Pioneering Green and Energy -Efficient Material Handling: A Decision Support System for Battery Charging Strategy Selection in Warehouse Operations

Cannava L. *, Ferraro S. **, De Carlo F. **, Perotti S. *

** Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Via Lambruschini 4/B, 20156 – Milan – Italy (luca.cannava@polimi.it; sara.perotti@polimi.it)*

*** Department of Industrial Engineering (DIEF), University of Florence, Viale Morgagni, 40 59100 – Florence – Italy (saverio.ferraro@unifi.it; filippo.decarlo@unifi.it)*

Abstract: The demand for faster and more efficient supply chain operations has increased the need for higher performance in warehouse management, particularly in material handling (MH) activities. MH processes contribute significantly to warehouse energy consumption, particularly in forklifts, where battery charging can account for 40-50% of total energy usage in ambient-temperature warehouses. This underscores the necessity for energy-efficient charging strategies that do not compromise warehouse operational activities. Although the topic is of increasing relevance, the literature lacks decision-making tools for both academics and practitioners (Zajac & Rozic, 2022). To address this challenge, this study proposes a decision support system (DSS) to evaluate the optimal charging strategy for electric forklifts, considering both opportunity charging (OC) and battery energy storage system (BESS) integration. OC aims to leverage photovoltaic (PV) surplus energy during peak generation periods, while BESS aims to store surplus energy and optimize charging times. For the selection of optimal charging strategy, the study follows a three-phase methodology: data collection, charging strategy evaluation, and scenario selection. In the data collection phase, information on warehouse operations, energy consumption, and energy production from PV panels are gathered. OC and BESS integration are then assessed economically and environmentally. Finally, the developed DSS assists facility managers in selecting the most suitable charging strategy based on their specific warehouse characteristics and operational requirements. Findings suggest that the optimal charging strategy depends on multiple warehouse features such as operational tasks and solar energy surplus. On one hand, OC is effective in facilities with high PV generation and predictable energy demand patterns. On the other hand, BESS integration offers flexibility for facilities with more variable energy demands. This study contributes to the advancement of green warehousing concept by providing a systematic approach to evaluating and implementing energy-efficient forklift charging strategies. Implications are discussed and streams for future investigation are reported.

Keywords: Sustainable Warehousing, Decision Support System (DSS), energy-efficiency, Material Handling.

1. Introduction

The role of warehouses in the supply chain has dramatically changed over time to effectively address multiple challenges such as the competitive pressure arising from the increasing demand of shorter delivery time to the final customers (Baglio et al., 2020). This transformation is even boosted by the rise of e-commerce which has led to a paradigm shift in warehouse operations, design, and management, where efficient material handling (MH) activities are essential to ensure faster and more precise lead times (Mangiaracina et al., 2016). MH is a key aspect of warehousing operations, with significant implications for operational efficiency and cost reduction. MH is also crucial, as well as for warehouse greenhouse gas (GHG) emissions – often measured in terms of carbon dioxide equivalent (CO_{2e}) – due to the large amount of energy required (Modica et al., 2021). The energy consumption of MH processes significantly contributes to warehouse environmental impact, accounting for up to 40-50% of the total energy usage in unchilled warehouses (Dobers et al., 2023). Academic research on energy efficiency practices of MH processes has intensified due to their significant impact on energy consumption and emissions, further powered by the emergence of sustainable logistics practices (Onstein et al., 2019; Baglio et al., 2020). These practices are grounded on the concept of Green Warehousing (GW), defined by several scholars as the organisational approach that incorporates environmentally friendly practices within a warehouse with the primary objective of reducing energy consumption, lower energy expenses and mitigate GHG emissions (Oloruntobi et al., 2023; Bartolini et al., 2019; Dubey et al. 2017). Nevertheless, most of the studies have essentially focused on reducing the energy consumption of MH equipment itself, rather than addressing the primary source of energy demand, which in the case of electric forklifts is related to the battery charging process. According to (Oloruntobi et al., 2023), the most widely discussed topic in this context is related to the energy-aware Vehicle Routing Problem (VRP) aiming to optimize the related-energy consumption. As far as the authors know, a comprehensive literature analysis on energy-reducing strategies for MH battery charging processes still lacks in the literature.

