# Circular Energy Supply Chain Design for Sustainable Manufacturing: A Study on Intelligent Algorithms and Multi-Objective Optimization

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***Abstract*—Under the dual challenges of climate change and resource constraints, manufacturing parks are increasingly required to coordinate energy supply, material recovery, and emission reduction in an integrated manner. However, many existing studies focus on either one-way energy supply or isolated emission-control measures, while the joint design of renewable energy use, energy storage, waste heat recovery, and material circulation remains insufficiently explored. To address this issue, this study develops a scenario-based circular energy supply chain design framework for sustainable manufacturing parks. A multi-objective mixed-integer linear programming model is formulated to balance economic cost, carbon emissions, and local employment. To improve computational tractability, a hybrid solution framework combining K-means scenario reduction, NSGA-II, and variable neighborhood search is proposed.A numerical case is constructed based on a representative manufacturing park setting, public meteorological characteristics, literature-based technical parameters, and synthetic load profiles calibrated to typical industrial operating patterns. The proposed approach is compared with a commercial solver on small- and medium-scale benchmark instances and is further tested on larger instances under a fixed computational time limit. The results show that the circular design strategy can reduce total system cost and carbon emissions in the constructed benchmark scenario, while increasing local employment opportunities. Sensitivity analyses on carbon price, renewable-energy equipment cost, and load outliers further illustrate the influence of key parameters on system configuration. The findings provide a reproducible modeling and computational framework for preliminary planning of circular energy and material networks in manufacturing parks, rather than a direct validation of a specific real industrial project.***

***Keywords—Sustainable Manufacturing, Circular Energy Supply Chain, Multi-objective Optimization, Hybrid Intelligent Algorithm, Industrial Symbiosis***

## I. INTRODUCTION

The problem of climate change and the depletion of resources are very serious threats to the global industrial system. As the world's population continues to grow and industrialization progresses, it becomes essential to increase the efficiency of manufacturing systems in sustainable development initiatives especially those that aim at promoting clean production and net-zero emission objectives [1]. The conventional linear economic paradigm of manufacturing (i.e., take-make-dispose) does not only use up enormous volumes of fossil fuels but also produces enormous volumes of industrial waste and greenhouse gases. In response to such issues, implementing Circular Economy (CE) as a part of manufacturing supply chain and building circular networks aimed at sustainable manufacturing has been identified as an important way to reduce the risks of environmental risks and implement carbon neutrality strategies [2].

In the sustainable manufacturing perspective, the designing of energy supply chains should not be centered merely on the reduction of costs but rather should be integrated with environmental and social performance. Nevertheless, modern industrial parks are subject to complicated technical and organizational barriers during the practice of net-zero principles [3]. The available supply chain decision-making models have concentrated more on one economic indicator or simply added carbon emission limitations to unidirectional logistic networks and have not been able to explore the full synergistic capabilities between energy flows and material flows (e.g., waste heat recovery and byproduct utilization and remanufacturing of end-of-life equipment). Such piecemeal design prevents the system in attaining an actual circular closed loop and restricts enhancement of overall sustainable performance.

The present analysis is concerned with the network design problem of park-level circular energy supply chains. To be more precise, it intends to address the question of how an overall optimum can be reached regarding economic costs, carbon emissions, and social employment with several constraints of multi-energy complementarity (renewable and conventional energy), energy storage structure, and material recovery. The optimization of closed-loop supply chain and industrial symbiosis networks have seen some advance in previous studies but when working with large-scale mixed-integer programming problems that involve complicated energy conversion processes and reverse logistics, conventional exact algorithms tend to suffer significantly from the so-called curses of dimensionality [4]. Simultaneously, the available literature does not often combine cutting-edge methods of machine learning (e.g., clustering algorithms) closely with metaheuristic algorithms to improve the efficiency of multi-objective solutions.

