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A variable-scale dynamic clustering method

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ABSTRACT

With the high intensity and density of aerospace launch in China, aerospace project materials management faces various challenges, such as multiple aerospace projects concurrent, high supply timeliness and high quality level. Although several enterprises have successfully explored a versatile material management regulation for multiple aerospace projects, the low inventory turnover problem still exist due to the difficulty in versatile material recognition and inventory distribution. This paper studies the dynamic inventory management problem of aerospace project materials. Firstly, a numerical concept space model is established to describe the data characteristics of aerospace project materials. Then, we propose the variable-scale clustering algorithm based on the numerical concept space, which is utilized to automatically recognize versatile materials. Also, the obtained satisfy scale feature supports managers making inventory-related decision. Finally, a dynamic adjustment algorithm of inventory classification based on the variable-scale clustering is proposed, in order to dynamically maintain the inventory management plan of aerospace project materials. Experiments select the inventory data of aerospace project metal materials during Jan 1, 2015 to Mar 31, 2018 from the logistics center in China Academy of Launch Vehicle Technology. And experiment results illustrate that our proposed variable-scale clustering algorithm has high efficiency and practical application value in solving dynamic inventory management problem of aerospace project materials.

1. Introduction

Under the circumstances of intensive launch missions in China, how to establish the appropriate inventory management mechanism of aerospace project materials plays a significant role for aerospace enterprises, in order to keep their sustainable development and win the economic growth. Hence, guo et al. [1] put forward a versatile materials management mechanism for the enterprises' inventory optimization in aerospace industry, where materials with multi-projects, stable quality performance, controllable material delivery cycle and high frequency of usage will be classified as aerospace versatile materials for unified management.

Compared to the traditional materials management mechanism, the advantages of the versatile materials management mechanism are accomplishing the centralized inventory control, which could utilize the inventory to meet the dynamic demands of different aerospace engineering projects through improving the auto-supply level of versatile materials [2]. Therefore, the division and identification of aerospace versatile materials should consider not only the characteristics of materials (such as the demand universality, supply stability, material value, etc.), but also the dynamic changes of aerospace launch and production tasks in different time observation intervals (time scales).

There are two commonly utilized inventory classification methods, i.e., the classification analysis method [3] and multi-criteria decision making method [4]. On the one hand, classification method could train a classification model (classifier) by using the pre-set labeled data, and complete the object prediction by using the classification model that has passed the accuracy test [5]. However, aerospace enterprises need to undertake both national high density launch projects and research projects with different development cycle, which usually leads to great changes in the demand plans of aerospace project materials. Only inventory or procurement managers themselves are not able to accurately predefine the versatile material data label. Thus, the traditional classification method could not be applied for the recognition and prediction task of aerospace versatile materials.

On the other hand, the multi-criteria decision making method aims to build an evaluation index system with different index weights according to expert experience, and complete the object classification by ordering the evaluation results of all objects [6]. Nevertheless, the weights of evaluation index system under different tasks vary greatly, and change dynamically with the combination of multiple aerospace projects in different temporal scales. Aerospace enterprises could not timely and repeatedly organize expert committee to revise the evaluation index system and index weight value of versatile materials for

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every demand change. Therefore, the traditional multi-criteria decision making method also faces those challenges in solve the aerospace versatile materials recognition problem in practice.

This paper studies the versatile materials recognition problem for the dynamic inventory management of aerospace enterprises. The main contributions are as follows. Firstly, a numerical concept space model is established to describe the data characteristics of aerospace project materials. Secondly, according to the traditional (categorical) variable-scale clustering (VSC) method, we propose variable-scale clustering algorithm based on the numerical concept space (NVSC), which is utilized to automatically recognize versatile materials. Also, the obtained satisfy scale feature supports managers making inventory-related decision. Finally, a dynamic adjustment algorithm of inventory classification based on the variable-scale clustering (NVSC-A) is put forward. Experiments selected the inventory data of aerospace project metal materials during Jan 1, 2015 to Mar 31, 2018 from the logistics center of a real aerospace enterprise in China. And experiment results illustrate that our proposed method NVSC-A has high efficiency and practical application value in solving dynamic inventory management problem of aerospace project materials.

The rest of the paper is organized as follows. Section 2 presents the related research works, including the aerospace versatile materials management strategy, multi-criteria inventory classification and dynamic clustering analysis. Section 3 describes the main methodology part of our research, i.e., the numerical concept space model, the variable-scale clustering algorithm based on the numerical concept space (NVSC) and the dynamic adjustment algorithm of inventory classification based on the variable-scale clustering (NVSC-A). Experiments on a real inventory dataset are conducted in Section 4. And the paper is concluded in Section 5.

2. Literature review

2.1. Aerospace versatile materials management strategy

Facing the prosperous Chinese aerospace industry, enterprises gradually forms the aerospace versatile materials management strategy (AVM_MS), in order to meet the dynamic materials demand and reduce inventory management costs [1,7]. According to the AVM_MS, only materials that serve various aerospace projects and have relatively high supply stability could be defined as versatile materials, other materials with relatively high material value are classified as strategic materials, while the rest is general materials [8,9].

Compared to the classic inventory management strategies, the characteristics of the AVM_MS lies in adopting the rolling procurement plan of fixed time interval [10,11].

The fixed time rolling procurement plan requires that inventory managers arrange material purchasing following the demands of aerospace engineering projects in temporal reverse order. It not only assists the material purchasing department (logistic center) to make reasonable and economical order quantities of versatile materials, but also optimizes suppliers' production plans. That earns a win–win solution for both aerospace enterprises and material suppliers [12].

