THE LINK BETWEEN CARBON FOOTPRINT SIZE AND PV ENERGY SYSTEM INITIAL INVESTMENT, ESPECIALLY REGARDING STORAGE ELEMENTS AND THEIR EXPLOITATION MODALITY

Mihaita Nicolae ARDELEANU¹, Emil Mihail DIACONU¹, Otilia NEDELCU¹, Sorin IONITESCU²

¹University Valahia Targoviste, 13 Aleea Sinaia, 130004, Targoviste, Romania ²Romanian Academy, School of Advanced Studies of the Romanian Academy, Doctoral School of Economic Sciences, National Institute for Economic Research "Costin C. Kiriţescu", Institute for World Economy, 13 Calea 13 Septembrie, District 5, Bucharest, Romania

Corresponding author email: otilia.nedelcu@valahia.ro

Abstract

The carbon footprint is inherent in any production process, even more so in the case of the production of batteries for the storage of electrical energy. The structure of the photovoltaic (PV) energy system determines the initial investment and, with it, the way of exploitation of the storage elements is outlined. The idea of reducing the investment usually determines an intensive exploitation of the batteries, which leads to the shortening of their exploitation period and implicitly their replacement with new ones. In addition to the problem of fitting the new batteries to the group of existing ones, it goes without saying that their purchase involves another manufacturing exercise that inherently requires a new carbon footprint. By optimizing the way batteries are used, their life is extended up to double, which means that the environmental impact of the production process is halved. The simulation exercise carried out, based on the concrete data provided by the specialized literature and the data of the LIFEPO4 battery manufacturers, demonstrated that it is possible to reduce the mentioned carbon footprint through an optimal structuring of the PV system starting from the very initial investment.

Key words: PV system, initial investment, batteries exploitation, batteries production, carbon footprint.

INTRODUCTION

A photovoltaic system with electrical energy storage requires batteries. Electric batteries are chemical products resulting from highly polluting production processes. In this context, the use of batteries requires a prior analysis that allows a choice process with very precise optimization criteria to allow a maximum possible exploitation time for a given set of conditions. The European Union has regulated the choices of specific elements for PV systems, within a directive generically called Ecodesign by which it establishes carbon footprint thresholds with a minimum qualification for the European market.

The carbon footprint calculation methodology imposes a number of different parameters that are considered, but the most important are the lifetime of a photovoltaic module as well as the degradation rate (Khan et al., 2024)). The Ecodesign Directive thus eliminates those least sustainable PV modules, with the precise aim of reducing the carbon footprint associated with all the constituent elements of the designed PV system. The systemic carbon footprint is determined by adding together all the individual elemental carbon footprints, resulting in a cumulative total (Polverini et al., 2023).

The environmental cost of PV system production includes all carbon emissions generated from all specific phases of the production supply chain, and work is currently underway on dynamic data tracking systems that allow the exact calculation of the carbon footprint related to the purchase of a PV module (You et al., 2017). The life cycle assessment of PV modules is based on statistical analyzes of case studies on the net energy produced and the associated carbon footprint (Cellura et al., 2023).

The concept of the 'Big Data Value Chain' provides a comprehensive framework for managing data, from acquisition to utilization, enabling more accurate and efficient calculations of carbon footprints in photovoltaic systems (Ionitescu et al., 2024). The carbon footprint of the photovoltaic cells that make up the PV capture part, as a module of the energy system, depends on the materials and methods specific to their manufacturing technologies (Stylos & Koroneos, 2014). The type of PV cell and its production technology is directly related to the lifetime and energy efficiency, so the higher the two parameters in absolute value, the lower the manufacturing effort and the frequency of replacement to maintain the capability of the system over time will be reduced, both aspects leading to a substantially reduced carbon footprint. The carbon footprints generated by the establishment and operation of PV energy systems are much reduced compared to those involved in an energy system based on a Diesel plant, but even in this advantageous context for the renewable resource, the optimal structural system must be consistently pursued.

The issue of the carbon footprint involves many socio-economic aspects, in all cases the modelling of polluting systemic states is essential to correlate the cause with the effect. Carbon emissions increase 25 times when idling for a stationary and starting car, or, in acceleration/braking situations, there is an increase of 1.5-2 times higher than during constant driving (Ruscă et al., 2022).

