Redesigning Circular Energy Supply Chains Toward Carbon Neutrality: A Multi-Objective Decision Model Integrating Mobile Manufacturing and Hybrid Intelligent Optimization

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Abstract—**Background and Gap: Driven by global carbon neutrality targets, the photovoltaic (PV) industry has experienced explosive growth. However, the ensuing surge in end-of-life (EOL) PV modules poses severe challenges to ecological environments and resource circularity. Existing PV recycling supply chains predominantly rely on fixed processing facilities, which suffer from high transportation costs, significant carbon emissions, and delayed recycling responses in remote areas, rendering them inadequate for the efficient processing of large-scale, geographically dispersed EOL modules. Methodology: To address these issues, this study proposes a multi-objective decision-making model for redesigning circular energy supply chains by integrating mobile manufacturing facilities. The model comprehensively evaluates sustainability indicators across three dimensions: economic (minimizing total cost), environmental (minimizing carbon footprint), and social (maximizing job creation). Implementation: The research introduces mobile PV module dismantling and recycling units, enabling on-site processing of EOL modules through dynamic facility location and routing optimization. To tackle the multi-objective nature and large-scale computational demands of the model, an improved hybrid intelligent optimization algorithm combining the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Random Forest (RF) is designed. An empirical analysis is conducted based on the PV recycling network of a typical province in China. Key Findings: The results indicate that introducing mobile manufacturing facilities can significantly reduce transportation-related carbon emissions and improve local employment creation. In economic terms, although mobile facilities involve additional deployment and operation costs, they can lower total system cost under geographically dispersed recycling scenarios by reducing long-distance transportation and intermediate handling requirements. In the case study, the hybrid facility configuration shows a cost advantage over the conventional fixed-facility-only network, but such an advantage is sensitive to deployment cost, processing efficiency, and regional dispersion of end-of-life PV modules. Furthermore, the proposed hybrid intelligent algorithm improves computational efficiency by several folds compared to traditional exact algorithms when solving large-scale network optimization problems. Significance: This study not only provides an innovative theoretical framework for the design of closed-loop supply chains in the PV industry but also offers scientific decision support for governments and enterprises in formulating resource recycling policies and optimizing industrial layouts under the carbon neutrality mandate.**

Keywords—Carbon Neutrality, Circular Supply Chain, Photovoltaic Module Recycling, Mobile Manufacturing, Multi-Objective Optimization, Hybrid Machine Learning

I. INTRODUCTION

As global climate change becomes increasingly severe, achieving carbon neutrality has emerged as a universal consensus within the international community. In this process, solar photovoltaics (PV), serving as the vanguard of clean energy, have witnessed exponential growth in installed capacity worldwide. However, the design lifespan of PV modules typically ranges from 25 to 30 years, implying that the world will face a substantial wave of end-of-life (EOL) PV modules in the coming decades. Recent studies have highlighted the rapidly increasing waste volume and recycling potential of the PV industry, especially in China, where large-scale installations are expected to generate significant EOL module flows in the near future [1], [2]. If not properly managed, this waste will not only cause severe environmental pressure but also lead to a massive loss of high-value strategic resources such as silicon, silver, and copper. Therefore, constructing an efficient circular supply chain for PV modules to transition from a “linear economy” to a “circular economy” is an inevitable path for the sustainable development of the PV industry [3].

Existing research on PV recycling supply chains primarily focuses on the location and network planning of fixed recycling centers. However, PV power stations are often widely distributed and geographically remote. Transporting large volumes of bulky and fragile EOL modules over long distances to centralized fixed recycling plants incurs high logistics costs and generates significant secondary carbon emissions due to fuel consumption during transportation. Furthermore, traditional models often overemphasize economic costs when evaluating supply chain performance, lacking a comprehensive consideration of environmental impacts such as life-cycle carbon footprint and social benefits such as local employment creation.