2.2. Multi-criteria inventory classification

Inventory classification focuses on dividing materials into different categories following the inventory management demands, in order to apply the differentiated management strategies for each material cluster. That shows great benefit to manufacturing enterprises in improving production efficiency and reducing operation costs [13].

The traditional ABC inventory classification method uses the single classification criterion (that is materials value) to quickly identify material categories, which classifies the most important inventory as Class A, generally important inventory as Class B and unimportant inventory as Class C [14]. The ABC method is widely used to optimize the inventory structure and reduce the occupancy of inventory funds [15]. As for the continuous improvement of material data collection techniques, this single-criteria method could not fully cover all characteristics of materials, and more evaluation criteria is necessary to be taken in consideration for inventory classification [16].

Lolli et al. [17] selects multiply criteria, like the replenishment lead time, unit purchase cost, average demand quantity, zero demand times within a fixed time interval, to predict the inventory inspection interval using the decision tree algorithm; While Anton et al. [18] applies more criteria, including price, average annual usage, number of suppliers, quantity of batch purchase, delivery date, material volume diameter and number of users, to divide material categories based on the clustering algorithm, and also designs the optimal inventory maintenance strategy for each material cluster.

It can be seen that, the basic idea of multi-criteria inventory classification approach could help aerospace enterprises recognize aerospace project material categories (especially versatile materials) through multiple inventory criteria such as supply stability and material value. But the dynamic inventory classification method that could automatically adjust or revise pre-classified material clusters following the change of observation temporal scales is still needed to be established.

2.3. Dynamic clustering analysis

As for the traditional clustering method usually suffers from the low efficiency problem when solving huge amount of incremental data, dynamic clustering analysis has won great attention since its first appearance [19]. There are three common approaches for dynamic clustering, i.e., data correlation-based dynamic clustering analysis, similarity parameter-based dynamic clustering analysis and iterative mechanism-based dynamic clustering analysis [20].

(1) Data correlation-based dynamic clustering analysis

Ji and Xiao [21] proposes a dynamic k-means clustering algorithm for time series data (DKCA/TSD), which utilizes the correlation of adjacent time data to directly adjust the clustering center. Similarly, Chen et al. [22] put forward a dynamic density clustering algorithm for time series data (DDCA/TSD). That could obtain the same results of re-clustering data on the whole latter time slice, through only adjusting the partial cluster structure.

(2) Similarity parameter-based dynamic clustering analysis

Wang et al. [23] proposed a dynamic clustering algorithm based on the local grid. A dimension radius measurement is built for incremental dynamic grid division, which successfully avoids the mistaken deletion of cluster boundaries and improves the grid clustering accuracy.

(3) Iterative mechanism-based dynamic clustering analysis

Zheng et al. [24] puts forth a fast clustering method based on the representative points and the density peaks. That builds a three-stage clustering iterative mechanism. In the beginning, initial clustering on the original dataset. Then, filter outliers of original dataset referring to the structure of incremental data, and select representative data. Last but not least, re-clustering on the updated dataset.

Variable-scale clustering (VSC) is an emerging clustering method, that could accomplish the object division using multiple observation scales. Although the VSC has great advantages on designing differentiated management strategy for each satisfied cluster [25,26], it still lacks the time-driven data representation models and scale transformation mechanism to solve the dynamic inventory classification of aerospace materials.

3. Dynamic numerical variable-scale clustering analysis

3.1. Numerical concept space structure model

According to the scale transformation theory [27], the concept space model, that consists of the concept chain and value space, provides the structural foundation for establishing the multi-scale data

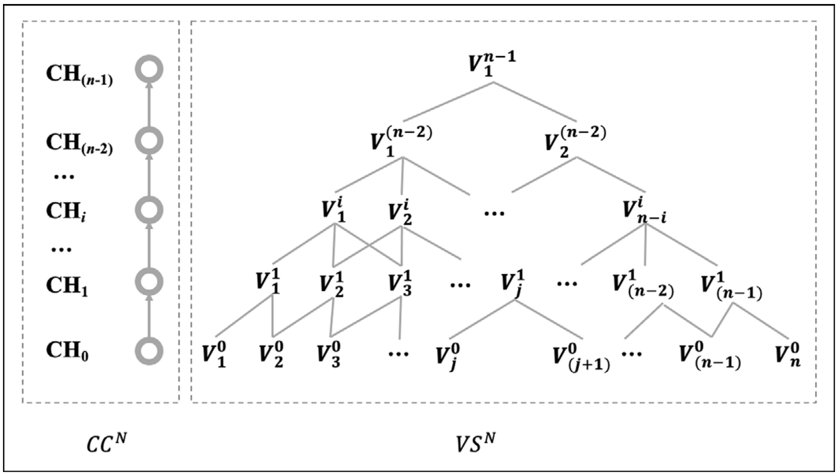


Fig. 1. The numerical concept space model.

