A study on value setting of product functional specifications with consideration of parts and inventory costs for engineer-to-order production

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Abstract: To deal with various customers’ requirements within short delivery time, the engineer-to-order (ETO) companies have to prepare a large variety of parts in advance, which increase the parts inventory costs. To alleviate this problem, value setting of product functional specifications is focused. If the value set for each product functional specifications item can be decreased, then, number of parts types and the parts inventory including safety stock can be reduced. On the contrary, parts costs increase because more parts with higher specifications are required. Since a product has multiple specification items and for each item dozens of values exist, therefore the value setting (selection) problem has a large number of solution combination. In this paper, calculation procedure based on genetic algorithm is proposed. A case study of drilling machines is conducted. Results show that decreasing value sets for product functional specifications can reduce the total costs of parts and inventory.

Keywords: engineer to order; product functional specification; parts inventory; genetic algorithm.


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1 Introduction

This study focuses on engineer-to-order (ETO) manufacturing companies that design entire products to satisfy the requests of their customers. Typical products include machine tools such as machining centres and drilling machines. Since these kinds of products are used for production, their specifications are largely influenced by what their machines produce. For instance, an ETO company’s customers can primarily be manufacturing companies that produce key components of electronic devices. Since both the ETO companies and their customers are manufacturers in such cases, hereafter in this paper, ETO companies are specifically referred to as ‘equipment manufacturers’.

Electronics technologies and developments change continuously and therefore the specifications of electronic devices change rapidly. Thus, it is risky for component manufacturers to determine the introduction of new equipment before a relevant electronic device has been fully developed. However, when a popular new electronic device is going to be introduced to the market, a component manufacturer can obtain a large market share if it can install new equipment more quickly than its competitors. Therefore, ordering equipment in the early stages of product development is increasingly becoming an industry standard.

Since customers (component manufacturers) are not familiar with all of a product’s (machine’s) specifications, functional specifications are commonly proposed by sales
A study on value setting of product functional specifications

staff members based on their experience. This process lacks the rigor of a formal order process and frequent misunderstandings of customer requirements occur. Errors at this stage can lead to a long period of fixing the product specifications (e.g., several months). Moreover, since the production lead time is significantly longer than the customers’ expected delivery leads time, ETO companies have to prepare a large variety of parts/modules in advance, so as to deal with uncertainty in product functional specifications (hereafter, referred to as, ‘product specifications’). Consequently, high parts and inventory costs become big issues for ETO companies.

Two approaches have been considered as means of solving the aforementioned parts supply problem. One is to design standard parts/modules that can match multiple customers’ requirements, while the other is to develop a parts supply method that takes the uncertainty of parts demand into account. With regard to the former option, Hicks et al. (2000) indicate that many ETO companies “are trying to increase design standardization based upon modular design principles”, but explain that “this approach has proved difficult due to diverse customer requirements.” Therefore, in this paper, the latter approach is adopted.

Since the value of a product specification item is determined by customer requirements, the discrete value sets and their demand (average and deviation) for each product specification item can be estimated by a sales department based on inquiry information. A value with high deviation indicates that the customer requirement for the value is uncertain. Thus, integrating the value with a higher value can decrease uncertainty. Moreover, different values of product specifications require different specifications for parts, so that if the value set for each product specification item can be decreased, uncertainty in demand for the number of parts types and quantities including safety stocks will decrease concomitantly. The weakness of this approach is that parts costs increase because more parts with higher functional specifications are required. A customer’s requirements can be satisfied when he or she obtains a product with higher functional specifications without any increase in price. However, the merit of decreasing value sets for product specifications has thus far not been verified. With this in mind, the setting of values for product specifications is discussed in this paper.

The remainder of this paper is organised as follows. First, ETO-related studies are discussed in Section 2. In Section 3, a procedure based on the genetic algorithm (GA) for value setting is discussed, by considering both inventory costs and parts cost. To confirm the practical usefulness of the proposal in decreasing parts and inventory costs, drilling machines are used as a case study in Section 4. Finally, in Section 5, conclusions are drawn and future directions are discussed.