Following the same reasoning of determining the cause-and-effect vector in the case of carbon emissions, in PV systems, the systemic composition and the way of exploitation of the elements can lead to an unnecessary increase in the carbon footprint throughout the life of use, as in the case of to a vehicle in traffic, if an automatic engine shutdown system is added and/or the driver approaches a driving style without unnecessary acceleration/deceleration, the carbon footprint over the lifetime of the vehicle's operation will be substantially lower than the careless case of working with the same system.

The electrification strategies of some areas with undeveloped national grids require mini grids based on PV, and in this case, precise calculations have highlighted a reduced carbon footprint of 200gCO2/1KWh (Chamarande et al., 2024). To produce each KWh of capacity for a LiFePo4 battery, a carbon footprint of between 100 and 200 Kg CO₂ is estimated, depending on the materials, the manufacturing technology and its energy efficiency. This dimensioning of the carbon emission was considered for the simulations carried out in this work, respectively the average of $CFP_{1KWh}=150 \text{ KgCO}_2$.

Simulating the structure of a PV system is essential to determine from the design phase the technical-economic benefits, the calculation model having to consider all socio-economic aspects, including incentives per KWh offered by society to encourage the production and storage of renewable energy. (Hassan et al., 2017). Storage in batteries involves a different calculation in the case of small PV system energy capacities compared to large PV power plants. In a mini-grid application the group of batteries will work as a unit, in PV plants the battery degradation model becomes essential for replacing the required ones and accommodating the new ones in the large groups to maintain the nominal energy storage capacities (Yao & Cai, 2021).

Recycling of Li-ion Cathodes (Or et al., 2020) and Direct Regeneration of Cathode Materials from Used Electric Batteries (Lan et al., 2024) represent concrete actions to reduce pollutant emissions generated by the function of electric energy storage in PV systems, but optimizing the way the battery works and modeling the initial investment to ensure a long life cycle for the entire system is a source of significant carbon footprint reduction, as demonstrated by the simulations presented in this paper.

PV SYSTEM LIFETIME PARADIGM

Simulating the amount of energy produced during the lifetime of a PV system is a complex problem, which takes into account many factors such as: the energy characteristics of the geographical place for which the estimate is made. the geoclimatic conditions. the probability density applied to the annual predictions regarding the amount of solar energy for each season, degradation rates of system modules, uncertainties applied to energy production, energy prediction risks, module reliability, maintenance requirement induced by integrated modules (Georgitsioti et al., 2019). Having accurately estimated the energy result of the investment, for the case where the PV system is made, decisions can be made in a wellfounded way. For these calculations to follow the reality throughout the operating life, it is necessary that the predominant technical factors are set to the values that allow maximum durability of the modules of the PV system.

In this paper we focused our attention on the storage module, namely the battery. The reliability of the battery is a decisive factor enabling a long lifetime of the PV system. In addition to reliability, the way the battery is operated produces irreversible effects on the electrochemical mechanisms, accentuating or reducing the degree of its degradation. To create a measure of system reliability, we consider a first parameter of the simulation, namely the operating time of a module of the PW system until the first maintenance intervention, namely the operating time without maintenance abbreviated Without TWM (Time Maintenance), expressed in months.

Figure 1 illustrates the flow of energy captured by a photovoltaic (PV) system and circulated through an energy storage module. Three scenarios are depicted – Cases A, B, and C – each with an increasing number of battery groups within the storage module, while maintaining a constant input of PV-generated energy.



Figure 1. The same energy captured by the PV system, transited through storage groups with different capacities

The operational lifespan of batteries in a photovoltaic (PV) system, represented by the Time Without Maintenance (TWM) parameter, is significantly influenced by the stress levels experienced due to various chemical processes. Consequently:

$$TWM_A < TWM_B < TWM_C$$
 [1]

The initial investment in a photovoltaic (PV) system plays a crucial role in determining both its operational lifespan and the cost of energy production throughout its service life. A well-

planned initial investment minimizes the need for major maintenance, repairs, or replacements of modules or critical components, which can incur significant expenses. A reduced reliability of a system component induces a lower initial price but a higher maintenance cost, while an increased reliability of the same component transfers the cost of quality into its price, eliminating subsequent maintenance costs for considerable periods of time, so a higher TWM. The decision on investment must quantify the mentioned aspects, as a result we introduced a ratio between the total investment involved over the entire lifetime and the operating time until the first major maintenance intervention on any of the basic components of the PV system. This ratio is called OIDF (Optimal Investment Decision Factor) and represents a way of quantifying the return on investment. Figure 2 shows the method of calculating OIDF, with only the values with the green arrow being active for calculation. The inclusion of the red arrow values leads to a global analysis factor during the operation of the PV system.