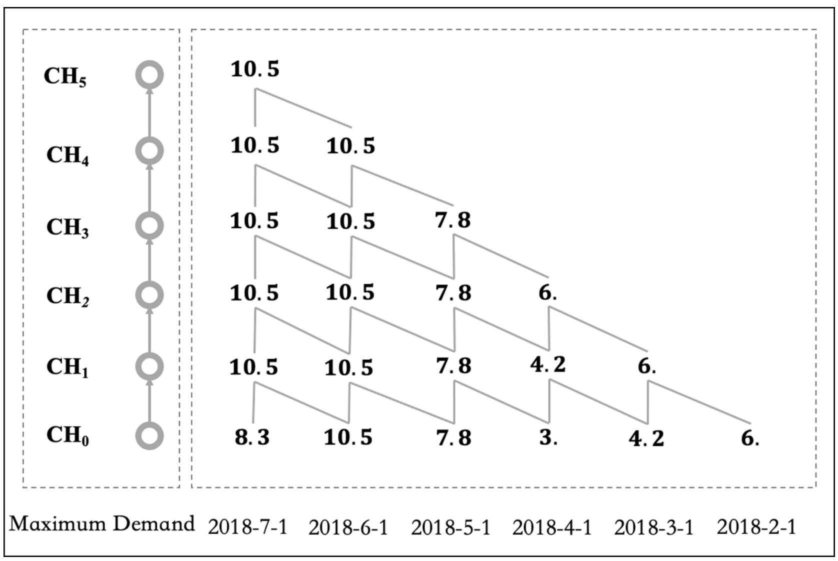


Fig. 2. Example: The numerical concept space of YY100X demand.

model [28]. And the partial order relation in the concept space model is utilized to represent the closely relationship between different scale hierarchies [11].

However, the original concept space model mainly focuses on the categorical variable data and binary variable data [29,30]. Since the inventory data used for versatile materials recognition belongs on the numerical variable data, as well as the fixed time rolling procurement plan (that demands in the latest period has more significance on inventory classification) in Section 2.1, this paper establishes the numerical concept space model based on the sliding time window (see Fig. 1).

Definition 1 (*Numerical Concept Space*). Given the numerical time series on the lowest scale hierarchy of an attribute $TS = (v_1, v_2, \dots, v_n)$, v_t represents the observation scale value at time t, CH_k represents the kth hierarchy of observation scale, and $v_{t:t+k}$ represents all the values of TS within the time interval $[t, t+k]$, the numerical concept space could be defined as $NCS(TS) = \{CC^N, VS^N\}$, where $CC^N = \{CH_k | 0 \le k \le (n-1)\}$, $VS^N = \{V_{kt} | (V_{kt} = f(v_{t:t+k})) \wedge (1 \le t \le n-k)\}$, $V_t^k = f^{max}(v_{t:t+k}) = \max(v_{t+0}, v_{t+1}, \dots, v_{t+k})$.

According to Definition 1, the feature of the numerical concept space (NCS) are as follows. ① The lower hierarchy observation scale has the partial order relation to the higher scale, i.e., $CH_k \preccurlyeq CH_{(k+1)}$ $(k \in [0, n-2])$; ② The observation scale decides the scale values on the same hierarchy, and the number of scale values in each hierarchy decreases with the increase of scale level, i.e., $V_{kt} \in CH_k$ $(1 \le t \le n-k)$ and $|CH_k| < |CH_{(k+1)}| (k \in [0, n-2])$; ③ The scale values of different levels follow the partial order relation between the observation scales they belong to, i.e., $CH_i \preccurlyeq CH_k \rightarrow V_{it} \le V_{kt} (1 \le t \le n-k; i, k \in [0, n-2])$.

Table 1
The monthly demand of aerospace engineer material YY100X in 2018.

Summary date	7/1	6/1	5/1	4/1	3/1	2/1
Demand (10^2 kg)	8.3	10.5	7.8	3.	4.2	6.

For example, Table 1 shows the monthly demand (10^2 kg) of an aerospace project material YY100X from Jan, 2018 to Jun, 2018. Hence, the numerical concept space of YY100X demand could be established (see Fig. 2).

It can be seen that the lowest scale hierarchy $[t, t+0]$ of the NCS in Fig. 2 is just the original monthly demand of YY100X in 2018. With the continuous improvement of the observation scale hierarchy, the time interval represented by every observation scale keeps increasing, like CH_5 ={10.5} indicates that the maximum demand of YY100X within the latest six months till July 1, 2018 is 1050 kg.

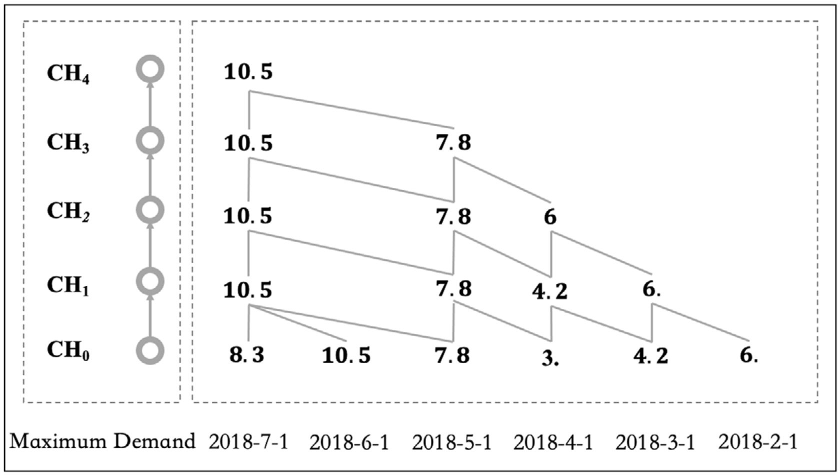


Fig. 3. Example: The reduced numerical concept space of YY100X demand.