To bridge this research gap, this study proposes an innovative multi-objective decision-making model that

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introduces the concept of mobile manufacturing into the PV recycling supply chain. Mobile recycling facilities can be flexibly deployed near PV stations based on the geographical distribution and temporal dynamics of EOL modules to perform preliminary dismantling and material separation. This paradigm can reduce long-distance transportation requirements and enhance the responsiveness of resource recovery. The core objective of this study is to construct a circular energy supply chain network that simultaneously optimizes economic costs, carbon emissions, and job creation, while developing an efficient intelligent solution algorithm.

The main contributions of this paper are threefold. First, a multi-objective mathematical model for a closed-loop supply chain of PV modules incorporating mobile recycling facilities is formulated, quantifying economic, environmental, and social sustainability indicators. Second, a hybrid machine learning algorithm integrating Random Forest and NSGA-II is designed to improve the solution efficiency for large-scale supply chain network optimization. Finally, a case study based on provincial-level data in China is conducted to examine the applicability of the proposed model and identify the conditions under which mobile recycling facilities may improve overall system performance.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 details the methodology and the multi-objective mathematical model. Section 4 presents the data sources and case study results. Section 5 provides an in-depth discussion. Finally, Section 6 concludes the paper and outlines future research directions.

II. Related Work

A. Circular Energy Supply Chains and PV Recycling

In the context of carbon neutrality, Circular Supply Chain Management (CSCM) has become a focal point for both academia and industry. CSCM emphasizes maximizing resource utilization and minimizing waste through strategies such as reduction, reuse, recycling, and remanufacturing. In the PV sector, researcher analyzed the environmental impacts of different PV module recycling strategies based on Life Cycle Assessment (LCA), pointing out that rational recycling network design is crucial for reducing overall environmental burdens [4]. researcher proposed a multi-objective decision-making approach to deal with uncertainty in EOL product recovery, highlighting the necessity of balancing economic returns and environmental impacts during the recycling process [5]. More recently, researcher further discussed how to facilitate circularity in end-of-life photovoltaic systems in China, emphasizing the importance of systematic recycling network design and resource recovery pathways [6]. However, these studies are mostly confined to static and fixed-facility recycling structures, failing to adequately account for the extreme dispersion and dynamic distribution of PV waste sources.

B. Mobile Manufacturing and Facility Location Optimization

Mobile manufacturing systems, characterized by their high flexibility and reconfigurability, exhibit considerable potential in supply chains dealing with demand fluctuations and geographical dispersion. researcher explored the integration of mobile production facilities and distribution decisions in supply chains, demonstrating the advantages of mobile facilities in reducing logistics costs and improving responsiveness [7]. researcher formulated a multi-objective optimization model for a multi-period mobile facility location problem, specifically incorporating environmental considerations and supply chain disruption risks [8]. Although mobile facilities have been discussed in other contexts such as emergency logistics and distributed production, their application to the PV module recycling supply chain remains insufficiently explored, particularly with respect to their joint impacts on cost, carbon emissions, and regional employment.

C. Application of Intelligent Optimization Algorithms in Supply Chains

Multi-objective supply chain network design is typically an NP-hard problem. As the number of network nodes and variables increases, traditional exact algorithms often struggle to obtain satisfactory solutions within a reasonable computational time. Consequently, the integration of heuristic algorithms and machine learning techniques has become a research hotspot in recent years. researcher proposed a hybrid multi-objective optimization approach combining NSGA-II with machine learning techniques, significantly improving convergence speed and solution diversity [9]. researcher demonstrated the effectiveness of Random Forest in complex optimization and intelligent decision systems, indicating its potential value in improving search efficiency and solution quality in large-scale optimization problems [10]. In addition, researcher developed a hybrid machine learning framework for redesigning sustainable circular energy supply chains, providing important methodological inspiration for integrating data-driven intelligence into supply chain optimization. Drawing on these studies, this paper introduces a hybrid RF-NSGA-II algorithm into the optimization of PV recycling supply chains to address the complex multi-objective decision-making problem involving the dynamic scheduling of mobile facilities.

