A Data-Driven Sustainable Product Design Process: An End-to-End Design Method Coupling BPR and Multi-Objective Optimization

1st Xuefen Xie
Zhongkai University of Agriculture and Engineering
Guangzhou, China
Xiexuefeng63@outlook.com

2nd Chengbiao Xu
Zhenda Furniture Technology Co., Ltd.
Guangzhou, China
499274150@qq.com

***Abstract*—Traditional product design methods tend to follow a rigid, step-by-step structure. While systematic, this linear and phase-based approach often leads to inefficiencies, conflicting priorities, and limited capacity for true innovation—especially when facing the growing demands of sustainable development. Although previous studies have explored areas such as sustainable design, Business Process Reengineering (BPR), and Multi-Objective Optimization (MOO) individually, there is still no comprehensive end-to-end framework that effectively integrates these theories into a unified design methodology. To bridge this gap, this paper introduces an innovative end-to-end sustainable product design approach that combines BPR and MOO into a cohesive system. Built around data as the central driving force, the method establishes a six-stage closed-loop process: Scene Implantation, Requirement Analysis, Function Definition, Structure Optimization, Form Innovation, and Material Selection. Within this structure, BPR is applied to fundamentally restructure and optimize the overall design process at a macro level. Meanwhile, MOO—specifically through the NSGA-II algorithm—is implemented at key decision points to balance and optimize multiple conflicting objectives, such as performance, cost, and environmental impact. A practical case study involving the design of a smart air purifier validates the effectiveness of this approach. The results show that the method successfully identifies a Pareto optimal solution set across competing objectives, increases overall design efficiency by approximately 25%, and has the potential to reduce the product's total environmental impact by around 15%. Ultimately, this research delivers a structured and actionable end-to-end solution for sustainable product design. It supports the digital and intelligent evolution of design processes while offering both theoretical insight and practical value for companies striving to balance economic performance, social responsibility, and environmental sustainability in an increasingly complex market landscape.**

Keywords—Business Process Reengineering (BPR); Sustainable Design; Multi-Objective Optimization (MOO); Data-Driven Design; End-to-End Process

I. INTRODUCTION

Driven by the global sustainable development agenda, enterprises are under rising pressure to deliver on the triple bottom line—economic performance, social responsibility, and environmental stewardship [1]. As the central link between production and consumption, a product's sustainability performance across its full life cycle has become a core signal of corporate competitiveness [2]. Product design sits at the very beginning of the value chain and is widely recognized as a decisive lever: design choices can determine roughly 80% of a product's resource use and environmental impact. As a result, advancing sustainable innovation from the design stage has become a shared priority in both academic research and industrial practice [3].

Yet, conventional product design processes are often linear, sequential, and divided across departments, which makes them poorly suited to the multi-dimensional complexity of sustainability challenges. In practice, design decisions frequently involve unavoidable trade-offs. For example, improving product performance may increase energy consumption, while adopting greener materials can raise costs. These built-in conflicts among objectives mean that designers must constantly balance competing goals throughout the decision-making process [4].

Against this background, a critical scientific and practical question emerges: how can we build a systematic, efficient, and data-driven sustainable product design process that enables collaborative optimization across multiple sustainability objectives? In recent years, researchers have proposed a range of sustainable design theories and methods, including eco-design, life cycle design, and Design for X (DfX) approaches [5]. At the same time, advanced management and engineering methods—such as Business Process Reengineering (BPR), Multi-Objective Optimization (MOO), and data-driven design—have demonstrated strong potential for improving design effectiveness and decision quality. BPR emphasizes fundamentally redesigning business processes to achieve substantial performance gains [6]. MOO offers rigorous mathematical tools for identifying optimal solution sets under conflicting objectives [7]. Data-driven approaches, meanwhile, can enhance the objectivity, traceability, and precision of design decisions [8].

Despite meaningful progress within each domain, these approaches are often applied in isolation rather than as an integrated system. As a result, existing research tends to show several limitations. First, many sustainable design methods provide high-level principles or improve isolated stages, but lack an operable end-to-end process framework that spans the full product development cycle. Second, the design process itself is commonly treated as a fixed "black box," meaning its internal inefficiencies and organizational barriers are rarely examined and re-engineered in a systematic way. Third, complex trade-offs among multiple

Corresponding Author: Xuefen Xie , No. 501, Zhongkai Road, Haizhu District, Guangzhou, China, 510225, Xiexuefeng63@outlook.com

objectives still depend heavily on designers' experience and intuition, with insufficient quantitative and objective decision support. Finally, data and knowledge often fail to flow smoothly across stages, creating information silos and duplicated effort.