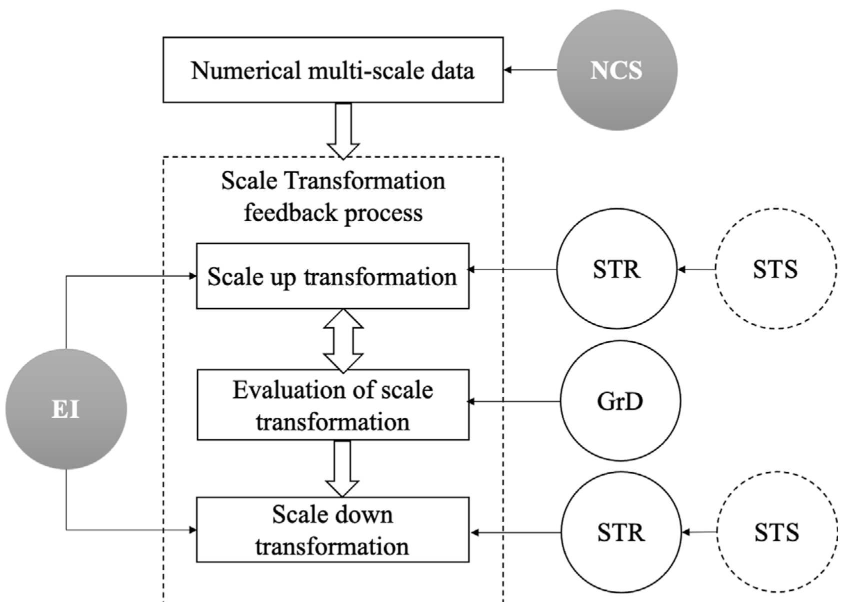


Fig. 4. The scale transformation mechanism of numerical multi-scale data.

Moreover, in order to reduce the computational complexity of the subsequent scaling transformation process, merge all observation scale hierarchies with exactly the same scale values and obtain the reduced NCS of YY100X (see Fig. 3). That could reduce the scale transformation space simultaneously.

3.2. Numerical variable-scale clustering analysis

Since the numerical concept space has already clearly describe the partial order relation between different observation scales (see Section 3.1), an equivalent interval data model is also put forward to further control the scale transformation process of the numerical multi-scale data.

Definition 2 (*Equivalent Interval*)**.** Given the observation scale hierarchy CH_k and CH_{k+1} $\left(CH_k \preccurlyeq CH_{k+1}\right)$, let $X_I = \left\{x_i | x_i \in U, i \in N^+\right\}$ represents a satisfied cluster [31] on CH_k and $\left|X_I\right| > 1$, V_{ik} represents the scale value of x_i under CH_k, and $V_{i(k+1)}$ represents the scale value of x_i under CH_{k+1}, the equivalent interval data model on CH_{k+1} could be defined as $EI_i^{k+1} = \left[\min\left(V_{i(k+1)}\right), \max\left(V_{i(k+1)}\right)\right]$, where $\left[x_i\right]_k = \left\{x_t | \left(x_t \in X_I\right) \cap \left(V_{tk} = V_{ik}\right)\right\}$.

After combining the proposed equivalent interval data model (EI) with other previous scale transformation measurements (that is the scale transformation strategy STS, scale transformation rate STR and granular deviation GrD [32]), the scale transformation mechanism for numerical multi-scale data is established (see Fig. 4). Compared to the previous single scale up/down transformation mechanism [32], the numerical scale transformation mechanism is able to build the feedback process via adding or deleting equivalent interval on each observation scale hierarchy, which improves the efficiency of scale transformation.

According to the numerical scale transformation mechanism (see Fig. 4), the variable-scale clustering method based on the numerical concept space (NVSC) is proposed. The algorithm steps of the NVSC are shown in Algorithm 1.

The time complexity of the proposed NVSC is $O(t\varphi)$ and $\varphi = \min(m, n^r)$, where r is the number of attributes, n is the largest number of scales within one attribute, m is the number of initial objects, and

Table 2
Summary of Variables.

Variable	Description
Single Scale Variable	
Arrival Date (A_D)	The arrival date of each purchase plan (Date) before 2018
Ordering date(O_D)	The ordering date of each purchase plan (Date) before 2018
Ordering Quantity(OQ)	The ordering quantity of each purchase plan (kg) before 2018
Usage Quantity(AQ)	The usage quantity of each purchase plan (kg) before 2018
Unit Price(UP)	The unit price of each purchase plan (¥) before 2018
Multi-Scale Variable	
Max-Purchasing Cycle(MPuC)	The maximum purchasing cycle of each material with multiple temporal scales, i.e., latest half year, latest one year, latest two year till Dec 31, 2017
Max-Demand Quantity(MDeQ)	The maximum demand quantity of each material with multiple temporal scales, i.e., latest half year, latest one year, latest two year till Dec 31, 2017
Max-Cost of Sales(MCoS)	The maximum sale costs of each material with multiple temporal scales, i.e., latest half year, latest one year, latest two year till Dec 31, 2017
Incremental inventory data	
New Arrival Date(A_D+)	The arrival date of new purchase plan (Date) in 2018
New Ordering date(O_D+)	The ordering date of new purchase plan (Date) in 2018
New Ordering Quantity(OQ+)	The ordering quantity of new purchase plan (kg) in 2018
New Usage Quantity(AQ+)	The usage quantity of new purchase plan (kg) in 2018
New Unit Price(UP+)	The unit price of new purchase plan (¥) in 2018

t is the time complexity of the (meta) clustering process during once scale transformation.