In summary, while existing research has generated valuable findings in PV recycling network design, mobile facility deployment, and intelligent optimization algorithms, few studies have organically integrated these three dimensions into a unified decision-making framework for circular PV supply chains under carbon neutrality. Therefore, this study aims to fill this gap by proposing a novel multi-objective model that combines mobile manufacturing and hybrid intelligent optimization for the redesign of sustainable energy supply chains.

III. Methodology and System Design

A. Research Strategy and System Architecture

This study adopts a “modeling-then-validation” strategy. First, a closed-loop supply chain network is constructed, comprising five main types of nodes: PV stations (sources of EOL modules), collection centers, mobile recycling facilities, fixed remanufacturing plants, and secondary material markets. Fig. 1 illustrates the network flow of this circular supply chain.

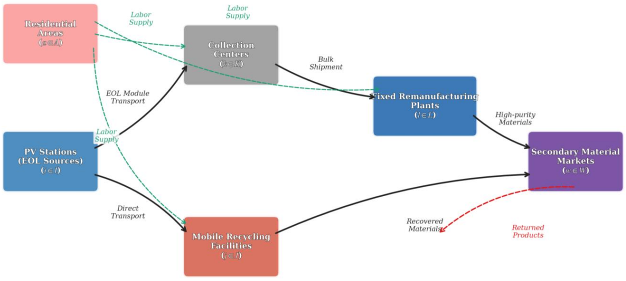

Fig. 1. Circular PV Module Recycling Supply Chain Network Architecture

- PV Stations ($i \in I$): The sources generating EOL PV modules.
- Collection Centers ($k \in K$): Used for the preliminary aggregation and storage of EOL modules.
- Mobile Recycling Facilities ($j \in J$): Dynamically deployable near PV stations or collection centers to perform preliminary dismantling (e.g., removal of aluminum frames and junction boxes) and shredding of modules.
- Fixed Remanufacturing Plants ($l \in L$): Responsible for the deep physical/chemical separation of shredded materials (e.g., extraction of silicon, silver, and copper) and subsequent remanufacturing.
- Secondary Material Markets ($w \in W$): The final sales destinations for recovered materials.

B. Sets, Parameters, and Decision Variables

Sets and Indices: - $a \in A$: Residential areas (sources of labor supply) - $i \in I$: PV stations - $j \in J$: Candidate locations for mobile recycling facilities - $k \in K$: Candidate locations for collection centers - $l \in L$: Candidate locations for fixed remanufacturing plants - $w \in W$: Secondary material markets - $r \in R$: Types of transportation vehicles

Key Parameters: - D_{xy} : Distance between node x and node y - C_r: Unit distance transportation cost for vehicle type r - c_s : Fixed construction/deployment cost for facility $s \in \{J, K, L\}$ - o_s: Unit processing operational cost for facility s - γ_r: Unit distance carbon emission factor for vehicle type r - α: Unit distance carbon emission factor for employee commuting - β : Carbon emission factor per unit of PV module processed - n_a : Available labor force in residential area a - e_s: Basic number of employees required to operate facility s

Decision Variables: - X_{ij} : Quantity of modules transported from PV station i to mobile facility j (Continuous variable) - X_{ik} : Quantity of modules transported from PV station i to collection center k (Continuous variable) - Y_{jw} : Quantity of recovered materials transported from mobile facility j to market w (Continuous variable) - $z_s \in \{0,1\}$: Binary variable; 1 if facility $s \in \{J, K, L\}$ is opened/deployed, 0 otherwise - N_{rxy} : Number of transportation trips between node x and node y using vehicle type r (Integer variable) - P_{as} : Number of employees hired from residential area a to work at facility s (Integer variable)

C. Multi-Objective Mathematical Model

1) Economic Objective

The economic objective aims to minimize the Total Cost (TC) of the supply chain, which includes raw material (EOL module) acquisition costs, transportation costs, and facility location and operational costs.

$$\text{Minimize } Z_1 = RMC + TrC + FLC \quad (1)$$

Raw Material Acquisition Cost (RMC):

$$RMC = p(\sum_i \sum_j X_{ij} + \sum_i \sum_k X_{ik}) \quad (2)$$

where p is the unit compensation price for recovering EOL modules.