To remediate these shortcomings, the current study seeks to offer a repeatable situation-oriented modeling framework in the context of circular energy supply chain designs in manufacturing parks. There are three main contributions. To begin with, a multi-objective optimization model is created that takes into account both power supply, storage arrangement, wa

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ste heat regeneration, materials cycle, cost, carbon emission, and employment in the local area simultaneously. Secondly, a hybrid algorithmic structure consisting of K-means scenari o reduction, NSGA-II and variable neighborhood search is d eveloped to enhance the computational efficiency of large-sc ale benchmark problems. Thirdly, a case study, based on clea r assumptions, publicly available or literature-based variables, and hypothetical but understandable load profiles, is designe d to assess the possible advantages and disadvantages of the suggested framework. The research limit is restricted to medi um and long term static planning, and real time electricity ma rket bidding, high frequency operation control, and process o ptimization at plant level are not included in this study.

The rest of the paper will be organized in the way that fol lows: The systematic review of the relevant literature is prese nted in Section 2; Section 3 elaborates on the background of t he problem and formulates the multi-objective mathematical model; The design of the hybrid intelligent algorithm is intro duced in Section 4; Section 5 shows the optimization outcom es by means of a case study and a sensitivity analysis; Sectio n 6 offers a more thorough examination of the findings; lastl y, Section 7 summarizes the paper and gives suggestions on what to investigate in future.

## II. Related Work

### A. Sustainable Manufacturing and Circular Economy Supply Chains

Over the past few years, the circular economy, as an alter native to the unsustainable linear economy, has gained much attention in scholarship and the industry. Circular supply chai ns are based on the principles of reuse, reduction, recycling, r edesign and remanufacturing in order to provide the continuo us flow of products and energy across their lifecycles [5]. Stu dies by the manufacturing sector have investigated the relatio nship between digital technologies and industrial symbiosis i n facilitating the creation of closed-loop systems. As an exa mple, literature [6] highlighted the importance of data-driven methods in the circularization of manufacturing, whereas lite rature [7] examined the synergistic optimization mechanisms of multi-energy networks and material flows in the industrial parks. Nevertheless, the majority of research studies are con ceptual frameworks or focus on optimizing reverse logistics of a particular product (batteries or plastics) without any mod el of quantitative analysis to deeply integrate energy and man ufacturing processes. This work incorporates the idea of a cir cular energy supply chain and combines both the concept of cascading energy use and recovery of manufacturing waste i nto a single physical network, and emphasizes the need to op timize the system.

### B. Energy Networks and Multi-Objective Optimization

Sustainable supply chains require that decision-makers m ust balance the three pillars of economy, environment, and so ciety [8]. The Multi-Objective Optimization (MOO) approac h has been widely used in bioenergy and distributed energy n etwork design. According to literature [9] there has been a bi ofuel supply chain model which takes into account both costs and carbon footprints and the subsequent literature [10] addi tionally introduces social benefits (like jobs) into the objectiv e function and uses weighted goal programming method to s olve them. However, these studies formed the basis of multi-dimensional assessment but weighted method fails to find a f ull Pareto front when dealing with complex park networks wi th many discrete variables and non-linear constraints and it is highly dependent on subjective weighting. Thus, this paper e mbraces Pareto optimization idea, attempting to demonstrate the natural trade-offs between different objectives in an objec tive manner.

### C. Application of Intelligent Optimization Algorithms in Supply Chains

Regarding the NP-hard large-scale supply chain network design problem, metaheuristic algorithms (e.g., genetic algori thms, particle swarm optimization) have already shown consi derable benefits [11]. As a typical multi-objective evolutiona ry algorithm, NSGA-II has been confirmed by numerous stu dies in the optimization of closed-loop supply chains [12]. N evertheless, when increasing in size of models and in the nu mber of uncertain situations (e.g., changes in wind and solar output), traditional metaheuristic algorithms are vulnerable to premature convergence or computationally expensive time. This bottleneck has started to be addressed by more recent re search that has tried to integrate the methods of machine lear ning with heuristic search. As an example, the article [13] ap plied the K-means algorithm to cluster and minimize the vol ume of scenario data, which is much larger than the original ones, which greatly enhanced the performance of future opti mization algorithms. Based on this interdisciplinary concept, this paper proposes a hybrid intelligent algorithm by applyin g unsupervised learning to shrink the size of scenarios and in tegrating local search strategies to improve the optimization of NSGA-II and thus successfully address the challenging re quirements of circular energy supply chains.