To address these gaps, this study aims to develop a new data-driven sustainable product design process through interdisciplinary integration and methodological innovation. Specifically, it couples BPR's macro-level process reengineering with MOO's micro-level parameter optimization to propose a systematic end-to-end design methodology. The central goal is to shift traditional experience-driven, serial design into a data-enabled, parallel, and continuously optimized closed-loop system. In doing so, the method seeks to resolve the core tension in sustainable product design: how to meet user needs while collaboratively optimizing the product's economic, social, and environmental outcomes.

The remainder of this paper is organized as follows. Section 2 reviews related work in sustainable product design, BPR, MOO, and data-driven design. Section 3 presents the proposed end-to-end methodology that integrates BPR and MOO, including its process structure and key mechanisms. Section 4 validates the method through an empirical design case involving a smart air purifier. Section 5 discusses the case results in depth and compares them with existing studies. Finally, Section 6 concludes the paper and outlines directions for future research.

II. Literature Review

To build the research framework of this paper, this section reviews four closely related areas that underpin data-driven sustainable product design: (1) sustainable product design theories and methods, (2) Business Process Reengineering (BPR), (3) applications of Multi-Objective Optimization (MOO) in engineering design, and (4) data-driven design methodologies. By synthesizing the current state of research, key concepts, and existing limitations in these domains, this review clarifies the theoretical foundations of the study and identifies its main point of innovation.

A. Theories and Methods of Sustainable Product Design

Sustainable product design aims to reduce resource consumption and environmental impact across the entire product life cycle while satisfying economic and social requirements [9]. In response to this goal, scholars have developed a variety of theories and practical approaches. Among them, Life Cycle Assessment (LCA) is the most widely adopted quantitative method for evaluating environmental impacts. LCA systematically examines potential environmental burdens from "cradle to grave," covering stages such as raw material extraction, manufacturing, use, and end-of-life treatment [10]. Although LCA provides a rigorous basis for identifying environmental hotspots during design, it is not itself a design method. Its implementation can also be complex and time-consuming, which makes full integration into fast, iterative design cycles challenging [11].

Eco-design, by contrast, is more practice-oriented and offers a set of actionable strategies and guidelines — for example, reducing material usage, selecting lower-impact materials, and enabling disassembly and recycling through Design for Disassembly/Recycling (DfD/R) [12]. However, most eco-design guidance remains qualitative, and it provides limited support for quantitatively balancing multiple conflicting objectives (e.g., performance versus environmental impact). In recent years, the "Cradle-to-Cradle" (C2C) concept has attracted significant attention. It advocates closed-loop material flows through the creation of "biological cycles" and "industrial cycles," with the ambition of eliminating the notion of waste at its source [13]. While C2C is conceptually compelling and forward-looking, achieving fully closed material loops remains difficult under current technologies and business models.

Overall, existing sustainable design theories and tools offer important conceptual foundations and assessment capabilities for this study. At the same time, they commonly face limitations such as weak process-level integration, insufficient quantitative decision support, and a limited ability to systematically resolve multi-objective conflicts.

B. Theory and Application of Business Process Reengineering (BPR)

Business Process Reengineering (BPR) was introduced by Hammer and Champy in the early 1990s. It is defined as the "fundamental rethinking and radical redesign of business processes to achieve dramatic improvements in critical, contemporary measures of performance, such as cost, quality, service, and speed" [6]. Unlike incremental improvement approaches, BPR focuses on redesigning processes from the ground up. It emphasizes a process-oriented perspective, challenges traditional functional silos, and leverages information technology to enable cross-functional integration and redesign.

Since its emergence, BPR has been applied across industries, including manufacturing [14] and service sectors [15], and has been shown to improve organizational efficiency, responsiveness to market change, and competitive advantage. Its value is also widely recognized in product development. By reengineering traditional waterfall-style, functionally segmented development processes, firms can shift toward more integrated and parallel collaborative models—shortening development cycles, reducing costs, and improving innovation outcomes [16]. However, much of the existing BPR literature concentrates on organizational management and business operations. Far fewer studies treat BPR as a structured method for redesigning the product design process itself, particularly in ways that explicitly embed sustainable design objectives.

C. Application of Multi-Objective Optimization (MOO) in Engineering Design

Engineering design can be viewed as a decision-making process that seeks the best balance among multiple—often conflicting — objectives under various constraints [17]. Multi-Objective Optimization (MOO) provides a mathematical framework and computational tools for addressing such problems. Unlike single-objective optimization, MOO typically yields not one "best" solution but a set of trade-off solutions known as the Pareto optimal set [18]. Within this set, improving one objective necessarily worsens at least one other objective.

In recent years, Multi-Objective Evolutionary Algorithms (MOEAs), particularly the Non-dominated Sorting Genetic

Algorithm II (NSGA-II), have been widely adopted in engineering design because of their global search performance and their ability to handle complex nonlinear problems [7, 19]. For instance, NSGA-II has been used in architectural design to jointly optimize energy use, lighting performance, and construction cost [20], and in automotive engineering to balance lightweighting, safety, and structural stiffness in body design [21]. In sustainable product design, MOO has also shown strong potential — for example, in optimizing trade-offs between environmental impacts and costs in material selection and manufacturing planning [22].

