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A multi-objective optimization method for engineering change paths of complex products considering a multi-process complex network

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ABSTRACT

This study addresses the optimization of change propagation paths in complex product engineering, where multiple disciplines and heterogeneous knowledge sources are involved. In such settings, design, production, and modification processes are often simultaneous, parallel, and collaborative, while the knowledge driving these changes is extensive, dynamic, and unstructured. To manage these challenges, a multi-objective optimization method is proposed within a multi-process complex network. A multi-stage network is constructed covering product design, process planning, and manufacturing, and an optimization model is developed considering change propagation intensity, total cost, and carbon emissions. The model is solved using the non-dominated sorting genetic algorithm III (NSGA-III) algorithm, and its feasibility and effectiveness are validated through a case study on engineering changes in a household refrigerator.

1. Introduction

In recent years, the development of the manufacturing industry has been promoted to the height of the national development strategy. Complex products are a crucial component in the manufacturing industry. There are many parts in the complex product, involving a wide range of technical fields.

Due to the change of demand, design, process, and manufacturing, it faces many kinds of continuous engineering changes in the production process. Engineering changes generally require the collaboration of multiple professional systems. When one of the components changes, it may lead to a series of changes in other parts. The propagation of changes will increase the complexity of the development process, costs, and risks. The research on changing propagation path will optimize change decisions and reduce design costs. Therefore, how to select the optimal change propagation path becomes an important issue with practical significance.

In the field of complex product changes, scholars have conducted in-depth explorations and achieved notable results. Guo (2018) proposed a method of design change propagation risk prediction based on a small-world network. Riascos et al. (2025) proposed a practical method to implement Dione in Product Lifecycle Management. Herac et al. (2024) used the incremental growth operation tree data structure to find potential conflicts in time after the model changes. Othman designed a hybrid research method combining qualitative and quantitative methods to explore the role of concurrent engineering in the management of design changes in the process of architectural design. Njualem and Pandey (2025) used the technology acceptance model to evaluate the adoption intention from the perspective of users and discussed the integration of Blockchain Technology in the enterprise system to improve the engineering change management process. In the study of Kalender (2024), the methodology of interval valued hesitant fuzzy decision-making experiment and evaluation laboratory is integrated into the change matrix. It provided an objective way to continuously evaluate and determine key processes and strategies consistent with changing conditions.

On the other hand, scholars have also considered the influencing factors of product engineering change from different aspects. Qiao et al. (2015) combined structured path information with all constrained assemblies to construct an adaptive assembly, proposed an adaptive assembly change algorithm, and discussed the scalability of adaptive assembly. Masmoudi et al. (2017) used an ant colony optimization algorithm to search for the optimal

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change propagation path by taking the maximum value of cumulative CPI as the goal (Xue and Imaniyan, 2021). Zheng et al. (2018) proposed a new multi-change requirement algorithm and a mathematical model considering the overall propagation risks to explore a cost-effective change propagation path.

From the above research, we can see that complex product engineering change has received considerable attention from researchers and practitioners. In the extant literature, there are several studies that dealt with complex product engineering changes. It can be divided into two groups: one is about the research on the description model; another is about the research on change path choice. But there are few studies focused on multi-stage production and carbon emissions.

However, since complex product engineering changes involve multiple production stages and departments, it is necessary to consider multi-stage production relationships. In addition, it usually involves interdisciplinary integration, long life cycles, and deep collaboration in the supply chain. The impact of design changes is systematic - small material or process adjustments may cause supply chain reshaping, energy efficiency fluctuations, or environmental risks in the waste stage.

Therefore, in the design change process of complex products, paying attention to environmental indicators is not only an inevitable choice to respond to global sustainable development trends, but also a strategic consideration determined by their particularity. This paper proposes a new representation method and path optimization method to enrich the research in this area.

Previous studies have explored change propagation models from multiple perspectives. Most studies describe engineering changes in complex products by establishing relationships or networks between components. However, engineering changes occur across various aspects of product production, such as design, process, and manufacturing. It is essential to consider multiple production processes when managing changes. Consequently, this paper adopts a multi-process network approach to describe and represent the engineering change process in complex products (Hamraz et al., 2012).

This research has primarily focused on single factors such as time, cost, and change impact. However, in actual production, numerous factors influence production, and environmental constraints must also be considered. With the rise of green manufacturing and increased public environmental awareness, greater attention should be given to the impact of carbon emissions on product design and manufacturing (Liu et al., 2025).

Therefore, this paper establishes a multi-objective optimization model with objectives including change propagation intensity, total change cost, and carbon emissions. Based on the characteristics of the multi-objective optimization model, the non-dominated sorting genetic algorithm III (NSGA-III) algorithm is employed to solve Pareto optimal solutions (Ma and Zou, 2025).

Finally, an engineering change case study involving household refrigerators is used to demonstrate the feasibility and effectiveness of the proposed method. The research framework is illustrated in Fig. 1.

The remainder of this paper is organized as follows. The construction of a multi-process complex network for engineering change is shown in Section 2. Section 3 presents the problem description and optimization modeling. In Section 4, we introduce the algorithm design and process based on NSGA-III. In Section 5, we present a case study to demonstrate the applicability of the proposed method. Finally, some conclusions from this study are presented in Section 6.

2. Multi-process complex network

Engineering changes occur in product design, process, manufacturing, and other stages. When these changes occur, all processes will be affected. It is necessary to respond to changes to achieve a real-time change design response. In complex product development, changes can occur at various stages, from initial design through manufacturing and assembly. These changes often generate a significant amount of information that needs to be systematically captured and managed. Effectively gathering, organizing, and managing dispersed knowledge pertaining to product engineering changes is essential for maintaining the integrity of the product assembly structure. Therefore, this paper constructs a complex network of multi-process expressions from the aspects of design, process, and manufacturing process.

In the complex product design stage, the structure and function are determined according to the market demand, which is the key to guiding the subsequent production and manufacturing. There are three sources of knowledge in product design. One of them is the functional knowledge from the transformation of customer requirements, the other one is selected knowledge from the basic parts, and the last one is redesigning knowledge according to the subsequent changes. This knowledge network, based on process, must be able to accurately record the comprehensive information of each part for a complex product. Knowledge network of the complex product manufacturing stage is associated with the assembly material attribute information, supplier, and quota information. In addition to material attribute information, the self-made parts should also be associated with material quota, man-hour quota, work center, tools, accessories, equipment, and other information. The multi-process complex network construction process of complex products is shown in Fig. 2.

The single process network is represented as: $G_k = (V, E_K, W_K)V = (V_i, i = 1,2, \ldots N)$. If there are connecting edges between parts of knowledge, then $e_{k,j}^{k} = 1$, else, $e_{k,j}^{k} = 0$. For the same connected edge, the weight value is $w_{i,j} = \sum_{\alpha}^{3} w_{i,j}^{\alpha}$. The schematic diagram of the multi-process network is shown in Fig. 3. In the integration of heterogeneous knowledge across multiple domains, functional knowledge, behavioral knowledge, and structural knowledge are abstracted into a hierarchical knowledge space. This space is organized into lists of functional, behavioral, and structural knowledge, which supports classification and integrated management. When two components work together by exchanging material, information, or energy flows, they form a functional combination and establish functional interdependencies.

