged, while only redistributing load temporally. Eq. (12) calculates surplus energy available during each period for potential storage or grid export.

For warehouses with battery-powered robots, a microcharging strategy can be adopted and modelled as here proposed. A number of robots $n_{robot}(t)$ is sent to charge (see Eq. 13) for a very short time period during working hours, while satisfying the required MHE availability in each time slot as well as the provided charging stations (see Eq. 14).

$$E'_{load}(t) = E_{min} + n_{robot}(t) \cdot E_{robot} \quad \forall t \in T_{flex} \tag{13}$$

$$n_{robot}(t) \leq min\left(N_{robot} \cdot (1 - \alpha_{min}) \cdot N_{mch},\ N_{cs} \cdot N_{mch}\right) \quad \forall t \in T_{flex} \tag{14}$$

$$n_{robot}(t) = 0 \quad \forall t \in T_{start} \cup \{t \mid E_{PV}(t) \leq E_{min}\} \tag{15}$$

$$\sum_{t=1}^{24} n_{robot}(t) \leq \max\left(0, \frac{E_{surplusDAY} - \frac{Cap_{BESS} \cdot n_{BESS}}{\eta_{ch}}}{E_{robot}}\right) \qquad where \quad E_{surplusDAY} = \sum_{t=1}^{24} \max\left(0, E_{PV}(t) - E_{min}\right) \tag{16}$$

Eq. (15) prevents charging during early operational hours and periods with insufficient renewable energy generation. The system prioritizes BESS charging over robot microcharging through Eq. (16), which limits total daily robot charging operations according to the available surplus energy estimated after accounting for BESS charging requirements.

The objective function implements a hierarchical optimization that primarily minimizes energy surplus, while secondarily maximizing consumption during favourable tariff periods:

$$\min\left(\sum_{t=1}^{24} E'_{surplus}(t) - \frac{1}{M}\sum_{t \in T_{fav}} w_t \cdot E'_{load}(t)\right) \tag{17}$$

where M represents a very large number that maintains the hierarchy between objectives, T_{fav} is the set of evening and night hours at the lower supply tariff, and w_t are exponentially decreasing weights that can be introduced to prioritize some preferred periods.

2.2. Implementation

The proposed implementation of the two-phase optimisation framework is described in Fig. 2. The first phase, i.e. the dimensioning process, combines Constraint Programming (CP) with procedural computation. It integrates MiniZinc and C++, achieving both easy modeling and computational efficiency. This approach is particularly valuable whenever an exhaustive enumeration of all possible configurations is computationally prohibitive. We addressed this challenge by extending the `fzn-minicpp` solver [31], a C++ version of MiniCP [32] that supports the MiniZinc modeling language. During optimization, MiniZinc manages the constraint propagation and search strategies, while C++ handles the calculations for energy balance and economic evaluation. The dimensioning phase processes data on

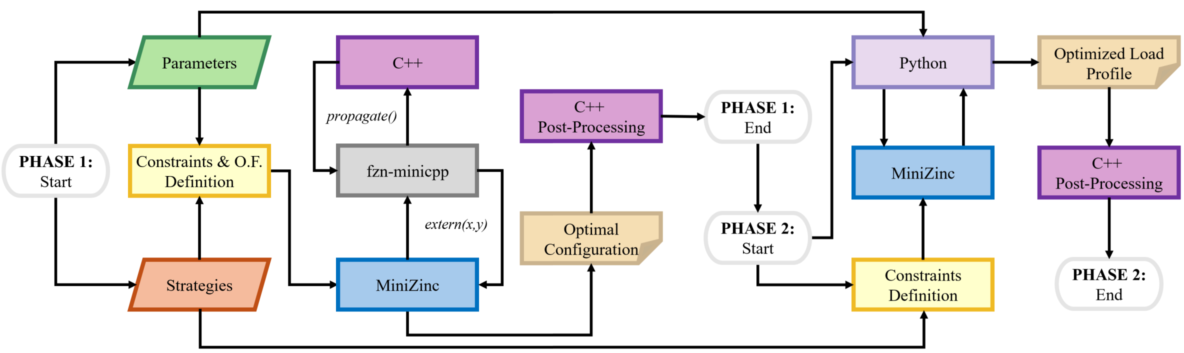

Fig. 2. Two-phase optimization framework: system dimensioning through constraint programming and procedural computation integration (Phase 1) and energy demand redistribution through iterative daily optimizations (Phase 2).

an hourly basis for a full year. For each candidate solution, the solver invokes C++ functions to compute performance indicators that guide the optimization trajectory. The CP component efficiently prunes infeasible regions without explicit evaluation, outperforming traditional enumeration techniques. After that the optimal configuration has been identified, a post-processing phase employs the same C++ to analyze the complete performance profile of the solution. This assessment is followed by an exploration of the solution neighborhood. It systematically evaluates alternative configurations by incrementally varying component quantities within defined intervals.