In this context, on-site renewable energy generation units such as photovoltaic (PV) panels could pave the way for the application of new battery charging strategies. In the building market, global installation for PV panels has notably increased, due to improvements in efficiency and costs, reaching a global power capacity of 1,185 GW (IEA, 2023). Nonetheless, not all the energy generated is self-consumed because of the mismatch between the energy generated by PV panels (i.e., which has a random pattern profile strictly dependent on the availability of sunlight) and the building's energy demand (i.e., driven by their specific operations and activities). During periods of low energy demand, PV panels may generate a lot of electricity surplus, which if not used or stored on-site, is either fed back into the grid or dissipated, leading to economic inefficiencies and energy waste (Dadras Javan et al., 2023). However, this energy surplus could mitigate operational costs and environmental impact of battery charging processes of MH equipment if properly exploited enhancing self-consumption ratio of a logistics facility. For this purpose, two primary strategies emerged from literature to effectively harness this energy surplus (Waldron et al., 2022; Aravindaraj & Chinna 2022; Modica et al., 2021): a) Opportunity charging strategy (OC) – i.e., strategy that performs partial fast charges - which could bring substantial benefits if performed during PV peak generation timeframe (i.e., it is strictly dependent on the aleatory performance of sunlight availability); b) Battery Energy Storage System (BESS) – i.e., energy storage systems that can be integrated into grid-connected PV systems – which could increase solar power utilization efficiency by providing energy to recharge the batteries of the MH equipment. By implementing these strategies, logistics facilities can maximize the utilization of surplus solar energy, reducing operational expenses, enhancing sustainability, and paving the way for a greener future of logistics operations. However, highlighting the most cost-effective and environmentally friendly solution is extremely challenging and evidence from previous studies is still lacking.

The paper aims to fill this gap by employing a simulation-based research process to compare different charging strategies for electric forklifts. The study aims to evaluate the best charging strategy under various boundary conditions (variables, parameters, constraints). This analysis is not tied to any business sector and aims to be suitable for all types of logistics facilities. To ensure robustness and to identify and assess the effectiveness of battery charging processes, a Decision Support System (DSS) has been adopted to address the complexity and uncertainty inherent in the logistics systems. A DSS can be defined as a computer-based information system that provides interactive support to logistics and supply chain management operations in making decisions by analysing relevant data and presenting it in a comprehensible format (Fanti et al., 2015). Within this work the DSS is provided to support the selection of the best electric forklift charging strategy addressing multiple operating and management parameters (Malinowska, 2022). The remainder of the paper is structured as follows. Section 2 analyses the methodology used for conducting the analysis. Section 3 presents the formulated mathematical models while results with an in-depth discussion are reported in Section 4. To conclude, the main findings are drawn and suggested directions for further research are provided.

2. Methodology

A three-phase methodology has been developed to evaluate the feasibility of different strategies for electric forklift charging process. This methodology has followed the structured framework outlined in Figure 1, comprising three main phases: problem definition, data preprocessing, and scenario selection. The problem definition phase encompasses two specific sub-phases: mathematical modelling and data definition. More in detail, two mathematical models are formulated - one for the cost analysis and the other for the environmental one - to assist in selecting the optimal scenario. The necessary data are defined by consulting the literature and the secondary sources. Following the problem definition, the data preprocessing phase is executed. Here, data for each mathematical model are generated, and relevant variables with a significant impact on determining the optimal scenario are identified using a feature selection algorithm. Finally, in scenario selection, the optimal battery charging strategy is determined through significant classification functions of the most relevant parameters for both economic and environmental assessments are provided as DSS.