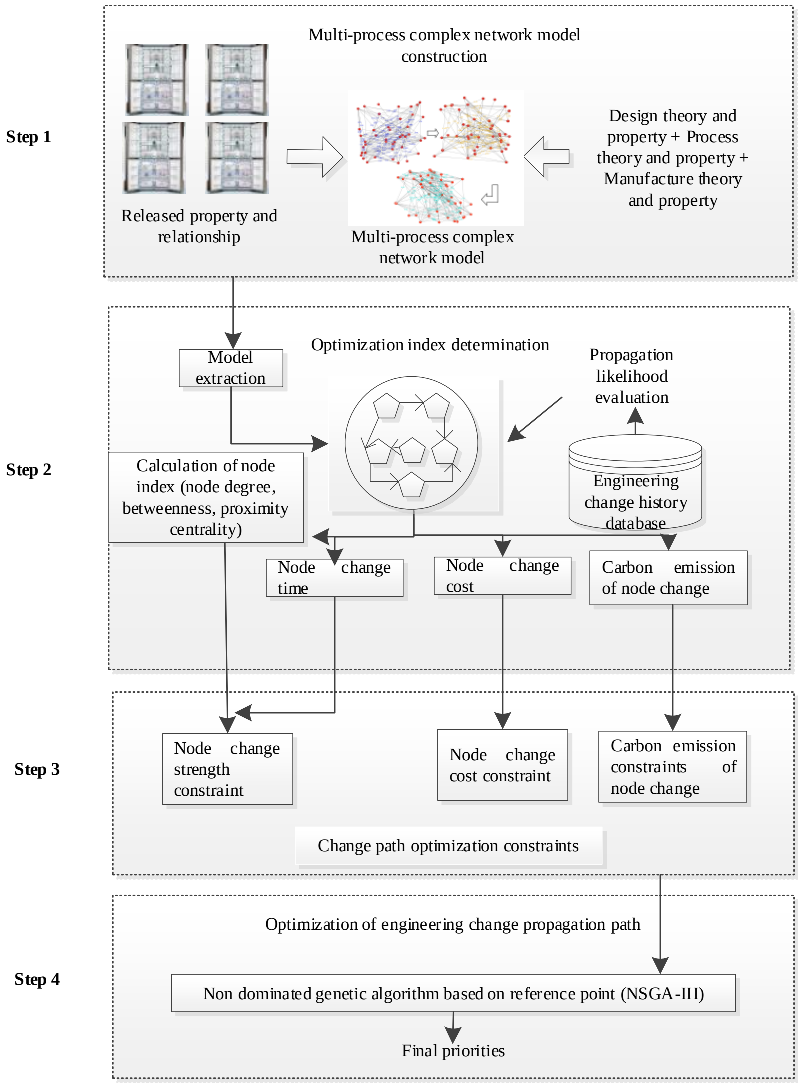

Fig. 1: Engineering change propagation multi-objective optimization method framework

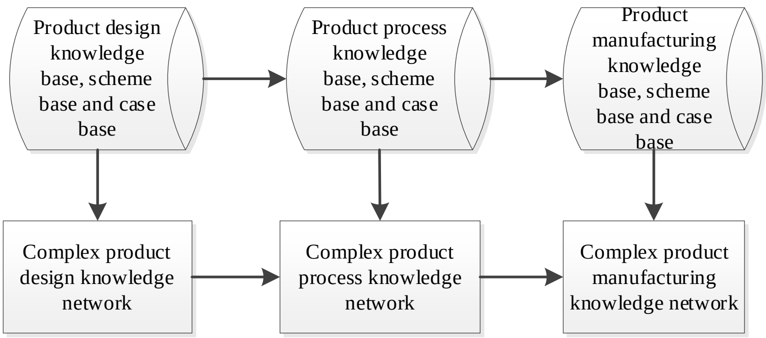

Fig. 2: Multi-process complex network of complex products

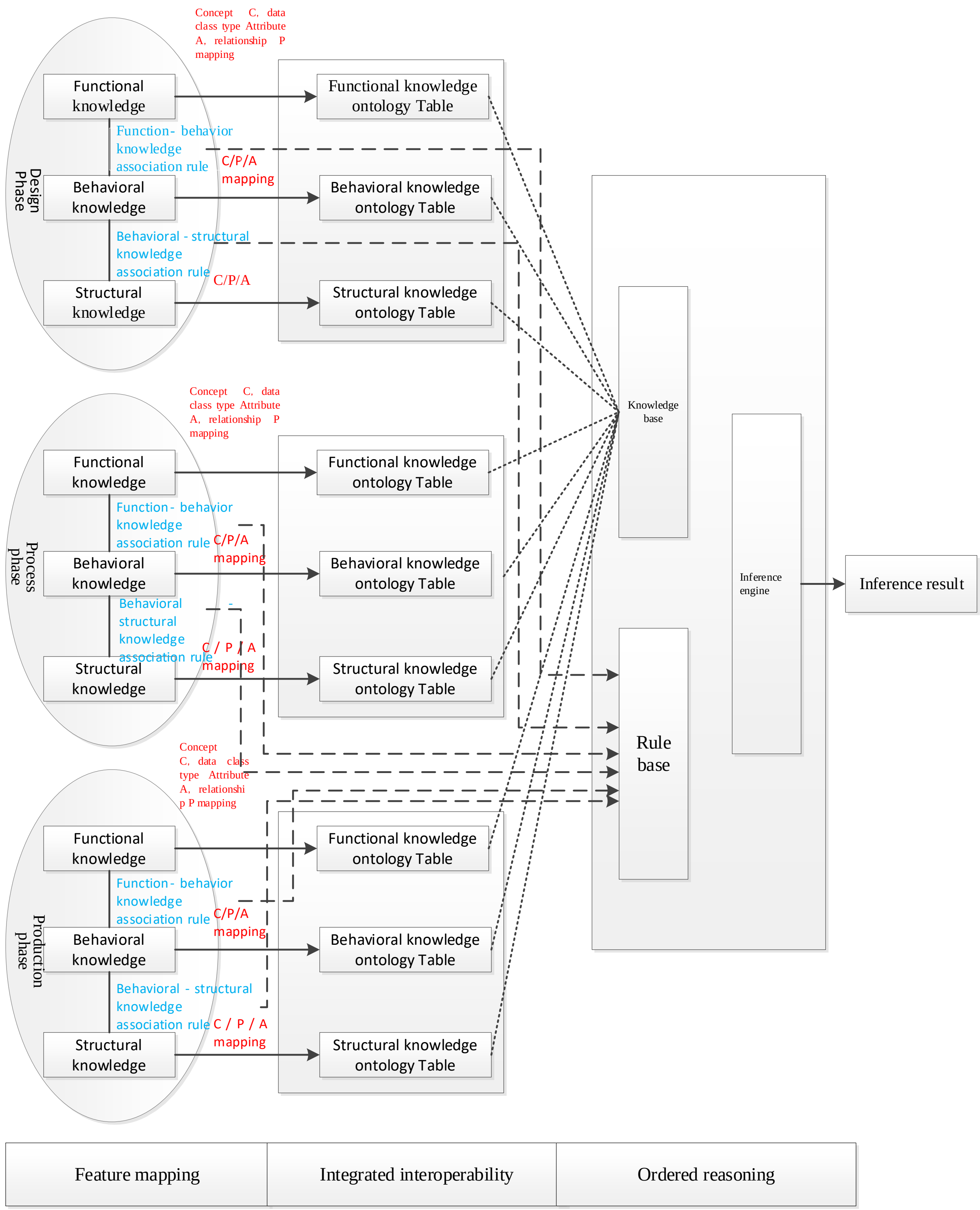

Fig. 3: Process diagram of multi-domain knowledge integration based on the semantic X list

Behavioral knowledge refers to all knowledge required to satisfy product behavior requirements. This includes mechanical properties (e.g., strength, inertia, elasticity), electrical characteristics (e.g., conductivity, resistance, charging), and thermal effects (e.g., heat conduction, temperature change, absorption). Structural knowledge represents the physical basis of function, focusing on the concrete composition of entities needed to realize that function.