The second phase processes daily 24-hour instances through an integrated Python-based framework using MiniZinc to optimize consumption patterns. The optimization generates new daily load profiles that, when combined, create an optimized annual consumption pattern. Such pattern is further processed through the C++ model used in phase one, to quantify potential improvements in key performance indicators for the selected system configuration, if demand response strategies are enabled after installation. It also establishes the methodological foundation for future predictive optimization systems operating on day-ahead forecasts.

3. Case Study

The proposed methodology has been applied to an automated logistics facility located in Northern Italy. It adopts a robotic compact warehouse system with battery-powered mobile robots operating two 6-hour work shifts from 7:00 to 19:00, with potential to cover three shifts. A significant challenge in this application is the temporal misalignment between photovoltaic production and energy consumption. Robot charging takes place mainly in the evening at the end of the second shift (see the red line in Fig. 3), making necessary the adoption of a battery to exploit renewable energy. To embrace the Industry 5.0 perspective, the company has set a minimum threshold of 40% for both self-consumption and self-sufficiency, as well as maintaining the net-zero energy ratio within the specified range of 1.0-1.5, the latter to accommodate the potential increase in energy requirements due to the introduction of a third shift.

The models are implemented using MiniZinc version 2.6.4 employing the `fzn-minicpp` solver integrated with C++17 for Phase 1, and the COIN-BC 2.10.8 solver for Phase 2. All experiments were carried out on a workstation equipped with Windows 11, 32 GB RAM, and an Intel Core i7-14700 running at 2.10 GHz. The system sizing optimization (Phase 1) completed in 43 seconds, while the load redistribution analysis (Phase 2) required 38 seconds to process all 365 daily scenarios. Hourly energy PV efficiencies were retrieved from PVGIS database [29] by averaging the last 5 available years for the location.

For specific investment costs, PV system was valued at 1021 €/kWp based on national survey data [33], while the battery storage modules at 1800 €/unit according to local suppliers' quotations. The operation and maintenance costs were set at 10 €/kWp annually for the PV system and at 2% of the investment cost for the battery modules. The lifetime of the system components was set to 24 years for PV panels and 12 years for BESS modules, requiring a battery replacement at mid-system lifetime. Financial parameters included an inflation rate of 2%, consistent with ECB targets, and a discount rate of 5%. Energy pricing followed the time-of-use tariff negotiated by the company with its energy supplier, while renewable energy selling prices were derived from the Italian Energy Service Company [30].

The first dimensioning phase determined a minimum cost configuration of 70 photovoltaic panels (31.5 kWp) and 5 Li-ion battery modules (25.6 kWh total storage capacity), reaching a self-sufficiency of 55.8%. Considering the Italian electricty generation factor of 0.225 $kgCO_2e$/kWh [34], greenhouse gas emissions of 3718 $kgCO_2e$/year are avoided by replacing energy supply from the grid with renewable energy. This size leads to a self-consumption of 40.4%, meeting the minimum requirement, while the net-zero energy ratio of 147.4% is aligned with the upper bound of the allowed range. Thus, while the potential for PV generation is fully exploited, energy storage is kept at the minimum required to satisfy self-consumption due to its high investment costs. In Fig. 3 the energy flows of two representative days in summer and winter are illustrated. The solution presents an initial investment of 41161 €, annual operation and maintenance costs of 495 €, annual energy savings from renewable self-consumption of 2780 €, and grid sales of 3159 €. It demonstrates positive returns, with a Simple Payback Period equal to 7.6 years, about a third of the system expected lifespan, and a Net Present Value (NPV) of 44923 €.