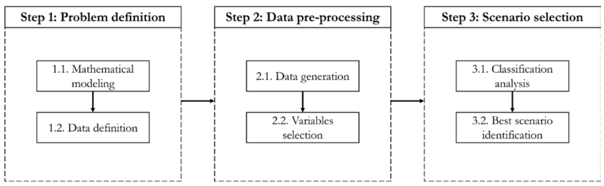

Figure 1: Three-step methodological framework

In the data generation phase, a Sobol quasi-random low discrepancy sequence is employed as the generation strategy (Sobol and Levitan, 1999). The sequence generates a series of uniformly distributed intermediate values, as described in Equation 1. Each parameter (par) is generated as a set of values limited by lower ($par_{lower\ value}$) and upper ($par_{upper\ value}$) values uniformly distributed through Sobol sequence (S).

$$par = par_{lower\ value} + S \cdot (par_{upper\ value} - par_{lower\ value}) \quad (1)$$

Before proposing the DSS for selecting the best strategy for the electric forklift charging process, it is necessary to reduce the number of variables by employing a feature selection approach (Diaz and Jiju, 2022). The use of these approaches allows for better results in terms of the accuracy of the DSS. In this study, the Minimum Redundancy Maximum Relevance (mRMR) algorithm was chosen due to its broad applicability across various problem types (Bugata and Drotar, 2020). The mRMR algorithm, through a joint optimization problem, weights variables with high correlation to the output (in this case, the decision regarding the optimal electric forklift charging strategy) and low mutual correlation (Radovic et al., 2017). Finally, the dataset derived from the data pre-processing stage was utilized to create classification functions based on significant parameters. The classification functions are created by interpolating the boundary points, based on a certain percentile from the extreme, of one of the two alternatives, allowing the identification of a classification curve among the available solutions. To evaluate the accuracy of the identified function, the accuracy measure (Acc), as in Equation 2, is used as a performance parameter of the DSS.

$$Acc = \frac{No.\ scenarios\ correctly\ classified}{Total\ No.\ of\ scenarios} \quad (2)$$

3. Model description

Selecting the optimal charging strategy for MH equipment hinges on evaluating two mathematical models that compare economic and environmental factors. Both analyses investigated the key features of the two systems being compared to calculate their annual total costs and the yearly savings in CO_2e. The optimal electric forklift charging strategy is determined by these mathematical models through the evaluation of the variables outlined in Table 1, focusing on the minimum annual total cost and maximum total annual carbon emission savings. These models operate on the following assumptions:

A. The evaluation considers a system where Li-Ion batteries are utilized for the OC strategy, recharged via a high-frequency system, and a singular storage system for the BESS strategy, which recharges vehicle batteries using a 50 Hz system.

B. OC strategy occurs once daily after half of the daily operational hours, necessitating a pause in vehicle activity during recharge periods. To make up for the reduced throughput capacity, an increase in the number of vehicles was estimated so that both adopted solutions have the same throughput capacity being fulfilled.

C. Both systems are assumed to have identical daily energy consumption, implying that a greater number of vehicles are required for the OC strategy compared to the BESS strategy.

D. Integration with a PV panel system is a common feature of both strategies. In the OC strategy, vehicle batteries are recharged using excess energy within not operating time intervals, while in the BESS strategy the batteries are recharged at the end of the workday based on the stored energy levels. In the considered scenario analysis, OC is carried out at a fixed time, i.e. during work shifts and breaks. For this reason, in the analysis of the OC strategy, the hours in which the vehicles are charged are compensated by increasing the number of vehicles to ensure the same throughput capacity and achieve the same daily energy demand of vehicles for BESS scenario strategy.

E. The evaluation of energy consumption focuses on Jungheinrich EFG-220 forklift which is one of the most popular in the logistics industry (Zajac & Rozic, 2022) energy consumption is based on single command cycles for storing or retrieving.

F. The annual economic assessment adopts a similar time horizon for both strategies, during which the degradation of involved components is not factored in.