3.3. Dynamic inventory classification based on the numerical variable-scale clustering

According to the dynamic aerospace project materials recognition problem In Section 2.1, the variable-scale clustering method based on the numerical concept space (NVSC) has already been able to identify satisfied material clusters with clear scale feature in a fixed time interval. In this section, a dynamic adjustment algorithm of inventory classification based on the variable-scale clustering (NVSC-A) is proposed, following the basic idea of the iterative mechanism-based dynamic clustering in Section 2.3. The algorithm steps of the NVSC-A are shown in Algorithm 2.

Definition 3 (*Multi-Scale Aerospace Material List*)**.** Given a multi-scale material list $List_t^S = (\mathcal{U}, \mathcal{A}^S, d^t, \mathcal{V}^S, f)$, $\mathcal{U} = \{x_1, x_2, \ldots, x_k\}$ represents the material set (universe); $\mathcal{A}^S = \left\{A^1, A^2, \ldots, A^r\right\}$ represents the observation attribute set, where at least one attribute within $\mathcal{A}^S$ has multiple scales in its numerical concept space, i.e., $\exists A^\alpha, CC^N(A^\alpha) = \langle A_0^\alpha, A_1^\alpha, \ldots, A_n^\alpha \rangle (\alpha = 1, 2, \ldots, r)$; $d^t = d_1^t, d_2^t, \ldots, d_k^t$ represents the material type at time t; $f : \mathcal{U} \times \mathcal{A}^S \rightarrow \mathcal{V}^S$ is the information function, and $\mathcal{V}^S \in \{VS^N(A^\alpha), \alpha = 1, 2, \ldots, r\}$.

Compared to fully recalculating the inventory classification results with each data update using the NVSC, the dynamic adjustment method NVSC-A could keep the accuracy and stability of material clusters, which helps managers develop relatively consistent inventory management policies.

4. Dynamic inventory classification experiments and discussions

4.1. Experiment design and data preparation

The experimental dataset is collected from the logistics center of a real aerospace enterprise in China, which includes 310 000 records of aerospace project metal materials from Jan 1, 2015 to Mar 31, 2018. After interviewing aerospace project and inventory managers, 109 sample metal materials and thirteen variables are selected to verify efficiency of the proposed method NVSC-A.

Table 2 depicts the variables used in the inventory classification experiments. Since the NVSC-A is a dynamic adjustment algorithm following the material data update, the original inventory dataset is divided into two parts, that is sub dataset before 2018 for recognizing aerospace material categories, as well as sub dataset after 2018 (incremental inventory data) for evaluating dynamic adjustment performance. Moreover, the three multi-scale variables (i.e., Max-Purchasing Cycle, Max-Demand Quantity, and Max-Cost of Sales) respectively have three scale hierarchies, that is the latest half year, latest one year, latest two year till Dec 31, 2017.

4.2. Experiment results and discussions

During the first stage, the sub inventory dataset before 2018 is utilized to recognize aerospace project material clusters using the NVSC. The experiment results are shown in Fig. 5, where strategic material clusters, versatile material clusters and general material clusters are respectively depicted by green, orange and blue rectangles. It can be seen that the NVSC method divides 109 aerospace metal materials into nine satisfied clusters.

In Fig. 5(a), we could find out that the granular deviation (GrD) of all material clusters stays in a relatively low level (less than 3.33). That indicates that materials within one cluster have high similarity and clear scale feature, which fully verifies the effectiveness of the variable scale clustering method in solving the inventory classification for aerospace enterprises.

Moreover, although the scale transformation process has increased the observation scale of target attribute MPuC from the latest half year scale hierarchy to the latest two years (where the equivalent interval is [30,307], the average purchasing cycle of versatile materials and general materials is still lower than strategic materials, which is consist with managers' actual business experience.

In Fig. 5(b), after analyzing the MDeQ feature in different scale hierarchies of each material cluster and their average number of ordering, it can be seen that the demand quantity of versatile materials and strategic materials is significantly larger than that of general materials, and even the maximum growth rate could reach 273%.

Fig. 5(c) shows the number of materials in every satisfied cluster. The versatile materials occupies the largest proportion, that is 36.7%. In addition, the sale costs of strategic materials has been maintained at

Algorithm 1 *Variable-Scale Clustering based on the Numerical Concept Space*

Input : Numerical multi-scale data ND^S,

Scale transformation strategy (OSTS or PSTS).

Output: Satisfied clusters with scale feature,

Scale transformation path.

Step 1: (Initial clustering on the basic scale hierarchy) Apply the basic scale hierarchy data ND_0 of ND^S for initial clustering, and evaluate the initial clustering results via GrD [9].

$$GrD(X_I, A^\lambda) = \sqrt{\sum_{j=1}^{r} \bar{d}(x_{ij}, x_{Ij})/G(\mathcal{U}/A^\lambda)} \tag{1}$$

$$G(\mathcal{U}/A^\lambda) = \sum_{k=1}^{t} |U_k^\lambda|^2/n^2 \tag{2}$$

$$\bar{d}(x_{ij}, x_{Ij}) = \sum_{i=1}^{n} \delta(x_{ij}, x_{Ij})/n \tag{3}$$

$$\delta(x_{ij}, x_{Ij}) = \begin{cases} 0, & x_{ij} = x_{Ij} \\ 1, & x_{ij} \neq x_{Ij} \end{cases} \tag{4}$$

Step 2: (Decide the satisfaction judgement threshold) Identity all the satisfied clusters within the initial clustering results, and take their largest GrD as the satisfaction judgement threshold R_0.