A semantic “X list” enables the semantic description of knowledge within complex product systems. The isomorphism of heterogeneous knowledge across multiple domains is represented by constructing ontology spaces for functional, behavioral, and structural knowledge. For this purpose, the Web Ontology Language (OWL) is used to describe ontology concepts and attributes. On this basis, cross-list Semantic Web Rule Language (SWRL)-based trigger rules, namely Rule RS and

Rule DS, are developed to link resources with creative knowledge and allow their dynamic combination on demand.

An intelligent agent system is then built, consisting of a knowledge base, a rule base, and a reasoning engine. The knowledge base and rule base store trigger rules related to elements, behaviors, and constraints of each ontology list. These rules and knowledge are processed by the reasoning engine, which performs knowledge reasoning. Through knowledge fusion, new knowledge is generated, and integration results are obtained.

Overall, these operations achieve the isomorphism of heterogeneous knowledge across domains and enable effective integration, sharing, mutual understanding, and interoperability in the innovation process of complex product systems.

3. Problem description and model

3.1. Engineering change path optimization requirements

To reduce the negative effects of engineering changes, we aim to limit their overall impact on the network while also minimizing costs, time, and carbon emissions. In this process, nodes with higher influence should be avoided to reduce chain effects. The duration required to implement changes should be kept as short as possible, and the costs involved should be minimized. At the same time, carbon emissions generated at change points should be reduced to support environmental sustainability objectives.

3.2. Description of the optimal index for engineering change path

The evaluation of node importance usually requires a comprehensive consideration of multiple indicators. Given the complexity and uncertainty of product knowledge, this study applies the grey correlation evaluation method to identify and assess node importance. The selected indicators are node betweenness, node degree, and node proximity.

Node betweenness represents the extent to which a node lies on the shortest paths between other nodes. It is defined as the fraction of all shortest paths in the network that pass through the node. Mathematically, the betweenness of node i is expressed as $B_i = \sum_{j,k \in V} \frac{\eta_{\mathrm{jk}}(i)}{\eta_{\mathrm{jk}}}$, where, η_{jk} is the number of shortest paths between node j and node k.

Node degree reflects the number of direct connections of a node, serving as a fundamental property in network theory. Node proximity is the reciprocal of the sum of the shortest distances from a node to all other nodes, expressed as $C_{i,j} = \frac{1}{\sum_{j=1}^{n} \beta_{ij}}$, where, β_{ij} is the number of edges in the shortest path from node i to node j, and n is the total number of nodes. A higher proximity value indicates a node is closer to the network center and thus more important. The importance of multi-process node connections is further calculated using the evaluation of the multi-level grey correlation degree, expressed as $\frac{1}{m}\sum_{k=1}^{m} \omega_i \gamma(x_0(k), x_i(k))$, where, m is the number of the above-mentioned node evaluation indicators (multi-stage network node importance evaluation index). $\gamma(x_0(k), x_i(k))$ is a discrete function constructed to determine multiple subsequences X_i to the reference sequence.

In addition to node indicators, edge betweenness is considered. It measures the fraction of shortest paths passing through a given edge relative to the total number of shortest paths in the network. Edge betweenness test is an important index to measure the role of connected edges in the whole network. The edge betweenness is expressed as:

$$G_{i,j} = \sum_h^N \sum_m^N \frac{L_{h,m(e_{i,j})}}{g_{h,m}} / [h \neq m, \ (h,m) \neq (i,j)]$$

Several practical factors also affect engineering change evaluation. The time of engineering change is defined as the duration of the design task associated with the affected node j, denoted as t_j, with units in days. Since rapid redesign enhances product competitiveness in highly competitive markets, shorter task durations make change propagation along the corresponding edge more likely.

The propagation probability of a connected edge is denoted by $p_{i,j}$ is the probability of propagation from node i to node j. If node j does not belong to the next connected edge, the propagation probability is 0. It is easier to pass through this connecting edge when the propagation probability of the edge is greater. It can be expressed as:

$$P_{ij} = p(v_j|v_i) = \frac{p(v_i \cap v_j)}{p(v_i)} = \frac{p(v_j|v_i)p(v_j)}{p(v_i)} = \frac{p_{ji}p(v_j)}{p(v_i)}.$$

The cost of engineering change includes all direct expenses associated with the affected parts, such as labor, patent fees, and material costs, expressed in yuan.

Finally, carbon emissions are also considered. These emissions are generated by the parts undergoing engineering changes. In line with national regulations on greenhouse gas emissions, the company is expected to implement a carbon emission policy, setting the product emission limit in kilograms of CO_2 equivalent.

3.3. Parameter interpretation

To establish and describe the multi-objective 0-1 integer programming model, parameters are defined in Table 1. For example, i, j are the node numbers, where, $i = 1,2,\ldots N, j = 1,2,\ldots N$. S_j is the multi-level grey correlation evaluation index of the node j. $G_{i,j}$ refers to the edge between nodes $i \, and \, j$. t_j is the time taken by the whole product to implement the change task after the change of node j. $p_{i,j}$ is the propagation probability from the node i to node j. The carbon emissions generated in the design, process and manufacturing stages after the change of node j are respectively represented by e_j^r, e_j^m, e_j^g. x_j is a 0-1 decision variable. If node j is involved in the change, then x_j=1. If node j is not involved in the change, then x_j=0. $y_{i,j}$ is a 0-1 decision variable. If the edge i, j is involved in the change, then b=1. If the edge i, j does not need to be involved in the change, then $y_{i,j}$=0.

$$f_1 = \min[\sum_j^N S_j \cdot x_j + \sum_i^N \sum_j^N y_{i,j} \cdot G_{i,j} + \sum_i^N \sum_j^N t_{i,j} \cdot x_j - \sum_i^N \sum_j^N (1-P) \cdot y_{i,j}] \quad (1)$$
$$f_2 = min(\sum_{j=1}^N C_i x_j) \quad (2)$$
$$f_3 = min(\sum_{j=1}^N e_j^r + e_j^m + e_j^g) \cdot x_j \quad (3)$$

s.t.

$$y_{i,j} = \{0,1\} \quad (4)$$
$$x_j = \{0,1\} \quad (5)$$
$$\sum_i^N x_i \leq N \quad (6)$$
$$x_j \leq y_{i,j} \quad (7)$$
$$\sum_i^N \sum_i^N x_{i,j} \leq 2N \quad (8)$$
$$\sum_j^N (e_j^r + e_j^m + e_j^g) \leq E_q \quad (9)$$
$$\sum_{j=1}^v p_j \geq \Delta p_i \quad (10)$$

Eq. 1 is the first objective function, the purpose of it is to minimize the impact of change propagation on other parts. Eq. 2 is the second objective function, which is to achieve the minimum cost of changing configuration. Eq. 3 is the third objective function, which is to minimize the carbon emission of products. Eqs. 4 and 5 are the domains of decision variables. Eq. 6 limits the number of nodes. Eq. 7 indicates that the decision variable is constrained y_{ik} by the decision variable x_j. Eq. 8 represents the number of connected edges. Eq. 9 indicates that the total carbon emission of the node is lower than the carbon limit standard. Eq. 10 represents that the change propagation will stop when the cumulative sum of changes absorbed is greater than or equal to the ICI of each initial change node.

