Securing EU Clean Technology Supply Chains: Learning Rates in Material Recycling and Strategic Stockpiling

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***Abstract*—This study examines how the European Union (EU) can achieve its 40% target for domestically sourced clean technologies by 2030, using solar photovoltaic (PV) modules as a case study. We determine the cost-optimal power generation capacities at the EU level through 2050, categorizing solar PV supply into four sources: imports, domestic manufacturing, remanufacturing (via upstream material recycling), and withdrawals from a strategic stockpile. A key feature of our approach is the explicit modeling of learning rates, linking remanufacturing investment costs to cumulative installed capacity. Results indicate that learning rates between 3.5% and 5.0% enable remanufacturing to supply 13.2% to 36.6% of newly installed solar PV capacity. The strategic stockpile plays a crucial role in meeting the 40% benchmark, particularly in the late 2020s and early 2040s. Moreover, only under very high learning rate assumptions—approaching 25%, consistent with historical trends in solar module manufacturing outside the EU—does the reliance on stockpiling diminish entirely. We conclude that under anticipatable cost reductions in material recycling and remanufacturing, stockpiling remains a critical mechanism for complementing domestic remanufacturing, enhancing supply security, and advancing energy autonomy.**

***Index Terms*—Clean Technology, Critical Raw Materials, Solar PV, Learning Rates, Recycling, Strategic Stockpile**

I. MOTIVATION

This study examines how the European Union (EU) can enhance its energy autonomy by promoting domestically manufactured clean technologies and establishing strategic stockpiles. Specifically, it focuses on policy measures to strengthen the resilience of the solar photovoltaic (PV) module supply chain, which is a critical component of the EU's clean energy transition. A major challenge in this transition is the EU's heavy reliance on imported solar PV modules, primarily from China, which exposes the region to potential supply disruptions [1].

The EU's high dependence on imports is primarily driven by two factors. First, the lower production costs of Chinese manufacturers make it difficult for European producers to remain cost-competitive. Second, structural constraints on securing critical raw materials pose an additional barrier, as the EU lacks substantial domestic mining capacity for many key materials used in clean technologies [2]. Given that the EU is a resource-scarce region in this regard, its supply chains remain vulnerable to external shocks [3].

Against this backdrop, this study aims to explore how the EU can develop a viable recycling industry for solar PV modules to reduce import dependency and mitigate critical raw material constraints. At present, no such recycling industry exists at scale within the EU, primarily due to economic challenges. The unit costs of material recycling and remanufacturing remain too high to compete with imported solar modules. Furthermore, we acknowledge concerns regarding the feasibility of scaling up a costly European solar PV industry once again, as opposed to continuing to leverage low-cost imports from China. To address these concerns, we consider an alternative strategy: the creation of a strategic stockpile for solar modules as a means to enhance supply security while minimizing reliance on domestic production [3].

This study, therefore, addresses the following key research questions:

- What learning rates in material recycling are necessary for solar PV module remanufacturing to achieve cost competitiveness and play a significant role in advancing the EU's energy autonomy objectives?
- What role does strategic stockpiling play in securing solar PV module supply, and how does its effectiveness depend on the presence or absence of remanufacturing capacity?

To assess these questions, we examine the 40 % domestic production target established in the EU's Net-Zero Industry Act, which mandates that at least 40 % of newly installed clean energy technologies from 2030, including solar PV modules, must originate from domestic sources [4]. Our analysis determines the cost-optimal pathway for the EU's solar PV sector under this requirement, considering three domestic supply options:

1) Domestic manufacturing (module assembly),
2) Remanufacturing from recycled materials, and
3) Withdrawals from a strategic stockpile.

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It is important to clarify our definition of ”domestic supply options.” While stockpiled modules may initially be imported, we still classify withdrawals from the stockpile as a domestic supply source for energy autonomy calculations. This is because stockpiling, regardless of the modules' origin, provides a buffer against external supply shocks and increases the EU's control over its energy transition [5], [6].

The remainder of this study is structured as follows: Section II describes the methodology, data sources, and case study framework. Section III presents the results, while Section IV provides conclusions and directions for future research.

II. METHODOLOGY

We employ a cost-minimizing energy system model, which builds upon [7] and [8], to determine the optimal technology capacities, including solar PV, while ensuring that power demand is met. Our assumptions regarding power demand and other relevant parameters are aligned with ENTSO-E's Ten-Year Network Development Plan [9]. To account for the three distinct solar PV supply options—domestic manufacturing, remanufacturing (via material recycling), and strategic stockpiling—we extend the conventional modeling approach, which typically considers a single investment cost implicitly based on imports. This is achieved by integrating tailored functionalities that allow for differentiated cost structures and deployment dynamics across these supply pathways. Overall, our methodological framework aligns with standard energy system models, with the primary distinction being a more detailed representation of solar module supply dynamics.

