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Research Article

Multiobjective Optimization of Propagation Path in Automotive Product Design Change Based on MOPSO

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In optimizing the propagation paths of automotive product design changes, we applied the complex network theory to automotive product structure modeling and established a directed weighted auto part network model. In this model, we defined the parts as the nodes, the physical connections between the parts as the edges, and the impacts of change propagation as the weights of the edges. According to the characteristics of change propagation, we constructed a multiobjective optimization model that simultaneously considered the development time, development cost, and change risk. Using a multiobjective particle swarm optimization (MOPSO) algorithm, we solved the model and obtained the Pareto set of optimal solutions, which provided a basis for designers to choose the optimal design change plan. We conducted the multiobjective optimization of the air-conditioning system design change propagation path in a car model to verify the feasibility and effectiveness of the method.

1. Introduction

Product design is a dynamic change process. From capturing user needs and corporate preferences to obtaining product concepts, product development progress and expected costs are affected by design changes [1]. The phenomenon of design changes is particularly significant in the design process of automotive products. The parts of automotive products have the characteristics of high complexity, long research and development cycles, and high levels of design coupling and customization [2]. The design change in a single part directly affects the change in adjacent parts. The propagation of design changes affects the comprehensive development results of the product and poses risks that are difficult to estimate [3]. Research on the propagation path of design changes for automotive products can effectively reduce the change risks, development time, and costs [4]. Different change propagation paths yield different change fulfillment costs with development expenditures, lead times, quality losses, and so on.

For one thing, Gan et al. constructed an expanded Petri net model to describe the propagation relationship of product attribute design change [5]. Wang et al. presented an optimization method of mechanical product change propagation path based on a dimension parameter-associated network model [6]. Yin et al. proposed an optimal change propagation path based on complex theories, and by using this approach, the cost of development expenditures, lead times, and quality losses change can be minimized [7].

For another thing, Tohidi and AlGeddawy presented two mathematical models to optimize the use of a passive modular assembly fixture plan in an automated assembly system by considering different production scenarios and constraints [8]. Wei et al. developed a multiobjective reallocation model with a feasible assumption that the task executing time is controllable, where a compressing executing time strategy is proposed in the product design process [9]. Li et al. proposed a data-driven mechanism to construct the design change model with an improved dendritic neural networks [10]. Li et al. developed a general model to depict the dynamic design change propagation based on complex networks [11]. Delaney et al. reviewed the fundamental factors in which product design has the ability to influence and improve the overall environmental sustainability of a product [12]. The part design changes can propagate along various paths. By changing different parts to meet the initial change requirements, designers can select the corresponding propagation path and make decisions [12, 13]. Therefore, for the non-uniqueness characteristic of a change propagation path, it is of practical significance to study the propagation paths of complex product design changes while considering the product development time, cost, and risk factors.

In this research, based on complex networks [13, 14], we performed multiobjective optimization on design change propagation paths. We first built the physical connection relationship network of complex product parts. Next, we introduced the optimization objectives of development time, development cost, and change risk, and we established a multiobjective optimization model based on the characteristics of design change propagation. Then, we solved the model and obtained the Pareto solution set through iteration using a multiobjective particle swarm optimization (MOPSO) algorithm [14]. We achieved the effective control of the propagation of automotive product design changes, which could quickly provide designers with design change plans to improve design agility.

2. Model Construction

2.1. Construction of Part Network. The complex networks can well describe the complex interrelation models [15, 16] in the fields of natural science, social science, management science, engineering technology, etc. In recent years, four types of complex network models (undirected and unweighted network, undirected and weighted network, directed and unweighted network, and directed and weighted network) have been proposed [16]. A complex network can be expressed as $G = (V, E)$, where $\mathbf{V} = (v_1, v_2, \ldots, v_n)$ represents the set of the nodes and $\mathbf{E} = \{e_{ij}\}$ $(1 \leqq i \leq n, 1 \leqq j \leq n)$ represents the set of edges. A complex product consists of a large number of parts. In the network, each part is abstracted as a node and the structural connection relationship between two parts is abstracted as an edge. According to research subjects in this area, some researchers have used part design parameters [17], design tasks [18], and parts [19] as the nodes in a network. Because we studied the optimization of the development process of change propagation with parts as the development units, we used a directed, weighted network model to model the product on the part level. During the propagation of design changes, changes in the upstream parts had an impact on the downstream parts. Mapped to the network, a design change propagated along the direction of an edge and the part connection network could be represented by the adjacency matrix A (composed of elements a_{ij}).