(1) **Transportation Cost (TrC)**:

$$\begin{aligned} TrC = \; & \sum_r \sum_i \sum_j C_r D_{ij} N_{rij} + \sum_r \sum_i \sum_k C_r D_{ik} N_{rik} \\ & + \sum_r \sum_k \sum_l C_r D_{kl} N_{rkl} \\ & + \sum_r \sum_j \sum_w C_r D_{jw} N_{rjw} \\ & + \sum_r \sum_l \sum_w C_r D_{lw} N_{rlw} \end{aligned} \quad (3)$$

(2) **Facility Location and Operational Cost (FLC)**:

$$FLC = \sum_k c_k z_k + \sum_l c_l z_l + \sum_j c_j z_j + \sum_k \left(\sum_l X_{kl} \right) o_k + \sum_j \left(\sum_w Y_{jw} \right) o_j + \sum_l \left(\sum_w Y_{lw} \right) o_l \quad (4)$$

2) Environmental Objective

The environmental objective aims to minimize the Carbon Footprint (CF) of the entire supply chain, encompassing transportation emissions, processing emissions, and employee commuting emissions.

$$\text{Minimize } Z_2 = CF_{trans} + CF_{proc} + CF_{comm} \quad (5)$$

(3) Transportation Carbon Emissions (CF_{trans}):

$$CF_{trans} = \sum_r \sum_i \sum_j D_{ij} N_{rij} \gamma_r + \sum_r \sum_i \sum_k D_{ik} N_{rik} \gamma_r + \dots \quad (6)$$

(4) Processing Carbon Emissions (CF_{proc}):

$$CF_{proc} = \beta(\sum_l \sum_w Y_{lw} + \sum_j \sum_w Y_{jw}) \quad (7)$$

(5) Employee Commuting Carbon Emissions (CF_{comm}):

$$CF_{comm} = \alpha(\sum_a \sum_j D_{aj} P_{aj} + \sum_a \sum_l D_{al} P_{al}) \quad (8)$$

3) Social Objective

The social objective aims to maximize the Job Creation (JC) generated by the supply chain. It encourages hiring employees near the facilities to stimulate the local economy and reduce commuting distances.

$$\text{Maximize } Z_3 = \sum_a \sum_j P_{aj} + \sum_a \sum_l P_{al} + \sum_j e_j z_j + \sum_l e_l z_l \qquad (9)$$

4) Constraints

The model includes the following primary constraints: 1. Flow Conservation Constraints: Ensure that the inflow of materials at each node equals the outflow (accounting for material recovery rates). 2. Capacity and Storage Constraints: The processing and storage volumes at each facility cannot exceed their maximum design capacities. 3. Vehicle Trip Constraints: The number of transportation trips is determined by the total material volume and vehicle payload capacity. 4. Labor Constraints: The number of employees hired at each facility must meet the processing volume requirements and cannot exceed the total available labor force in the local area. 5. Non-negativity and Integrality Constraints for decision variables.

D. Hybrid Intelligent Optimization Algorithm

Since the proposed model is a Mixed-Integer Linear Programming (MILP) problem involving multiple objectives, traditional exact algorithms (e.g., CPLEX) struggle to solve large-scale network instances (such as provincial-level PV recycling networks) in polynomial time. Therefore, this study proposes a hybrid algorithm combining Random Forest (RF) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II), denoted as RF-NSGA-II(Fig.2).