Table 1: Parameter interpretation

Symbol	Description
$y_{i,j}$	0-1decision variable of connecting route. If edge $e_{i,j}$ is selected as the design change propagation path, then $y_{i,j}$= 1, otherwise, $y_{i,j}$= 0.
x_j	0-1 decision variable of selected node. If edge $e_{i,j}$ is involved in the design change propagation path， then x_j = 1; otherwise, x_j = 0.
i, j	Node numbers, where i=1, 2, ..., N; j=1, 2, ..., N. N is the total number of nodes.
S_j	Node importance
$G_{i,j}$	Betweenness of edge $e_{i,j}$
t_i	The execution time of the redesign of node v_i
$e_{jk}^r, e_{jk}^m, e_{jk}^g$	The carbon emissions produced by node j in the stages of raw material acquisition, manufacturing, and logistics.
C_j	The change cost of node j
Δp_i	The initial change impact of the initial change node (ICI)
p_j	The node's ability to absorb changes
v	The number of steps of initial change node propagation

4. Algorithm design

The solution of the above model belongs to the class of multi-objective optimization (MO) problems. To handle such problems, multiple objectives are usually transformed into a single-objective optimization task, or alternatively, specialized multi-objective algorithms are applied. Although a single-objective approach can identify an optimal solution, it does not ensure Pareto optimality, which is the core concept in multi-objective optimization. In addition, single-objective optimization cannot search for multiple optimal solutions simultaneously and lacks the flexibility required for decision-making with conflicting objectives.

For this reason, multi-objective algorithms are employed. These algorithms aim to generate a set of Pareto optimal solutions, from which decision-makers can select the most appropriate option based on trade-offs among competing objectives. Unlike single-objective optimization, which focuses on identifying one best solution, multi-objective optimization recognizes the complexity of real-world problems where several conflicting objectives must be optimized at the same time.

Representative algorithms in this field include the multi-objective genetic algorithm, niche genetic algorithm, differential evolution algorithm, strength Pareto evolutionary algorithm, non-dominated sorting genetic algorithm (NSGA), NSGA-II, NSGA-III, and others. Among them, NSGA-II has shown strong performance in terms of search ability, solution distribution, and coverage, and it is widely applied in practice. However, when the number of objectives increases to three or more, the convergence and diversity of NSGA-II become less effective. To address this limitation, NSGA-III was developed as an extension of NSGA-II.

Therefore, in this study, NSGA-III is adopted to solve the given multi-objective optimization problem. The design steps of the algorithm are outlined as follows.

4.1. Chromosome coding and initialization

The chromosome code in this paper is composed of changing the node number. Combined with the propagation path problem of complex product design changes, the feasible solution must satisfy the following two constraints:

1. The downstream neighboring node of node i is set U_i. Node j is the node selected for the next search. Then it should meet: $j \in U_i$.
2. When ICI < 0.01, the change stops propagation.

Based on the above two constraints, based on two constraints, a stochastic method is adopted to generate the initial chromosomes. The encoding method is shown in Fig. 4. Where the gene represents the node number, and the population with N chromosomes is initialized.

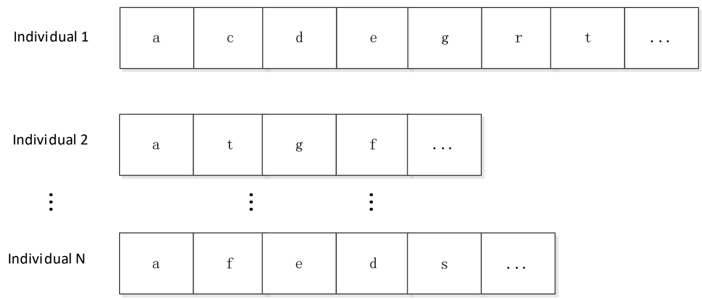

Fig. 4: Coding pattern of the chromosome

4.2. Crossover and mutation of operators

4.2.1. Crossover operator

In the process of iterative evolution, crossover and mutation can improve the search performance of the genetic algorithm. Crossover and mutation are the operations of generating individual offspring. The single-point crossover method is utilized to solve the established multi-objective optimization model for propagation paths. In this process, a single crossover point on the parent chromosomes is selected, and genetic material is exchanged between them to produce offspring. If there is the same node number except for the initial gene in the two chromosomes, they will cross at the same node number.

If there are multiple optional intersections, one intersection will be selected randomly. The process of crossing is shown in Fig. 5. If there is no same number except for the initial gene in the two chromosomes, the two parent individuals are discarded, and the parent individuals will be reelected to determine whether they can be crossed. At the end of the crossover, we judge whether the two generated generations satisfy the feasible solution constraint. The chromosomes of too short progeny will be supplemented, and the chromosomes of long offspring will be cut until the feasible solution is satisfied.

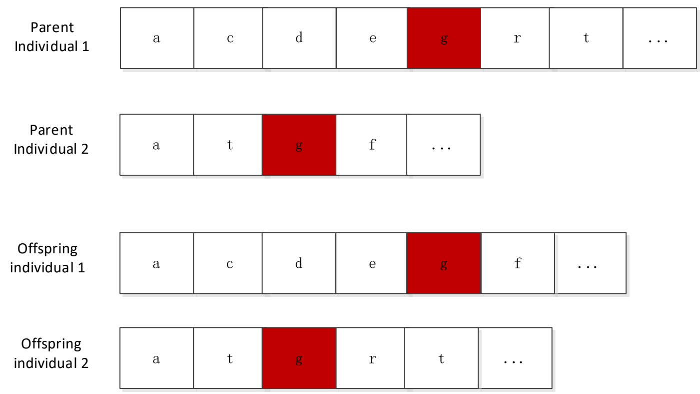

Fig. 5: Crossing pattern of a chromosome

4.2.2. Mutation operator

The chromosome is randomly selected, the gene position is randomly selected to change the node number, and whether the chromosome meets the constraints is judged. If the constraints are met, the individual will be accepted and added to the population; otherwise, the original dye will be added to the population.

4.2.3. Non-dominated sorting

In the solving process of the optimal solution, the whole population must be sorted non-dominated first. The target value of everyone (path propagation plan) in the population is compared with the corresponding target value of other individuals (path propagation plan) to determine the dominance relationship between individuals (path propagation plan) in the non-dominated sorting algorithm. For any two individuals p and q,p dominates q when all the objective values of p are not less than the objective function values of q. Where $f_1(p)$ and $f_1(q)$ are the values of the objective function corresponding to individuals respectively. Individuals will be ranked according to the dominance relationship between individuals. Then the solution set with the highest rank in the population is the Pareto optimal solution. The specific ranking process is as follows:

- For each individual p, the corresponding target value is compared with other individuals. Then, the number of individuals n_p dominating p in the population is calculated, and the individuals dominated by p are included in the set S_p.
- All individuals $n_p = 0$ in the population are graded as 1. Then perform $n_q = n_q - 1$ on individual q in S_p.
- Repeat step (2) to generate the next level.
- Select the highest-ranking individuals in the population to form a Pareto optimized solution set.