$$A = \begin{cases} a_{ij}, & \text{if node } i \text{ and node } j \text{ are connected}, \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

where element $a_{ij} \geq 0$ is the weight of an edge in the directed weighted network, represented by the thickness of the edge in Figure 1, which shows the conversion of the adjacency matrix to the directed weighted network.

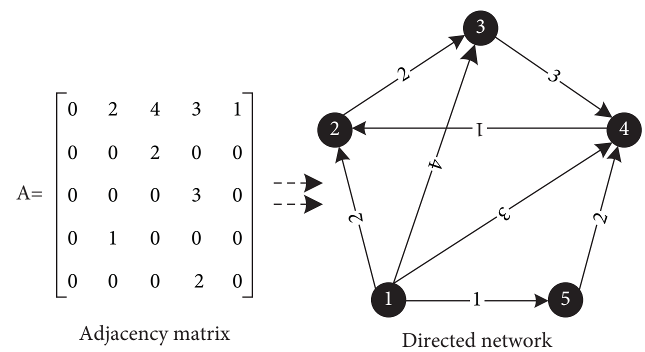

Figure 1: Schematic of the weighted and directed complex networks.

2.2. Design Change Propagation. Because the part network model established in this study was of low granularity and the research object was automobile products, the model assumption included design iterations; that is, each part might undergo multiple changes during the propagation process. There were two modes of part design change propagation: serial propagation and parallel propagation. In the serial propagation mode, the change in one part could only propagate to one connected part at a time. In the parallel propagation mode, the change in one part could simultaneously propagate to two or more connected parts. The parallel propagation path was composed of multiple serial propagation paths. We only studied serial propagation, that is, only one part could be selected at a time along the search paths.

In order to establish the propagation process model, we introduced the propagation likelihood and the propagation impact. The propagation likelihood l_{ij} was the likelihood that the upstream part i affected the downstream part j in the likelihood interval (l_{ijl}, l_{iju}). l_{ijl} was the minimum propagation likelihood. l_{iju} was the maximum propagation likelihood. The propagation impact i_{ij} was the redesign ratio of the upstream part i in relation to the downstream part j with the propagation likelihood l_{ij}. Both the propagation likelihood and the propagation impact were in the range of 0 to 1. The propagation likelihood and the propagation impact matrices were determined by experienced design and manufacturing engineers using design change databases. Additionally, the weights of the opinions of design and manufacturing engineers in their respective professional fields were considered in order to obtain more reasonable propagation likelihood and propagation impact matrices. i_{ij0} represented the maximum redesign ratio caused by the propagation of the upstream part i to the downstream part j with the maximum propagation likelihood, and i_{0i} represented the initial change impact of the initial change node i. The propagation impact of the kth iteration was calculated according to the following:

$$i_{ij}(k) = \frac{l_{ij}(k) - l_{ijl}}{l_{iju} - l_{ijl}} \times i_{ij0}^{k}. \tag{2}$$