Figure 2. OIDF calculation scheme

The meanings of the notations in figure 2:

- BIP Batteries Initial Price;
- Bam Baterries Maintenance cost;
- EIP Equipements Initial Price;
- EqM Équipements Maintenance cost;
- PIP PV panels Initial Price;
- PaM PV panels Maintenance cost;
- TWM(B) TWM for batteries;
- TWM(E) TWM for equipements;
- TWM(P) TWM for PV panels;
- I Investment for PV system.

The calculation formula for OIDF is:

$$OIDF = \frac{(BIP + EIP + PIP)}{MIN (TWM(B), TWM(E), TWM(P))}$$
[2]

The meaning of the unit of measure of this factor is monetary unit for unit of time of good operation: Euro/Month. The lower the OIDF, the more profitable the investment for the PV system. The paradigm of the lifetime of the PV system is reduced to obtaining the longest operating times until the first major maintenance intervention, for the same amount of initial investment.

BATTERY. EXPLOITATION MODALITY

The battery is essential, having the function of storing the energy captured by the PV system at certain times of the day, and making it available to the distribution network at other times of the day, when the sun is no longer geographically active in the photovoltaic production area.

Depending on the internal chemical mechanisms, batteries are of several types. For the exercise of this paper, we have chosen the LiFePo4 battery type, as it is the most widely used in residential energy systems. The LiFePO4 battery is part of the Li-ion battery family. The cathode is made by the lithium-ironphosphate chemical structure, and the anode is geophytized carbon on a metal support. Manufacturing costs are low, with low toxicity, no fire risk, and a long-life cycle, all of which propel this type of battery to the top of the energy storage battery charts. Even the Tesla Company has turned to this type of batteries, 68% of the LiFePo4 batteries produced in 2022 being purchased by it. In the same year, LiFePo4 batteries reached, as a market share, 31% of the battery sector for electric vehicles.

Among the characteristics of a battery, we present those relevant to the study undertaken:

- DoD Depth of Discharge (%)
- C Nominal Capacity (Ah)
- CC Charge Capacity (Ah)
- DC Discharge Capacity (Ah)
- DL₂₅°_C Design Life at @25°C (Years)
- CL- Cycle Life at @25°C & @DOD 80% (number of charge-discharge cycles)
- SoC State of Charge (%)

After a study of the technical documentation provided by major brands of LiFePo4 batteries, we define below the optimal operating condition that provides the longest battery life (over 10 years lifetime):

- Exploitation temperature: 25°C
- DoD: 80%
- SoC (maximum charge): 90%

- SoC (minimum discharge): 10%
- CC: 0.2C (Ah)
- DC: 0.2C (Ah)

Figure 3 shows a graph from the technical documentation of the EV-Lithium battery manufacturer (https://www.evlithium.com/), respectively the EVL battery with C=5KWh, in which the dependence between the battery discharge mode and battery life in number of charge-discharge cycles, at constant operating temperature of 25°C.



Figure 3. Storage capacity of EV-Lithium's LiFePo4 battery, according to DoD. Web source of original graphic: https://www.evlithium.com/home-energystorage-system.html

Thorough and in-depth research has been carried out by a team of researchers funded by a large Belgian manufacturer of industrial LiFePo4 battery electric storage groups, and the results of this research are presented in the paper (Omar et al., 2014). The graph shown in Figure 4 is built based on the original data presented in the work (Omar, 2014), a graph that shows the dependence between the Operating Temperature (OT) of the battery and its lifetime in the number of charge-discharge cycles. The reproduced data were processed to determine the polynomial regression function necessary to approximate the evolution determined experimentally in the work mentioned above. Using this retrieved data, the percentage increase or decrease of the lifetime of a LiFePo4 battery depending on OT was modeled and simulated. Through the data presented in Figures 3 and 4, characteristics of some ways of operating LiFePo4 batteries were presented, with consequences on the variation of the life span, a fact that influences their premature replacement and the increase of the carbon footprint determined by the new purchase of these modules of PV system.