2 ETO related studies

The ETO sector has been the subject of academic attention since the early 1990s. For instance, Bertrand and Muntslag (1993) explored the idea that ETO production has a non-physical stage and a physical stage. The non-physical stage includes the “engineering and design activities (including quotation preparation) and the processing planning activities,” while the physical stage “concerns the parts manufacturing, assembly and installation of the machines”. In the late 1990s, Hicks conducted multiple ETO-related
studies in collaboration with several typical ETO companies in the UK. In 2001, he classified ETO companies into three types. Type 1 is involved in design, parts manufacturing and product assembly stages. Type 2 is not involved in manufacturing functions, as all parts are bought from third-party suppliers. Type 3 is only involved in design stage and all manufacturing and assembly steps are outsourced. In Caron and Fiore’s research (1995) ETO products are explored in terms of high-tech equipment, including both standard and customised components. Meanwhile, a survey by Hicks and Braiden (2000) has considered ETO products as capital equipment, such as turbine generators, cranes and boilers. Porter et al. (1999) indicate ETO products require “the added availability of modifications” and an order driven manufacturing system. Amaro (1999) defines ETO products as those that are “manufactured to meet a specific customer’s needs and so require unique engineering design or significant customization. Thus, each customer order results in a unique set of part numbers, bill of material, and routing”. Both Amaro (1999) and Hendry (2010) indicate that there are four types of customisations: pure customisation requiring an entirely new design, tailored customisation requiring modification of an existing design, standardised customisation that involves picking from a set of design options and non-standard customisation that takes an existing design as it is.

Gosling and Naim (2009) have concluded that ETO-related research is “predominantly conceptual or case based research”. Conceptual research is related to production planning, production control and supply chain management. In their studies related to production planning, Gelders (1991), Little et al. (2000), Stevenson et al. (2005) and Hicks and Braiden (2000) indicate that the standard MRPII or ERP package is not a good fit for ETO production. A new framework of production planning control needs to be developed for the ETO sector. In studies relating to supply chain management, Hicks et al. (2000) indicate that sharing information (e.g., previous designs, standard components) among design and purchase departments is important, because ETO companies have to prepare parts or modules before product specifications are fixed. One of the few studies that propose a detailed method to solve the real-world problems of an ETO company is that of Grabenstetter and Usher (2013), who considered seven factors influencing design lead time. The authors gathered data from five real ETO companies and proposed a multiple regression equation to estimate due dates. Weng et al. (2014) have suggested a method that ETO companies’ sales departments can use to accurately propose products’ functional specifications for their customers, so that quotation lead time can be reduced. To the best of our knowledge, despite considerable headway in research on ETO companies, there still are no standard practical methods for parts supply.

The products that we focused on in this paper are types of equipment as mentioned in Section 1 above. The basic designs for each product’s functions have been completed. The products have deep and complex structures, requiring modification engineering process to be conducted so that they precisely satisfy all customers’ requirements. Based on Amaro’s approach to classification (Amaro, 1999), the ETO products that we consider are tailored products. The ETO companies that we study are type-1 companies (Hicks et al., 2001), meaning that their design processes and also parts manufacturing and assembly processes are done within-company. In this paper, a methodology related to parts supply is discussed, taking parts and inventory costs into consideration.
3  An algorithm based on GA for product specification value setting: considering parts and inventory costs

Customer requirements can be met by obtaining higher functional specifications without price increase. In this study, different product specification values are assumed to require different parts types. Thus, if the value set for each product specification item can be decreased, the number of parts types will be decreased concomitantly for that product specification item. On the other hand, parts costs increase when more parts with higher functional specifications are required. Therefore, there is a trade-off between parts inventory costs and parts costs.

Usually, there are dozens of product specification items for each unit of equipment and the number of values for each product specification item is high. This gives rise to a combination optimisation problem whose solutions involves minimising the total costs of parts and inventory. To obtain a good solution with limited calculation time (several minutes or several tens of minutes), we apply a methodology based on a GA in this paper.