Step 3: (Output initial satisfied clusters and update data) Output all the satisfied clusters and their scale feature. Also, delete all the objects within every satisfied cluster from ND^S.

Step 4: (Scale up transformation) Perform scale up transformation on the updated ND^S.

Step 4.1: (Select the target attribute for scale up transformation) If the OSTS is selected, take the attribute in ND^S with the largest STR as the target attribute; Otherwise, if the PSTS is selected , take the attribute in ND^S with the smallest STR as the target attribute.

Step 4.2: (Add the equivalent interval on the target attribute) Establish the EI of the target attribute via satisfied clusters obtained by the last clustering.

Step 4.3: (Update data) Replace the object value under the target attribute of ND^S as the average of EI, and obtain the updated single-scale target data ND'.

Step 5: (Clustering on the target scale hierarchy) Apply the target scale hierarchy data ND' of ND^S for clustering, and evaluate the clustering results via GrD.

Step 6: (Auto recognize satisfied clusters) Identify all clusters whose GrD evaluation results are lower than or equal to R_0 as satisfied clusters, and go to Step 8. While if the GrD of all clusters is larger than R_0, then go to Step 7.

Step 7: (Scale down transformation) Perform scale down transformation on the updated ND^S.

Step 7.1: (Select the target attribute for scale down transformation) Take the last scale up transformed attribute as the target attribute.

Step 7.2: (Delete the equivalent interval on the target attribute and update data) Delete the EI the target attribute and replace ND^S as the original object value, and go to Step 4.

Step 8: (Output satisfied clusters and update data) Output all the satisfied clusters and their scale feature. Also, delete all the objects within every satisfied cluster from ND^S.

Step 9: (Terminate scale transformation) Identify whether the scale transformation process could be terminated. If there is still unclassified objects in ND^S (that is $ND^S \neq \emptyset$), go to Step 4; Otherwise, output the whole scale transformation path.

a high level, but the MCoS feature of various versatile and general material clusters is quite different due to the dynamic aerospace projects demand.

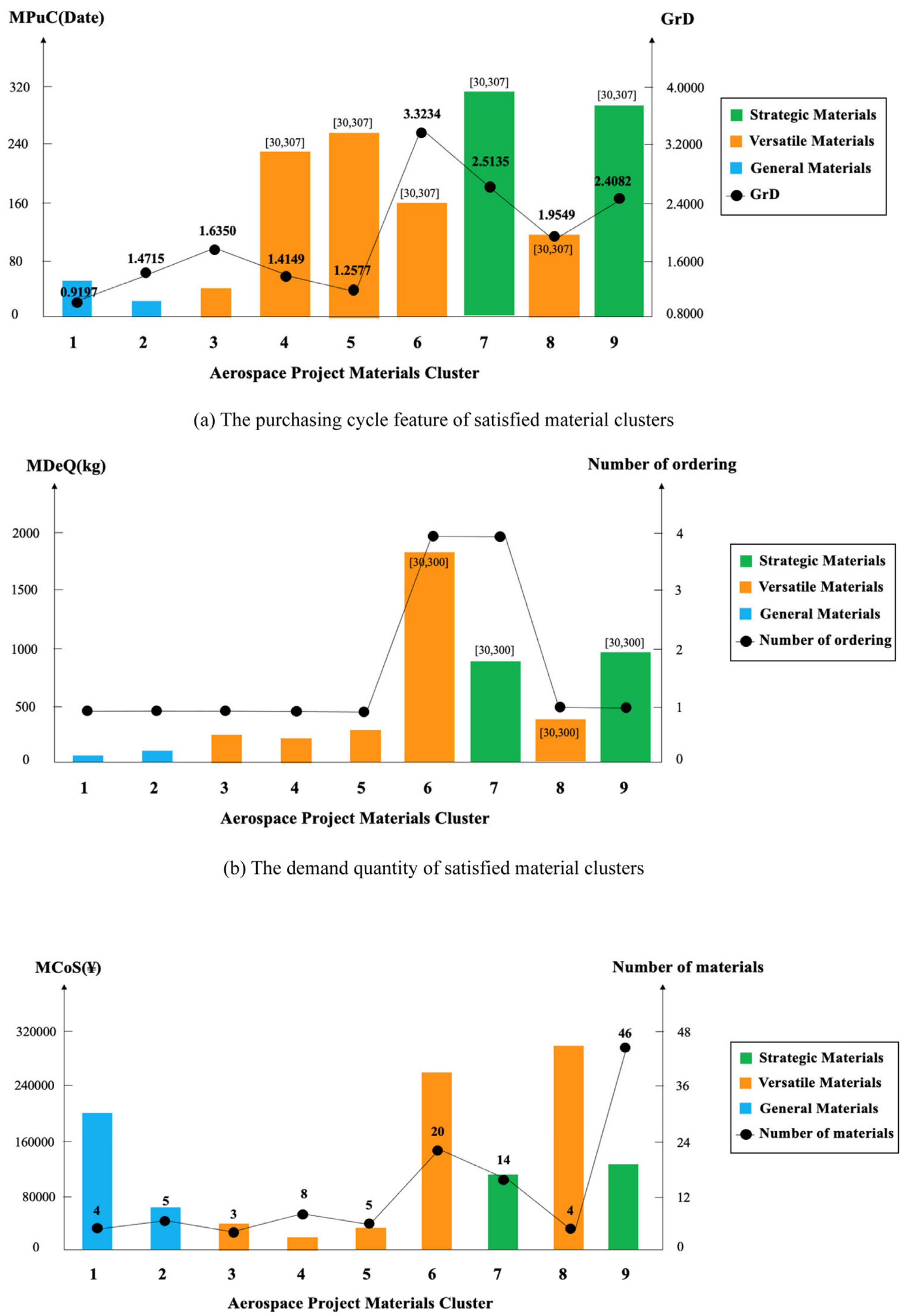
According to the inventory classification experiment above, the predefined multi-scale aerospace material list has already been established by the NVSC, including two strategic material clusters, five versatile material clusters and two general material clusters. Therefore, we further apply that predefined aerospace material list for verifying the dynamic inventory classification adjustment performance of the proposed NVSC-A method.