Figure 4. LiFePo4 battery storage capacity relative to OT

MODELING SIMULATION RESULTS

This study investigated a 5kWh off-grid photovoltaic (PV) system with an EVL5KWh battery for energy storage. Using manufacturer data (Figure 3) and a mathematical model, Table 1 presents a simulation of the system's performance with a 300-kWh average monthly consumption. Interestingly, the relationship between the battery's Depth of Discharge (DOD) and its lifespan, as depicted by the model, is linear. This linear relationship can be expressed through the following equations:

$$CL = -DoD \cdot 66,667 + 10667 \quad [3]$$

$$Storage = 5 \cdot CL \quad [4]$$

$$Lifetime = \frac{Storage}{AMC} \quad [5]$$

$$Increase = \frac{Lifetime_k - Lifetime_{100}}{Lifetime_{100}} \cdot 100 \quad [6]$$

$$CFP = C \cdot \left(1 - \frac{increase}{100}\right) \cdot CFP_{1KWh} \quad [7]$$

This study further explored the performance of an off-grid PV energy system under varying temperature conditions. Utilizing data from Figure 4 and a mathematical model, Table 2 presents a simulation where the ambient temperature fluctuates around 25°C. The specified temperature was meticulously chosen as it aligns perfectly with the optimal operational parameters for the LiFePO4 battery integrated within the system. This value is also consistently documented within the technical specifications provided bv leading manufacturers of these batteries, serving as a benchmark temperature. This temperature is a critical prerequisite for establishing the applicability of other operational characteristics (DoD, CC, DC, SoC) that guarantee the extended lifespan of the products marketed. It is noted that the mathematical model describing the dependence between OT and battery life is a 3rd order poinomial, expressed by the relation [8] below.

$$CL = -0.0373 \cdot OT^3 - 0.3072 \cdot OT^2 + 51.008 \cdot OT + 2150$$
[8]

To assess the impact of temperature on battery performance, the percentage variation in lifespan compared to the maximum lifetime at 25°C is determined using equation [9]. Subsequently, the corresponding effect on the carbon footprint is calculated using equation [10].

$$Variation = \frac{CL_{25} - CL_k}{CL_{25}} \cdot 100 \quad [9]$$
$$CFP = \frac{Variation_{25} - VAriation_k}{100} \cdot CFP_{1KWh} \quad [10]$$

Simulation analysis reveals the relationship between LiFePO4 battery Depth of Discharge (DoD) and carbon footprint within a photovoltaic system

Table 1. Battery lifetime depending on DOD & CFP

DoD	CL	Storage	Lifetime	Increase	CFP
%	cycles	KWh	months	%	KgCO2/KWh
100	4000	20002	67	0	750
95	4334	21668	72	8	688
90	4667	23335	78	17	625
85	5000	25002	83	25	563
80	5334	26668	89	33	500
75	5667	28335	94	42	438
70	6000	30002	100	50	375
65	6334	31668	106	58	313
60	6667	33335	111	67	250
55	7000	35002	117	75	188
50	7334	36668	122	83	125

Table 2. Battery lifetime depending on OT & CFP

ОТ	CL	Variation	CFP
°C	cycles	%	KgCO2/KWh
-5	1647	-40	60
0	1892	-31	47
5	2150	-22	33
10	2393	-13	19
15	2592	-6	9
20	2720	-1	2
25	2749	0	0
30	2650	-4	5
35	2397	-13	19
40	1960	-29	43
45	1312	-52	78

CONCLUSIONS

Any PV system has an operating optimum that battery manufacturers indicate very precisely through customized values of specific parameters (DoD, SoC, CC, DC, OT). Without systems to control battery temperature and operating parameters, achieving optimal efficiency is challenging. This optimal state, representing minimal pollution, serves as a benchmark for calculating the carbon footprint of a PV system. Any deviation from this ideal state increases the carbon footprint, measured as a percentage increase from the baseline optimal value.

The initial investment can ensure a greater reserve for the storage capacity of the PV system, this fact leading to a decrease in the demand for the chemical mechanisms in the batteries and implicitly extending life and postponing the moment of their replacement with new ones. It can be seen in Figure 1 that tripling the storage capacity leads to a relaxation of the batteries, and purchasing three times the number of batteries does not necessarily mean tripling the price.