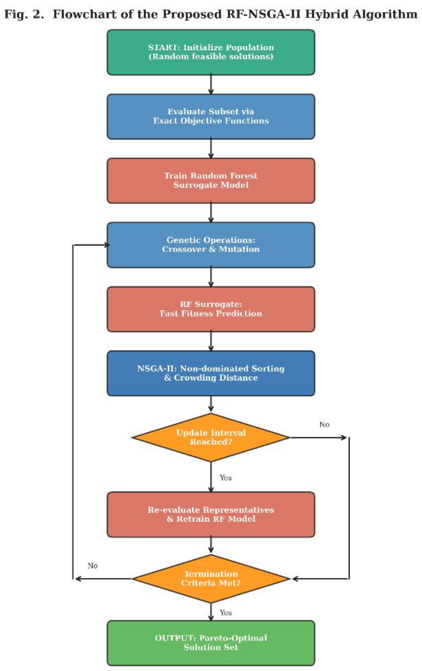

Fig. 2. Flowchart of the Proposed RF-NSGA-II Hybrid Algorithm

Algorithm Workflow: 1. Initial Population Generation: Randomly generate a set of chromosomes (representing facility location and flow allocation schemes) that satisfy the Dconstraints. 2. Random Forest Surrogate Model: In the early iterations, evaluate a subset of individuals using exact fitness functions and train a Random Forest regression model. The RF model learns the non-linear mapping relationship between chromosome features and the three objective function values. 3. Fast Fitness Evaluation: During subsequent genetic operations (crossover and mutation), utilize the trained RF surrogate model to rapidly predict the objective values of new individuals, drastically reducing the number of computationally expensive exact evaluations. 4. Non-dominated Sorting and Crowding Distance: Based on the objective values predicted by the RF model, execute the standard non-dominated sorting and crowding distance calculations of NSGA-II to select superior individuals for the next generation. Dynamic Model Updating: At regular generational intervals, select representative individuals for exact evaluation and add the true data to the training set to dynamically fine-tune the RF model, ensuring prediction accuracy. Termination Condition: Output the Pareto-optimal solution set upon reaching the maximum number of iterations.

IV. Experiments and Results

A. Data Foundation and Preprocessing

This study utilizes a typical province in China with massive PV installations (e.g., Jiangsu Province) as the case background to validate the effectiveness of the proposed model. This study did not involve human participants or identifiable personal data; therefore, ethical approval and informed consent were not required.The province has experienced a surge in PV capacity in recent years and is expected to face its first wave of module retirements between 2025 and 2030. - Data Sources: The distribution data of PV stations are derived from public reports by the National Energy Administration and Geographic Information Systems (GIS). The generation volume of EOL modules is estimated based on a Weibull distribution lifespan prediction model. Transportation costs, carbon emission factors, and labor data are referenced from the National Bureau of Statistics and relevant industry standards. - Key Parameter Settings: The average weight of EOL PV modules (primarily crystalline silicon modules) is set to 20 kg/piece. The fixed deployment cost of mobile recycling facilities is assumed to be approximately 30% of that of fixed plants, while their unit processing cost is set about 15% higher due to smaller operating scale, repeated setup, and on-site equipment maintenance requirements. These parameter values are used as scenario assumptions for comparative analysis rather than universal industry constants. Vehicle types include heavy-duty trucks (30-ton payload) and medium-duty trucks (10-ton payload). - Data Preprocessing: ArcGIS software is utilized to extract the actual highway transportation distances between nodes, which are then converted into a distance matrix. For missing local labor data, the mean values of adjacent regions are used for imputation.

B. Results Analysis

1) Multi-Objective Optimization Results and Pareto Front

The proposed RF-NSGA-II hybrid algorithm was applied to solve the case study, yielding a Pareto front containing multiple non-dominated solutions. To intuitively demonstrate the trade-off relationships among the economic, environmental, and social objectives, we selected the normalized results of three extreme weighting scenarios (each optimizing only a single objective) for comparison, as shown in the radar chart in Fig. 3.