In the process of change propagation, the smaller the propagation likelihood was, the less the downstream parts were affected. We had the following hypotheses. In the kth design iteration process, the propagation likelihood and the propagation impact were linearly related. In the equation, i_{ij0}^{k} represents the designer's familiarity with or learning outcome for the part design. Because i_{ij0} was less than one, i_{ij0}^{k} represented the decrease in the propagation impact in subsequent design iterations. This was because as designers became more familiar with the design unit, the impact of the design change on the design unit diminished. $l_{ij}(k)$ represents the propagation likelihood of the kth iteration of the upstream part i to the downstream part j. In the process of change propagation, when a part was less affected by the propagation of the upstream parts, it was less likely for the part to affect its downstream parts. Therefore, assuming that the propagation likelihood during the kth design iteration was proportional to the propagation impact, the propagation likelihood of the kth iteration was as follows:

$$l_{ij}(k) = l_{iju} \times i_{i-1,i}(k), \tag{3}$$

where $i_{i-1,i}(k)$ represents the impact of the kth propagation to part i in the design of an upstream part of part i. In this study, it was assumed that when the impact of the initial change propagated down to less than 0.001, the propagation of the change stopped.

2.3. Multiobjective Optimization. Due to fierce market competition, companies need to develop high-quality and low-cost products, and at the same time, companies need to shorten the product development cycle and improve design agility. Design change propagations extend product lead time and increase development costs. Change processing consumes a large amount of manpower and material resources. Determining how to balance the development time and development cost and how to reduce the change risk are the key issues that many companies face in change control. The propagation of design changes has a profound impact on the design phase and manufacturing phase of a product. Therefore, we considered the development time, development cost, and change risk as the optimization objectives. Reference [13] proposed a method of analyzing the impact of changes based on the impact of likelihood. The change risks defined in this study were direct change risks, excluding indirect change risks. The change risk r_{ij} was the product of the change propagation likelihood and the change propagation impact, as shown in equation (4). The propagation process is shown in Figure 2.

$$r_{ij} = l_{ij} \times i_{ij}. \tag{4}$$

It was assumed that each part had a fixed development time and development cost. For different propagation impacts, the redevelopment cost and time were different for each part: the greater the propagation impact was, the greater the resultant development cost and the development time were. Therefore, the development time, development cost, change risk of each change propagation path, and the objective function of the model could be defined as follows:

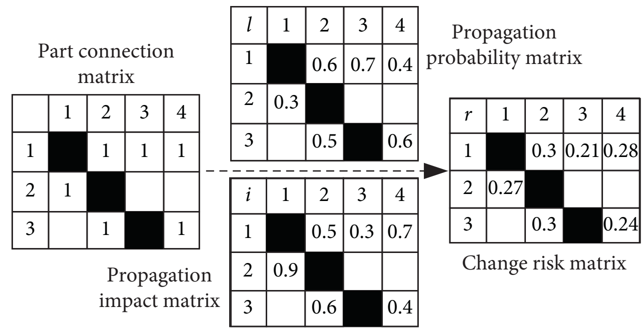

Figure 2: Flow of propagation risk.

$$\min F(x) = \left\{ T = \sum_{i=1}^{n} i_{i-1,i} \times T_i, C = \sum_{i=1}^{n} i_{i-1,i} \times C_i, R = \sum_{i=1}^{n} i_{i-1,i} \times R_i \right\}, \tag{5}$$

$$\text{s.t.}\ C \leq Cm, \quad T \leq Tm, \tag{6}$$

where T represents the total development time of all parts on the change propagation paths, C represents the total development cost, and R represents the total change risk. T_i and C_i are the development time and the development cost of part i, respectively. $l_{i-1,i}$ represents the propagation likelihood of the design change in an upstream part of part i propagating to part i. $i_{i-1,i}$ represents the impact of the design changes in an upstream part of part i propagating to part i. n is the sum of the number of changes in all parts on the change propagation paths. Because the design changes in actual engineering consume a large amount of manpower and material resources, the optimization model of complex product design change propagation also needs to meet the constraint defined in equation (6), where C_m and T_m represent the maximum development cost and the longest product lead time, respectively, that the product design change can accept.