- First, manufacturing and remanufacturing are incorporated as investment options, analogous to other generation technologies, each with distinct investment costs for capacity expansion.
- Second, we adapt the conventional approach for modeling energy storage to represent the stockpiling of solar modules, treating it as a technology stock rather than an energy carrier.

The model optimizes the cost-effective expansion of solar PV capacity while ensuring compliance with the $40\,\%$ domestic supply benchmark. Equation 1 defines the balance constraint for newly installed solar PV capacity (Π_y) as the sum of imported ($\Pi_{\text{import},y}$), manufactured ($\Pi_{\text{man},y}$), remanufactured ($\Pi_{\text{rem},y}$), and stockpile-withdrawn ($\Pi_{\text{stock},y}$) solar PV modules for each year y until 2050.

$$\Pi_y = \Pi_{import,y} + \Pi_{man,y} + \Pi_{rem,y} + \Pi_{stock,y} \quad (: \forall y) \tag{1}$$

The additional capacities required to fill the stockpile ($\Pi^{in}_{stock,y}$) increase the net demand for solar PV modules. These capacities can be sourced through imports ($\Pi^{stock,in}_{import,y}$), domestic manufacturing ($\Pi^{stock,in}_{man,y}$), and remanufacturing ($\Pi^{stock,in}_{rem,y}$), as expressed in Equation 2.

$$\Pi^{in}_{stock,y} = \Pi^{stock,in}_{import,y} + \Pi^{stock,in}_{man,y} + \Pi^{stock,in}_{rem,y} \tag{2}$$

Equation 3 ensures the $40\,\%$ benchmark with respect to newly installed capacities. $\bar{y}$ is a subset of y and includes all years between 2030 and 2050 where the benchmark constraint is active.

$$0.4 \times \Pi_{\bar{y}} <= \Pi_{man,\bar{y}} + \Pi_{rem,\bar{y}} + \Pi_{stock,\bar{y}} \quad (: \forall \bar{y}) \tag{3}$$

For manufacturing, the investment cost is set at $303\,600\,\mathrm{EUR/MW}$ in 2024, decreasing annually by $1.5\,\%$. The same cost reduction applies to imported solar modules, which have an initial cost of $250\,240\,\mathrm{EUR/MW}$ in 2024.

For remanufacturing, the initial specific investment cost is set at $414\,000\,\mathrm{EUR/MW}$ in 2024. Unlike manufacturing and imports, remanufacturing costs decline endogenously based on cumulative installed capacity. Specifically, the specific investment cost of remanufactured solar modules in year y ($sc^{inv}_{rem,y}$) is defined as a function ($\mathcal{F}$) of cumulative installed remanufacturing capacity ($\sum_{\tau}^{y} \Pi_{rem,\tau}$), as expressed in Equation 4:

$$sc^{inv}_{rem,y} = \mathcal{F}\Big(\sum_{\tau}^{y} \Pi_{rem,\tau}\Big) \tag{4}$$

The function ($\mathcal{F}$) represents the learning rates in remanufacturing. Equation 5 shows the typical expression that links cumulative capacity, the learning rate, and specific investment costs.

$$sc^{inv}_{rem,y} = sc^{inv}_{rem,2024} \times (1 - LR)^{\log_2 \frac{\Pi_{rem,2024}}{\sum_{\tau}^{y} \Pi_{rem,\tau}}} \tag{5}$$

In this equation, $sc^{inv}_{rem,y}$ represents the specific investment cost for remanufacturing at year y, $\Pi_{rem,2024}$ the installed remanufacturing capacity in 2024, and LR the learning rate (e.g., $1\,\%$). Details on the chosen approach regarding the specific modeling of the endogenous decision can be found in [10].

Table I provides further insights in the relationship between the remanufacturing capacity, costs, and learning rates. Note that a wide range of learning rates, from $1\,\%$ to $25\,\%$, is analyzed. For clarity, only selected learning rates are presented in the table. For further details in this regard, we refer to recent publications dealing in great detail with clean technologies' manufacturing learning rates [11] and [12].