During Jan 1, 2018 to Mar 31, 2018, the incremental inventory data of Table 2 contains sixteen purchasing plans in total from thirty different aerospace metal materials, which accounts for 28%. We firstly recalculate the GrD evaluation results of all nine predefined clusters at every data update moment (Table 3).

Table 3 depicts that although the GrD of each cluster increases slightly following the new material purchasing demands, only Cluster 6 and 7 exceeds the satisfaction judgment threshold 3.33 (shown in black box line of Table 3), which illustrates the predefined material list is able to meet 81.2% of new purchasing demands. But it is still necessary to dynamically adjust the materials classification results to satisfy inventory managers' practical requirements, following the boxplot [33] of clusters' GrD during new ordering period (see Fig. 6).

Table 4 shows the dynamic adjustment results of the aerospace material classification by the NVSC-A. Compared to the recalculation results in Table 3, the newly partition clusters of the NVSC-A are highlighted in dotted box line of Table 4.

On the one hand, the NVSC-A divides the unsatisfied Cluster 7 into two sub material clusters (whose GrD are respectively 1.30 and 1.79), which overcomes the impact of new purchasing plan on Jan 3, 2018.



(a) The purchasing cycle feature of satisfied material clusters

(b) The demand quantity of satisfied material clusters

(c) The sale costs feature of satisfied material clusters

Fig. 5. The aerospace project material clusters via the NVSC.

On the other hand, the NVSC-A directly divides the unsatisfied Cluster 6 into two sub material clusters (whose GrD are respectively 2.96 and 3.19), which overcomes the impact of new purchasing plan on Jan 12, 2018. Although the next purchasing plan keeps enlarging the GrD of a newly divided sub cluster from 2.96 to 3.08, it still satisfy managers' requirements for making inventory strategies (less than 3.33), which practically proves the effectiveness of the proposed dynamic adjustment method NVSC-A.

5. Conclusions

Inventory classification plays a significant role in helping managers make differentiated inventory management strategies especially for aerospace enterprises. This paper studies the dynamic materials recognition problem based on the scale transformation theory. Firstly, a numerical concept space model is established to describe the data characteristics of aerospace project materials. Secondly, according to the traditional (categorical) variable-scale clustering (VSC) method, the variable-scale clustering algorithm based on the numerical concept

Algorithm 2 *Dynamic adjustment of inventory classification based on the variable-scale clustering*

Input : Multi-scale aerospace material list at moment t $List_t^S$,
Incremental inventory data at next moment t+1 ND_{t+1}
Satisfaction judgement threshold R_0.

Output: Multi-scale aerospace material list at next moment t $List_{t+1}^S$.

Step 1: (Update data) Update all the scale values of each material in $List_t^S$ using ND_{t+1}, and obtain the updated list $List_t^{S'}$.

Step 2: (Accuracy determination of inventory classification) Calculate the GrD of all pre-defined satisfied material clusters in $List_t^{S'}$. If all evaluation results are larger than R_0, which means there is no pre-defined material cluster still meet the requirement of inventory managers at moment t+1, then utilize the NVSC to recalculate the aerospace material list $List_{t+1}^S$ and go to Step 4; Otherwise, go to Step 3.

Step 3: (Adjust inventory classification) Identify the aerospace material list at next moment t $List_{t+1}^S$ using pre-defined satisfied material clusters in $List_t^{S'}$.

Step 3.1: (Retain satisfied clusters) Retain pre-defined satisfied clusters (whose GrD are still lower than or equal to R_0 at moment t+1) into $List_{t+1}^S$, and delete all the aerospace materials in those qualified clusters from $List_t^{S'}$.

Step 3.2: (Redivide unsatisfied clusters) Redivided the rest materials in $List_t^{S'}$ using the NVSC, and obtain the $List_{t+1}^S$.

Step 4: (Output latest inventory classification) Output the aerospace material list at next moment t $List_{t+1}^S$.

Table 3
The granular deviation (GrD) results of predefined aerospace material list.