4.2.4. Generation of reference points

According to the individual selection mechanism of reference point in NSGA-III, the reference vector is composed of the ideal point (new coordinate origin) and the reference point on the hyperplane. The generation mechanism is as follows:

1. Firstly, the minimum value z_i of each target dimension i in the objective function needs to be calculated. The set of z_i is the ideal points. Then the scalar formula $f_i'(x) = f_i(x) - z_i^{min}$ after obtaining the ideal point set can be obtained.
2. The objective function is all traversed, and then the smallest individual that satisfies the equation $ASF(x, w) = \overset{i=1}{\underset{M}{max}} f_i'(x)/w_i$ will be found, which is the extreme point. The intercept on the corresponding coordinate axis according to the specific function value of these points can be calculated, which is recorded as a_i. The normalization operation is performed according to $f_i^n(x) = \frac{f_i'(x)}{a_i}$.
3. According to the reference point selection mechanism, the reference points are divided on the hyperplane. Then the reference vector is constructed.
4. For each individual population, all reference vectors will be traversed, and the nearest reference point j will be found, and the shortest distance and the number of reference points will be recorded.

4.2.5. Algorithm flow

Based on the above coding structure, the NSGA-III algorithm is applied to the complex product change propagation path problem to obtain a Pareto optimization solution (The computation complexity of the method is O(NM^2), where M is the objective number and N is the iterations times.) The detailed process is as follows in Fig. 6.

5. Case study

The household refrigerator is a typical example of a complex product, consisting of several key components such as the compressor, condenser, evaporator, control system, casing, and door assembly. Each of these components may pose challenges in terms of material selection, dimensional accuracy, and assembly compatibility. Problems in any of these areas may require design modifications or adjustments.

Refrigerators must also comply with strict performance and safety standards, including cooling efficiency, energy consumption, noise levels, and the use of environmentally friendly refrigerants. Meeting national and international regulations is mandatory, and updates to these standards or growing market demands often lead to further design changes. In addition, regional and consumer preferences regarding functionality, aesthetics, and storage capacity increase the complexity of product development. To remain competitive, manufacturers frequently introduce customized products, which results in repeated design iterations.

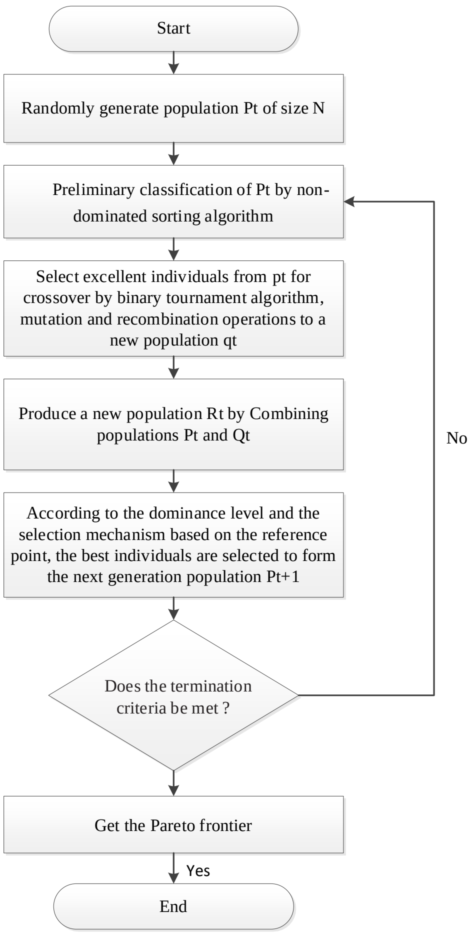

Fig. 6: Basic flow chart of the NSGA-III algorithm

Cost reduction is another major priority. Companies aim to lower expenses in materials, production, transportation, and maintenance. These efforts often involve engineering changes, such as replacing materials with cheaper but equally effective alternatives or simplifying structural designs. Issues discovered during prototype testing or small-scale pilot production also require correction, leading to multiple revisions before full-scale manufacturing.

For this reason, the household refrigerator is selected as a case study in this paper. In the production process of a particular type of refrigerator from Company D, the insulation process has been upgraded in line with technological advances. Product data show that this refrigerator consists of 43 main parts, organized into five modules: the insulation box, insulation door, refrigeration system, electrical system, and application attachments. A diagram of the main parts is provided in Fig. 7. Based on this, a change to the insulation layer is proposed, and the engineering replacement path for the refrigerator is optimized.

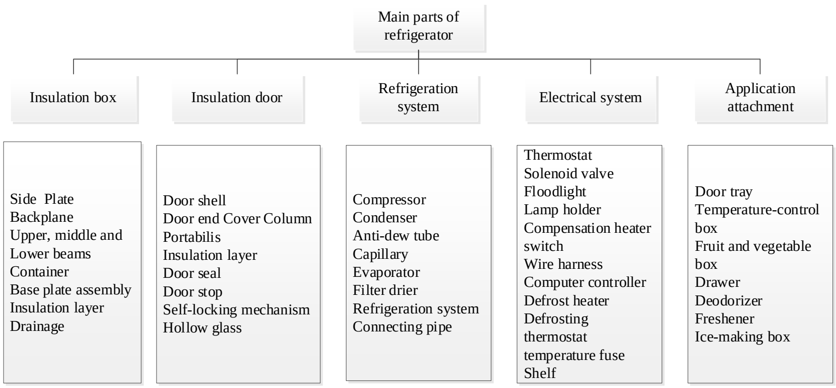

Fig. 7: Main parts diagram of a household refrigerator

Firstly, combining with the product knowledge base, design database, case base, and interviews with designers, the multi-process network diagram of this type of household refrigerator can be obtained. Based on the multi-objective optimization model, the importance of each node, the execution time and cost of changing tasks, the edge betweenness, and the propagation probability of each connected edge are calculated. The multi-stage network data is shown in Tables 2-4. The value of these indicators is shown in Tables 5 and 6.