## III. Methodology and Mathematical Model

### A. Problem Description and System Architecture

This study examines a typical sustainable manufacturing park, whose physical architecture comprises four core modules: the energy supply module (including photovoltaics, wind power, and the external grid), the manufacturing and consumption module (multiple production lines), the energy storage module (battery energy storage and thermal energy storage), and the circular recovery module (waste heat recovery network and waste remanufacturing center)(Fig.1).

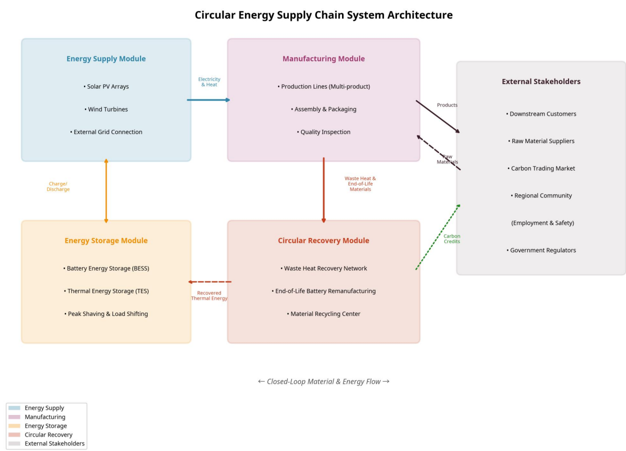


Fig. 1. System Architecture of the Circular Energy Supply Chain for Sustainable Manufacturing

The overall research strategy follows the technical route of “system modeling — algorithm design — benchmark validation.” First, the energy and material flows within a representative manufacturing park are abstracted into a network structure. Second, decision variables such as facility opening, capacity selection, energy transmission, storage charging and discharging, and material recovery flows are defined. Third, a multi-objective optimization model is formulated and tested through a parameterized numerical case. The numerical case is intended to examine the internal consistency, computational performance, and sensitivity of the proposed framework, rather than to claim direct validation of a specific real-world industrial park.

### *B. Multi-Objective Mathematical Model*

Economic ObjectiveThe economic objective aims to minimize the annualized total cost (TC) of the system, including facility construction and fixed operation costs (FC), variable production and energy procurement costs (VC), and logistics and transmission costs (TrC).

$$\min T\,C = FC + VC + TrC \qquad (1)$$

Where facility costs involve the depreciation of new energy generation equipment, energy storage units, and recovery centers; logistics costs cover the transportation expenses of raw materials, finished products, and reverse recovered materials.

Environmental ObjectiveThe environmental objective aims to minimize the life-cycle carbon footprint (TE) of the system. This indicator is composed of direct carbon emissions from energy consumption ($CE_{energy}$), carbon emissions from logistics transportation ($CE_{trans}$), and carbon emissions generated by employee commuting ($CE_{commute}$), while deducting the carbon emission credits ($CE_{credit}$) brought by substituting virgin materials through recycling.

$$\min T\,E = CE_{energy} + CE_{trans} + CE_{commute} - CE_{credit} \qquad (2)$$

By introducing waste heat recovery and material regeneration, the system can significantly increase the $CE_{credit}$ term, thereby reducing the net carbon footprint.

Social ObjectiveThis study adopts regional job creation as the quantitative indicator for the social dimension. Synergistic with the logic of minimizing commuting distances (to reduce carbon emissions) in the environmental objective, the social objective aims to maximize the provision of local jobs (SJ).

$$\max S\,J = \sum_i \sum_j \quad E_{ij} \cdot X_{ij} \qquad (3)$$

Where $E_{ij}$ represents the number of direct jobs created by constructing a facility of capacity j at node i, and $X_{ij}$ is the corresponding construction decision variable.

### *C. Core Constraints*

The model is limited by a series of physical and operational constraints, mainly including:

*1) Supply-Demand Balance Constraint:* In any time period, the sum of energy (electricity, heat) input, local production, and storage release at each node must equal the sum of energy consumption and storage absorption.

*2) Capacity and Storage Constraint:* The output of the manufacturing center, the processing volume of the recovery center, and the charge/discharge power of the energy storage system cannot exceed the upper limits of their design capacities.

*3) Circulation Ratio Constraint:* Lower limits are set for the waste recovery rate and waste heat utilization rate to ensure the system meets basic circular economy standards.

