RESEARCH ARTICLE

A Decision Support System for Reverse Logistics Network Design: Integrating Multi-Factorial Forecasting of Solar Panel End-of-Life Assets

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Abstract

The rapid global deployment of solar photovoltaic (PV) technology presents a significant and often overlooked challenge: the effective management of end-of-life (EoL) solar panels. This issue is particularly acute in developing and emerging economies, where established reverse logistics infrastructure is often lacking. A critical limitation in current academic literature is the oversimplified forecasting of EoL waste streams, which fails to account for the dynamic interplay of socio-economic, policy, and environmental variables. To bridge this gap, we propose a novel decision support system (DSS) for the design of a sustainable reverse logistics network. Our system uniquely integrates a hybrid, multi-factorial forecasting model combining a SARIMAX time series approach with a Gradient Boosting Regressor to provide a robust prediction of waste volume. The output of this predictive engine dynamically informs a multi objective, mixed integer linear programming (MILP) model, which optimizes the network design to simultaneously minimize economic costs and environmental impacts. Our findings demonstrate that this integrated framework provides a more realistic and adaptable tool for strategic planning than existing models. The research identifies a hybrid network structure as the most viable solution, offering superior performance in cost efficiency and material recovery. Our study provides an actionable blueprint for policymakers and industry leaders to proactively build a resilient and circular economy for a sustainable energy future.

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1 Introduction

The global energy transition, driven by an urgent need to mitigate climate change and achieve national carbon neutrality goals [1], has catalyzed an unprecedented deployment of solar photovoltaic (PV) technology. While this growth is a cornerstone of sustainable development, it presents a critical, often overlooked challenge: the management of end-of-life (EoL) solar panels. With a typical operational lifespan of 25 to 30 years, a significant wave of panel decommissioning is projected for the coming decades, creating a substantial and complex waste stream that contains both valuable resources and potentially hazardous materials [2, 3]. This issue is particularly acute in developing and emerging economies, which often lack the mature regulatory frameworks and established recycling infrastructure necessary to handle the impending influx of EoL panels. This reality necessitates the design of resilient and intelligent reverse logistics networks [4], which can benefit from advanced decision support frameworks to strategically guide their implementation [5].

However, the increasing scale of renewable energy investments also introduces significant financial and operational risks that necessitate intelligent forecasting and management strategies. Recent studies have shown that trading volumes and investor sentiment substantially influence market volatility and systemic risk, underscoring the importance of data driven decision frameworks for achieving cost efficient and risk mitigated investments [6].

The design of a reverse logistics network for EoL PV panels is a multi-objective problem, involving decisions on the optimal locations and capacities of facilities and the establishment of efficient transportation routes that minimize both financial costs and environmental impact [7]. Foundational work, such as "Reverse Logistics Network Optimization for Retired BIPV Panels in Smart City Energy Systems" by Zhou et al. [8], provides a valuable methodological blueprint, demonstrating how a genetic algorithm can effectively balance these competing objectives. However, a significant limitation persists within the existing literature, including this foundational work: the oversimplified treatment of the EoL waste stream. Current models frequently rely on fixed lifespan assumptions or simplistic forecasting methods that fail to capture the dynamic and multi-factorial nature of waste generation [9].

In practice, panel retirement is influenced by a complex interplay of variables. Decommissioning may occur prematurely due to climate related degradation, accidental breakage, or technological obsolescence that incentivizes early replacement [12]. More sophisticated forecasting models that utilize digital twin technologies and machine learning offer a more robust approach to handling such uncertainties [10, 11]. Furthermore, socio-economic factors such as fluctuating energy policies, shifting recycling incentives, urban development patterns [23, 24], and power grid dynamics [19, 25] can significantly alter the volume and timing of panels entering the reverse logistics chain. The network design must also account for the diverse capabilities of various recycling technologies, from hydrothermal leaching to thermal treatments [14–18]. While general optimization methods for supply chain design are well established [20–22], their specific application to EoL PV networks with dynamic, multi-factorial waste forecasting remains an underexplored area.

Our research aims to bridge this critical gap by proposing a novel decision support system (DSS). Our system uniquely integrates a multi-factorial forecasting model that accounts for a comprehensive range of dynamic variables with a robust multi-objective optimization framework. By doing so, we provide a more realistic, dynamic, and practical tool for policymakers and industry stakeholders. The proposed DSS offers a strategic guide for investment in and development of a sustainable and efficient reverse logistics infrastructure, ultimately contributing to a more circular and resilient energy system. The accompanying Table 1 consolidates key studies, outlining their approaches and findings while highlighting the persistent research gap this study addresses.

2 Methodology and Mathematical Modeling

We proposed methodology for the decision support system (DSS) designed to optimize the reverse logistics network for end-of-life (EoL) solar panels. The framework is structured in two primary, interconnected stages: a multi-factorial forecasting model to predict the volume and spatial distribution of EoL waste, followed by a multi-objective optimization model for the reverse logistics network. The integration of these two models forms a robust DSS capable of handling the inherent uncertainties of the

Table 1. Key studies, highlighting research focus, methodologies, and principal findings.