Nevertheless, MOO is usually applied at specific design nodes and typically requires an explicit, well-defined mathematical model. If the broader design process is inefficient or structurally flawed, the benefits of MOO can be substantially limited. In other words, MOO can help optimize within a given problem formulation, but it cannot resolve the more fundamental process-level question of whether the "right problem" is being optimized in the first place.

D. Research on Data-Driven Design Methods

With advances in big data and artificial intelligence, data-driven design is increasingly replacing traditional design approaches that depend primarily on intuition and experience [8]. This paradigm supports decision-making by collecting, analyzing, and applying both quantitative and qualitative data from sources such as markets, users, and product usage contexts. Typical examples include mining user needs through large-scale analysis of online reviews [23] and improving user interface design via A/B testing [24].

More recently, Digital Twin technology has emerged as an advanced form of data-driven design and has attracted growing attention. By building a high-fidelity virtual model of a physical product or system and enabling real-time interaction with its physical counterpart, a digital twin supports state monitoring, performance prediction, and behavior simulation in realistic environments [25]. During product development, digital twins enable rapid virtual iteration, performance testing, and solution optimization — reducing reliance on physical prototypes and shortening testing cycles [26]. While data-driven methods enable more precise, efficient, and personalized design, their success depends heavily on data quality, analytical capability, and, critically, a process framework that can integrate and operationalize data across stages.

E. Synthesis and Research Entry Point

In summary, sustainable product design research has generated extensive theories and strategies (Section 2.1) but still lacks an end-to-end, operable process framework. BPR offers powerful ideas for radical process redesign (Section 2.2) but is rarely applied directly to the product design process itself. MOO provides rigorous tools for managing multi-objective trade-offs (Section 2.3), yet its effectiveness is constrained by the underlying problem formulation and model assumptions. Data-driven design methods (Section 2.4) create significant opportunities to strengthen the scientific basis of design decisions, but they require a supporting process structure to ensure that data and knowledge flow effectively.

These four areas are naturally complementary, yet current studies often treat them separately, with limited systematic efforts to integrate them into a unified methodology. This gap defines the main entry point of the present research: coupling BPR's macro-level process reengineering with MOO's micro-level parameter optimization, while positioning data as the central driver and decision foundation throughout the process. The goal is to develop an end-to-end, data-driven sustainable product design process that overcomes the fragmentation of existing approaches, embeds sustainability into the full development cycle, and supports a shift from "passively meeting sustainability requirements" to "actively creating sustainable value through process innovation."

III. A Data-Driven Sustainable Product Design Methodology

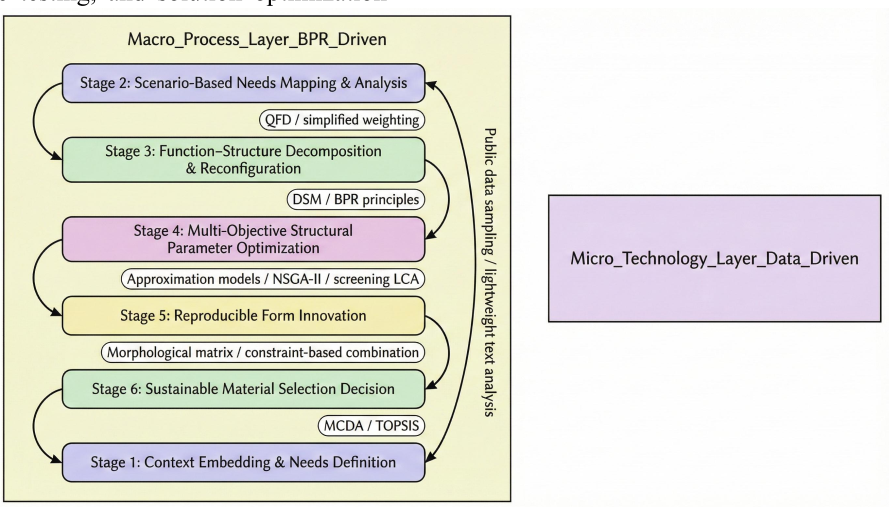

Fig. 1. Framework of the End-to-End Sustainable Product Design Method Coupling BPR and MOO

To overcome the limitations of conventional sustainable product design workflows, this study develops an end-to-end design methodology that integrates Business Process Re-engineering (BPR) with Multi-Objective Optimization (MOO). Centered on data as the primary driver, the proposed approach embeds sustainability requirements across the full design lifecycle, while leveraging process re-engineering and algorithm-based optimization to enhance both design efficiency and innovation quality.