*4) Logical and Non-negativity Constraint:* All state variables (e.g., whether a facility is open) are 0-1 variables, and all flow variables (e.g., energy transmission volume, material turnover volume) must be non-negative.

### *D. Data and Reproducibility Assumptions*

To improve the reproducibility of the numerical study, all input parameters are classified into three categories: publicly available parameters, literature-based parameters, and scenario-assumed parameters. Publicly available parameters include general meteorological indicators such as solar irradiance and wind-speed patterns. Literature-based parameters include investment cost, operation and maintenance cost, emission factors, and recovery efficiency ranges reported in previous studies. Scenario-assumed parameters include the number of production nodes, candidate facility locations, demand levels, and employment coefficients. These parameters are not intended to represent a confidential industrial park. Instead, they are used to construct a transparent benchmark scenario for testing the proposed optimization model and algorithm. In practical applications, the same model should be recalibrated using site-specific data before supporting investment decisions.

## IV. Hybrid Intelligent Algorithm Design

Exact optimization methods can be computationally expensive when solving park-level multi-objective optimization models with mixed-integer decisions and multiple uncertain scenarios because the number of nodes, time periods, and candidate facilities grow. In this view, this paper uses a hybrid heuristic paradigm in order to produce approximate Pareto solutions at a manageable computation time. The proposed framework is based on the use of NSGA-II as the primary multi-objective search algorithm, the K-means clustering to reduce the number of scenarios, and the variable neighborhood search to refine the results locally. Due to the fact that heuristic algorithms cannot ensure the global optimality, the outcomes are analyzed by means of benchmark comparison, convergence behavior, and sensitivity analysis instead of being viewed as precise optimal solutions (Fig.2).

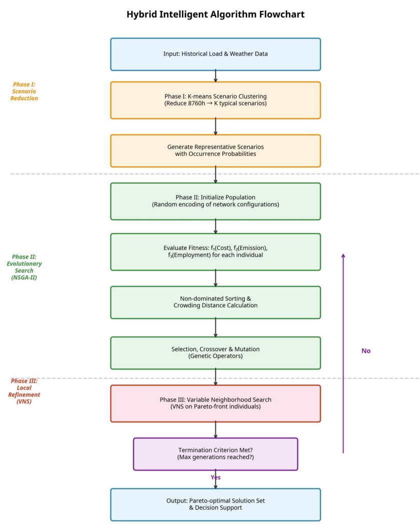


Fig. 2. Flowchart of the Proposed Hybrid Intelligent Algorithm (K-means + NSGA-II + VNS)

### A. Scenario Dimensionality Reduction Based on K-means

Output of renewable energy and manufacturing loads can fluctuate greatly during different seasons, weekdays, and operating conditions. All 8,760 hourly observations cannot always be represented directly in a planning model, which would result in excessive computational costs. Hence, K-means clustering is applied as a scenario reduction technique. The daily profiles of both renewable generation and manufacturing load are classified into a small number of representative scenarios. Elbow method and silhouette coefficient are used to choose the number of clusters and the weight of each typical scenario is given by the number of original days that fall into that cluster. This step decreases the time span but preserves the key seasonal and operational features of the initial profiles. It is worth noting that clustering can even out the extreme occurrences; thus, an outlier and sensitivity test are part of the experiment portion.

### B. Improved NSGA-II Framework and Local Search

Following the scenario dimensionality reduction, the hybrid algorithm proceeds into the evolutionary search stage. Initially, a population (a set of candidate solutions) is created in a random way so that every single individual is a network configuration scheme. Afterwards, the fitness function (economic, environmental, and social objective values) of each individual is computed and non-dominated sorting and crowding distance computation are performed.

In order to enhance the functionality of local search, the variable neighborhood search mechanism is incorporated after crossover and mutation. Neighborhood operations of selected non-dominated individuals will be to change the energy-storage capacity of the individual within an allowed range, switch connection status of the candidate recovery links and shift the proportion of recovered materials between the remanufacturing centers. The penalty function is used to address constraint violations, and unfeasible solutions that have serious imbalance or capacity violations are eliminated at environmental selection. All algorithmic experiments are performed with various random seeds (30 times) and average, standard deviations, and optimum values of major performance measures are reported. This design can make the robustness of the heuristic algorithm more transparent.