Table 1: Nomenclature for mathematical modeling

Index	Description	Unit of measure
i	Type of battery charging strategy. $i = 1,2$	-
Decision variable(s)	**Description**	**Unit of measure**
C_{TOT}	Total annaul operating costs for charging activities	€
E_{TOT}	Total annual carbon emission savings	kg CO_{2e}
Auxiliary variable(s)	**Description**	**Unit of measure**
$C_{battery_i}$	Annual costs of fleet battery	€
$C_{devices_i}$	Annual costs of battery charging devices	€
$C_{storage_i}$	Annual costs of energy storage	€
S_{energy_i}	Annual savings of energy consumption	€
S_{carbon_i}	Annual savings of carbon emission	kg CO_{2e}
Input parameter(s)	**Description**	**Unit of measure**
$vehicles_i$	No. of vehicles	No.
h_{day}	No. of daily operating hours	h
$THR_{capacity}$	Average daily throughput capacity for MH activities	No. Cycle/day
$r_{design_{BESS}}$	Share of BESS capacity design	%
$r_{overproduction}$	Share of energy overproduced for MH activities	%
h_{OC}	No. of OC hours	h
$c_{vehcile\ battery}$	Cost of single vehicle battery per kWh	€/kWh
c_{BESS}	Total capital cost of BESS per kWh	€/kWh
c_{energy}	Cost of energy per kWh	€/kWh
$c_{devices}$	Cost of single charging device	€
$Q_{battery}$	Effective vehicle battery capacity	kWh
η_{rf}	Charging efficiency for regulated frequency (50 Hz)	-

η_{hf}	Charging efficiency for high frequency (300 Hz)	-
gg	No. of working days per year	day
$V_{energy\ cons}$	Vehicle energy consumption per single cycle	kWh/cycle
V_u	Vehicle utilization factor	-
c	CO_{2e} conversion factor	kg CO_{2e}/kWh

Within both mathematical models, the variable i represents the electric forklift battery charging strategy. Specifically, when $i = 1$, it denotes the OC strategy, and when $i = 2$, it refers to the BESS strategy. The first mathematical model assesses the annual total cost (C_{TOT}) of the MH equipment charging strategy by comparing the two alternatives based on the following objective function in Equation 3.

$$\min[C_{TOT}] \ for\ i = 1{,}2 \tag{3}$$

The decision variable C_{TOT} considers additively auxiliary variables: the annual cost of fleet batteries ($C_{battery_i}$, Equation 4), the annual cost of battery charging devices ($C_{devices_i}$, Equation 5), the annual cost of energy storage ($C_{storage_i}$, Equation 6), net of the annual energy savings (S_{energy_i}, Equation 7).

$$C_{battery_i} = \begin{cases} \frac{C_{vehicle\ battery}}{Y} * Q_{battery} * vehicles_i \ for\ i = 1 \\ 0 \ for\ i = 2 \end{cases} \tag{4}$$

$$C_{devices_i} = \begin{cases} \frac{C_{devices}}{Y} * devices \ for\ i = 1 \\ 0 \ for\ i = 2 \end{cases} \tag{5}$$

$$C_{storage_i} = \begin{cases} 0 \ for\ i = 1 \\ \frac{C_{BESS}}{Y} * Q_{BESS} \ for\ i = 2 \end{cases} \tag{6}$$

$$S_{energy_i} = \begin{cases} Grid_{cons_1} * gg * r_{overproduction} * c_{energy} \ for\ i = 1 \\ Q_{BESS} * gg * c_{energy} \ for\ i = 2 \end{cases} \tag{7}$$

Where Q_{BESS} denotes the energy capacity of the storage system, measured by Equation 8 calculated as the product of the design parameter ($r_{design_{BESS}}$) and the excess energy (E_{excess}), which, from a technological perspective, must not exceed 1,400 kWh according to Chen et al., (2011). In further detail, $r_{design_{BESS}}$ specifies the storage system's size to supply energy to the material handling loads, by reducing reliance on the electrical grid during demand peaks and providing power to the load during insufficient renewable source production (Noorollahi et al., 2020). Thus, this parameter is defined as the ratio between energy stored by BESS and the energy required by the electric vehicle fleet. In turn, the parameter E_{excess} is determined by Equation 9, identified as the product of the overproduced energy by the PV panels ($r_{overproduction}$) and the energy required for MH equipment activities ($Grid_{cons_2}$).