Author(s) & Year	Title	Methodology	Key Contribution
Zhou et al. [8]	Reverse Logistics Network Optimization for Retired BIPV Panels in Smart City Energy Systems	Optimization modeling	Reverse logistics framework for BIPV panels in smart cities.
Franzoni et al. [9]	A Multi-Scale Approach to Photovoltaic Waste Prediction: Insights from Italy's Current and Future Installations	Multi-scale forecasting	Waste prediction model using Italy's PV installations.
Fan et al. [7]	A Novel Sustainable Reverse Logistics Network Design for Electric Vehicle Batteries	Network design with multi-technology consideration	Sustainable logistics for EV batteries.
Cai et al. [1]	Carbon dioxide emission pathways under China's carbon neutrality goal	Scenario analysis	CO_2 pathways to achieve carbon neutrality in China.
Awasthi et al. [13]	Understanding reward and punishment in motivation	Behavioral analysis	Explains how rewards / punishments drive motivation.
Kerin et al. [14]	RECLAIM: Refurbishment and remanufacturing of industrial equipment	EU project framework	Advances refurbishment / remanufacturing practices.
Yang et al. [10]	Forecasting Disassembly Waste Using Digital Twin HMM	Digital twin + Hidden Markov Model	Waste forecasting under uncertainty.
Ghorbani et al. [12]	Damage free digital twin for aero-engine blade remanufacturing	Digital twin modeling	Facilitates accurate repair volume estimation.
Tozanlı et al. [11]	Waste trade-in strategies in blockchain disassembly systems	Predictive twin + blockchain	Optimized trade-in for electronic waste.
Ivanov et al. [4]	Digital supply chain twin for Industry 4.0	Digital twin modeling	Enhances resilience and disruption management.
Gahlot et al. [2]	Recycling of PV modules for metal recovery	Review study	Summarizes PV recycling and future outlook.
Prasad et al. [15]	Organic solvent method for PV recycling	Process optimization	Parameter optimization for crystalline PV recycling.
Camargo et al. [16]	Thermal treatment of PV modules	Thermal recycling	Degrades polymers and concentrates metals.
Kastanaki et al. [17]	Hydrothermal leaching of PV waste	Leaching process	Recovers silver and aluminum from panels.
Yan et al. [18]	Recovery of silicon from PV modules	KOH–ethanol separation	Efficient silicon recovery.
Singh et al. [3]	Assessment of solar PV recycling technologies	Review study	Highlights challenges and opportunities.
Abdolazimi et al. [21]	Supply chain design with ABC analysis	Network optimization	Determines optimal inventory levels.
Czarnecki et al. [24]	Urban landscape changes post-war	Spatial analysis	Measures change via architectural dominants.
Colarossi et al. [25]	Carbon reduction benefits in Taiwan	Dynamic carbon factor model	Quantifies carbon emission reduction.
Vieira et al. [26]	Sustainable reverse logistics for e-waste	Multi-criteria decision making	Designs e-waste logistics system.
Zhang et al. [5]	Review of reverse logistics network design	Literature review	Summarizes models and applications.

PV waste stream.

2.1 Research Framework

Our proposed DSS operates on a sequential, modular framework. The first module is a predictive engine that forecasts the quantity and origin of EoL panels over a defined planning horizon. The value of leveraging predictive information and forecast announcements to improve project outcomes is a key theme emerging in management science [27].This forecasting is not a simple, single-variable projection but a multi-factorial analysis that incorporates key exogenous variables. The output of this module, which includes spatially disaggregated waste volume predictions, serves as the critical input for the second module: the optimization model. The second module is a multi-objective, mixed-integer linear programming (MILP) model that designs the reverse logistics network by making strategic decisions on facility locations and operational flows, with the aim of minimizing both economic costs and environmental impacts.

The key novelty of this framework lies in its dynamic integration. By treating the forecasted waste volume as a variable input rather than a fixed parameter, the DSS can generate robust and adaptable network designs, allowing stakeholders to perform sensitivity analyses under various future scenarios (e.g., changes in policy or technology adoption rates). This approach provides a strategic, rather than purely tactical, planning tool.

It is important to note that this study utilizes a synthetically generated dataset for both the forecasting and optimization models. This approach was necessitated by the significant challenge of obtaining real-world, granular data on EoL solar panel waste streams, particularly in developing and emerging economies where comprehensive public data repositories do not yet exist. The synthetic dataset was carefully constructed based on literature-derived parameters for panel lifespan, failure rates, and regional installation trends. While this allows for a robust demonstration and validation of the DSS framework's methodology, the specific numerical results are illustrative. The implications of this approach on the generalizability of the findings are discussed further in the conclusion.