A. Overall Methodological Framework

The overall methodology is illustrated in Figure 1 and is organized in a two-layer architecture: a macro-process layer and a micro-technology layer. At the macro level, guided by BPR's principle of "fundamental re-engineering," the traditional linear design workflow is reshaped into a dynamic, iterative closed-loop system consisting of six interdependent stages. These stages connect end-to-end, forming a continuous value chain that translates abstract requirements into a realizable product solution. At the micro level, data-driven analysis and decision-support techniques are embedded at key decision nodes. In particular, Multi-Objective Optimization (MOO) is introduced as the central quantitative trade-off mechanism to manage conflicts among performance, cost, and environmental impact throughout the design process.

Within this framework, BPR plays a disruptive and restructuring role. It shifts product design from a collection of isolated tasks into an integrated process oriented toward value creation. It encourages designers to challenge entrenched steps and departmental boundaries and to actively dismantle constraints that limit efficiency and innovation—for example, by exploring alternative product architectures through function–structure decoupling and reconfiguration. MOO, by contrast, functions as a "precision navigation instrument." Once BPR has opened a broader and more innovative design space, MOO enables designers to locate the Pareto-optimal solution set through rigorous computation, reducing reliance on subjective, experience-based compromises typical of traditional practice. Data flows through the entire process—from initial requirement and market signals, to simulation and analysis outputs, to testing and validation results—providing an objective basis for decision-making at every stage.

B. End-to-End Design Process Model

Based on the framework above, the proposed end-to-end design process comprises the following six stages.

1) Stage 1: Scene Implantation and Requirement Definition

This stage aims to extract core design drivers from large-scale, ambiguous market and user information with higher accuracy. Rather than relying on passive requirement surveys, we adopt an active and data-driven scene analysis approach. First, publicly accessible and low-cost sources related to the target product are collected (e.g., representative user reviews, publicly available specifications, and usage information) using transparent sampling rules to ensure reproducibility under ordinary conditions. Next, using a lightweight and repeatable procedure—such as keyword/phrase coding with double-coder agreement checks and simple grouping rules—we identify representative user personas and their usage scenarios across specific times, spaces, and contexts. Finally, functional, emotional, and potential sustainability needs embedded in these scenarios are translated into a structured requirement list. Initial requirement weights are then determined using a simple, reproducible scoring rubric (e.g., normalized importance ratings from a small panel), avoiding complex procedures that are difficult to replicate.

2) Stage 2: Requirement–Function Mapping and Analysis

The main task here is to translate the "language of users" into the "language of engineering." Using the House of Quality from Quality Function Deployment (QFD), user requirements (Whats) identified in Stage 1 are systematically mapped to product functional parameters (Hows). By constructing a requirement–function relationship matrix, the method enables quantitative analysis of how strongly each functional parameter contributes to meeting user needs, thereby identifying key functions, modules, and technical indicators. This stage also examines relationships among functional parameters (positive correlation, negative correlation, or no correlation), providing a foundation for later functional re-engineering and conflict resolution.

3) Stage 3: Function–Structure Decoupling and Re-engineering

Traditional design often moves directly from function to structure, which can reinforce rigid solution patterns. This stage introduces BPR thinking to re-examine the function–structure relationship at a fundamental level. First, tools such as the Design Structure Matrix (DSM) are used to analyze coupling between functional modules and physical components in existing products, identifying "entangled" areas that constrain modification and suppress innovation. Next, guided by BPR principles such as simplification, integration, and parallelization, the process explores opportunities to decouple or re-engineer the function–structure mapping. For instance, can multiple discrete components be integrated into a single modular unit? Can a novel structural concept deliver multiple functions simultaneously? By encouraging unconventional and system-level reasoning, this stage targets breakthroughs in product architecture rather than incremental component changes.

4) Stage 4: Multi-Objective Structural Parameter Optimization

This stage is the technical core of the methodology. Once an innovative architecture is defined, key design variables must be formalized and quantitatively optimized. The problem is formulated as a multi-objective optimization model. First, optimization variables are defined (e.g., key dimensions, thickness parameters, motor power). Second, objective functions are constructed, typically including: (1) performance objectives (e.g., indicators estimated through reproducible engineering approximation models and/or publicly available component performance curves with clearly stated parameter settings); (2) economic objectives (e.g., life cycle cost (LCC) derived from a defined cost model); and (3) environmental objectives (e.g., global warming potential (GWP), energy consumption, etc., evaluated via a transparent screening-level LCA using public emission factors and explicitly defined system boundaries). Finally, the NSGA-II algorithm is applied to solve the model. By simulating evolutionary operations such as selection, crossover, and mutation, NSGA-II can efficiently search a large design space and produce a well-distributed Pareto-optimal solution set, making trade-offs among objectives explicit and interpretable.