Solar module stockpiling is modeled similarly to energy storage systems, such as battery storage, as shown in Equation 6. The stockpile level is denoted by $\Pi^{level}_{stock,\tilde{y}}$, where $\tilde{y}$ includes all simulated years except the starting year. For the starting year, an initial stockpile level of $40\,\mathrm{GW}$ is assumed (value taken from [3]).

$$\Pi^{level}_{stock,\tilde{y}} = \Pi^{level}_{stock,\tilde{y}-1} + \Pi^{in}_{stock,\tilde{y}} - \Pi_{stock,\tilde{y}} \quad (: \forall \tilde{y}) \tag{6}$$

The stockpiling cost is set at $25\,\mathrm{EUR/MW/year}$, representing the cost of maintaining a given stockpile level ($\Pi^{level}_{stock,\tilde{y}}$)

[3]. To prevent technological obsolescence, we implement a turnover mechanism that ensures the stockpile remains aligned with ongoing technological advancements.

Additional required data is sourced from [8] and [13], including, among others, the specific investment costs of other generation technologies such as wind and hydropower.

III. RESULTS

The results indicate that approximately 2000 GW of solar PV capacity is newly installed by 2050 in the EU. Notably, the cost-optimal total installed capacity remains relatively consistent across scenarios. However, the composition of supply sources enabling these additions varies significantly. In particular, the contribution of remanufacturing as a supply option for solar modules, which is the focus of this study, exhibits a substantial range between 0 and 65 %, depending on the assumed learning rates in the recycling industry.

Figure 1 summarizes the scenario results regarding the supply share of remanufacturing in total newly installed capacity. The supply shares are categorized into four groups based on learning rate assumptions: (i) low, ranging from 0 to 3.5 %; (ii) moderate, between 3.5 and 4.0 %; (iii) high, between 4.0 and 5.0 %; and (iv) very high, spanning from 5.0 to 25.0 %.

The results demonstrate that at low learning rates, remanufacturing does not contribute to newly installed capacity. However, once learning rates surpass 3.5 % (moderate category), remanufacturing becomes a cost-optimal option, contributing between 13.2 and 15.3 % of new capacity, with a median share of 14.3 %. As learning rates increase further, the share of remanufacturing expands, reaching 31.3 % in the high category and peaking at 65.3 % under very high learning rate assumptions.

Interestingly, the variability in remanufacturing shares is most pronounced in the high learning rate range (4.0 to 5.0 %), where shares vary from a minimum of 19.5 % to a maximum of 36.6 %. This range, as illustrated in the boxplots, represents the highest dispersion among all four categories.

The variation in remanufacturing shares across scenarios is accompanied by differences in stockpile levels. While no substantial stockpiling occurs under low and very high learning rates, scenarios with moderate and high learning rates (i.e., between 3.5 and 5.0 %) exhibit notable stockpiles, reaching up to 90 GW. Figure 2 illustrates the average stockpile levels along with the minimum-maximum range for each of the four learning rate groups.

In the case of moderate learning rates, stockpiling peaks at 18.8 GW in 2032 and 28.5 GW in 2044. In contrast, under high learning rates, the peak stockpile reaches 90.3 GW in 2039. Notably, beyond the higher peak values compared to other learning rate groups, the variability in stockpile levels is also substantially greater under high learning rates. This is evident in 2039, where the stockpile ranges from 0 GW to approximately 90 GW, representing the widest spread across all scenarios. This variability is visually captured by the shaded areas between the dashed lines in Figure 2.

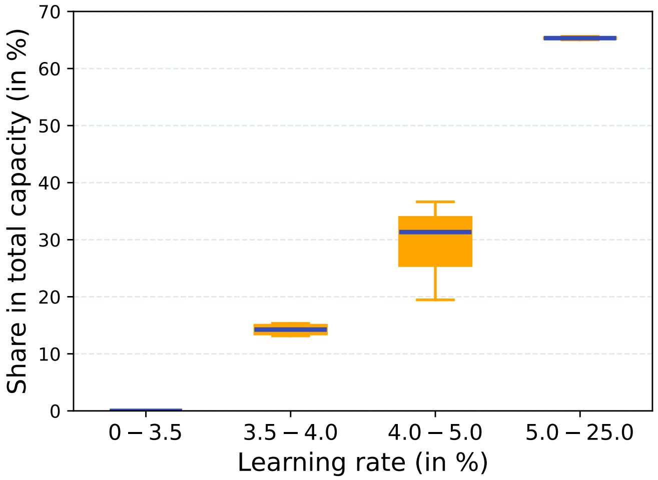

Fig. 1: Supply share of remanufacturing in total newly installed solar PV capacity until 2050. For each of the four categories of learning rate assumptions, whiskers indicate the minimum and maximum values, bars the median, and box the first and third quartile.