## V. Experimental Results and Analysis

### A. Case Data and Experimental Setup

The given model is assessed using a benchmark manufacturing park scenario as opposed to a non-disclosed real-world industrial project. The benchmark park assumes an area of about 20 square kilometres and contains hypothetical photovoltaic facilities, wind power access, battery energy storage, thermal storage, a waste heat recovery system, and an end-of-life battery reprocessing facility. The meteorological profiles are developed based on the average yearly solar irradiance and wind-speed features and the manufacturing load profiles are created depending on the weekday/weekend production trends and seasonal variations in demand. The cost parameters, emission factors, recovery efficiency, and employment coefficient are derived using typical values in literature with adjustments to keep them physically and economically consistent.

The entire computational experiment is done in Python on a Windows 10 workstation with an Intel Core i7 3.40GHz processor and 16GB RAM. In the case of the hybrid algorithm, population size is fixed at 100, maximum number of generations is fixed at 300 and crossover and mutation probabilities are fixed at 0.8 and 0.15 respectively. In order to decrease the role of randomness, every experiment is repeated independently 30 times. Commercial solver CPLEX serves as a benchmark in the case of small- and medium-scale examples. In the case of large-scale examples, both CPLEX and the proposed algorithm are tested within the same time frame and compared based on solution quality, computational time, and feasibility instead of precise global optimality.

### B. Algorithm Performance Evaluation

To confirm the effectiveness of the suggested algorithm, this paper has developed test cases of small, medium and large scales and compared the hybrid intelligent algorithm to the commercial exact solver (CPLEX).

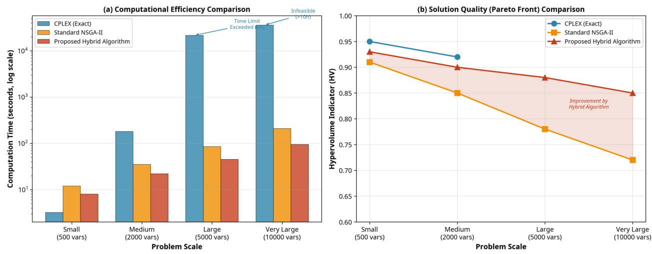


Fig. 3. Computational Performance Comparison on Benchmark Instances

The findings shown in Fig.3 imply that CPLEX has good quality solutions to small scale problems and is a valuable reference point to check the validity of model formulation. Nonetheless, when the number of possible facilities, time scenarios, and decision variables grows, the computational complexity of the exact solver becomes significantly higher. On the same time constraint, the proposed hybrid algorithm can also produce feasible non-dominant solutions set of larger instances at reduced computational time. However, the solutions generated by the hybrid algorithm must be seen as approximate Pareto solutions. Hence, convergence curves, the diversity of the Pareto front, and statistics on repeated runs are used to assess the algorithm performance.

### C. Multi-Objective Trade-off and Comprehensive Benefit Analysis

The findings obtained in the model optimization indicate that there are strong trade-offs between economic, environmental, and social goals. Table I displays the worst performance of the system in case of each of the three objectives in turn.

TABLE I. COMPARISON OF SYSTEM OPTIMAL SOLUTIONS UNDER DIFFERENT OPTIMIZATION ORIENTATIONS

| **Optimization Orientation** | **Economic Objective (Annualized Cost, ×10⁴ CNY)** | **Environmental Objective (Carbon Emission, $tCO_2e$)** | **Social Objective (New Jobs Created)** | **Unit Energy Cost (CNY/kWh)** |
|---|---|---|---|---|
| Minimize Total Cost | 3,250 | 18,450 | 120 | 0.45 |
| Minimize Carbon Emission | 4,890 | 9,230 | 185 | 0.68 |
| Maximize Employment | 5,120 | 11,560 | 310 | 0.71 |

As shown in Table I, if only the lowest cost is pursued, the system tends to rely on the external fossil energy grid and reduce the construction of recovery facilities, resulting in persistently high carbon emissions. Conversely, the environment-oriented scheme will deploy photovoltaics and waste heat recovery systems on a large scale, dropping carbon emissions by about 50%, but due to excessive initial equipment investment, the total cost rises by about 50.4%. The social objective orientation tends to build labor-intensive remanufacturing centers, significantly boosting the employment rate(Fig.4).