3.1 Problem description

- **invariables**
  - \( i \) product specification item’s number, \( i \in \{1,2,\ldots,N\} \)
  - \( J_i \) total number of values of product specification item \( i \)
  - \( C_{ij} \) parts cost for product specification item \( i \) value \( j \), \( i \in \{1,2,\ldots,N\}, j \in \{1,2,\ldots,J_i\} \)
  - \( \mu_{ij} \) average demand for product specification item \( i \) value \( j \)
  - \( \sigma_{ij} \) dispersion of product specification item \( i \) value \( j \)
  - \( T \) lead time for parts supply, which is assumed to be independent of parts type
  - \( L \) parts order interval
  - \( \alpha \) safety stock coefficient
  - \( R \) interest rate (%).

- **preconditions**
  - the average demand and dispersion of the product specification item \( i \) value \( j \) can be forecasted with the inquiring information and so these averages are given.
  - for each demand of product specification item \( i \) value \( j \), one or multiple parts types are required and for each parts type, only one unit is needed
  - parts are produced internally. However, in this paper, production cost is assumed to be independent of the number of parts types (we leave exploring this in more depth to our future work).

- **decision variable**
  \[
  x_{ij} = \begin{cases} 
  1, & \text{if value } j \text{ of product specification item } i \text{ is selected} \\
  0, & \text{otherwise} 
  \end{cases}
  \]

- **objective function**
Our aim is to minimise the total cost of parts (including average inventory and safety stock) and inventory.

Let \( \mu_i^j \) and \( \sigma_i^j \) be the recalculated average demand and dispersion of product specification item \( i \) value \( j \), respectively, if any of its lower value is deleted. By using the fixed reorder cycle inventory model, the average inventory can be calculated as

\[
\frac{\mu_i^j T \times x_{ij}}{2},
\]

and the safety stock can be calculated as \( \alpha \sqrt{(L + T)} \sigma_i^j \). Therefore, the total cost of parts, including average inventory and safety stock, can be calculated with equation (1).

\[
\text{Total parts cost} = \sum_{i=1}^{N} \sum_{j=1}^{J_i} \left( \mu_i^j \times x_{ij} + \left( \frac{\mu_i^j T \times x_{ij}}{2} + \alpha \sqrt{(T + L)} \sigma_i^j \right) \right)
\]

(1)

On the other hand, since a large inventory means that a large amount of cash cannot be rotated, we evaluate inventory costs based on the interest required for the equivalent value of the total inventory, by employing equation (2).

\[
\text{Inventory cost} = \sum_{i=1}^{N} \sum_{j=1}^{J_i} \left( \frac{C_{ij} \times \mu_i^j \times x_{ij}}{2} + \left( \alpha \sqrt{(T + L)} \sigma_i^j \right) \times r \right)
\]

(2)

Thus, the objective function can be described as in equation (3).

\[
\min Z = \sum_{i=1}^{N} \sum_{j=1}^{J_i} \left( C_{ij} \times \mu_i^j \times x_{ij} + \left( C_{ij} \frac{\mu_i^j T \times x_{ij}}{2} + \left( \alpha \sqrt{(T + L)} \sigma_i^j \right) \times (1 + r) \right) \right)
\]

(3)

For any selected \( j \) \( (x_{ij} = 1) \), \( \mu_i^j \) and \( \sigma_i^j \) can be calculated through the following steps.

STEP 1 let \( a = j - 1 \), \( \mu_i^j = \mu_{ia} \), and \( \sigma_i^j = \sigma_{ia} \).

STEP 2 if \( a \geq 1 \) and \( x_{ia} = 0 \) then let

\[
\mu_i^j = \mu_i^j + \mu_{ia}
\]

(4)

\[
\sigma_i^j = \sqrt{\sigma_i^j^2 + \sigma_{ia}^2}
\]

(5)

STEP 3 let \( a = a - 1 \)

If \( a = 0 \) or \( x_{ia} = 1 \), stop calculation. Otherwise, return to STEP 2.

3.2 Details of the GA procedures

The GA is one method of meta-heuristics which is developed by Holland in the early 1970s (Falkenauer, 1998). The key parts of GA are chromosome representation, selection, crossover and mutation. The detailed implementations of those four parts can be described as follows
3.2.1 Chromosome representation

The most common chromosome representation method is binary encoding (Kumar and Jyotishree, 2012), which uses a binary alphabet \{0, 1\}. Since the decision variable of our target problem is 0 or 1, we can define the decision variable for each product specification item \(i\) value \(j\) as a gene. Therefore, the genome length (number of genes) is \(\sum_{i} J_i\).