The post-processing analysis generates the multi-dimensional performance mappings in Fig. 4. It shows different configurations when varying PV power (color) and battery storage capacity (symbols), with NPV values represented by the bubble size. The yellow bubble with the + symbol represents the best configuration within the previously established constraints, while this analysis extends beyond to examine alternative configurations and their impact on

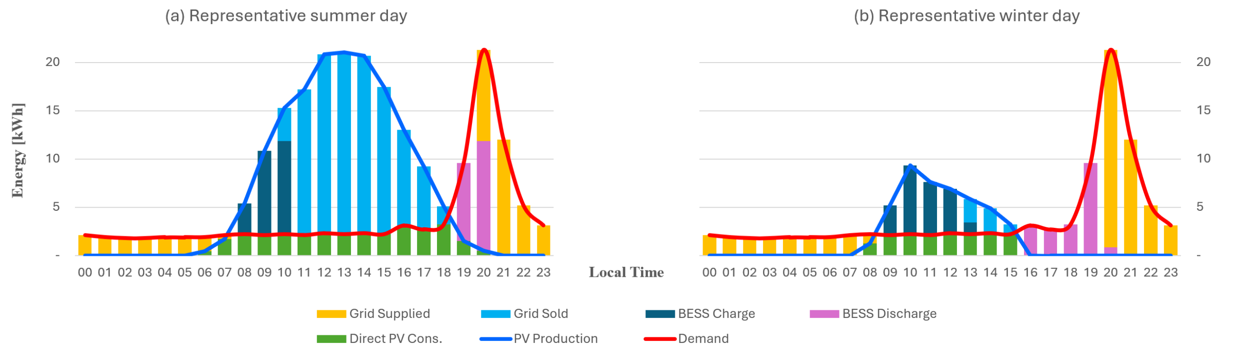

Fig. 3. Energy flows for a Tuesday in June (a) and December (b).

KPIs. Increasing PV power (e.g. 45.0 kWp, blue bubbles) leads to the highest NPV values but negatively impacts self-consumption since the system is oversized, and slightly affects self-sufficiency. These configurations were considered not feasible in the previous optimization, as they exceed the net-zero energy ratio limit (e.g. 210.6% for blue bubbles). For a given number of PV panels, increasing battery capacity substantially enhances both self-sufficiency and self-consumption, since renewable energy can be used in the evening to charge the robotic fleet. However, economic performance is reduced. In this case study, the optimal solution was confirmed as aligned with company's goals and transferred to the second phase.

The demand redistribution relies on high-power battery charging mode, implementing 5-minute microcharging sessions that provide a robot with enough energy for one hour of operational autonomy (70 Wh). To maintain warehouse productivity, a minimum fleet availability of 90% is required, so that at most 10% of robots can be charged simultaneously. Each robot is limited to a maximum of one microcharging session per hour, and no microcharging can occur during the first three working hours to ensure sufficient battery depletion. In the evening, the controlled charging mode is activated to extend the robot battery lifespan while ensuring all robots are sufficiently charged for the following day operations. Starting from the lowest energy supply cost period (23:00), a more conservative charging rate is activated, resulting in a controlled power consumption of approximately 8 kWh for charging plus 2 kWh for the warehouse baseline consumption. The temporal redistribution of charging operations for two representative days is illustrated in Fig. 5. Note how the energy profiles differ from the original ones in Fig. 3. The load redistribution, if actually implemented, can lead to remarkable improvements across all key performance indicators without