Conversely, stockpiling plays a negligible role in scenarios with very high learning rates, except for the early 2020s, when existing stockpiles are gradually discharged. This shows that under very high learning rates, rapid cost reductions in recycling and remanufacturing diminish the need for stockpiling as a strategic reserve.

Since only scenarios with very high learning rates exhibit no need for stockpiling, most scenarios involve a combination of remanufacturing and stockpiling. Figure 3 illustrates an example of how these two supply options interact over time. The results indicate that stockpiled material is utilized until 2030, facilitating the gradual ramp-up of remanufacturing capacities. Once these capacities are sufficiently established, stockpiling resumes in the mid-to-late 2030s (not explicitly shown in the figure), ensuring a stable supply contribution in the 2040s. Note that withdrawals occur in the initial simulation years (2024–2028) due to the assumed initial stockpile level of 40 GW.

Notably, during the 2030s, remanufacturing contributes an average supply of 32.7 GW. In comparison, its average supply is lower in the 2020s (15.5 GW) and further declines to 11.5 GW in the 2040s. This dynamic highlights the strategic interplay between stockpiling and remanufacturing, where stockpiles serve as a buffer to support supply security during periods of capacity expansion.

Learning rate (LR)	$LR = 1\,\%$		$LR = 5\,\%$		$LR = 10\,\%$	
Cumulative remanufacturing capacity (GW)	Relative cost share of initial (%)	Specific investment cost (EUR/MW)	Relative cost share of initial (%)	Specific investment cost (EUR/MW)	Relative cost share of initial (%)	Specific investment cost (EUR/MW)
0.01	100	414 000	100	414 000	100	414 000
0.1	96.72	387 127	84.33	349 140	70.47	291 741
1	93.54	361 999	71.12	294 442	49.66	205 586
10	90.47	338 502	59.98	248 313	34.99	144 874
100	87.50	316 530	50.58	209 410	24.66	102 091
1000	84.63	295 984	42.66	176 603	17.38	71 942
10 000	81.85	276 772	35.97	148 935	12.25	50 697

TABLE I: Relationship between cumulative remanufacturing capacity and specific investment costs (EUR/MW) for learning rates of $1\,\%$, $5\,\%$, and $10\,\%$.

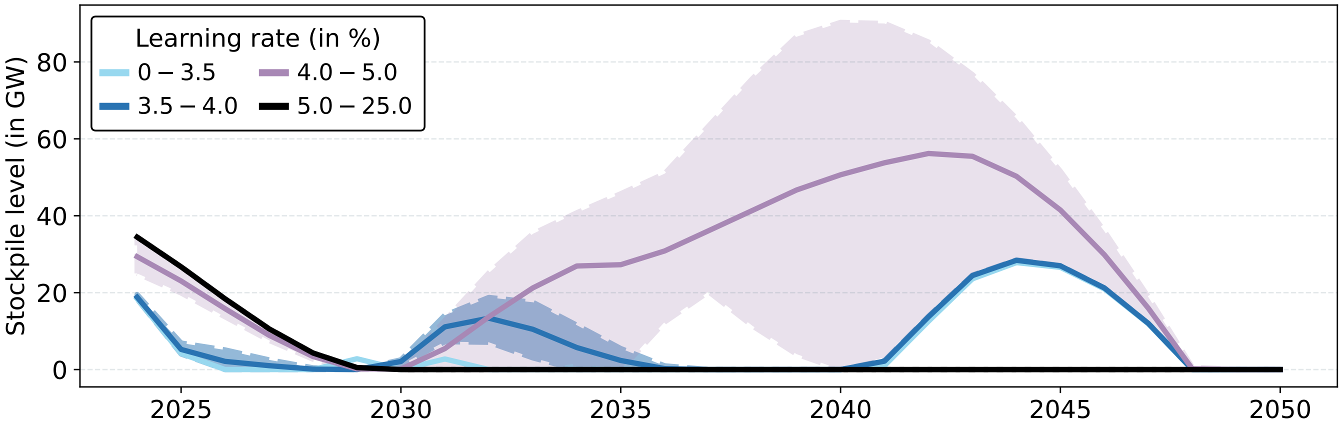

Fig. 2: Stockpile levels (in GW) from 2024 to 2050 for different learning rates of solar PV remanufacturing. Learning rates range from 1% to 25% and are categorized into four distinct groups.