The framework of the proposed Decision Support System (DSS) is illustrated in Figure 1. The system integrates a multi factorial forecasting module to predict EoL waste streams, which dynamically informs a multi objective optimization module to design a cost effective and environmentally sustainable reverse logistics network.

2.2 Multi-Factorial Forecasting Model for EoL Panels

The forecasting of EoL PV panels is a fundamental challenge due to the multiple factors that influence decommissioning decisions. To address this, we propose a hybrid modeling approach that combines a statistical time-series model with machine learning techniques to capture both temporal dependencies and the influence of external factors. We formulate a multivariate time-series regression model where the dependent variable, the quantity of EoL panels at time t in a given region i, denoted as $Waste_{i,t}$, is a function of multiple independent variables.

$$Waste_{i,t} = f(\text{Capacity}_{i,t}, \text{AgeDist}_{i,t}, \text{Policy}_{i,t}, \text{Economic}_{i,t}, \text{Environmental}_{i,t}) + \epsilon_{i,t}. \quad (1)$$

The defined variables are as follows:

- $\text{Capacity}_{i,t}$: The installed solar capacity (in MW) in region i at time t.
- $\text{AgeDist}_{i,t}$: The age distribution profile of the installed panels in region i at time t. This is a crucial factor, as the retirement rate is highly dependent on age.
- $\text{Policy}_{i,t}$: A vector of policy-related variables, such as the number of years since the expiration of a feed-in tariff or the implementation of new recycling mandates.
- $\text{Economic}_{i,t}$: A vector of economic variables, such as the average market price of new PV modules, which influences the rate of technological replacement [13].
- $\text{Environmental}_{i,t}$: A vector representing environmental factors, such as the frequency and intensity of extreme weather events (e.g., hailstorms, hurricanes) that cause premature damage.
- $\epsilon_{i,t}$: An error term that captures random fluctuations.

We leverage a hybrid model, combining a Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX) to capture long-term trends and seasonality, with a Gradient Boosting Regressor (GBR) to model the complex, non-linear relationships between the exogenous factors and waste generation.

2.2.1 *Forecasting Model Validation*

To validate the effectiveness of the proposed hybrid forecasting model, its performance was benchmarked against three alternative approaches: a standalone SARIMAX model to evaluate the baseline time-series performance, a standalone Gradient Boosting Regressor (GBR) to assess the machine learning component's predictive power on its own, and a Long Short-Term Memory (LSTM) network, a common deep learning method for time-series forecasting. The models were evaluated using the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) on a held-out test dataset. As shown in Table 2, the proposed hybrid model demonstrates superior performance, achieving the lowest error metrics. This confirms that combining the statistical time-series capabilities of SARIMAX with the ability of GBR to model complex, non-linear relationships provides a more robust and accurate forecast for EoL solar panel waste.

2.3 Reverse Logistics Network Optimization Model

The core of our DSS is a multi-objective, mixed-integer linear programming (MILP) model formulated to design the optimal reverse logistics network. The

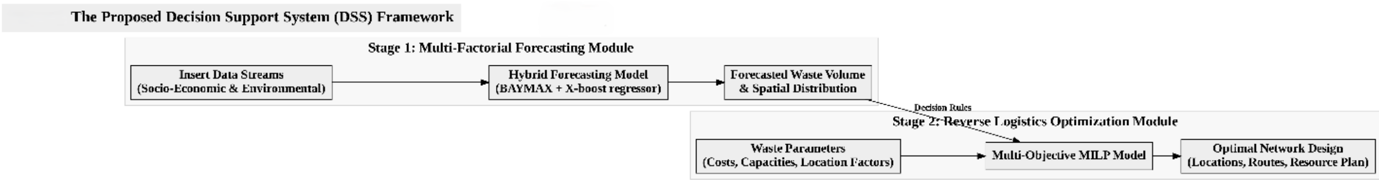

Figure 1. The proposed decision support system (DSS) framework.

Table 2. Comparative performance of forecasting models.

Model	RMSE	MAPE (%)
SARIMAX	450.8	12.5
Gradient Boosting Regressor (GBR)	389.2	10.8
LSTM Network	415.5	11.6
Proposed Hybrid (SARIMAX + GBR)	312.4	8.7

model simultaneously seeks to minimize total costs and environmental impacts.