2.4. Model-Solving Process Based on MOPSO. It is difficult for traditional mathematical programming methods to solve the above multiobjective combination problem within a reasonable time. The MOPSO proposed in [17, 20] is effective at solving such problems. The algorithm includes two fixed-size solution sets. One set was used to achieve the global nondominated solutions, and the other set was used to achieve the historical record of each particle reaching the best solution, which also represented the elitism of the evolutionary algorithms. In the iterative process, the density-based fitness calculation method was used to update the velocities and positions of the particles and to select the global optimal solution. Only when the former dominated the latter was the local solution set replaced. Accordingly, we used the algorithm to solve the multiobjective model of the design change propagation path. The algorithm flowchart is shown in Figure 3.

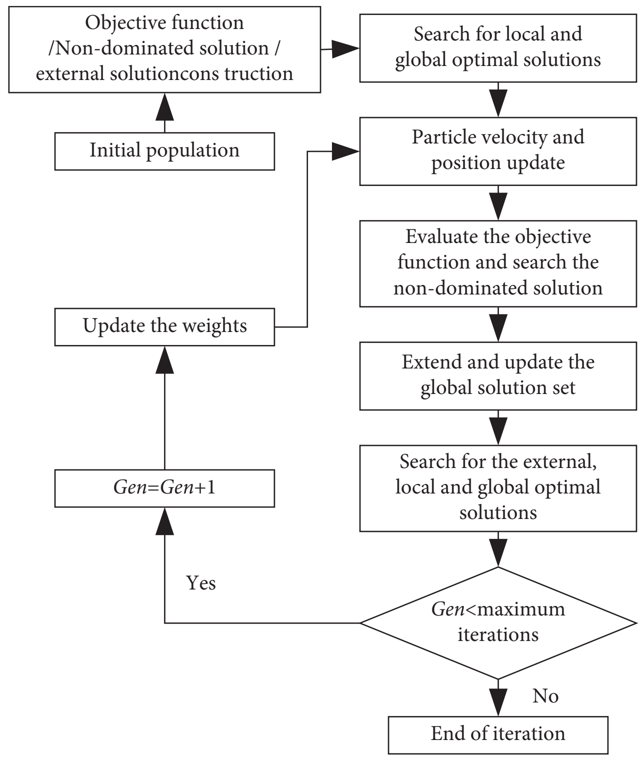

Figure 3: The calculation flowchart of MOPSO.

The detailed steps are as follows:

Step 1. (Initialization): First, N particles, $\{X_i(0), i = 1, \ldots, n\}$, were randomly generated in the feasible solution space with an initial velocity of $\{V_i(0), i = 1, \ldots, n\}$. The particles of the initial population were evaluated according to the objective function. The local best positions were set to the particles themselves, $\{X_i^*(0) = X_i(0), i = 1, \ldots, n\}$. Then, the local nondominated solution set $S^*(0)$ was constructed, from which the nondominated solutions were sought. Next, the global nondominated solution set $S^{**}(0)$ was constructed, and the particles with the closest distances to the local optimal solution were selected as the global optimal solution. Finally, the number of iterations was set to $t = 0$, and the maximum number of iterations was set to T.

Step 2. (Velocity and position updates): The velocity $v_{ij}(t)$ and the position $x_{ij}(t)$ of the i-th particle in the t-th iteration in the j-dimensional space were updated according to the following equation.

$$\left\{\frac{v_{ij}(t+1) = w(t)v_{ij}(t) + c_1 r_{1j}(t)\left(x_{ij}^*(t-1) - x_{ij}(t)\right) + c_2 r_{2j}(t)\left(x_{ij}^{**}(t-1) - x_{ij}(t)\right)}{x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1)}\right., \tag{7}$$

where $w(t)$ is the weight coefficient, c_1 and c_2 represent the individual learning coefficient and the global learning coefficient, respectively, and r_{1j} and r_{2j} are the random numbers in [0, 1].