$$Q_{BESS} = r_{design_{BESS}} \cdot E_{excess} \tag{8}$$

$$E_{excess} = r_{overproduction \cdot Grid_{cons_2}} \tag{9}$$

In this regard, both systems are evaluated basing on the energy required for MH equipment activities ($Grid_{cons_i}$, Equation 10). This energy is assessed according to the daily demand ($Daily_{energy_i}$, Equation 11) from the vehicle fleet ($vehicles_i$). Specifically, the daily demand is measured relying on the average hourly throughput capacity ($THR_{capacity}$), the number of hours the vehicles are engaged in operational activities (h_{day}), and the energy consumption per single cycle ($V_{energy\ cons}$). Finally, based on assumption C, $vehicles_1$ is measured as a function of $vehicles_2$(Equation 12) imposing the same energy consumption $Grid_{cons_i}$, for both charging strategies.

$$Grid_{cons_i} = \begin{cases} \frac{Daily_{energy_1}}{\eta_{hf}} \cdot vehicles_1 \ for\ i = 1 \\ \frac{Daily_{energy_2}}{\eta_{rf}} \cdot vehicles_2 \ for\ i = 2 \end{cases} \tag{10}$$

$$Daily_{energy_i} = \begin{cases} THR_{capacity} * (h_{day} - h_{OC}) * V_{energy\ cons} * V_u \ for\ i = 1 \\ THR_{capacity} * h_{day} * V_{energy\ cons} * V_u \ for\ i = 2 \end{cases} \tag{11}$$

$$vehicles_1 = \frac{h_{day}}{(h_{day} - h_{OC})} \cdot \frac{\eta_{hf}}{\eta_{hz}} \cdot vehicles_2 \tag{12}$$

The second mathematical model, on the other hand, assesses the environmental effectiveness between the two MH equipment charging strategies based on the annual carbon emission savings (E_{TOT}), evaluated according to the objective function in Equation 13.

$$\max[E_{TOT}] \ for\ i = 1{,}2 \tag{13}$$

The decision variable considers the sole auxiliary variable S_{carbon_i} as a function of the annual energy consumption savings S_{energy_i} via the conversion coefficient c, as shown in Equation 14.

$$S_{carbon_i} = S_{energy_i} \cdot c \tag{14}$$

4. Results and discussion

Within this study, 10,000 Sobol generations were launched for each input parameter (Table A1) to evaluate both models, aiming to identify the optimal MH equipment charging strategy from both an economic and environmental perspective. For both models, where necessary, a 10-year time horizon was considered to annualize the cost items representing the incurred investment costs. Regarding the economic analysis, the comparison between the two alternatives highlights the cost-effectiveness of the OC strategy in 27 % of cases and that of BESS in 73 % of cases. As for the environmental analysis, the advantage is not as clear-cut, with a majority favoring OC in 51 % of cases compared to BESS in 49 % of cases. However, these ratios do not provide practitioners with enough insight to reconsider their processes and evaluate the best electric forklift charging strategy. To address this issue, following the methodology proposed in this study, the mRMR procedure identifies the significant parameters to outline the classification curve, which determines the most advantageous strategy - from economic and environmental perspectives - under varying input conditions. Concerning the economic assessment, the parameters with the highest scores are $THR_{capacity}$

with a value of 0.1915, $r_{overproduction}$ with a score of 0.1665. For the environmental assessment, the parameter $r_{design_{BESS}}$ stands out as the most relevant, registering a score of 0.6834. Based on these considerations, a three-dimensional scatterplot comparison of strategies for both analyses can be presented in Figures 2 (economic assessment) and Figure 3 (environmental assessment). In these graphs, blue dots represent the OC strategy, while yellow ones represent the BESS strategy. These representations offer a practical DSS by depicting specific classification curves represented by hyperplanes, described by suitable functions of relevant parameters obtained from the mRMR procedure. For the economic assessment, a classification curve was utilized using interpolation points at a boundary equal to the 5th percentile of the minimum value of the OC solution. The interpolation function used was a power function of the form $f(x) = ax^b + c$, considering $THR_{capacity}$ as the independent variable and $r_{overproduction}$ as the dependent variable.