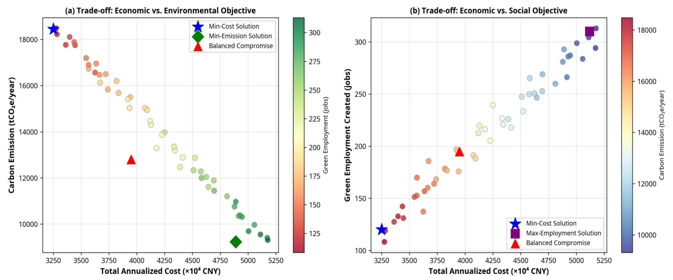


Fig. 4. Approximate Pareto Front Obtained in the Benchmark Scenario

The Pareto front and radar chart show that the circular configuration can achieve better overall performance than the traditional one-way energy supply configuration in the constructed benchmark scenario. In the balanced solution, total system cost and carbon emissions are lower than those of the baseline case, while local employment is improved due to the introduction of recovery, maintenance, and remanufacturing activities. These results suggest that coordinated planning of renewable energy, storage, waste heat recovery, and material circulation may bring economic and environmental benefits under suitable parameter conditions. However, the exact magnitude of improvement depends on input assumptions such as carbon price, equipment cost, recovery efficiency, and local demand structure, and should not be generalized without site-specific validation(Fig.5).

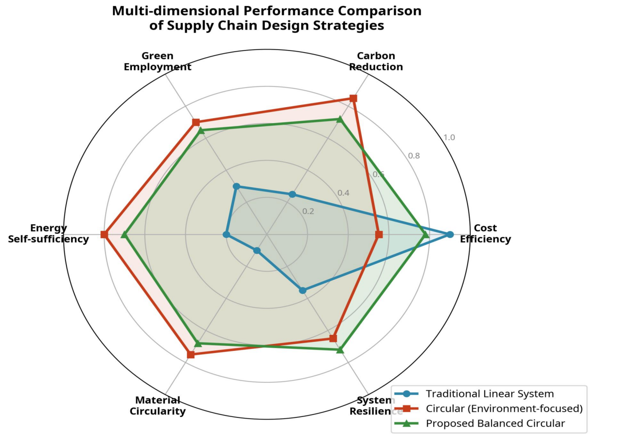


Fig. 5. Performance Comparison under Different Scenario-Based Strategies

## D. Sensitivity Analysis

To examine whether the main conclusions are sensitive to key assumptions, a one-factor-at-a-time sensitivity analysis is conducted for carbon trading price, renewable-energy equipment cost, and load outliers. The purpose of this analysis is not to predict actual market behavior, but to identify which parameters have the strongest influence on the optimal configuration and performance of the circular energy supply chain(Fig.6).

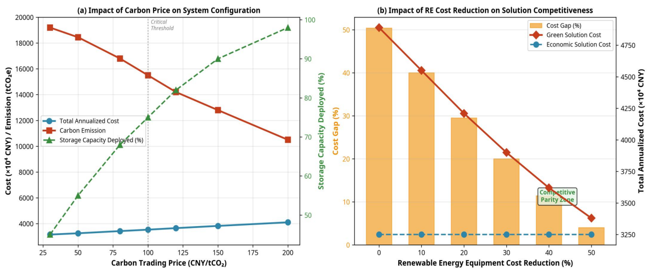


Fig. 6. One-Factor Sensitivity Analysis of Key Parameters

*1) Carbon Trading Price Fluctuation:* When the carbon price increases from the baseline of 50 CNY/ton to 150 CNY/ton, the total system cost increases by 8%. However, simultaneously, the high carbon price prompts the model to spontaneously increase energy storage capacity and the waste heat recovery ratio by 30%, further reducing the carbon footprint by 12%. This indicates that the carbon pricing mechanism plays a decisive role in driving the deep circular transition of the park.

*2) Decline in Renewable Energy Equipment Costs:* If the capital costs of photovoltaic and energy storage equipment drop by 20%, the total cost of the environment-oriented scheme will significantly fall back, narrowing the cost gap with the purely economic-oriented scheme to within 15%, greatly enhancing the market competitiveness of green schemes.