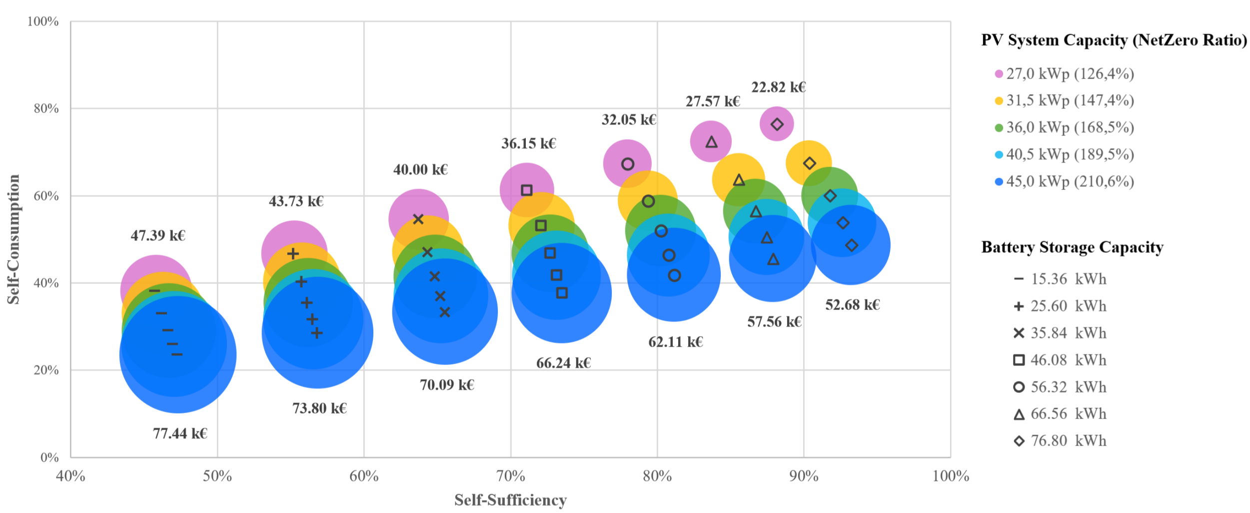

Fig. 4. Configuration trade-off analysis between self-consumption, self-sufficiency, and NPV (bubble size).

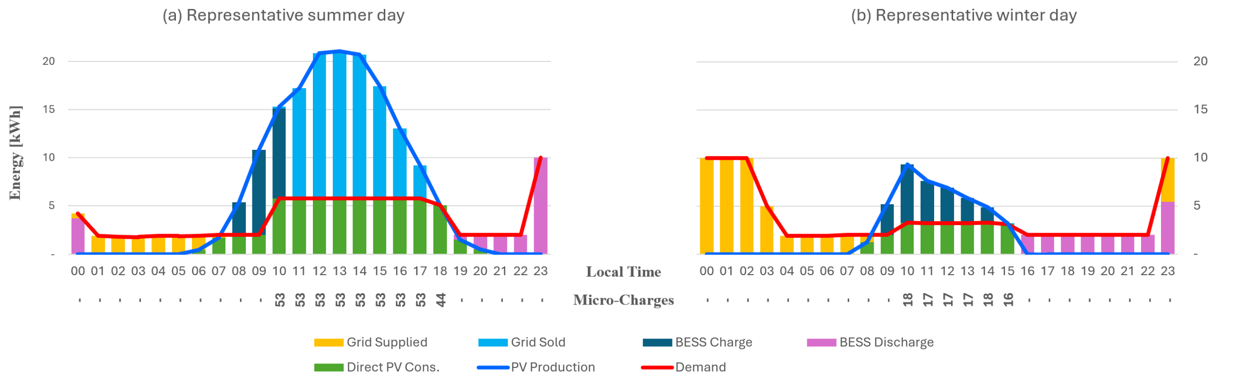

Fig. 5. Energy flows with microcharging strategy for a Tuesday in June (a) and December (b). Numbers below each graph indicate total robots scheduled for microcharging during each hour.

requiring any additional capital investment. Self-sufficiency increases substantially from 55.8% to 77.9% with avoided emissions of 5195 kgCO_2e/year, while self-consumption rises from 40.4% to 56.0%, leading to greater environmental sustainability and resilience. From an economic perspective, the annual total cost decreases by 10.9%, mainly due to energy saving during daylight at the highest tariff. The payback period is shortened to 7.3 years, improving the attractiveness of the investment. Thus, the commitment to renewable energy integration can be enforced.

4. Conclusions

This study presents a methodological framework that embeds Industry 5.0 principles into renewable energy feasibility studies, by integrating self-consumption, self-sufficiency, and net-zero energy metrics as optimization constraints. The methodology empowers organizations to pursue sustainability and resilience goals confidently from the earliest planning stages, ensuring that renewable energy investments align with long-term strategic vision. This is achieved by a combination of Constraint Programming and procedural computation, that allows for a rapid exploration of the solutions space. Then, a multi-dimensional analysis reveals the relationships between system configuration, sustainability and resilience performances, and economic outcomes. By making these trade-offs clear and more comprehensible, decision makers can iteratively refine their objectives and identify configurations that genuinely reflect organizational commitments to the Industry 5.0 vision. Moreover, anticipating the analysis of potential demand response strategies in the early design phase enforces the selection of the proper PV-BESS system solution and the final commitment to renewable integration. Demand redistribution can also be regarded as an indicative assessment of potential improvements achievable in the future, by adopting predictive optimization based on climate and operational forecasts. The proposed methodology has been successfully tested with real data from a robotic warehouse, proving its validity.

While the sizing phase is scalable to larger and more complex logistics systems, the demand response model specifically relies on microcharges of the robotic fleet and can be applied to warehouse configurations where MHE can be subjected to opportunity charging. To overcome such limitation, a possible extension of this work consists of enhancing the second phase of demand distribution by modelling other types of storage and retrieval systems. Furthermore, to fully embrace Industry 5.0, the human centricity pillar can be introduced by considering workers' rest periods in the demand response strategy.

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