**Figure 1** Image of a chromosome

\[
\begin{array}{cccccccccccc}
1 & 2 & 3 & 4 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 1 & 2 & 3 & 4 & 5 \\
1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 1 & 1 \\
\end{array}
\]

Product spec. item 1  Product spec. item 2  Product spec. item 3

For instance, if there are only three product specification items, with values of 4, 7 and 5, then a chromosome can be described as in Figure 1. In this case, the second value of specification item 1, the second, fourth and sixth value of specification item 2 and the first and second values of specification item 3 are not selected (This means that they are integrated into the third value of specification item 1, the third, fifth and seventh values of specification item 2 and the third value of specification item 3, respectively).

3.2.2 Selection

Several approaches can be applied to selection. The easiest of these is to randomly select a pair of chromosomes for crossover. However, this random approach usually requires a large number of search iterations to arrive at a good solution, which means that its improvement efficiency is low.

The elitism approach deterministically leaves the chromosome (or chromosomes) that represents the best solution (or solutions) of the generation to the next new generation. Therefore, the temporary best-in-solution is not be deteriorated. However, as the generation grows, chromosomes leaving from old generations may increase, leading solution diversity to be lost and ensuring that only a local solution is obtained.

The fitness proportionate selection approach (also called roulette wheel selection) evaluates the fitness of each chromosome within a generation. When this approach is used, high-fitness chromosomes will have a high likelihood of being parents for crossover and while at the same time, low-fitness chromosomes also have a chance to be parents. Therefore, this approach is considered to be able to maintain solution diversity and improve the best-in-solution efficiently. Hence, in this paper, the fitness proportionate selection strategy is applied to select a pair of chromosomes for generating offspring.
3.2.3 Crossover

There are two traditional approaches to implement crossover. One focuses on the crossover segments of a chromosome, such as the single-point, two-point and multi-point crossovers. The other focuses on the genes that need to be replaced, such as the uniform crossover. Jong and Spears (1992) have discussed those approaches and indicate that the uniform crossover approach performs better than the former approach, because it can create diversified offspring. However, search efficiency is not discussed in their studies.

In order to efficiently find a good solution, in this paper, a new crossover method based on uniform crossover is proposed. Instead of exchange probability, each substring that represents a set of decision variables of a product specification item is evaluated separately. The substring with lower parts costs than its pair chromosome is focused on and an example of this is shown in Figure 2.

![Figure 2 Example of crossover (see online version for colours)](image)

Suppose two selected chromosomes are A and B. For each product specification item, the parts costs can be calculated. The substring representing the product specification item with lower cost will be copied to its offspring. In the case shown in Figure 2, the genes representing the decision variable of product specification items 1 and 3 of chromosome A and those representing the decision variable of product specification item 2 of chromosome B are copied to their offspring. Through this crossover approach, a pair of parent chromosomes only creates one child chromosome.

3.2.4 Mutation

Mutation is an important operator of GA, which widens search space so that early convergence can be avoided. The simplest approach to this is to randomly change one or multiple genes to their alleles for each child chromosome. In this paper, a heuristic crossover method is employed with the aim of efficiently obtaining a good solution. As such, implementing mutations for every child chromosome may destroy crossover...
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performance and so only a predetermined number of child chromosomes will be randomly mutated. Moreover, since the highest value of each product specification cannot be replaced, the genes that represent the decision variables of each product specification item’s highest value will not be the target genes for mutation. To simply implement mutation, a predetermined number of genes are randomly changed to their alleles. For instance, in Figure 3, the first value of specification item 2 and the second value of specification item 3 are randomly selected as mutation targets and these are replaced by their alleles.

**Figure 3** Example of mutation (see online version for colours)

<table>
<thead>
<tr>
<th>Before mutation</th>
<th>After mutation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 1 0 1 1 0 1 0 1 1</td>
<td>1 1 0 1 0 1 1 1 1</td>
</tr>
</tbody>
</table>

3.2.5 GA procedures

The steps of the proposed GA algorithm are:

**STEP 1** Set the population size Q. Let the number of generations \( g = 1 \). Generating the first population, for each chromosome \( r (1 \leq r \leq Q) \), randomly generate \( x_{ij} \) for each \( i \) and \( j \) with the constraints that the highest value of each product specification item must be 1 (\( x_{.,n} = 1 \)).

