Analysis of the composition of ancient glassware based on grey correlation and principal component analysis

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Abstract. Power load forecasting is very important for power dispatching. Accurate load forecasting is of great significance for saving energy, reducing generating cost and improving social and economic benefits. In order to accurately predict the power load, based on BP neural network theory, combined with the advantages of Clementine in dealing with big data and preventing overfitting, a neural network prediction model for large data is constructed.

Keywords: Grey correlation, principal component analysis, glass classification study.

1. Introduction

In ancient times fluxes were often added to the production of glass to lower the melting point of pure quartz sand [1]. During the smelting process, the addition of different products resulted in significant changes in the internal composition of the glass products [2-3]. This paper examines and analyses a sample of ancient glass products based on their data. This paper uses grey correlation and principal component analysis to determine the main components within the glass products, respectively, and the study suggests the main factors of glass composition. The validity of the model is verified based on the specific results of the study, which provide a reference for the smelting and composition identification of glass products [4].

2. The fundamental of grey association

The relationship between the surface weathering of these glass artefacts and their glass type, decoration and color was analyzed. This paper uses grey correlation analysis to analyses the grey correlation between surface weathering and glass type and decoration and color, resulting in grey correlation coefficients, grey correlation coefficient plots and grey correlation degrees. SPSSPRO was used to simulate the algorithm, and the dimensionless treatment was homogenized (the data were divided by the mean, and since the mean of series with large orders of magnitude is larger, the division normalized them to around the order of 1), with a discrimination factor ρ = 0.5.

Grey correlation analysis (GRA), a statistical multi-factor analysis method proposed by Professor Deng Julong, quantifies the trends in the dynamic matching process of the geometric correlations of the statistics related to systematic time series and calculates the grey correlation between the original series and each original series to determine the degree of association between different factors [5].

$$\xi_i = \frac{\min_j \min_k |x_0(k) - x_i(k)| + \rho \max_j \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max_j \max_k |x_0(k) - x_i(k)|} \tag{1}$$

The correlation coefficient represents the value of the degree of correlation between the unique heat code, type digitization, and title color indicator pair of that sub-sequence of ornamentation and the corresponding dimension of the parent sequence, with larger numbers representing stronger correlations. The SPSSPRO run, yielded the relationships between surface weathering and its glass type, ornamentation and color as shown in Table 1 Correlation results. For the influence factor of surface weathering, decorations > color > glass type.

Based on the grey correlation results shown in Table 1, the highest correlations are for lead oxide, strontium oxide and barium oxide [6-7]. The data can be fitted using MATLAB and the fitted equation is derived by least squares as

$$Con = -0.0017X^3 + 0.15X^2 - 2.49X + 17.29 \tag{2}$$

Table 1. Grey correlation results.

Evaluation items	Relevance	Ranking
Lead oxide (PbO)	0.953	1
Strontium oxide (SrO)	0.947	2
Barium oxide (BaO)	0.943	3
Silicon dioxide (SiO_2)	0.939	4
Aluminium oxide (Al_2O_3)	0.933	5
Copper oxide (CuO)	0.932	6
Magnesium oxide (MgO)	0.929	7
Phosphorus pentoxide (P_2O_5)	0.926	8

Based on the grey correlation results shown in Table 1, it can be seen that the highest correlations are for lead oxide, strontium oxide and barium oxide [8]. The data can be fitted using matlab and the fitted equation is derived by least squares as

$$Con = -0.0017X^3 + 0.15X^2 - 2.49X + 17.29 \tag{3}$$

The fitted image is shown in Figure 1.