IV. CONCLUSION AND OUTLOOK

The European Union (EU) has identified energy autonomy as a strategic objective, closely linked to its commitment to achieving net-zero emissions by 2050. As part of this effort, the EU aims to meet at least $40\,\%$ of its demand for clean technologies, including solar PV modules, through domestic manufacturing by 2030. This study examined cost-optimal pathways for achieving this benchmark by evaluating three strategic options: domestic manufacturing, remanufacturing from recycled materials, and strategic stockpiling of solar modules. These options were integrated into an energy system model as investment choices, allowing for the endogenous determination of cost-efficient capacity allocations. A key feature of our approach was the explicit modeling of learning rates, linking the investment costs of remanufactured solar modules to their cumulative installed capacity.

Our results indicate that learning rates between 3.5 and $5.0\,\%$ enable remanufacturing to contribute between 13.2 and $36.6\,\%$ of newly installed solar PV capacity by 2050. Additionally, the strategic stockpile plays a crucial role in achieving the $40\,\%$, compensating for potential shortfalls in the late 2020s and complementing remanufacturing capacities in the early 2040s.

Moreover, we find that only under very high learning rate assumptions—approaching $25\,\%$, in line with historically observed learning rates in solar module manufacturing outside the EU—does the need for a strategic reserve disappear entirely. This suggests that in the absence of significant cost reductions in material recycling and remanufacturing, stockpiling serves as an essential mechanism to stabilize supply and support the EU's energy autonomy objectives.

Future research should refine learning rate estimates for remanufacturing. While this study incorporated learning rates endogenously within the model, our assumptions regarding their magnitude and variability remain preliminary and require further empirical validation. In particular, the interaction between learning rates in remanufacturing, conventional manufacturing, and imports warrants closer examination. To date, we have only considered moderate cost

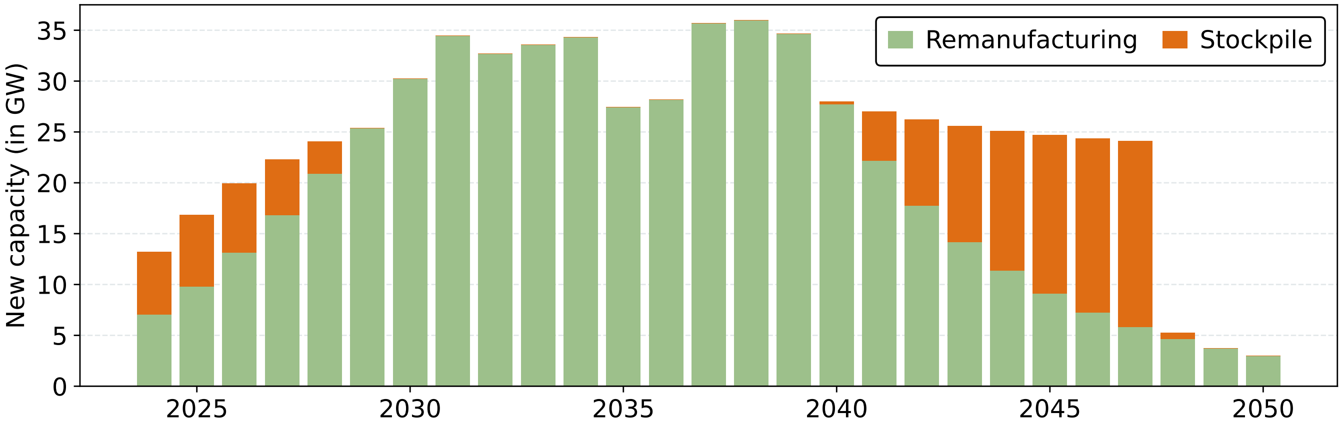

Fig. 3: Annual new solar PV capacity from remanufacturing and stockpile withdrawals between 2024 and 2050 (in GW).

reductions for manufacturing and imports, in the range of a few percent annually. Additionally, given the critical role of solar module stockpiling, further research should investigate optimal policy mechanisms for managing strategic reserves, including potential price effects when establishing and utilizing such stockpiles. Notably, this should also address the robustness of the results, particularly the strategic stockpile levels, in light of uncertainties in material recycling learning rates.

Finally, while methodological refinements remain an ongoing research priority, our broader focus lies in addressing a fundamental question: what does true energy autonomy in the EU entail? In this study, we considered domestic manufacturing and stockpiling as key strategies for achieving energy autonomy. However, both approaches remain dependent on imports of raw materials, components, and advanced technologies. Looking ahead, we anticipate that a stricter definition of energy autonomy—one that accounts for deeper supply chain dependencies—will underscore the increasing importance of recycling-based capacities as a means of reducing external dependencies and enhancing long-term resilience.

DATA AVAILABILITY

All materials and source code are available at https://github.com/oitzingermaximilian/urbssolar.

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