Step 3. (Nondominated solution set updates): The updated position of the ith particle was added to the nondominated local solution set $S_i^*(t)$. The dominated solution set in $S_i^*(t)$ was truncated. Then, all the nondominated local solution sets were merged and the nondominated solution sets except for those in the local solution sets were added to the global nondominated solution set $S_i^{*\,*}(t)$. If the size of $S_i^{*\,*}(t)$ exceeded the predetermined range, the excess part of the solution set would be eliminated. $S_i^{*\,*}(t)$ was copied to the external Pareto solution set, and all the dominated solutions are searched and removed. Similarly, if the number of nondominated individuals achieved in the external Pareto solution set exceeded a predetermined range, the set was truncated by a clustering algorithm.

Step 4. (Local optimal solution and global optimal solution updates): If $X_i^*(t)$ and $X_i^{*\,*}(t)$ were the minimum distances in $S_i^*(t)$ and $S_i^{**}(t)$, respectively, they were selected as the local optimal solution and the global optimal solution of the ith particle.

Step 5. (End of iteration): If the current number of iterations exceeded the maximum number of iterations, the iteration was stopped. Otherwise, Step 2 was returned and the next iteration was performed.

3. Case Analysis

3.1. Model Construction and Solution. In order to verify the effectiveness of the proposed model and algorithm, an air-conditioning system of a car model was used in the case analysis. The air-conditioning system contained 32 parts. In order to reduce the design cost, save the design time, and shorten the delivery time, the optimization of the propagation path of air-conditioning in automotive product design change needs to be performed. Through the structural model of the air-conditioning system and the historical data, and by talking with a number of research and development and manufacturing engineers of an air-conditioning manufacturing company, we obtained the adjacency matrix, development time, and cost of each part. The development cost included the cost required for the design process and the manufacturing process, and it mainly included the costs of materials, energy, equipment, manpower, and other related factors. The development time included the time required for redesign and manufacturing. The development time was similar to the evaluation process of the development cost. The part list, development time, and cost of the air conditioner are shown in Table 1.

According to the research and development and manufacturing engineers, and the design change database, we obtained the change propagation likelihood interval of each connected edge, and through the maximum likelihood of the change propagation impact through each edge, we obtained the change risk matrix, as shown in Table 2. An edge weight represented the impact of the change propagation with the greatest likelihood of passing through each edge. The value of an edge weight corresponded to the value of the cross data. The larger the value of an edge weight was, the larger the value of the corresponding cross data in the table was.

A compressor is the power source of an air conditioner and its design changes for the diversification of customer needs often. The compressor with node number 18 was used as the initial change node in this case for verification. The initial change impact was set to 0.6. The maximum acceptable cost of the solution was 1600 (yuan). The longest product lead time was 10 (days). The NSGA-II algorithm was used to solve the model. The algorithm parameters were set as follows. The population size was 100. The solution set size was 100. The maximum iteration was 100. The individual learning coefficient and the global learning coefficient were set to 1. The weight for the maximum transfer velocity was 0.8. MATLAB was used to solve the model. The Pareto optimal solution set is shown in Figure 4, where each point represents a design change propagation path.

Table 1: The development times and costs of the parts of an automobile air conditioner.

No.	Part	Cost (yuan)	Time (day)
1	Controller	1000	4
2	Evaporator core	100	0.5
3	Warm-air core	100	0.5
4	Air conditioner box assembly	400	1
5	Air conditioner duct	500	2
6	Piping	200	2
7	Connection wires	500	3
8	Switch button	500	3
9	Fan blades	300	1
10	Water tank	700	6
11	Condenser	600	4
12	Expansion valve	1000	6
13	Low-pressure service valve	200	1
14	High-pressure service valve	100	1
15	High-voltage switch	160	1
16	Damper	1200	8
17	Liquid storage and dryer tank	400	1
18	Compressor	600	2
19	Radiator fan motor	600	2
20	Condenser fan motor	500	4
21	Air volume adjustment starter	700	4.5
22	Heater controller	300	2
23	Filter	400	5
24	Internal and external gas conversion starter	400	6
25	Compressor belt	1000	7
26	Condenser deck	800	3
27	Compressor deck	600	4
28	Evaporator deck	800	5
29	Water tank deck	400	4
30	Mounting parts	600	4
31	Compressed intake pipe 1	200	3
32	Compressed outlet pipe 2	600	5

Table 2: The change risk matrix of an air conditioner.