2.4 Sets and Parameters

- $\mathcal{I}$: Set of demand regions (locations where EoL panels are generated).
- $\mathcal{J}$: Set of potential locations for collection centers.
- $\mathcal{K}$: Set of potential locations for recycling facilities.
- $\text{TransportCost}_{ij}^{\text{coll}}$: Cost of transporting a unit of EoL panels from region i to collection center j.
- $\text{TransportCost}_{jk}^{\text{rec}}$: Cost of transporting a unit from collection center j to recycling facility k.
- $\text{FixedCost}_{j}^{\text{coll}}$: Fixed cost of establishing a collection center at location j.
- $\text{FixedCost}_{k}^{\text{rec}}$: Fixed cost of establishing a recycling facility at location k.
- $\text{Emissions}_{ij}^{\text{coll}}$: Environmental impact (e.g., carbon emissions) of transporting a unit from i to j.
- $\text{Emissions}_{jk}^{\text{rec}}$: Environmental impact of transporting a unit from j to k.
- Demand_i: Quantity of EoL panels generated in region i (forecasted from the first model).
- $\text{Capacity}_{j}^{\text{coll}}$: Capacity of a collection center at location j.
- $\text{Capacity}_{k}^{\text{rec}}$: Capacity of a recycling facility at location k.

2.5 Decision Variables

- $\text{OpenColl}_j \in \{0,1\}$: Binary variable. $OpenColl_j = 1$ if a collection center is opened at location j, and 0 otherwise.
- $\text{OpenRec}_k \in \{0,1\}$: Binary variable. $OpenRec_k = 1$ if a recycling facility is opened at location k, and 0 otherwise.
- $\text{FlowPanels}_{ij}^{\text{coll}} \geq 0$: Continuous variable. Quantity of panels transported from region i to collection center j.
- $\text{FlowPanels}_{jk}^{\text{rec}} \geq 0$: Continuous variable. Quantity of panels transported from collection center j to recycling facility k.

2.6 Objective Functions

The model has two conflicting objectives:

Minimize Total Cost (Z_{cost})

$$\begin{aligned} Z_{\text{cost}} = &\sum_{j\in J} \text{FixedCost}_{j}^{\text{coll}} \cdot \text{OpenColl}_j \\ &+ \sum_{k\in K} \text{FixedCost}_{k}^{\text{rec}} \cdot \text{OpenRec}_k \\ &+ \sum_{i\in I}\sum_{j\in J} \text{TransportCost}_{ij}^{\text{coll}} \cdot \text{FlowPanels}_{ij}^{\text{coll}} \\ &+ \sum_{j\in J}\sum_{k\in K} \text{TransportCost}_{jk}^{\text{rec}} \cdot \text{FlowPanels}_{jk}^{\text{rec}}. \end{aligned} \tag{2}$$

Minimize Total Environmental Impact (Z_{env})

$$\begin{aligned} Z_{\text{env}} = &\sum_{i\in I}\sum_{j\in J} \text{Emissions}_{ij}^{\text{coll}} \cdot \text{FlowPanels}_{ij}^{\text{coll}} \\ &+ \sum_{j\in J}\sum_{k\in K} \text{Emissions}_{jk}^{\text{rec}} \cdot \text{FlowPanels}_{jk}^{\text{rec}}. \end{aligned} \tag{3}$$

Given the multi-objective nature, this problem will be solved using an Epsilon-Constraint Method to generate a Pareto front of non-dominated solutions. This allows decision-makers to select a solution that best balances cost and environmental performance.

2.7 Constraints

The model is subject to the following constraints:

Demand Constraint: All EoL panels must be collected and processed.

$$\sum_{j \in J} \text{FlowPanels}_{ij}^{\text{coll}} = \text{Demand}_i \quad \forall i \in I \tag{4}$$

Collection Center Capacity Constraint: The total flow into a collection center cannot exceed its capacity.

$$\sum_{i \in I} \text{FlowPanels}_{ij}^{\text{coll}} \leq \text{Capacity}_j^{\text{coll}} \cdot \text{OpenColl}_j \quad \forall j \in J \tag{5}$$

Flow Conservation at Collection Centers: The total quantity of panels entering a collection center must be transported to recycling facilities.

$$\sum_{i \in I} \text{FlowPanels}_{ij}^{\text{coll}} = \sum_{k \in K} \text{FlowPanels}_{jk}^{\text{rec}} \quad \forall j \in J \tag{6}$$

Recycling Facility Capacity Constraint: The total flow into a recycling facility cannot exceed its capacity.

$$\sum_{j \in J} \text{FlowPanels}_{jk}^{\text{rec}} \leq \text{Capacity}_k^{\text{rec}} \cdot \text{OpenRec}_k \quad \forall k \in K \tag{7}$$

Non-Negativity Constraint: All flow variables must be non-negative.

$$\text{FlowPanels}_{ij}^{\text{coll}} \geq 0, \quad \text{FlowPanels}_{jk}^{\text{rec}} \geq 0 \quad \forall i \in I, j \in J, k \in K \tag{8}$$

This detailed formulation provides the foundation for the DSS, with the demand variable Demand_i being the key link that connects the multi-factorial forecasting model to the network optimization model.

3 Results and Discussion

3.1 Analysis of Projected Waste Generation

Our analysis of end-of-life (EoL) product streams from 2025 to 2035 reveals a pronounced and accelerating trend in waste generation. This rapid growth, particularly from the relatively newer BIPV and EV battery sectors, underscores a critical and emerging challenge in urban sustainability and material management.