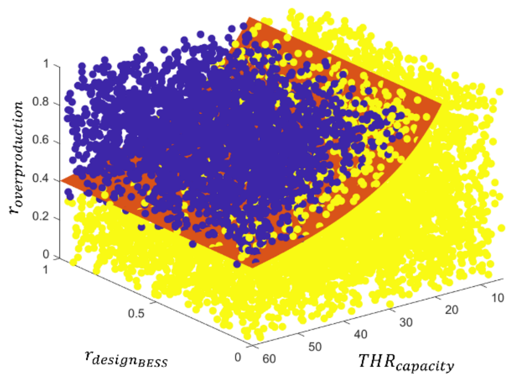

Figure 2: Classification analysis for economic assessment

For the environmental assessment, interpolation points were instead derived from a boundary represented by the minimum value of the BESS solution. Unlike the economic assessment, the classification function is of a first-order linear nature, described by the function $f(x) = ax + b$, where the independent variable is $THR_{capacity}$ and the dependent variable is $r_{design_{BESS}}$.

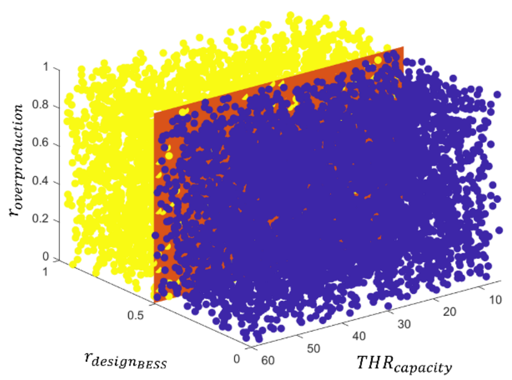

Figure 3: Classification analysis for environmental assessment

The outcomes of both classification curves, as shown in Table 2, underscore the economic feasibility of the OC strategy when the values for $THR_{capacity}$ and $r_{overproduction}$ values escalate. At the same time, they reveal a deterministic trend in selecting the environmentally optimal strategy, which is determined by the $r_{design_{BESS}}$ value. This parameter indicates that BESS strategy is preferred for values exceeding 0.5 of the design parameter, regardless of other variables considered. Nevertheless, for high $THR_{capacity}$ values (i.e., higher than 40) BESS strategy is economically suitable only for those cases where excess renewable energy is not particularly high (i.e., $r_{overproduction}$ less than 0.4). The economic viability of the BESS solution is challenged by the high storage requirements arising from the significant excess energy generation combined with the high $THR_{capacity}$ (which means huge energy consumption of MH equipment). Thus, Li-Ion batteries cost and storage facilities needed for such large solutions are too expensive to make economically convenient. For this reason, for those cases where $THR_{capacity}$ and $r_{overproduction}$ values are both high (i.e., higher than 40 and 0.4 respectively) the most convenient solution is OC strategy. These findings are reinforced by the classification curves, which show high accuracy (Acc) for both analyses: 94 % for the economic assessment and 99 % for the environmental one. Furthermore, there are commendable metrics regarding goodness-of-fit parameters (i.e., SSE, R-sq, Adj R-sq, RMSE).

Table 2: Classification curve parameters

Parameter	Economic assessment	Environmental assessment
percentile	5th	min
a	9.719	-7.861e-06
b	-0.784	0.5083
c	0.01352	-
Acc	94.37%	99.74%
SSE	0.02581	0.003283
R-sq	0.9712	0.0002753
Adj R-sq	0.9712	-0.01824
RMSE	0.02606	0.007797