No.	1	2	3	4	5	...	29	30	31	32
1	0	0.3	0	0	0	...	0.6	0	0	0.4
2	0	0	0.7	0	0	...	0	0	0	0
3	0	0	0	0.6	0	...	0	0.5	0	0.8
4	0	0	0	0	0.2	...	0.3	0	0.9	0
5	0.4	0	0	0	0	...	0	0	0	0
...	0	0	0.4	0	0.5	...	0.7	0	0.6	0
29	0	0	0	0	0	...	0	0	0	0.5
30	0.2	0	0	0.3	0.9	...	0	0	0	0
31	0	0.4	0	0	0	...	0	0	0	0.7
32	0.8	0	0	0.4	0	...	0	0.9	0	0

The obtained Pareto solution set contained 15 optimal solutions. The change paths and the values for three optimized objectives are shown in Table 3. The following three change propagation schemes might be recommended according to different design preferences (as shown in Table 4). The three schemes had their own advantages and disadvantages. For example, the development time of scheme A_1 was 5.09 (days), shorter than the development time of scheme A_6, 5.5 (days). The change risk of A_1 was 0.65, smaller than the change risk of

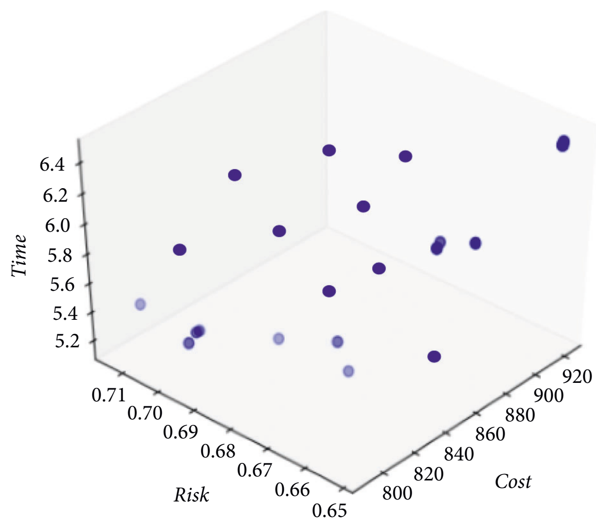

Figure 4: The optimal Pareto solution.

Table 3: The optimal schemes and objective values.

No.	Change path	Cost (yuan)	Risk	Time (days)
A_1	18–20–5–6	839.5	0.65	5.09
A_2	18–19–17–16–17	840.8	0.69	5.4
A_3	18–19–32–15–18–19	890.2	0.66	5.7
A_4	18–31–32–15–18–19–17	900.7	0.67	6.3
A_5	18–19–32–15–18–31	880.1	0.66	5.7
A_6	18–16–17–16–17	810.4	0.68	5.5
A_7	18–31–32–15–18–19–15	920.5	0.66	6.3
A_8	18–19–32–15–18–19	860.3	0.73	5.5
A_9	18–19–31–32–16–17	850.7	0.66	5.4
A_{10}	18–31–32–16–17	870.1	0.69	6.4
A_{11}	18–17–16–17	800.6	0.71	5.4
A_{12}	18–31–32–15–18	910.6	0.64	6.3
A_{13}	18–31–32–15–18–19	909.5	0.65	6.6
A_{14}	18–31–32–15–18–19–5	930.2	0.65	6.5
A_{15}	18–19–32–15–18–19	880.3	0.69	5.4

Table 4: The three recommended change propagation schemes.