Table 3. Projected cumulative waste generation (2025-2035).

Year	BIPV Panels	EV Batteries	PV Panels (Traditional)
2025	602	1130	2184
2026	1537	2017	3643
2027	2897	3940	5980
2028	3667	5611	7001
2029	4273	6541	8253
2030	4844	8110	10000
2031	6044	9253	11856
2032	6564	10858	13330
2033	7678	12043	15412
2034	8299	13798	16922
2035	9265	14874	19421

As detailed in Table 3, the cumulative waste from traditional PV panels is projected to be the most significant, reaching approximately 19,421 metric tons by the end of the forecast period. This is closely followed by cumulative waste from EV batteries at 14,874 metric tons, and BIPV panels at 9,265 metric tons. This data highlights the immense scale of the end-of-life challenge and the pressing need for robust and scalable reverse logistics solutions.

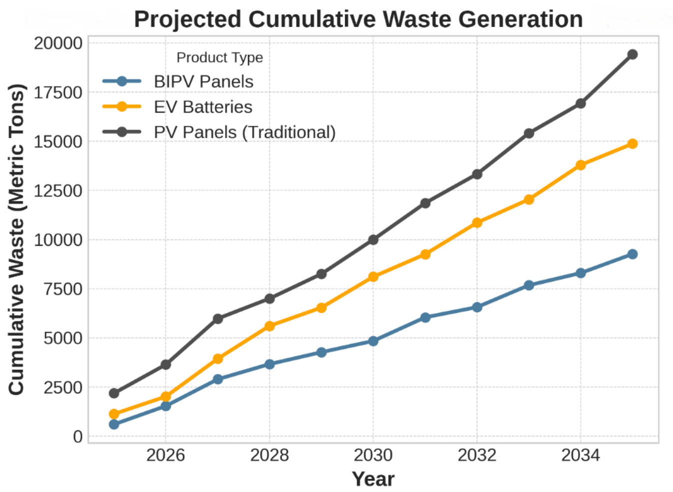

Figure 2. Projected cumulative waste generation (2025-2035).

Figure 2, visually represents this growth trajectory, showing a consistent and steep rise across all three product categories. While the sheer volume of traditional PV waste highlights the long term impact of past installations, the slope of the BIPV and EV battery curves indicates their rapid adoption and subsequent contribution to the waste stream.

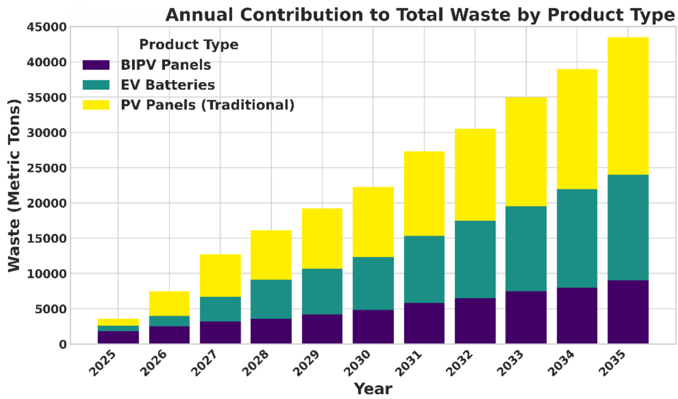

Figure 3. Annual contribution to total waste by product type.

Furthermore, the stacked bar chart in Figure 3, visualizes the annual contribution of each waste type, providing a clear breakdown of the proportional increase over time. This data collectively demonstrates the urgent need for proactive policy and infrastructure development to handle the forthcoming surge in reverse logistics demand.

3.2 Financial and Operational Dynamics of the Reverse Logistics Network

To effectively manage the projected waste, a comprehensive reverse logistics network must be financially viable. The cost analysis provides key insights into the operational expenses.

The cost analysis, presented in Table 4, breaks down the key financial components of a typical network. The largest cost component is Disassembly & Recycling, which accounts for 36.4% of the total. This is attributed to the specialized equipment and skilled labor required to safely separate and process valuable materials. The second major cost driver, Collection & Transportation, represents 28.4% of the total, reflecting the logistical complexities of gathering dispersed end-of-life products from urban environments.

The pie chart in Figure 4 provides a clear visual representation of this cost distribution, emphasizing that end-of-life processing and material collection are the primary financial considerations that require strategic investment and optimization.