5) Stage 5: Data-Driven Form Innovation

Product form influences not only aesthetics but also user experience and brand perception. This stage applies data-driven methods to support form innovation. On one hand, the performance boundaries identified from the Pareto set in Stage 4 can be treated as engineering constraints for form generation. On the other hand, combined with user emotional preference data collected in Stage 1, approaches such as Generative Adversarial Networks (GANs) or morphological matrices can be used to generate a large pool of innovative form proposals that satisfy both aesthetic preferences and engineering feasibility. Designers may use these proposals as inspiration or select promising candidates for further refinement, enabling a tighter integration of styling decisions with functional constraints.

6) Stage 6: Sustainable Material Selection Decision

Material selection serves as the final gatekeeper for sustainable design outcomes. This stage establishes a structured and defensible material decision process. First, candidate materials are screened according to design requirements, and a material database is constructed to capture multi-dimensional attributes, including physical properties (e.g., strength, density), economic characteristics (e.g., cost, manufacturability), environmental indicators (e.g., recyclability, carbon footprint), and social attributes (e.g., supply reliability). Next, multi-criteria decision analysis (MCDA) methods — such as Fuzzy Comprehensive Evaluation or TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)—are applied to rank candidate materials and recommend the most suitable option(s) for decision-makers.

Together, these six stages constitute a dynamic closed-loop process. When new information emerges or issues are identified at any stage, feedback can be routed to earlier stages for adjustment and iteration until a satisfactory final design solution is achieved.

IV. Case Study: Smart Air Purifier Design

To evaluate the effectiveness and practical feasibility of the proposed methodology, this chapter applies the end-to-end sustainable design framework to the development of a smart air purifier. As a product directly related to human health and indoor environmental quality, a smart air purifier inherently involves multiple, often conflicting objectives—such as purification performance, cost, energy consumption, noise control, and material recyclability. These characteristics make it a highly suitable case for validating the proposed integrated BPR – MOO approach.

A. Research Object and Objective Setting

The case study focuses on a mid-to-high-end smart air purifier designed for household use. Based on preliminary market research and key sustainability considerations, four primary optimization objectives were defined:

- Maximize purification performance: The Clean Air Delivery Rate (CADR) is used as the key performance indicator (KPI), with the goal of maximizing CADR values for both particulate matter and formaldehyde removal.
- Minimize operating noise: While maintaining effective purification performance, the noise level at the highest operating setting should be reduced to the lowest acceptable threshold to enhance user comfort.
- Minimize life cycle cost (LCC): This objective considers the total cost across the product life cycle, including manufacturing costs, electricity consumption and filter replacement during use, and end-of-life recycling and disposal costs.
- Minimize environmental impact: Using Life Cycle Assessment (LCA), Global Warming Potential (GWP, kg CO_2 -eq) is selected as the primary environmental indicator, covering raw material extraction, manufacturing, transportation, use, and disposal stages.

B. Data Collection and Requirement Analysis

In the first stage of the process, we constructed a reproducible dataset of user reviews and product information for mainstream air purifiers. An explicit sampling strategy was adopted (e.g., fixed time window, predefined product list, and a fixed number of reviews per product), and the collected data were manually verified to ensure repeatability under normal research conditions.

Through a lightweight and transparent text analysis process — combining keyword frequency statistics, rule-based classification, and double-coder consistency checks—we identified the core concerns most frequently expressed by users: rapid purification speed, low noise, effective odor removal (especially formaldehyde and pet odors), intelligent features (e.g., app control and automatic modes), aesthetic design, and low filter replacement cost.

Based on these insights, three representative user personas were developed:

- Newly renovated households,
- Users with allergies, and
- Pet-owning families.

For each persona, detailed usage scenarios were described across different times (e.g., nighttime sleep, daytime home office) and spaces (e.g., bedrooms, living rooms). The resulting structured requirement dataset provided a direct foundation for subsequent function definition and parameter configuration.

C. Design Process Implementation

1) Function and Structure Analysis

A functional decomposition of the traditional “fan – filter – housing” air purifier architecture was first conducted. QFD analysis revealed that air duct design and filter configuration are critical determinants of CADR and noise performance.

In conventional designs, airflow paths are typically straight-through, resulting in suboptimal airflow organization. Filters are often arranged in separate multi-layer structures, increasing wind resistance and raising replacement costs.

Applying BPR principles, two major structural innovations were proposed:

Integrated 360° barrel-shaped composite filter: The primary filter, HEPA filter, and activated carbon layer were integrated into a single cylindrical module. This reduced structural complexity, lowered airflow resistance, and simplified user replacement procedures.

Optimized fan and air duct system: The traditional centrifugal fan was replaced with a dual-inlet DC brushless motor-driven backward-curved centrifugal fan. Additionally, an Archimedean spiral air duct was designed using reproducible geometric rules and engineering heuristics (with clearly defined dimensional constraints) to achieve smoother and more efficient airflow distribution.