Table 2: Design phase network of the household refrigerator

a	b	c	a	b	c	a	b	c
1	2	0.53	13	16	0.14	23	32	0.45
1	3	0.32	14	15	0.31	23	35	0.46
1	4	0.21	14	16	0.21	23	38	0.22
2	3	0.12	14	36	0.23	23	43	0.46
2	4	0.17	15	16	0.17	24	25	0.4
2	5	0.31	15	26	0.12	24	38	0.46
2	6	0.12	15	31	0.11	24	43	0.21
3	6	0.33	15	32	0.23	25	26	0.4
3	8	0.31	16	25	0.11	25	29	0.48
3	9	0.23	16	33	0.10	25	32	0.51
4	5	0.46	16	34	0.15	25	34	0.46
4	6	0.50	16	35	0.12	25	35	0.55
4	7	0.24	17	18	0.65	25	28	0.11
4	8	0.38	17	19	0.61	26	27	0.17
5	6	0.15	17	20	0.57	26	28	0.16
5	7	0.34	17	21	0.58	26	31	0.37
5	8	0.37	17	23	0.63	26	32	0.51
6	13	0.57	17	24	0.56	26	35	0.41
6	15	0.44	17	25	0.46	27	28	0.58
6	16	0.29	17	26	0.51	27	31	0.43
7	17	0.56	17	32	0.57	27	30	0.22
7	18	0.48	18	19	0.59	29	32	0.55
7	21	0.56	18	20	0.53	29	38	0.58
8	9	0.51	18	21	0.58	30	31	0.35
8	10	0.22	18	22	0.37	30	32	0.28
8	11	0.37	18	23	0.56	30	33	0.33
8	12	0.36	18	24	0.44	30	34	0.37
8	13	0.39	18	25	0.51	30	35	0.29
8	14	0.48	18	26	0.31	31	32	0.44
9	10	0.11	19	20	0.55	31	33	0.39
9	11	0.30	19	23	0.61	31	34	0.34
9	12	0.33	19	24	0.50	31	35	0.28
9	13	0.42	20	21	0.56	32	33	0.41
10	11	0.22	20	22	0.31	32	34	0.38
10	12	0.17	20	23	0.61	32	35	0.33
10	14	0.10	20	24	0.38	33	34	0.42
10	16	0.21	20	36	0.14	33	35	0.39
11	12	0.46	21	22	0.43	34	35	0.51
11	13	0.11	21	23	0.25	36	39	0.25
11	14	0.09	21	24	0.37	36	40	0.33
11	16	0.12	21	29	0.36	36	41	0.16
11	17	0.33	21	38	0.39	36	42	0.22
12	13	0.38	22	23	0.52	37	8	0.52
12	25	0.58	22	24	0.30	37	9	0.49
12	29	0.56	22	25	0.27	37	12	0.10
12	33	0.40	23	24	0.53	37	13	0.33
12	34	0.39	23	25	0.61	43	1	0.13
						43	4	0.12

a: Source; b: Target; c: Weight

Table 3: Process phase network of the household refrigerator

a	b	c	a	b	c	a	b	c
1	2	0.43	13	16	0.16	23	32	0.42
1	3	0.35	14	15	0.33	23	35	0.43
1	4	0.34	14	16	0.25	23	38	0.24
2	3	0.14	14	36	0.26	23	43	0.45
2	4	0.15	15	16	0.16	24	25	0.43
2	5	0.34	15	26	0.19	24	38	0.41
2	6	0.15	15	31	0.15	24	43	0.22
3	6	0.32	15	32	0.36	25	26	0.33
3	8	0.33	16	25	0.15	25	29	0.48
3	9	0.25	16	33	0.18	25	32	0.53
4	5	0.37	16	34	0.15	25	34	0.44
4	6	0.42	16	35	0.13	25	35	0.51
4	7	0.25	17	18	0.55	25	28	0.21
4	8	0.26	17	19	0.63	26	27	0.18
5	6	0.14	17	20	0.55	26	28	0.14
5	7	0.33	17	21	0.54	26	31	0.38
5	8	0.38	17	23	0.59	26	32	0.48
6	13	0.49	17	24	0.49	26	35	0.39
6	15	0.33	17	25	0.44	27	28	0.56
6	16	0.37	17	26	0.53	27	31	0.42
7	17	0.55	17	32	0.55	27	30	0.25
7	18	0.61	18	19	0.61	29	32	0.48
7	21	0.63	18	20	0.49	29	38	0.57
8	9	0.64	18	21	0.56	30	31	0.34
8	10	0.24	18	22	0.35	30	32	0.25
8	11	0.36	18	23	0.53	30	33	0.32
8	12	0.38	18	24	0.42	30	34	0.35
8	13	0.32	18	25	0.49	30	35	0.26
8	14	0.45	18	26	0.35	31	32	0.43
9	10	0.14	19	20	0.52	31	33	0.34
9	11	0.34	19	23	0.59	31	34	0.35
9	12	0.35	19	24	0.5	31	35	0.26
9	13	0.44	20	21	0.58	32	33	0.4
10	11	0.21	20	22	0.32	32	34	0.36
10	12	0.34	20	23	0.6	32	35	0.31
10	14	0.23	20	24	0.39	33	34	0.42
10	16	0.25	20	36	0.13	33	35	0.31
11	12	0.39	21	22	0.44	34	35	0.51
11	13	0.13	21	23	0.26	36	39	0.22
11	14	0.12	21	24	0.36	36	40	0.32
11	16	0.14	21	29	0.35	36	41	0.14
11	17	0.35	21	38	0.32	36	42	0.24
12	13	0.34	22	23	0.5	37	8	0.51
12	25	0.55	22	24	0.33	37	9	0.36
12	29	0.53	22	25	0.26	37	12	0.15
12	33	0.42	23	24	0.51	37	13	0.24
12	34	0.36	23	25	0.55	43	1	0.22
						43	4	0.16

a: Source; b: Target; c: Weight

The example is solved by python programming, in which the initial change node is set to 17, the ICI is set to 1. Related parameters of NSGA-III are as follows. The maximum iteration number is 100, the population size is 300, the crossover probability is 0.9 and the mutation probability is 0.1. When the change impact of propagation is less than 0.01, the path search change will stop. Three Pareto optimal solutions are obtained after calculation. The optimal propagation path and the value of each objective function are shown in Table 7.

Table 4: Production phase network

a	b	c	a	b	c	a	b	c
1	2	0.26	13	16	0.21	23	35	0.41
1	3	0.31	14	15	0.29	23	38	0.23
1	4	0.22	14	16	0.31	23	43	0.42
2	3	0.15	14	36	0.25	24	25	0.39
2	4	0.12	15	16	0.18	24	38	0.38
2	5	0.35	15	26	0.15	24	43	0.23
2	6	0.15	15	31	0.13	25	26	0.38
3	6	0.31	15	32	0.24	25	29	0.39
3	8	0.29	16	25	0.13	25	32	0.53
3	9	0.22	16	33	0.12	25	34	0.48
4	5	0.34	16	34	0.15	25	35	0.53
4	6	0.48	17	18	0.62	25	28	0.21
4	7	0.21	17	19	0.63	26	27	0.15
4	8	0.37	17	20	0.55	26	28	0.16
5	6	0.16	17	21	0.49	26	31	0.35
5	7	0.46	17	23	0.41	26	32	0.55
5	8	0.34	17	24	0.49	26	35	0.39
6	13	0.55	17	25	0.46	27	28	0.56
6	15	0.41	17	26	0.39	27	31	0.46
6	16	0.32	17	32	0.46	27	30	0.21
7	17	0.58	18	19	0.63	29	32	0.49
7	18	0.41	18	20	0.69	29	38	0.39
7	21	0.54	18	21	0.48	30	31	0.29
8	9	0.52	18	22	0.31	30	32	0.26
8	10	0.33	18	23	0.37	30	33	0.31
8	11	0.31	18	24	0.39	30	34	0.34
8	12	0.35	18	25	0.49	30	35	0.23
8	13	0.36	18	26	0.28	31	32	0.41
8	14	0.43	19	20	0.54	31	33	0.35
9	10	0.11	19	23	0.59	31	34	0.41
9	11	0.31	19	24	0.38	31	35	0.26
9	12	0.32	20	21	0.58	32	33	0.39
9	13	0.38	20	22	0.29	32	34	0.34
10	11	0.24	20	23	0.58	32	35	0.32
10	12	0.16	20	24	0.36	33	34	0.41
10	14	0.13	20	36	0.32	33	35	0.29
10	16	0.25	21	22	0.41	34	35	0.55
11	12	0.48	21	23	0.38	36	39	0.24
11	13	0.15	21	24	0.35	36	40	0.34
11	14	0.13	21	29	0.37	36	41	0.23
11	16	0.15	21	38	0.29	36	42	0.15
11	17	0.36	22	23	0.55	37	8	0.42
12	13	0.32	22	24	0.38	37	9	0.41
12	25	0.54	22	25	0.28	37	12	0.13
12	29	0.55	23	24	0.39	37	13	0.26
12	33	0.41	23	25	0.58	43	1	0.15
12	34	0.38	23	32	0.51	43	4	0.13

a: Source; b: Target; c: Weight

From the Pareto optimal solution, four optimal solutions can be identified. In these four cases, the modified nodes are as follows:

- Case 1: 12, 34, 31, 33, 16, 10, 8, 4, 43
- Case 2: 12, 25, 17, 24, 25, 22
- Case 3: 12, 11, 14, 36, 42
- Case 4: 12, 25, 28, 26, 17, 19

In every examined scenario, node 12 consistently serves as the initial change point, although the subsequent nodes differ depending on the specific configuration. This observation indicates that three distinct change paths are capable of satisfying the established constraints. Such flexibility is valuable, as it enables managers to select the most appropriate path according to the central focus of their change requirements, whether related to efficiency, cost, or environmental considerations. The comparative analysis further demonstrates that the performance of the traditional genetic algorithm (GA) is notably inferior to that of NSGA-III. The solutions produced by NSGA-III clearly surpass those obtained by GA in terms of the defined objective function, highlighting its effectiveness and superiority in addressing complex optimization problems. To strengthen the validity of the chosen path impact factors, the grey comprehensive evaluation method was applied. The calculated grey relational degrees for change time, change cost, carbon emissions, and change propagation effects were 0.82, 0.85, 0.81, and 0.89, respectively. These values confirm strong correlations between the selected indicators and the outcomes of the change process, thus supporting the reliability of the evaluation framework.

6. Conclusion

Because of the characteristics of complex products, it is difficult to manage and control engineering changes, and managers often struggle to identify the optimal change propagation path. Traditional methods typically evaluate propagation paths only based on the impact of change propagation. However, this approach is limited, as complex product knowledge involves multiple disciplines, making knowledge extraction imprecise (Zhu et al., 2017).

In this paper, we propose an importance analysis of product knowledge using a multi-layer grey correlation method. Grey system theory has been widely applied in engineering evaluation problems because of its ability to handle uncertain and incomplete information (Zheng et al., 2025). We then conduct an optimization analysis of the engineering change path by considering three factors: change propagation, change cost, and carbon emissions. A multi-process complex network is used to describe the multi-process knowledge of complex products, and a multi-objective optimization model is developed. This model is solved using the NSGA-III algorithm (Chaudhari et al., 2022). To demonstrate the feasibility and effectiveness of the proposed approach, we apply it to a household refrigerator case study and compare the results with those of traditional methods.

The main conclusions of this study are as follows:

1. Introducing a multi-process knowledge network to describe engineering changes is of practical significance. It allows for a more comprehensive consideration of knowledge across product parts, improving the accuracy of indicator selection.
2. The engineering change propagation path developed in this study integrates node influence, change cost, and carbon emissions. Unlike traditional approaches that mainly focus on technical and cost factors, this study also incorporates environmental concerns, which are highly valued by both enterprises and society. This enhances the practical value of the research.
3. The NSGA-III model is better suited for multi-objective optimization problems, especially when dealing with three or more objectives. It addresses the issues of poor convergence and limited diversity seen in other algorithms.

Table 5: The attribute values of nodes in a multi-process knowledge network

Node	Parts	S_i	t_i	C_i (yuan)	Carbon emission ($kgCO_2$)
1	Side plate	0.59	0.38	78	42
2	Backplane	0.67	0.32	55	38
3	Upper, middle, and lower beams	0.69	0.51	65	40
4	Container	0.71	0.45	36	32
5	Base plate assembly	0.73	0.39	47	35
6	Insulation layer	0.75	0.56	71	40
7	Drainage	0.73	0.44	21	30
8	Door shell	0.62	0.51	45	38
9	Door end cover	0.55	0.42	23	22
10	Column	0.72	0.56	35	28
11	Partition	0.68	0.41	43	31
12	Insulation layer	0.72	0.52	55	38
13	Door seal	0.69	0.42	31	20
14	Door stop	0.55	0.21	20	16
15	Self-locking mechanism	0.52	0.28	36	15
16	Hollow glass	0.54	0.19	12	13
17	Compressor	0.85	2.18	400	50
18	Condenser	0.78	1.12	160	33.5
19	Anti-dew tube	0.76	0.41	21	20
20	Capillary	0.79	0.62	23	25
21	Evaporator	0.74	0.36	25	36
22	Filter drier	0.72	0.38	20	38
23	Refrigeration system	0.75	0.81	45	55
24	Connecting pipe	0.78	0.59	55	40
25	Thermostat	0.76	0.45	60	56
26	Solenoid valve	0.83	1.08	40	53
27	Floodlight	0.60	0.17	23	18
28	Lamp holder	0.59	0.19	28	22
29	Compensation heater	0.68	0.45	15	25
30	Switch	0.62	0.11	10	18
31	Wire harness	0.65	0.35	35	29
32	Computer controller	0.78	1.28	112	55
33	Defrost heater	0.69	0.56	35	46
34	Defrosting thermostat	0.79	0.50	32	45
35	Temperature fuse	0.77	0.38	13	22
36	Shelf	0.65	0.22	12	35
37	Door tray	0.68	0.21	20	37
38	Temperature-control box	0.76	0.39	19	45
39	Fruit and vegetable box	0.61	0.20	13	39
40	Drawer	0.65	0.22	45	46
41	Deodorizer	0.67	0.25	35	50
42	Freshener	0.65	0.19	29	52
43	Ice-making box	0.69	0.32	32	48

This study offers significant managerial insights that complement its theoretical contributions. Engineering changes frequently occur at various stages of the product lifecycle, such as design, production, and related processes. As a result, managers and designers should develop broad management capabilities rather than limiting themselves to narrow technical expertise. In particular, strong emergency management skills are essential for ensuring project control, improving success rates, reducing unnecessary costs and material waste, and ultimately enhancing organizational competitiveness. Effective interdepartmental communication also plays a crucial role. Establishing timely channels of information exchange enables firms to minimize disruptions caused by engineering changes and respond more effectively to unexpected challenges.

In addition to assessing direct costs and operational impacts, enterprises should consider environmental factors when managing change. By integrating sustainability into decision-making, organizations not only enhance their corporate responsibility but also build greater public trust and long-term legitimacy. Furthermore, personnel engaged in design, process planning, and manufacturing should be trained to identify and prioritize critical components in complex products. Paying focused attention to these key parts helps reduce the likelihood of large-scale propagation effects, which can magnify risks and complicate engineering change management.