5. Conclusion

Logistics facilities play a key role in the sustainability paradigm due to their increasing environmental impact, leading to a growing interest in sustainable and energy-efficient practices. MH is one of the most energy-intensive warehousing activities and contributes significantly to the environmental impact of warehouses. In this context, on-site renewable energy generation units could pave the way for a sustainable transition of logistics facilities by providing additional energy to warehouse operations. However, renewable energy sources (e.g., wind, solar, hydro) are associated with high unpredictability, and their ability to provide energy only for certain periods of time. To cope with this new challenge, two primary strategies emerged from literature to effectively mitigate the MH energy demand mismatch: OC strategy and BESS strategy. This contribution aims to assess the main features of these strategies by highlighting the variables that most significantly impact on the performance of such solutions and their related effectiveness from environmental and economic perspectives. Based on a three-phase methodology, a comparative analysis was conducted by highlighting the most relevant decision variables, their relationships, and the main differences based on a cost-effective and environmentally friendly perspective. A simulation-based approach was proposed to classify and select the best-case scenarios and provide practitioners with crucial insights to help them rethink their processes and evaluate the best electric forklift charging strategy. Results show that the average daily throughput capacity for MH activities ($THR_{capacity}$) and the share of energy overproduced for MH activities ($r_{overproduction}$) are the most significant parameters from an economic perspective in line with Zajac & Rozic (2022). On the other hand, in accordance with Hassan et al. (2024), the share of BESS capacity design ($r_{design_{BESS}}$) stands out as the most significant one from an environmental perspective.

This study offers both academic and practitioner-oriented implications. From an academic perspective, the study sheds light on GW strategies by offering a comparative analysis of key solutions for enhancing warehouse self-consumption, specifically focusing on MH equipment, thereby filling an identified literature gap (Topalović et al., 2022; Zajac & Rozic 2022). From a managerial perspective, these findings can guide and support practitioners engaged in decision-making processes aimed at increasing warehouse sustainability. This research sets the stage for future studies on optimizing and increasing self-consumption within logistics facilities. There are multiple available solutions that lack comprehensive economic and environmental analysis. Therefore, this study serves as a starting point for future lines of research that align with current academic trends (e.g., environmental and economic sustainability at logistics facilities) and meet practitioners' needs (e.g., aligning with sustainability objectives and selecting the most appropriate GW solutions).

Although the results of the study fill a major gap identified in the existing literature, there are some limitations. Specifically, maintenance costs, battery replacement expenses and some relevant metrics (e.g., Return on Investment, Payback Period, Net Present Value, etc.) were neglected. Nevertheless, this contribution can offer a starting point for future developments. Firstly, the comparative analysis can be extended by considering other strategies for MH equipment battery charging process, such as battery swapping strategy. Secondly, the framework developed can be further improved by providing bi-dimensional scatter plots (i.e., of the most significant parameters: $THR_{capacity}$ and $r_{overproduction}$), aiding companies in easily identify the most suitable strategy based on their warehouse operational characteristics. Thirdly, a detailed economic evaluation could be performed by providing a comprehensive cost analysis of the investigated electric forklift charging stra tegies. Lastly, the model could be applied in different industry sectors and logistics contexts, to evaluate how the different warehouse features (e.g., warehouse temperature, processes, size, location) could impact the results obtained, by exploring different implications of the investigated solutions. Finally, the effect of trends and seasonality on MH energy consumption and related emissions can be further investigated and incorporated into the DSS.

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Appendix A

Table A1: Values of the input parameters for mathematical modelling

Parameter	Min	Max	Reference
$vehicles_{BESS}$	5	30	Zajac & Rozic (2022)
h_{day}	12	16	-
$THR_{capacity}$	5	60	Jungheinrich (2024)
$r_{design_{BESS}}$	0.01	0.99	Akinyele & Rayudu (2014); Topalović et al. (2024)
$r_{overproduction}$	0.01	0.99	Ul Hassan et al. (2024)
h_{OC}	1	3	Modica et al. (2021)
$c_{vehicle\ battery}$	140	140	Jungheinrich (2024)
c_{BESS}	843	843	Topalović et al. (2022)
c_{energy}	0.23	0.23	ISPRA (2022)
$c_{devices}$	1500	1500	ISPRA (2022); Modica et al. (2021)
$Q_{battery}$	60	60	Jungheinrich (2024)
η_{hz}	0.78	0.78	European Standard (2005); International Organization for Standardization (2020)
η_{hf}	0.88	0.88	(European Standard, 2015; International Organization for Standardization (ISO), 2020)
gg	240	240	-
$V_{energy\ cons}$	0.08	0.08	European Standard, 2016; International Organization for Standardization (2020); Zajac & Rozic (2022)
V_u	0.85	0.85	Atashi Khoei et al. (2023)
c	0.259	0.259	ISPRA (2022)