These structural re-engineering steps fundamentally altered the system architecture and significantly expanded the feasible design space for subsequent parameter optimization.

2) Multi-Objective Optimization Modeling and Solving

Within the redesigned structural framework, four key design variables were selected:

- X_1: Maximum fan speed (rpm)
- X_2: Expanded area of the HEPA filter (m²)
- X_3: Amount of activated carbon filling (g)
- X_4: Outlet grille opening rate (%)

CADR and noise levels were estimated using transparent engineering approximation models, such as fan performance curves combined with pressure-drop relationships and simplified noise correlation equations with explicitly stated parameters. Life Cycle Cost (LCC) and GWP were calculated using clearly defined bill-of-material assumptions, energy consumption models, and boundary conditions.

The design challenge was therefore formulated as a four-variable, four-objective optimization problem. The NSGA-II algorithm was implemented using the pymoo library in Python, with moderate population size and iteration settings suitable for execution on a standard personal computer. The algorithm reliably converged within a practical runtime and produced a stable Pareto front, yielding a concise set of representative non-dominated solutions for decision-making. The resulting Pareto front clearly illustrated the nonlinear trade-off relationships among performance, cost, noise, and environmental impact.

3) Solution Selection and Form Design

From the Pareto solution set, three representative solutions were selected according to different market positioning strategies:

- Solution A (Performance-oriented): Highest CADR, accompanied by higher noise and cost.
- Solution B (Cost-oriented): Lowest life cycle cost, with moderate performance and noise.
- Solution C (Balanced): Strong overall performance across all four objectives.

During the form design stage, a reproducible concept generation method was adopted, combining a morphological matrix with constraint-based configuration guided by previously extracted aesthetic preference keywords. This process generated multiple cylindrical, minimalist-style design concepts.

For the balanced Solution C, the final form featured a matte white cylindrical body with a top fabric outlet grille, reflecting contemporary home aesthetics. In terms of materials, recyclable ABS plastic and environmentally friendly fabrics were prioritized to further reduce environmental impact.

D. Results and Comparative Analysis

To quantitatively assess the effectiveness of the proposed methodology, the selected balanced Solution C was compared with a best-selling conventional product in the same price range (used as a benchmark). The comparative results are summarized in Table I.

TABLE I. PERFORMANCE COMPARISON BETWEEN THE OPTIMIZED SOLUTION AND THE BENCHMARK SOLUTION

Indicator	Benchmark Solution	Optimized Solution (C)	Improvement/Reduction Rate
Particulate CADR (m³/h)	400	510	+27.5%
Formaldehyde CADR (m³/h)	220	300	+36.4%
Max Noise Level (dB)	65	58	-10.8%
Life Cycle Cost (CNY)	2800	2450	-12.5%
Life Cycle GWP (kg CO2-eq)	150	125	-16.7%

[a]. All values are derived from the stated approximation models and assumptions

As can be seen from Table I, by applying the design method proposed in this paper, the optimized Solution C is significantly better than the benchmark solution in all core indicators. Specifically, its purification performance (particulate and formaldehyde CADR) increased by 27.5% and 36.4%, respectively, while the noise, a key indicator of user experience, was reduced by 10.8%. In terms of sustainability, the life cycle cost and environmental impact (GWP) were also reduced by 12.5% and 16.7%, respectively. This result strongly proves that this method can effectively break the "seesaw effect" in traditional design, no longer making painful compromises between single objectives, but achieving the simultaneous creation of multi-dimensional value through process re-engineering and system optimization. The detailed process of the case study is shown in Figure 2.