Cluster / Ordering Date	1	2	3	4	5	6	7	8	9
Predefined GrD	0.92	1.47	1.63	1.41	1.26	3.32	2.51	1.95	2.41
20180102	0.92	1.47	1.63	1.41	1.26	3.32	2.51	1.95	2.41
20180103	0.92	1.47	1.63	1.41	1.26	3.32	3.35	1.95	2.41
20180104	0.92	1.47	2.45	1.41	1.26	3.32	3.35	1.95	2.41
20180105	2.94	2.45	2.45	1.41	1.26	3.32	3.35	1.95	2.41
20180112	2.94	2.45	2.45	1.41	1.26	4.56	3.35	1.95	2.41
20180118	2.94	2.45	2.45	1.41	1.26	4.63	3.35	1.95	2.41
20180123	2.94	2.45	2.45	1.41	1.26	4.63	3.35	1.95	2.41
20180129	2.94	2.45	2.45	1.41	1.26	4.63	3.35	1.95	2.41
20180205	2.94	2.45	2.45	1.41	1.26	4.63	3.35	1.95	2.41
20180209	2.94	2.45	2.45	1.41	1.26	4.63	3.35	1.95	2.41
20180227	2.94	2.45	2.45	1.41	1.26	4.63	3.35	1.95	2.41
20180228	2.94	2.45	2.45	1.41	1.26	4.63	3.35	1.95	2.41
20180301	2.94	2.45	2.45	1.41	2.26	4.63	3.35	1.95	2.41
20180306	2.94	2.45	2.45	1.41	2.26	4.63	3.35	1.95	2.41
20180313	2.94	2.45	2.45	1.41	2.26	4.63	3.35	1.95	2.41
20180314	2.94	2.45	2.45	1.41	2.26	4.63	3.35	1.95	2.41

space (NVSC), which could automatically identify material clusters with clear scale feature, including strategic, versatile and general materials. Finally, a dynamic adjustment algorithm of inventory classification based on the variable-scale clustering (NVSC-A) is put forward. Experiments on the real dataset from a Chinese aerospace enterprise verifies that the proposed method NVSC-A is able to timely obtain satisfied material clusters following the dynamic demands of aerospace projects in practice.

The limitation of the NVSC-A is that the efficiency of scale transformation process could still be affected by the satisfaction parameter threshold. Hence, the future research will focuses on optimizing the satisfaction judgment threshold of the variable-scale clustering algorithm,

Table 4
The granular deviation (GrD) results of the adjusted aerospace material list by the NVSC-A.

Cluster / Ordering Date	1	2	3	4	5	6	7	8	9
Predefined GrD	0.92	1.47	1.63	1.41	1.26	3.32	2.51	1.95	2.41
20180102	0.92	1.47	1.63	1.41	1.26	3.32	2.51	1.95	2.41
20180103	0.92	1.47	1.63	1.41	1.26	3.32	1.30 1.79	1.95	2.41
20180104	0.92	1.47	2.45	1.41	1.26	3.32	1.30 1.79	1.95	2.41
20180105	2.94	2.45	2.45	1.41	1.26	3.32	1.30 1.79	1.95	2.41
20180112	2.94	2.45	2.45	1.41	1.26	2.96 3.19	1.30 1.79	1.95	2.41
20180118	2.94	2.45	2.45	1.41	1.26	3.08 3.19	1.30 1.79	1.95	2.41
20180123	2.94	2.45	2.45	1.41	1.26	3.08 3.19	1.30 1.79	1.95	2.41
20180129	2.94	2.45	2.45	1.41	1.26	3.08 3.19	1.30 1.79	1.95	2.41
20180205	2.94	2.45	2.45	1.41	1.26	3.08 3.19	1.30 1.79	1.95	2.41
20180209	2.94	2.45	2.45	1.41	1.26	3.08 3.19	1.30 1.79	1.95	2.41
20180227	2.94	2.45	2.45	1.41	1.26	3.08 3.19	1.30 1.79	1.95	2.41
20180228	2.94	2.45	2.45	1.41	1.26	3.08 3.19	1.30 1.79	1.95	2.41
20180301	2.94	2.45	2.45	1.41	2.26	3.08 3.19	1.30 1.79	1.95	2.41
20180306	2.94	2.45	2.45	1.41	2.26	3.08 3.19	1.30 1.79	1.95	2.41
20180313	2.94	2.45	2.45	1.41	2.26	3.08 3.19	1.30 1.79	1.95	2.41
20180314	2.94	2.45	2.45	1.41	2.26	3.08 3.19	1.30 1.79	1.95	2.41

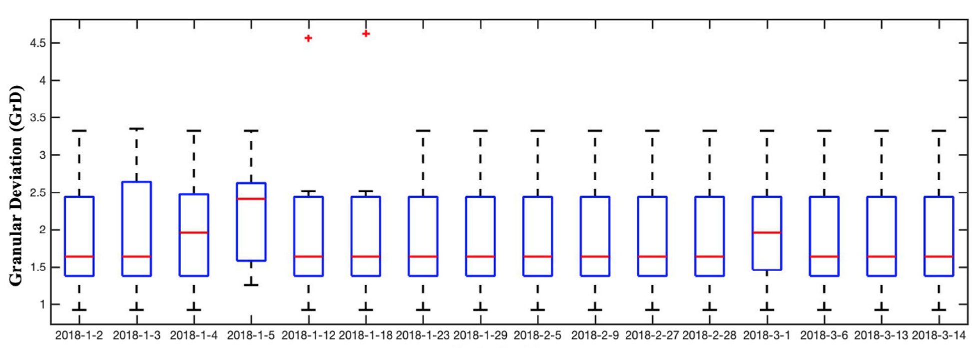


Fig. 6. Results of the dynamic inventory classification experiments.

in order to avoiding the subjective decision-making impact of inventory managers.

CRediT authorship contribution statement

Ai Wang: Conceptualization, Methodology, Software, Validation, Writing - original draft. **Xuedong Gao:** Supervision, Resources, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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