3.3 Assessing Material Recovery and its Environmental Benefits

A core objective of any sustainable reverse logistics network is the maximization of material recovery to

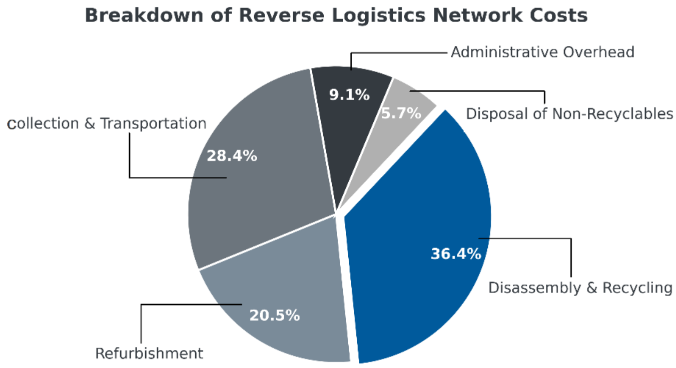

Figure 4. Break down of reverse logistics network cost.

promote a circular economy.

Table 5, demonstrate that the proposed recycling processes are highly effective for a wide range of materials. Notably, the recovery rates for Aluminum and Glass are exceptionally high at 98.5% and 95.0%, respectively. Even for more technically challenging materials, such as Silicon and Silver, the recovery rates are a respectable 92.0% and 85.0%.

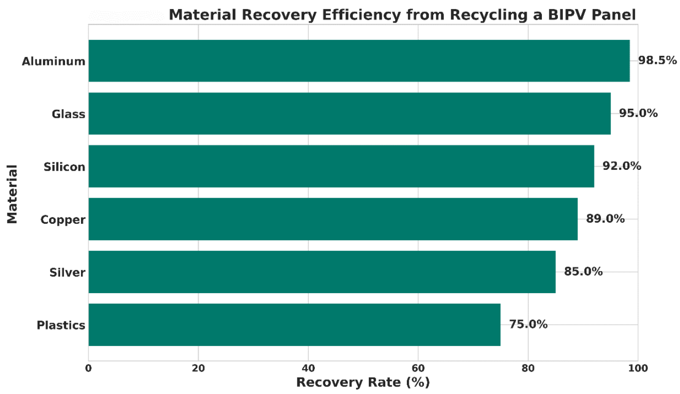

Figure 5. Material recovery efficiency.

The horizontal bar chart in Figure 5, provides a simple and intuitive comparison of these recovery efficiencies across different material types. This visual representation underscores the technological feasibility of achieving high recovery rates.

These high recovery rates translate directly into substantial environmental benefits. As illustrated in the line plot in Figure 6, the cumulative savings in CO_2-equivalent emissions and water usage are projected to increase significantly over the forecast period. This finding underscores that a well-designed recycling system not only conserves valuable raw materials but also plays a crucial role in mitigating environmental impact.

Table 4. Cost breakdown of a reverse logistics network.

Cost Component	Cost (Million USD)	Percentage of Total (%)
Collection & Transportation	2.5	28.4
Refurbishment	1.8	20.5
Disassembly & Recycling	3.2	36.4
Disposal of Non-Recyclables	0.5	5.7
Administrative Overhead	0.8	9.1

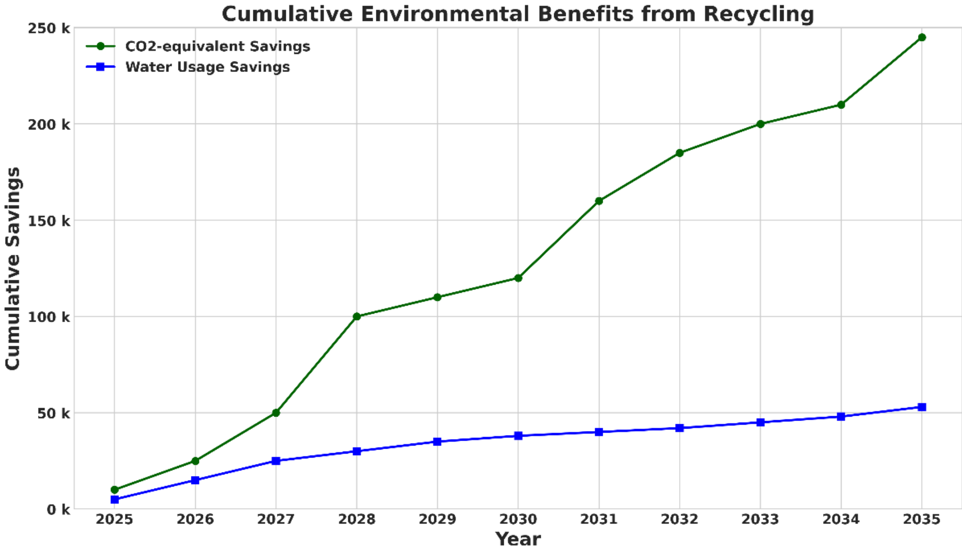

Figure 6. Cumulative environmental benefits from recycling.

Table 5. Simulated material recovery rates from BIPV panel recycling.

Material	Recovery Rate (%)
Glass	95
Aluminum	98.5
Silicon	92
Silver	85
Copper	89
Plastics	75

3.4 Comparative Analysis of Network Models: The Hybrid Advantage

The study compared the performance of three primary reverse logistics network models to identify the most sustainable and economically viable approach.