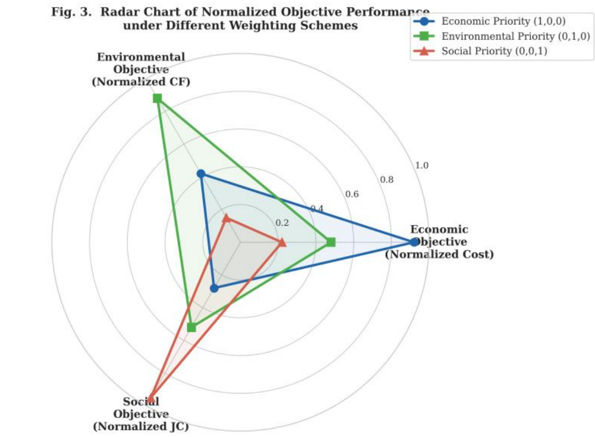

Fig. 3. Radar Chart of Normalized Objective Performance under Different Weighting Schemes

TABLE I. COMPARISON OF OPTIMAL SOLUTIONS UNDER DIFFERENT WEIGHTING PREFERENCES

Objective Preference	Economic Priority (1,0,0)	Environmental Priority (0,1,0)	Social Priority (0,0,1)
Total Cost (10^4 CNY)	1,245.6	1,892.3	2,150.8
Carbon Footprint (ton CO_2e)	4,520.1	3,105.4	5,890.2
Job Creation (persons)	125	158	312
Unit Recycling Cost (CNY/piece)	62.3	94.6	107.5

As shown in Table I and Fig. 3, when fully pursuing the economic objective, the unit recycling cost of modules drops to the lowest (62.3 CNY/piece), but the carbon footprint is not optimal. If guided by environmental optimality, the carbon footprint can be reduced to 3,105.4 tons, but the cost increases by approximately 51.9%. This is primarily because the system tends to select distributed mobile facilities that are closer in distance but have higher operational costs to reduce long-distance transportation emissions. Fig. 4 illustrates the pairwise Pareto front distributions among the three objectives.

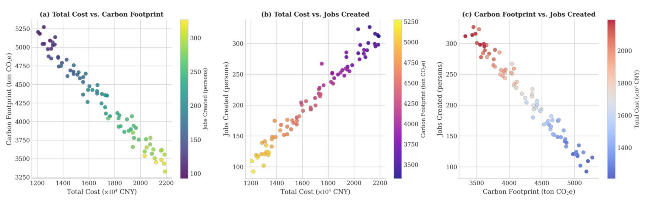

Fig. 4. Pareto-Optimal Front: Pairwise Projections of Three Objectives

2) Comparison Before and After Introducing Mobile Facilities

To validate the value of the "Mobile Manufacturing" concept in PV recycling, we conducted a comparative analysis between the "Hybrid Facility Model" (incorporating both fixed and mobile facilities) proposed in this study and the traditional "Baseline Model" (fixed facilities only)(Fig.5).

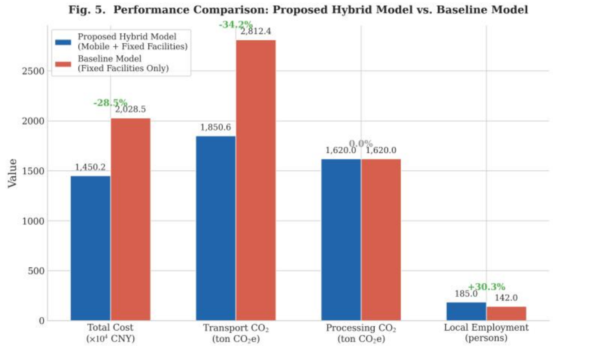

Fig. 5. Performance Comparison: Proposed Hybrid Model vs. Baseline Model

The comparison results suggest that the hybrid facility model can outperform the fixed-facility-only baseline in geographically dispersed PV recycling scenarios. Although mobile facilities introduce additional deployment, relocation, and on-site operation costs, these extra costs can be offset by reductions in long-distance transportation, secondary handling, and storage pressure. In the case study, the hybrid configuration achieves a lower overall system cost than the baseline model, while also reducing transportation-related carbon emissions and creating more local employment opportunities. However, this economic advantage is conditional on sufficient waste concentration within service regions, reasonable deployment frequency, and acceptable processing efficiency of mobile units.