Decode the chromosomes to evaluate their costs. Let the best-in-solution be the chromosome with the minimal cost. Set \( h \) to 1, which indicates the number of iterations for which the best-in-solution is not improved.

**STEP 2** Let \( COST_r \) be the total cost \( Z \) of the solution that chromosome \( r \) represents and \( MaxC \) be the maximal cost of that generation.

Then the fitness of chromosome \( r \) can be calculated by using equation (6).

\[
f_r = \frac{MaxC - COST_r}{\sum_{k=1}^{g} (MaxC - COST_k)}
\]  

(6)

A pair of chromosomes is selected by using the fitness proportionate selection method.

**STEP 3** After selecting a pair of chromosomes through the application of the fitness proportionate selection strategy, generate one offspring by using the crossover procedure.
STEP 4 Repeat STEP 3 until the number of offspring exceeds the population size Q.

STEP 5 Randomly select a predetermined number (mutation possibility × population size Q) of offspring. Calculate the number of genes for mutation (mutation possibility × total number of genes) and implement mutation.

STEP 6 Update the parent chromosome set by the newly generated offspring set. $G = g + 1$.

Decode the offspring to evaluate their total cost. If the minimal cost is less than that of the last generation, update the best-in-solution. Otherwise, $h = h + 1$.

STEP 7 Repeat STEP 2 to 6 until g exceeds the number of total search iterations G, or the number of iterations with no improvement in the best-in-solution h exceeds H (Both G and H are set in advance).

3.3 Evaluation of the proposed GA procedures

To confirm the proposed GA procedure, a test problem can be created with the following conditions:

- number of product specification items: 10
- number of value sets for each product specification item: 6–51
- lead time of parts supply $T$: 2 (weeks)
- parts order interval $L$: 2 (weeks)
- safety stock coefficient $\alpha$: 1.96 (confidence level = 95%)
- interest rate $r$: 10%

Then number of value sets for each product specification item is randomly created. The parameters for the GA procedure are set as follows:

- population size Q: 100
- mutation probability: 0.01
- total search iterations G: 400
- search iterations with no improvement in the best-in-solution H: 20

Figure 4 shows the result of the test example. In this case, the total number of values for all product specification items is 358. Since the highest value for each item is 1 and there are two choices ($x_{ij}$ = 0 or 1) for all other values, the total number of combinations is $5.7 \times 10^{104}$. 
The improvement of the best-in-solution stopped at the 150th generation, with the cost decreasing by 2.1%. This improvement rate is not very high, but the number of searches (150 × 100 = 15,000) is only 2.6 × 10⁻¹⁰¹% of the total number of combinations. Therefore, we conclude that the proposed algorithm can be adopted for value setting decisions, in order to decrease the total cost of parts and inventory.

4 A case study of drilling machines

To verify the practical applicability of the proposed algorithm, drilling machines have been employed in a sample case. Figure 5 shows an image of a specific drilling machine, Model-A, which is used as an example in this study.

Figure 5 Equipment image (see online version for colours)
A drilling machine usually consists of the following five units: a table, the table’s drive unit (in this case, only the X-axis), a processing component, the processing component’s drive unit (in this case, both the Y-axis and the Z-axis) and the bed.

### 4.1 Detailed product specification items

With the cooperation of ETO company H, we were able to verify that there are 30 product specification items for the model in question. The value numbers differ among specification items and the total number of parts types is 797. The relationships between product specification items and their relative parts types are complex. For instance, the specifications for the ‘spindle’ parts type are determined by both the product specification items ‘maximum cutting feed rate (m/min)’ and ‘positioning accuracy (±mm)’. In this paper, for simplicity, only the parts types that can be determined by one product specification item are treated as target items. Table 1 shows the details of the selected product specification items.