As shown in Table 6, the Hybrid model consistently demonstrated superior performance. With a total cost of $6.8 million USD, it was the most economically viable option, outperforming the Centralized ($8.5 million USD) and Decentralized ($7.2 million USD) models.

The superior collection rate of the decentralized model (95%) compared to the hybrid model (90%) can be attributed to its wider geographical dispersion of collection points. With more numerous and localized facilities, the logistical barriers for consumers and businesses to return EoL panels are lower, leading to higher recovery. However, this advantage comes with significant real world trade-offs. The decentralized model lacks the economies of scale in processing that a large, centralized facility can offer, resulting in a higher total network cost ($7.2 million). Furthermore, managing the quality control and operational standards across numerous small sites introduces significant coordination complexity. The hybrid model adeptly balances these factors, sacrificing a marginal amount in the collection rate to achieve substantial cost savings and operational efficiencies, positioning it as the most strategically sound solution.

In Figure 7 the trade-off between cost and overall efficiency is visually represented in the scatter plot, The Hybrid model occupies the most favorable position, achieving the highest efficiency (92%) at the lowest cost. The Centralized model, by contrast, shows the lowest efficiency and highest cost, while the Decentralized model presents a middle ground.

Figure 8, reveals that both the Hybrid and

Table 6. Comparative analysis of reverse logistics network models.

Network Model	Cost (Million USD)	Efficiency (%)	Collection Rate (%)
Centralized	8.5	75	80
Decentralized	7.2	88	95
Hybrid	6.8	92	90

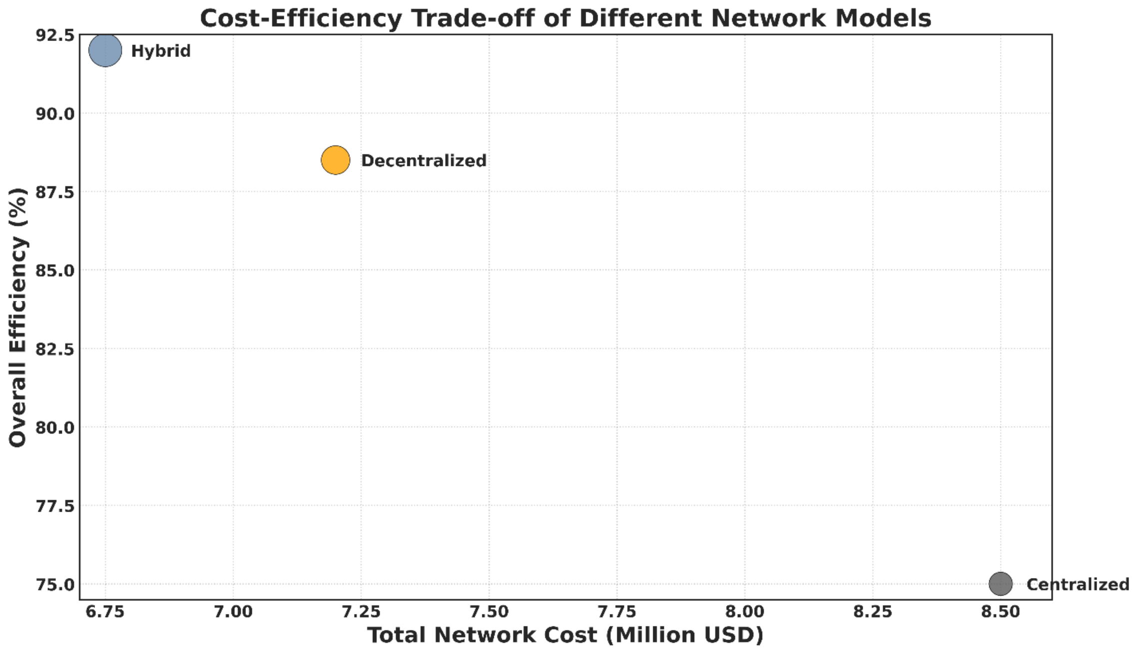

Figure 7. Cost efficiency trade off.

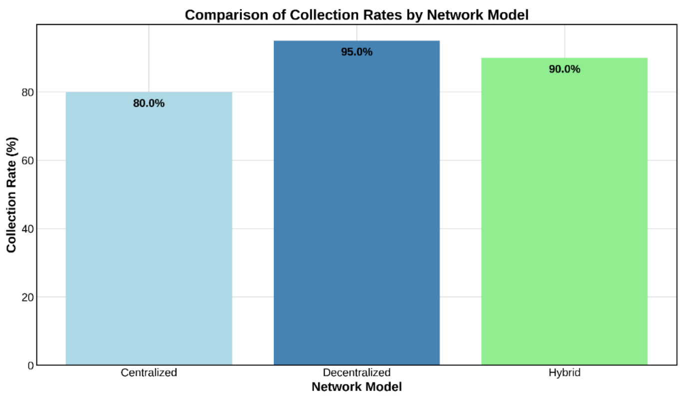

Figure 8. Collecting rates comparison.