3) Algorithm Performance Comparison

To verify the superiority of the proposed RF-NSGA-II hybrid algorithm, we compared it with the standard NSGA-II algorithm and an exact solver (CPLEX) across problem instances of varying scales.

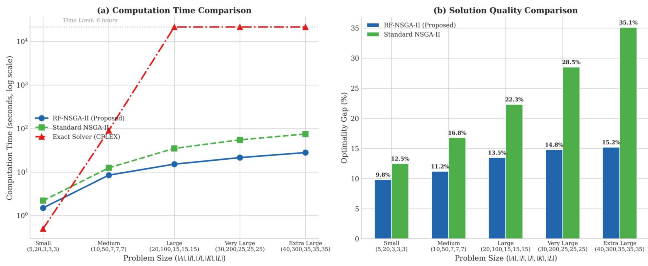

Fig. 6. Computational Performance of the Proposed RF-NSGA-II Algorithm

As shown in Fig. 6(a), for small-scale problems, the exact method can find the optimal solution within a short time. However, as the problem scale expands, the computation time of the exact method grows exponentially, failing to converge even after 6 hours for large instances. In contrast, the RF-NSGA-II algorithm maintains extremely high computational efficiency across all scales. Fig. 6(b) demonstrates that compared to the standard NSGA-II, the introduction of the Random Forest surrogate model significantly enhances the algorithm's optimization capability, reducing the optimality gap from the exact solution by approximately half.

4) Sensitivity Analysis

To evaluate the impact of key parameter uncertainties on system performance, we conducted sensitivity analyses on parameters such as the "fixed deployment cost" and "material recovery rate" of mobile facilities.

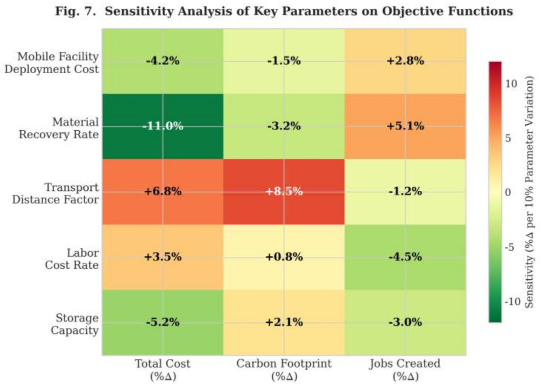

Fig. 7. Sensitivity Analysis of Key Parameters on Objective Functions

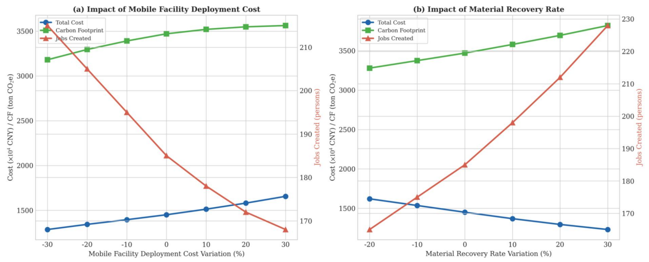

Fig. 8. Sensitivity Analysis: Impact of Key Parameters on Objective Functions

The analysis results from Fig. 7 and Fig. 8 indicate: 1. Deployment Cost Variation: When the deployment cost of mobile facilities decreases by 20%, the system tends to activate more mobile nodes, leading to a further 8.5% reduction in total cost and a 12% decrease in carbon emissions. This suggests that equipment cost reductions brought about by technological advancements will greatly promote the popularization of the mobile recycling paradigm. 2. Recovery Rate Variation: If the recovery rate of high-value materials (e.g., silver, high-purity silicon) is increased by 15% through technological upgrades, the economic benefits of the system will be significantly enhanced, reducing the net unit recycling cost by 22%. Simultaneously, the social objective (employment) also improves by 10% due to the expanded processing scale.