No.	Change path	Cost (yuan)	Risk	Time (days)
A_1	18–20–5–6	839.5	0.65	5.09
A_6	18–16–17–16–17	810.4	0.68	5.5
A_{12}	18–31–32–15–18	910.6	0.64	6.3

A_6, 0.8. However, the development cost of A_1, 839.5 (yuan), was higher than the development cost of A_6, 810.4 (yuan). Because the model in this study optimized three objectives at the same time, including the development time, development cost, and change risk, similar situations occurred in comparison with the other schemes. The conflict between these three objectives prevented simultaneous optimization. Therefore, the obtained optimal design change propagation schemes were a set of schemes instead of a single scheme.

3.2. Method Comparison. To show the feasibility and superior performance of the proposed method, we compared our method with the improved BFS (breadth-first search, BFS) algorithm proposed by Li et al. [19]. First, the BFS algorithm was applied to the case in the study. Because the algorithm could only solve single-objective problems, we set the development time to be the optimization objective and we obtained the optimal change scheme, which was the same as A_1 in Table 3: the propagation path of the change was 18–19–5–6, the development time was 5.2 (days), the development cost was 850.5 (yuan), and the change risk was 0.68. The optimization model proposed in this study used the MOPSO algorithm to optimize multiple objectives at the same time and to obtain multiple optimal change propagation schemes for designers to choose from according to different design requirements and preferences. At the same time, the space complexity defined by the improved BFS algorithm was $O(B^D)$, where B is the maximum branching factor and D is the maximum path length. Due to the requirement for large space, the BFS algorithm was not suitable for solving the problem of optimizing the propagation paths of complex product design changes with large network scales. In a traditional traversal method used to solve the problem, as the number of initial change nodes continues to increase, the number of feasible solutions for change propagation increases exponentially. When there are too many feasible solutions, the time required to solve the problem is too high. The time complexity defined by MOPSO is $O(M^* N^\wedge 2)$, where M is the number of objective functions and N is the number of individuals in the population. Therefore, the MOPSO algorithm is more efficient than the existing methods, it is especially suitable for solving the design change problem of complex products, and it allows the designers to choose their own preference scheme in the Pareto solution set to improve the design agility.

4. Concluding Remarks

To tackle the problem of multiple preference objectives not being considered in the research of the propagation path optimization of automotive product design changes, we proposed a multiobjective optimization model that simultaneously considered development time, development cost, and change risk. According to the physical connection structure between car parts, we established a directed, weighted network. We introduced the optimization objectives of development time, development cost, and change risk, and we established a multiobjective optimization model for the design change propagation path. We used a MOPSO algorithm to solve the model, and we obtained a set of Pareto solution schemes for design changes. We used the application and the method comparison of an air-conditioning system model to verify the feasibility of our method. Our method considered multiple optimization objectives in actual engineering. We learned from interviews with automotive air-conditioning research and development engineers that many optimization solutions could be obtained through this method, and this method could also provide companies with different preferences. However, problems such as uncertainty, dynamics, and excessive constraints exist in actual engineering practice, and thus, some solutions did not conform to actual engineering constraints. In future research, other constraints should be included to remove invalid solutions and to better obtain different preferred solutions to improve design agility. For example, the relationship between the parts can be defined only by the number of relation types between the parts. More uncertainties of these relationships including fuzzy uncertainties will be investigated in our future work.

Data Availability

The authors confirm that the data supporting the findings of this study are available within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] H.-Z. Zhang, G.-F. Ding, R. Li, S.-F. Qin, and K.-Y. Yan, "Design change model for effective scheduling change propagation paths," *Chinese Journal of Mechanical Engineering*, vol. 30, no. 5, pp. 1081–1090, 2017.

[2] K. L. Hansen and H. Rush, "Hotspots in complex product systems: emerging issues in innovation management," *Technovation*, vol. 18, no. 8-9, pp. 555–561, 1998.

[3] I. Ullah, D. Tang, and Q. Wang, "Least risky change propagation path analysis in product design process," *Systems Engineering*, vol. 20, no. 4, pp. 379–391, 2017.