*3) Outlier Removal Test:* After removing individual load outliers caused by extreme weather, the variation amplitude of the system optimization configuration results is less than 3%, verifying that the scenario dimensionality reduction method based on K-means clustering has good robustness.

## VI. Discussion

These findings point out the fact that combining energy networks and reverse material flows at the manufacturing-park level could have synergetic effects provided that the assumed benchmark conditions were met. In comparison with a linear energy supply design, the circular design enables recovered heat and regenerated materials to replace a fraction of the external energy and virgin material requirements. This is the mechanism whereby cost reduction and emission reduction may be achieved at the same time in certain Pareto solutions. Nevertheless, such results depend on the hypothetical cost parameters, recovery efficiencies, carbon emission factors, and demand profiles. Hence, the findings ought to be considered as scenario-based evidence and not the direct empirical evidence.

To start with, the findings of this research are in line with the available literature (e.g., literature [4] and [10]), i.e., that the use of multi-objective optimization could help to prevent the environmental catastrophes caused by the so-called profit supremacy. Nevertheless, as opposed to conventional studies which have been based on the unidirectional aspect of biomass logistics, it is revealed that the synergy effect of waste heat recovery and end-of-life battery remanufacturing is an important factor that contributes to the reduction of system embodied carbon emissions.

Second, in terms of vertical correlation, the analysis indicates that economic cost and environmental benefit are not an absolute zero-sum game. With an appropriate design of the ratio of energy storage and renewable energy, it is possible that the system, assuming that an acceptable level of initial investment is made, will use the carbon credits and energy self-sufficiency produced by the circular network to recover its costs and make profit throughout the entire lifecycle.

Finally, in terms of difference attribution, the social objective (job creation) and environmental objective of this study demonstrate high levels of positive correlation. This is due to the fact that waste sorting, equipment maintenance, as well as remanufacturing processes are inherently part of technical and labor intensive sectors. This result is different with the view that some literature expresses which states that: environmental investment crowds out local employment. A detailed examination of the causes indicates that the circular economy reorganizes the value chain, converting the resources that initially leaked out of the system into value-added services localized in the area.

## VII. Conclusion

The present research introduces a multi-objective optimization scheme based on scenarios in circular energy supply chain design of sustainable manufacturing parks. The proposed model takes into account all three factors, i.e., economic cost, carbon emissions, and local employment simultaneously, and integrates both renewable energy, energy storage, waste heat recovery and material remanufacturing into a consistent planning structure. Computational tractability can be enhanced by using a hybrid algorithm that comprises the K-means scenario reduction, NSGA-II, and variable neighborhood search.

As can be seen in the numerical results, in the created benchmark case, the circular shape will enhance the cost-emission-employment trade-off over the conventional one-way energy supply configuration. Algorithmic comparison also indicates that hybrid heuristic framework may offer viable approximate Pareto solutions of larger-scale problems in reasonably short computation time. Sensitivity analysis also reveals that carbon price, renewable-energy equipment cost, and load-profile uncertainty are of great significance when it comes to system configuration.

The primary message of this paper is to offer an open and repeatable computational model to plan circular energy and materials networks in manufacturing parks at an early stage. Nevertheless, the research has a number of drawbacks. To begin with, numerical case is founded on a representative benchmark situation instead of a totally revealed real industrial data set. Secondly, the model is concerned with medium and long term planning and cannot address high-frequency electricity market transactions or real time dispatch. Thirdly, the clustering can mask the extreme weather or abnormal load occurrences. The model needs to be verified with site-specific industrial data in future studies, other multi-objective algorithms need to be compared, and the framework extended to dynamic scheduling and cross-park industrial symbiosis.

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## AVAILABILITY OF DATA

Not applicable.

## AUTHOR CONTRIBUTIONS

Zhengui Li contributed to the conceptualization and design of the study, developed the multi-objective optimization model, designed and implemented the hybrid algorithmic framework, organized the benchmark data and scenario assumptions, conducted the computational experiments and sensitivity analyses, analyzed and interpreted the results, prepared the visualizations, and wrote and revised the manuscript. The author has read and approved the final version of the manuscript.

## COMPETING INTERESTS

The authors declare no competing interests.