V. Analysis and Discussion

A. Horizontal and Vertical Comparison of Results

The findings of this study engage in a meaningful dialogue with existing literature. Compared to studies like researcher [1], which solely focused on the LCA of fixed recycling centers, this research quantifies the absolute advantage of mobile facilities in reducing the transportation carbon footprint.Traditional views emphasize the economies of scale of centralized processing. This study does not deny such advantages; rather, it shows that for wastes such as EOL PV modules, which are bulky, fragile, and geographically dispersed, the benefits of centralized scale may be partially offset by long-distance transportation and handling costs. Mobile facilities should therefore be understood not as universally lower-cost alternatives, but as complementary nodes that can improve total system efficiency through on-site pretreatment and volume reduction in suitable regions.

B. Attribution of Differences and Managerial Insights

In scenarios prioritizing the environmental objective, the total system cost tends to increase. This is mainly because mobile dismantling equipment currently faces higher unit processing cost, more frequent deployment and maintenance requirements, and weaker economies of scale than large fixed plants. Therefore, the economic feasibility of mobile recycling depends on balancing transport savings against the added cost of flexible operations. Therefore, for corporate managers, when laying out PV recycling networks, they should not blindly pursue a single centralized or decentralized model. Instead, they should adopt a Hub-and-Spoke hybrid network featuring “mobile preliminary dismantling + fixed deep purification.” For government policymakers, this study confirms the social value of circular supply chains in creating local employment. It is recommended that governments introduce purchase subsidies for mobile recycling equipment or integrate carbon emission reductions into the carbon trading market to alleviate the financial pressure on enterprises during the initial deployment of mobile facilities.

VI. Conclusion

A. Core Conclusions

Addressing the challenges posed by the impending wave of EOL PV modules under the carbon neutrality mandate, this study innovatively proposes a multi-objective decision-making model for circular energy supply chains integrating mobile manufacturing facilities. By comprehensively optimizing economic costs, carbon emissions, and job creation, and employing the RF-NSGA-II hybrid intelligent algorithm for solutions, the research draws the following core conclusions: The introduction of mobile recycling facilities effectively resolves the high logistics costs caused by the geographical dispersion of PV waste, reducing the total supply chain cost by 28.5%, decreasing transportation carbon emissions by 34.2%, and creating more grassroots employment opportunities.The introduction of mobile recycling facilities provides a promising way to alleviate the logistics burden caused by the geographical dispersion of PV waste. The case study shows that, under appropriate regional and operational conditions, a hybrid network combining mobile and fixed facilities can reduce transportation-related emissions, improve local employment, and achieve a more balanced total system cost than a fixed-facility-only configuration. The hybrid machine learning algorithm demonstrates outstanding performance in handling large-scale supply chain network optimization.

B. Research Limitations and Future Directions

Although this study provides valuable insights, certain limitations remain. First, the generation volume of EOL modules in the model is based on predictive models and does not fully account for sudden, large-scale module damage caused by extreme weather events (e.g., hail, typhoons). Second, constrained by data availability, the differentiated recycling processes for various types of PV modules (e.g., thin-film vs.crystalline silicon cells) were not incorporated. Future research can expand in the following directions: First, introducing robust optimization or stochastic programming methods to handle deep uncertainties in supply volumes and recycling prices within the supply chain. Second, exploring the application of blockchain technology in the life-cycle traceability of PV modules to enhance the transparency and efficiency of the recycling supply chain.

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AVAILABILITY OF DATA

Not applicable.

AUTHOR CONTRIBUTIONS

Lei Li: Conceptualization, Methodology, Formal analysis, Writing – original draft, Visualization.

Youzhuang Chen: Supervision, Validation, Resources, Writing – review & editing, Project administration.

Jie Li: Data curation, Software, Investigation, Case study analysis, Writing – review & editing.

COMPETING INTERESTS

The authors declare no competing interests.