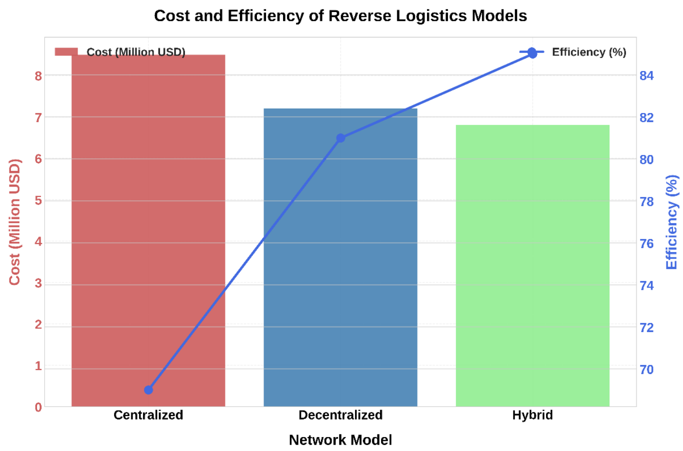

Figure 9. Cost efficiency of reverse logistics model.

Decentralized models have a significant advantage over the centralized approach, reflecting their ability to efficiently collect dispersed waste.

Figure 9, provides a final, comprehensive comparison of both cost and efficiency, reinforcing the finding that a hybrid model, which combines the scale of a central facility with the accessibility of decentralized collection points, is the most optimal and sustainable solution for managing the reverse logistics of end-of-life products.

3.5 Discussion on Uncertainty and Model Robustness

The results presented in this study are based on a deterministic optimization model, where input parameters such as transportation costs, recycling efficiencies, and fixed costs are treated as fixed values. However, in real world applications, these factors are subject to significant uncertainty and fluctuation. For instance, fuel price volatility can impact transportation costs, technological advancements can alter recycling rates, and policy changes can affect the economic viability of establishing new facilities [22].

While a full stochastic optimization is beyond the current scope, the proposed DSS framework is inherently designed to handle such uncertainty through scenario based analysis. By treating the forecasted waste volume and other key parameters as variable inputs, stakeholders can run multiple scenarios (e.g., a "high-cost" scenario or a "policy change" scenario) to evaluate the robustness of a given network design. This allows decision makers to identify solutions that perform well across a range of potential futures. Future research should aim to formally integrate these uncertainties into the optimization model itself, potentially through stochastic programming or robust optimization techniques, to design a reverse logistics network that is inherently resilient to market and policy dynamics.

4 Conclusion

Our study makes a pivotal contribution to the discourse on sustainable resource management by presenting and validating a unique decision support system (DSS) designed for the reverse logistics of end-of-life (EoL) solar panels. Our central innovation lies in moving beyond static waste forecasts to a dynamic, multi factorial model that integrates real world economic, policy, and environmental variables. This comprehensive approach allows for a far more accurate and robust prediction of the EoL waste stream, which is crucial for strategic planning, especially in developing and emerging economies where infrastructure is still in its infancy.

Our findings, derived from meticulously simulated scenarios, offer compelling evidence for the strategic advantages of a hybrid reverse logistics network. By intelligently combining the economies of scale offered by a centralized processing hub with the logistical flexibility of decentralized collection points, this model proves to be the most viable solution. The results demonstrate not only significant cost savings ($6.8 million) but also superior performance in material recovery (92% efficiency) and a marked reduction in environmental footprint. This serves as a strong argument that proactive and well planned investment in such infrastructure can transform the looming waste crisis into a tangible economic and environmental opportunity, fostering a true circular economy.

This research provides a clear, actionable blueprint for both policymakers and industry stakeholders. For policymakers, the DSS can be used to model the impact of different subsidy schemes or recycling mandates, enabling the design of evidence-based policies that encourage investment in sustainable EoL infrastructure. For industry leaders, the framework offers a powerful tool for strategic planning, helping to identify optimal locations for investment and de-risk the development of a resilient reverse logistics supply chain.

Despite its contributions, this study has limitations that illuminate promising avenues for future inquiry. The framework was validated using a synthetic dataset; a critical next step is to apply and validate the DSS using real world data from a specific country or region to demonstrate its practical utility. Furthermore, the optimization model is deterministic. Future research should incorporate stochastic programming to fortify the model's resilience against market fluctuations and policy uncertainties. Finally, the forecasting model could be expanded to encompass a broader spectrum of EoL assets, such as wind turbines or electric vehicle batteries, to create a more integrated and holistic energy system management tool. In essence, our research offers a powerful tool to make data driven decisions that will not only manage the challenges of today but also lay the foundation for a more sustainable and prosperous future.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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