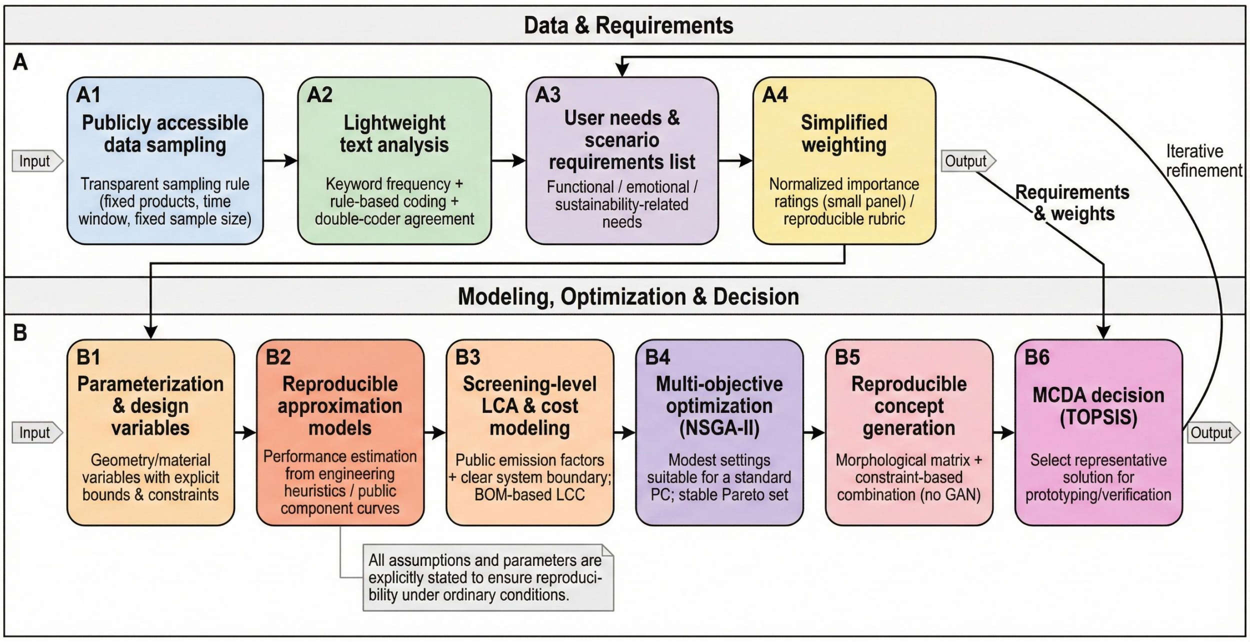

Fig. 2. Flowchart of the Smart Air Purifier Design Case Study

The sampling rules, key parameter tables, NSGA-II running code, and the derived result data of this case study have been organized and provided as attachments, enabling reproducibility without relying on costly or hard-to-access experimental/simulation setups.

V. Discussion

The findings from this case study clearly show how effective the end-to-end design approach—combining BPR and MOO—can be in advancing sustainable product design. This chapter offers a detailed interpretation of the results, compares them with existing studies, and discusses their theoretical and practical implications, along with the study's limitations.

A. Interpretation of Results

One of the most notable outcomes of the case study is that the optimized design achieved substantial and simultaneous improvements across four interconnected—and often conflicting — objectives: purification performance, noise reduction, life cycle cost, and environmental impact (see Table 1). This achievement challenges the traditional "seesaw" trade-off commonly seen in conventional design approaches.

The key reason behind this breakthrough lies in the method's dual-layer optimization structure: macro-level process re-engineering through BPR and micro-level technical refinement through MOO.

At the macro level, BPR played a transformative role in the third stage, "Function-Structure Decoupling and Re-engineering." By redesigning separate filters into an integrated barrel-shaped composite filter and optimizing both the fan and air duct structure, the product's physical architecture was fundamentally reconfigured. This was not merely a parameter adjustment — it represented a recombination of the product's core design logic. As a result, the feasible design space expanded significantly, creating a stronger and more flexible foundation for further optimization. Without this structural rethinking, MOO would have been constrained to incremental improvements within an outdated framework, limiting its overall impact.

At the micro level, the MOO approach—implemented using the NSGA-II algorithm — served as a scientific decision-support tool in the fourth stage. Faced with a complex design space involving multiple continuous variables such as fan speed and filter area, traditional trial-and-error methods would struggle to identify globally optimal solutions. In contrast, NSGA-II efficiently explored the entire solution space and generated hundreds of Pareto-optimal options. These solutions functioned as a "design map," clearly illustrating quantitative trade-offs between objectives—for instance, how much additional noise and cost would result from increasing CADR by 10%. This transformed decision-making from intuition-based judgments into transparent, data-driven, and traceable analysis. Designers could then select the most appropriate solution based on specific market strategies, whether prioritizing peak performance or cost efficiency.

Importantly, the integration of BPR and MOO is not a simple addition of two methods; it creates a synergistic effect. BPR expands structural possibilities and raises the performance ceiling, while MOO refines resource allocation within this newly expanded space. Together, they enable simultaneous multi-objective improvements that would otherwise be difficult to achieve.

B. Comparison with Existing Research

Compared to traditional sustainable design approaches discussed in the literature, this framework offers several distinct advantages. First, while methods such as LCA and eco-design mainly focus on evaluation or qualitative guidance, this framework provides a complete and actionable process from requirement analysis to final solution. It not only identifies what should be addressed but also explains how to implement it through structured steps and analytical tools.

Second, although BPR has been widely applied in organizational management and production systems, this study innovatively applies its principles to the product design process itself. By optimizing the "meta-process" of design, it achieves a stronger leverage effect.

Third, unlike many engineering studies that apply MOO only at isolated design stages, this research embeds MOO within a re-engineered system framework shaped by BPR. This integration allows the optimization algorithm to reach its full potential and achieve system-level performance gains.

Overall, the core innovation of this research lies in establishing an integrated framework that combines process re-engineering, data-driven analysis, and algorithm-based optimization. It directly addresses common limitations in existing research, such as fragmented processes, insufficient quantitative support, and difficulty in resolving multi-objective conflicts. In doing so, it offers a practical pathway for sustainable product design to evolve from conceptual advocacy toward a more rigorous engineering discipline.