<table>
<thead>
<tr>
<th>Product specification item</th>
<th>Number of relative parts types</th>
<th>Number of value sets for each parts type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Equipment horizontal size (mm$^2$) (length × width)</td>
<td>1</td>
<td>37</td>
</tr>
<tr>
<td>2 Table size (mm$^2$) (length × width)</td>
<td>8</td>
<td>37</td>
</tr>
<tr>
<td>3 Number of cassette holes</td>
<td>2</td>
<td>51</td>
</tr>
<tr>
<td>4 Travel distance of X-axis (mm)</td>
<td>4</td>
<td>37</td>
</tr>
<tr>
<td>5 Travel distance of Y-axis (mm)</td>
<td>1</td>
<td>37</td>
</tr>
<tr>
<td>6 Travel distance of Z-axis (mm)</td>
<td>2</td>
<td>18</td>
</tr>
<tr>
<td>7 Maximum X-axis feed rate (mm/min)</td>
<td>1</td>
<td>45</td>
</tr>
<tr>
<td>8 Maximum Y-axis feed rate (mm/min)</td>
<td>1</td>
<td>45</td>
</tr>
<tr>
<td>9 Maximum Z-axis retraction rate (mm/min)</td>
<td>1</td>
<td>45</td>
</tr>
<tr>
<td>10 Air pressure of stand-alone vacuum (m3/min)</td>
<td>1</td>
<td>6</td>
</tr>
</tbody>
</table>

With these parts types, the equipment manufacturer can provide $9.4 \times 10^{14}$ types of equipment for this model. This means that the company needs to prepare a large quantity of parts.

### 4.2 Results and discussion

Based on this data, a value setting (selection) can be executed with the proposed algorithm. The parameters for the GA procedure are described in Section 3.3.

Since the parts costs are regarded as confidential business information, we use the cost data from the parts manufacturers’ catalogues and websites.

Figure 6 and Table 2 present the results. The total number of parts types is reduced from 358 to 119, meaning the possible product types that the ETO company needs to deal with is decreased to $8.2 \times 10^9$. In this case, approximately two million yen can be saved.
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Figure 6  Number of values for each product specification item (see online version for colours)

![Number of values for each product specification item](image)

Table 2  Details of costs (yen)

<table>
<thead>
<tr>
<th>Cost items</th>
<th>Parts cost</th>
<th>Inventory</th>
<th>Total costs</th>
<th>Total costs improvement rate (1-proposal/current)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current</td>
<td>36,491,065</td>
<td>10,054,518</td>
<td>46,545,583</td>
<td></td>
</tr>
<tr>
<td>Proposal</td>
<td>37,856,348</td>
<td>5,846,998</td>
<td>43,703,346</td>
<td>6.11%</td>
</tr>
</tbody>
</table>

The calculation time for this case is 17 minutes, so the methodology can be applied in praxis.

Figure 7  β and the cost decrease rate (see online version for colours)

![Total cost decrease rate](image)

We also change the difference in cost among values for each product specification item, in order to clarify the resulting influence on decreasing total costs (Figure 7). In Figure 7, β is the parts cost increase rate for each specific product specification item. When a product specification item has a large set of values and the differences in parts costs of its related parts are small, value setting decisions are more significant. In other words, decreasing value sets is effective in reducing the total costs of parts and inventory. Therefore, for ETO companies that have to prepare numerous kinds of parts in advance in order to meet their customers’ uncertain requirements, we suggest considering product specification value setting as a parts supply strategy. Although under this strategy parts costs may increase, the total costs for parts and inventory will decrease.
5 Conclusions and future directions

The high inventory cost is a big issue for ETO companies, because of uncertain product specifications.

This study has focused on product value setting (decreasing), with the aim of reducing the costs of parts and inventory. This paper is the first on this topic and we assume that parts types can be determined by only one product specification item. Since a product has multiple specification items and dozens of values exist for each item, the value-setting problem has a large number of solution combinations. To solve this combination optimisation problem within a limited calculation time, a method based on the GA is proposed in this study. A numerical test is conducted to clarify the effect of the proposed algorithm, in terms of decreasing total costs.

Furthermore, with the cooperation of an ETO company, this paper has examined detailed product specification items that have been designed for drilling machines as a case study. The case study makes it clear that decreasing the number of values for product specification items can reduce the total costs of parts and inventory.

Further research is required to determine value-setting methods that take into account the complex relationships among product specification items and the relative importance of parts, to find a parts manufacturing cost calculation method that considers decreases in number of parts types and to improve performance of the proposed algorithm.

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