[4] D. B. Tang, L. L. Yin, Q. Wang, and U. Inayat, "Workload-based change propagation analysis in engineering design," *Concurrent Engineering*, vol. 24, no. 1, pp. 17–34, 2016.

[5] Y. Gan, Y. He, L. Gao, and H. Weiming, "Propagation path optimization of product attribute design changes based on petri net fusion ant colony algorithm," *Expert Systems with Applications*, vol. 173, Article ID 114664, 2021.

[6] D. Wang, B. Yang, J. Li, and H. Weiming, "Propagation Path Optimization of Dimension Change Based on Associated Network Model," in *Proceedings of the International Conference on Mechanical Design*, pp. 1699–1707, Springer, Singapore, July 2021.

[7] Y. Yin, S. Wang, and J. Zhou, "Complex network–based change propagation path optimization in mechanical product development," *IEEE Access*, vol. 10, pp. 17389–17399, 2022.

[8] H. Tohidi and T. AlGeddawy, "Change management in modular assembly systems to correspond to product geometry change," *International Journal of Production Research*, vol. 57, no. 19, pp. 6048–6060, 2019.

[9] M. Wei, Y. Yang, J. Su, L. Qiucheng, and L. Zhichao, "Task reallocating for responding to design change in complex product design," *Journal of Intelligent Systems*, vol. 28, no. 1, pp. 57–76, 2019.

[10] Z. Li, X. Sun, X. Chen, Y. Zhang, L. Qingkui, and C. Peng, "Model construction for complex product design change with improved dendritic neural network," in *Proceedings of the 2021 IEEE international conference on recent advances in systems science and engineering (RASSE)*, pp. 1–8, IEEE, Shanghai, China, December 2021.

[11] R. Li, H. Yi, and H. Cao, "Towards understanding dynamic design change propagation in complex product development via complex network approach," *International Journal of Production Research*, vol. 60, no. 9, pp. 2733–2752, 2021.

[12] E. Delaney, W. Liu, Z. Zhu, X. Yuchun, and D. Jian, "The investigation of environmental sustainability within product design: a critical review," *Design Science*, vol. 8, 2022.

[13] P. J. Clarkson, C. Simons, and C. Eckert, "Predicting change propagation in complex design," *Journal of Mechanical Design*, vol. 126, no. 5, pp. 788–797, 2004.

[14] Y. Li, M. Li, and Z. Wang, "Multi-source design change propagation path optimization for complex product based on weighted and directed network model," *Journal of Mechanical Engineering*, vol. 55, no. 06, pp. 213–222, 2019.

[15] Y. Li, X. Chu, D. Chu, and Q. Liu, "An integrated module partition approach for complex products and systems based on weighted complex networks," *International Journal of Production Research*, vol. 52, no. 15, pp. 4608–4622, 2014.

[16] Y. Li, Z. Wang, L. Zhang, and C. Xuening, "Function module partition for complex products and systems based on weighted and directed complex networks," *Journal of Mechanical Design*, vol. 139, no. 2, Article ID 021101, 2017.

[17] C. A. C. Coello, G. T. Pulido, and M. S. Lechuga, "Handling multiple objectives with particle swarm optimization," *IEEE Transactions on Evolutionary Computation*, vol. 8, no. 3, pp. 256–279, 2007.

[18] S. Ma, Z. Jiang, and W. Liu, "Evaluation of a design property network-based change propagation routing approach for mechanical product development," *Advanced Engineering Informatics*, vol. 30, no. 4, pp. 633–642, 2016.

[19] Y. Li, Z. Wei, and Y. Ma, "A shortest path method for sequential change propagations in complex engineering design processes," *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, vol. 30, no. 1, pp. 107–121, 2016.

[20] Y. Hou, G. Hao, Y. Zhang, G. Feng, and X. Wenyang, "A multi-objective discrete particle swarm optimization method for particle routing in distributed particle filters," *Knowledge Based Systems*, vol. 240, Article ID 108068, 2022.