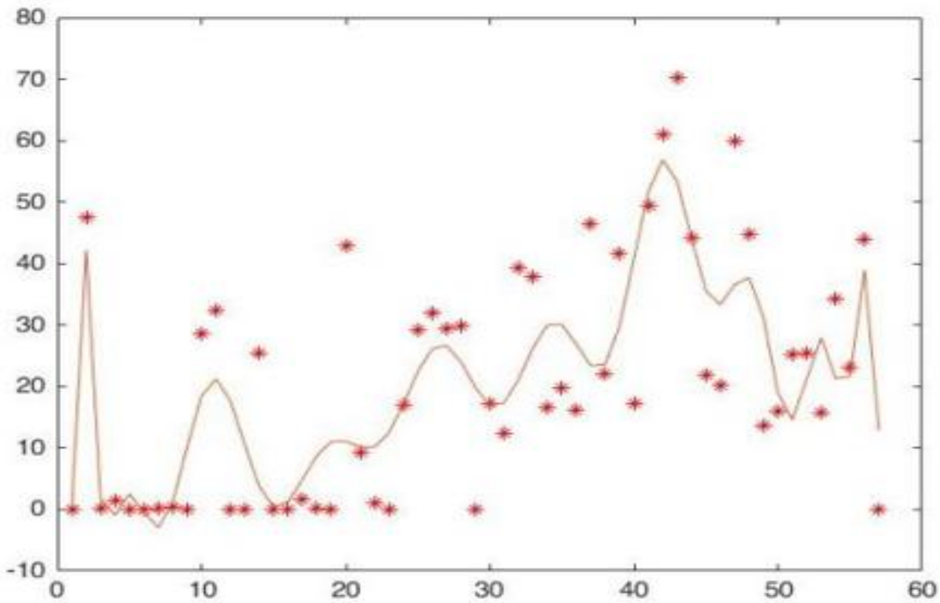

Figure 1. Fitting image of lead oxide.

3. Results

3.1. The establishment of simulation model

Firstly, the raw data were clarified, 15, 17, 02, 08 and 08 were removed from the table, and the empty data were filled in with zeros. Then the data were classified according to "high potassium" and "lead barium" and cluster analysis was performed. Cluster analysis is the process of grouping a collection of physical or abstract objects into multiple classes consisting of similar objects.

3.2. Analysis of experimental results

The results of the cluster analysis are shown in Tables 2 and 3.

Table 2. Results of the cluster analysis.

	Barium lead (n=39)	High potassium (n=30)	F	P
High Potassium	1.564±0.502	2.0±0.0	22.51	0.000***
Lead Barium	1.0±0.0	2.0±0.0	-	0.000***

The results of the ANOVA showed that: for the variable high potassium, the significant P-value was 0.000***, which is significant at the level of rejection of the original hypothesis, indicating that the variable high potassium is significantly different between the categories classified by the K-means cluster analysis; for the variable lead barium, the significant P-value was 0.000***, which is significant at the level of rejection of the original hypothesis, indicating that the variable lead barium is significantly different between the categories classified by the K-means cluster analysis. Means clustering analysis divided between the categories there is a significant difference [9-10].

Table 3. Calculated proportions of clustering categories.

Clustering categories	Frequency	Percentage
High Potassium	39	56.522%
Lead Barium	30	43.478%
Total	69	100%

Next, KMO tests and Bartlett's tests were carried out for 'high potassium' and 'lead-barium', respectively, as definite categories and other chemical elements as variables, as shown in Table 4.

Table 4. KMO test and Bartlett's test.

KMO values		0.511
Bartlett's test of sphericity	Approximate cardinality	492.888
	df	91.000
	P	0.000***

PCA principal component analysis was next performed on silica and sodium oxide, and the weights were calculated as shown in Table 5.

Table 5. Results of principal component weights.

Name	Explanation of variance	Cumulative variance explained	Weighting
Silicon dioxide	1.1460061332214255	57.3%	100%

4. Conclusions

This paper describes the classification and identification of ancient glass objects with a degree of accuracy and skill, using grey correlation and principal component analysis to classify and identify the components respectively. The advantages of grey correlation analysis are that the analysis is based on trends, there is no requirement for data, and no distribution pattern is required, making the prediction of grey systems very appropriate and reasonable. In addition, the paper uses principal component analysis to reduce the dimensionality of the main components of glass products, which effectively improves the efficiency of the data calculation. The analysis of this problem can also be applied to other complex composition product problems, and the parameters can be adjusted to solve the problem by referring to this model. In addition, the model is useful for planning and selecting industrial production.

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