C. *Theoretical and Practical Significance*

From a theoretical perspective, this research contributes a new interdisciplinary framework to sustainable design. By integrating BPR from management science with MOO from operations research within a data-driven design paradigm, it introduces a fresh approach to solving complex system design challenges. This supports the ongoing evolution of design science toward greater systemization, quantification, and intelligence.

From a practical standpoint, the method offers substantial value for enterprises:

- Improved R&D efficiency and quality: Structured workflows and automated optimization reduce design cycles, lower prototyping costs, and help identify higher-performing solutions.
- Enhanced market competitiveness: Data-driven requirement analysis and innovation enable companies to develop products better aligned with user needs and sustainability trends.
- Stronger organizational collaboration: Cross-functional integration helps break down silos between marketing, design, engineering, and manufacturing, fostering life-cycle-oriented teamwork.
- Support for sustainability strategies: The framework provides clear roadmaps and measurable tools to translate macro-level sustainability goals — such as carbon neutrality or circular economy principles — into actionable product specifications.

D. *Research Limitations*

Despite its positive outcomes, this study has several limitations. First, the reliance on a single case study — the smart air purifier—limits the generalizability of the findings. Further validation across more complex products, such as automobiles or industrial equipment with longer life cycles, is necessary.

Second, the research assumes high-quality user and performance simulation data. In real-world practice, companies may face incomplete, inaccurate, or costly data collection processes. Since the reliability of LCA and LCC models depends heavily on background data, uncertainties could influence optimization results.

Finally, while the proposed framework is systematic, it requires strong interdisciplinary collaboration and advanced data analysis capabilities. Successful implementation may demand organizational restructuring and targeted capability development within enterprises.

VI. CONCLUSION

This study responds to the shortcomings of traditional product design processes under the demands of sustainable development by developing and validating a new end-to-end, data-driven design methodology that integrates Business Process Re-engineering (BPR) and Multi-Objective Optimization (MOO). The main conclusions can be summarized as follows.

First, integrating the macro-level re-engineering logic of BPR with the micro-level parameter optimization capabilities of MOO provides an effective and systematic way to address multi-objective conflicts in sustainable product design. Through fundamental restructuring of the design process, BPR expands the space for innovation and removes structural constraints that often limit performance breakthroughs. Within this expanded solution space, MOO offers rigorous, quantitative decision-support tools that enable designers to balance complex trade-offs scientifically. The interaction between these two approaches creates a synergistic effect, making it possible to overcome the traditional tensions among performance, cost, and environmental impact, and to achieve coordinated improvements across multiple value dimensions.

Second, data functions as both the "circulatory system" and the connective tissue of the entire design process. From early-stage user requirement analysis, to mid-stage parameter optimization, and finally to solution validation, data underpins decision-making at every step. This continuous data integration reduces uncertainty, strengthens traceability, and enables systematic knowledge accumulation. As a result, the design process becomes more transparent, evidence-based, and resilient to subjective bias.

Third, the smart air purifier case study confirms the feasibility and practicality of the six-stage design framework proposed in this research: Scene Implantation, Requirement Analysis, Function Definition, Structure Optimization, Form Innovation, and Material Selection. The empirical findings demonstrate that the methodology is not only conceptually innovative but also capable of delivering measurable improvements in performance, economic outcomes, and environmental impact. It therefore provides companies with a clear and actionable roadmap for implementing sustainable development strategies through product innovation.

The contributions of this study can be understood at three levels. Theoretically, it introduces an integrated interdisciplinary framework that enriches sustainable design research by combining insights from management science and operations research within a data-driven paradigm. Methodologically, it establishes a structured, step-by-step end-to-end process model that translates sustainability principles into concrete design actions. Practically, it offers enterprises tangible guidance and analytical tools to systematically develop products that are both market-competitive and environmentally responsible.

Looking ahead, several directions can further expand this research. First, applying the methodology to more complex product systems—such as automobiles or building systems—would help test its scalability and general applicability. Second, deeper integration of real-time sensor data and digital twin technologies could enable dynamic, life-cycle-wide optimization, extending the framework beyond the initial design stage. Third, the development of an integrated collaborative software platform based on this methodology could reduce implementation barriers for enterprises while enhancing automation, coordination, and intelligent decision-making in sustainable product development.

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AUTHOR CONTRIBUTIONS

Xuefen Xie: Conceptualization; Methodology; Formal analysis; Software (optimization implementation);

Investigation; Writing — original draft; Visualization; Supervision; Project administration.

Chengbiao Xu: Resources (case-study context and practical inputs); Investigation; Validation; Data curation; Writing—review & editing.

COMPETING INTERESTS

The authors declare no competing interests.

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