Equation [2] highlights the importance of maximizing battery lifespan to optimize the initial investment in a PV system. This can be achieved by adhering to the optimal operating practices recommended by battery manufacturers. Table 1 demonstrates that reducing the Depth of Discharge (DoD) to 50% significantly decreases the carbon footprint (CFP) by a factor of six, while simultaneously extending battery life by 1.82 times. This extended lifespan enhances convenience by delaying maintenance and replacement needs within the battery storage system. Furthermore, Table 2 reveals that a temperature increase of 15°C above the optimal operating temperature results in a 20% rise in CFP. This finding underscores the need for PV system operators to prioritize optimal battery management practices to minimize environmental impact.

ACKNOWLEDGEMENTS

This research was carried out with the support of University Valahia Targoviste, Institute of Scientific and Technological Multidisciplinary Research.

REFERENCES

Cellura, M., Le Quyen, L., Guarino, F., & Longo, S. (2023, November). Net Energy Analysis and Carbon Footprint of Solar Cells. 2023 Asia Meeting on *Environment and Electrical Engineering (EEE-AM),* Hanoi, Vietnam, 2023, pp. 01-06.

- Chamarande, T., Hingray, B., & Mathy, S. (2024). Carbon footprint of solar based mini-grids in Africa: Drivers and levers for reduction. *Renewable Energy*, 121480.
- Georgitsioti, T., Pearsall, N., Forbes, I., & Pillai, G. (2019). A combined model for PV system lifetime energy prediction and annual energy assessment. *Solar Energy*, 183, 738-744.
- Hassan, A. S., Cipcigan, L., & Jenkins, N. (2017). Optimal battery storage operation for PV systems with tariff incentives. *Applied Energy*, 203, 422-441.
- Ionitescu S., Popescu A., Moagar-Poladian S., Gudanescu N.L., Aluculesei A.C. (2024). Value chains in raw materials, high-tech and agricultural products. international, European and Romanian perspectives. *Scientific Papers. Series "Management, Economic Engineering in Agriculture and Rural Development"*, 24(2), 537-548, PRINT ISSN 2284-7995.
- Khan, A.A., Molina, P., Reichel, C., Protti, A.A., Neuhaus, D.H., Rentsch, J., & Nold, S. (2024). The European Union's Ecodesign Directive–Analysis of Carbon Footprint Assessment Methodology and Implications for Photovoltaic Module Manufacturers. *Solar RRL*, 2301011.
- Lan, Y., Li, X., Zhou, G., Yao, W., Cheng, H. M., & Tang, Y. (2024). Direct Regenerating Cathode Materials from Spent Lithium-Ion Batteries. *Advanced Science*, 11(1), 2304425.
- Omar, N., Monem, M.A., Firouz, Y., Salminen, J., Smekens, J., Hegazy, O., & Van Mierlo, J. (2014). Lithium iron phosphate based battery–Assessment of the aging parameters and development of cycle life model. *Applied Energy*, 113, 1575-1585.
- Or, T., Gourley, S. W., Kaliyappan, K., Yu, A., & Chen, Z. (2020). Recycling of mixed cathode lithium-ion batteries for electric vehicles: Current status and future outlook. *Carbon energy*, 2(1), 6-43.
- Polverini, D., Espinosa, N., Eynard, U., Leccisi, E., Ardente, F., & Mathieux, F. (2023). Assessing the carbon footprint of photovoltaic modules through the EU Ecodesign Directive. *Solar Energy*, 257, 1-9.
- Ruscă, M., Dimen, L., & Mărcuță, L. (2022). environmental pollution due to road vehicles, alternative solutions (electric vehicles, hybrids, bicycles) sustainability of crowded centers of cities. Scientific Papers. Series E. Land Reclamation, Earth Observation & Surveying, Environmental Engineering, 11. Print ISSN 2285-6064.
- Stylos, N., & Koroneos, C. (2014). Carbon footprint of polycrystalline photovoltaic systems. *Journal of Cleaner Production*, 64, 639-645.
- Tu, M., Chung, W. H., Chiu, C. K., Chung, W., & Tzeng, Y. (2017). A novel IoT-based dynamic carbon footprint approach to reducing uncertainties in carbon footprint assessment of a solar PV supply chain. 2017 4th International Conference on Industrial Engineering and Applications (ICIEA), 249-254.
- Yao, M., & Cai, X. (2021). Energy storage sizing optimization for large-scale PV power plant. IEEE, 9, 75599-75607.