Future research could further expand the applicability of the proposed model in several directions. First, real-world production environments often involve the need to modify multiple nodes at the same time. Extending the model to address concurrent engineering changes would therefore be highly valuable. Second, future studies might analyze how simultaneous changes interact and the extent to which their combined influence shapes system-wide performance. Such investigations could provide a more comprehensive understanding of dynamic production settings. Finally, there is considerable potential for developing decision-support systems that assist managers and engineers in evaluating multiple changes under cost, time, and resource constraints. Leveraging advanced simulation methods, such systems could generate practical recommendations for complex scenarios involving numerous change points, thereby improving organizational adaptability and the effectiveness of decision-making in engineering change management.

Table 6: The attribute values of edges in multi-process knowledge network

Serial number	Edge	Edge betweenness	Connection probability	Serial number	Edge	Edge betweenness	Connection probability
1	(1,2)	3.26	0.55	73	(17,25)	10.99	0.47
2	(1,3)	13.48	0.34	74	(17,26)	21.61	0.53
3	(1,4)	10.18	0.21	75	(17,32)	20.58	0.58
4	(1,43)	22.76	0.13	76	(18,19)	5.73	0.61
5	(2,3)	9.35	0.16	77	(18,20)	16.18	0.55
6	(2,4)	4.91	0.18	78	(18,21)	4.24	0.59
7	(2,5)	6.39	0.32	79	(18,22)	3.97	0.38
8	(2,6)	18.50	0.11	80	(18,23)	4.91	0.58
9	(2,43)	19.28	0.14	81	(18,24)	4.35	0.43
10	(3,6)	14.40	0.35	82	(18,25)	16.29	0.55
11	(3,8)	20.33	0.32	83	(18,26)	21.33	0.32
12	(3,9)	12.61	0.24	84	(19,20)	7.03	0.56
13	(4,5)	2.40	0.48	85	(19,23)	9.59	0.62
14	(4,6)	15.13	0.52	86	(19,24)	5.47	0.54
15	(4,7)	19.70	0.23	87	(20,21)	17.69	0.57
16	(4,8)	30.26	0.39	88	(20,22)	9.30	0.32
17	(4,43)	16.80	0.12	89	(20,23)	26.37	0.63
18	(5,6)	12.15	0.14	90	(20,24)	17.19	0.44
19	(5,7)	19.85	0.35	91	(20,36)	90.65	0.15
20	(5,8)	20.44	0.38	92	(21,22)	3.88	0.43
21	(6,13)	10.94	0.56	93	(21,23)	7.28	0.25
22	(6,15)	34.10	0.45	94	(21,24)	4.16	0.38
23	(6,16)	33.12	0.32	95	(21,29)	18.43	0.35
24	(7,17)	22.60	0.57	96	(21,38)	7.13	0.41
25	(7,18)	17.36	0.49	97	(22,23)	6.08	0.53
26	(7,21)	15.73	0.58	98	(22,24)	3.91	0.32
27	(8,9)	6.13	0.52	99	(22,25)	20.39	0.28
28	(8,10)	7.36	0.21	100	(23,24)	2.78	0.54
29	(8,11)	11.27	0.38	101	(23,25)	17.52	0.62
30	(8,12)	27.03	0.35	102	(23,32)	24.01	0.47
31	(8,13)	6.24	0.41	103	(23,35)	26.47	0.43
32	(8,14)	47.88	0.49	104	(23,38)	14.58	0.26
33	(8,37)	14.19	0.53	105	(23,43)	42.36	0.45
34	(9,10)	5.32	0.12	106	(24,25)	22.63	0.41
35	(9,11)	12.53	0.32	107	(24,38)	9.55	0.45
36	(9,12)	18.48	0.35	108	(24,43)	29.02	0.23
37	(9,13)	2.95	0.42	109	(25,26)	11.15	0.42
38	(9,37)	3.03	0.48	110	(25,29)	31.59	0.45
39	(10,11)	5.76	0.23	111	(25,32)	10.04	0.52
40	(10,12)	11.52	0.18	112	(25,34)	6.71	0.47
41	(10,14)	11.95	0.11	113	(25,35)	11.92	0.53
42	(10,16)	11.49	0.24	114	(25,28)	6.69	0.12
43	(11,12)	8.74	0.47	115	(26,27)	23.14	0.18
44	(11,13)	9.69	0.12	116	(26,28)	10.35	0.15
45	(11,14)	16.38	0.10	117	(26,31)	6.90	0.38
46	(11,16)	8.42	0.12	118	(26,32)	4.79	0.55
47	(11,17)	43.78	0.34	119	(26,35)	5.65	0.42
48	(12,13)	10.59	0.39	120	(27,28)	5.34	0.60
49	(12,25)	39.85	0.59	121	(27,31)	6.84	0.41
50	(12,29)	24.29	0.55	122	(27,30)	10.78	0.21
51	(12,33)	18.05	0.43	123	(29,32)	12.84	0.56
52	(12,34)	16.94	0.40	124	(29,38)	13.39	0.59
53	(12,37)	19.99	0.11	125	(30,31)	3.35	0.34
54	(13,16)	13.87	0.13	126	(30,32)	14.87	0.29
55	(13,37)	4.78	0.34	127	(30,33)	7.90	0.32
56	(14,15)	33.03	0.31	128	(30,34)	8.60	0.36
57	(14,16)	35.29	0.22	129	(30,35)	9.43	0.31
58	(14,36)	109.60	0.24	130	(31,32)	7.83	0.42
59	(15,16)	7.23	0.18	131	(31,33)	6.27	0.38
60	(15,26)	22.56	0.13	132	(31,34)	6.40	0.35
61	(15,31)	21.80	0.11	133	(31,35)	5.54	0.27
62	(15,32)	19.20	0.25	134	(32,33)	10.64	0.42
63	(16,25)	30.21	0.12	135	(32,34)	6.02	0.39
64	(16,33)	17.24	0.11	136	(32,35)	2.51	0.35
65	(16,34)	16.51	0.16	137	(33,34)	1.66	0.48
66	(16,35)	20.25	0.12	138	(33,35)	5.68	0.42
67	(17,18)	4.52	0.68	139	(34,35)	3.33	0.52
68	(17,19)	14.18	0.62	140	(36,39)	42.00	0.23
69	(17,20)	25.25	0.59	141	(36,40)	42.00	0.35
70	(17,21)	9.43	0.60	142	(36,41)	42.00	0.14
71	(17,23)	7.55	0.64	143	(36,42)	42.00	0.21
72	(17,24)	8.89	0.58				

Table 7: Pareto optimal scheme and target value by NSGA-III and NSGA-II

	Serial number	Edge serial number	Change node	f_1	f_2	f_3
NSGA-III	1	51,131,130,63,41,27,15,16	12,34,31,33,16,10,8,4,43	106.02	589	210
	2	48,72,71,105,98	12,25,17,24,25,22	176.42	162	182
	3	42,44,57,142	12,11,14,36,42	112.21	322	321
	4	48,113,115,73,67	12,25,28,26,17,19	89.56	718	206
NSGA-II	1	50,123,134,138,53,48,54,63	12,29,13,37,32,33,35,37	130.16	631	235
	2	52,132,135,53,48,54	12,13,16,31,32,34,37	198.15	221	232
	3	40,48,54,64	10,12,13,16,33	112.25	278	281

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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