APEM journal

Advances in Production Engineering & Management
Volume 20 | Number 1 | March 2025 | pp 87–98
https://doi.org/10.14743/apem2025.1.529

ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

Enhancing aerospace products quality with ISOMAP key factor identification

Shen, D.Y.[a,b], **Liu, N.Z.**[a,*], **Liu, W.**[b], **Wang, Z.**[b]

[a]College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, Nanjing, P.R. China
[b]Beijing System Design Institute of the Electro-mechanic Engineering, Beijing, P.R. China

A B S T R A C T

The nonlinear and high-dimensional nature of the impact factors affecting the production quality of aerospace products represents a major difficulty for the quality control in the aerospace industry. To obtain the impact factors affecting the product quality, it is plausible to perform dimensionality reduction on acquired samples before further manipulation. In this work, the isometric feature mapping (ISOMAP) algorithm of stream learning is employed to perform nonlinear dimensionality reduction on aerospace data. This enables a calculation of the correlation coefficients between the principal components after dimensionality reduction and the original factors, the classification of the correspondence, and the ranking of the principal components according to their degree of influence. The experimental results show that the algorithm is able to carry out correlation analysis of 17 factors affecting the production quality of aerospace products, and analyze the 13 main factors affecting the production quality of aerospace products, and the degree of influence, in descending order, are the rationality of measurement methods, the rationality of test point design, tool wear, equipment normalization rate, the degree of equipment aging, the rationality of program design, the degree of material defects, the rationality of process route design, the rationality of tooling design, the technical level of personnel, the level of personnel experience, the personnel work status, and operational standardization. The ISOMAP algorithm was used to reduce the dimensionality of these 13 factors to form and rank the six main influence components, thus eliminating redundant factors, highlighting main influence features and extracting the intrinsic relation in data. The data analysis conclusions can facilitate a prevention of potential quality issues in aerospace production. To ensure the enhancement of the quality of aerospace product production, it is recommended that standard automated measurement methods be employed wherever feasible. Additionally, it is recommended that the regular maintenance of machining tools and equipment be strengthened to ensure that the machining tools and equipment are in perfect condition.

A R T I C L E   I N F O

Keywords:
Aerospace products;
Production quality;
ISOMAP;
Nonlinear dimensionality reduction;
5M1E framework;
Correlation analysis;
Quality control

**Corresponding author:*
liunz_tx@163.com
(Liu, N.Z.)

Article history:
Received 28 October 2024
Revised 8 April 2025
Accepted 21 April 2025

References

[1] Nazifa, T.H., Ramachandran, K.K. (2019). Information sharing in supply chain management: A case study between the cooperative partners in manufacturing industry, *Journal of System and Management Sciences*, Vol. 9, No. 1, 19-47, doi: 10.33168/JSMS.2019.0102.

[2] Shafiq, S.I., Sanin, C., Szczerbicki, E., Toro, C. (2017). Towards an experience based collective computational intelligence for manufacturing, *Future Generation Computer Systems*, Vol. 66, 89-99, doi: 10.1016/j.future.2016.04.022.

[3] Liang, Q. (2020). Production logistics management of industrial enterprises based on wavelet neural network, *Journal Européen des Systèmes Automatisés*, Vol. 53, No. 4, 581-588, doi: 10.18280/jesa.530418.

[4] Păun, M.-A., Coandă, H.-G., Mincă, E., Iliescu, S.S., Duca, O.G., Stamatescu, G. (2024). Improved multi-objective genetic algorithm used to optimizing power consumption of an integrated system for flexible manufacturing, *Studies in Informatics and Control*, Vol. 33, No. 1, 27-36, doi: 10.24846/v33i1y202403.

[5] Malega, P., Daneshjo, N. (2024). Increasing the production capacity of business processes using plant simulation, *International Journal of Simulation Modelling*, Vol. 23, No. 1, 41-52, doi: 10.2507/ijsimm23-1-669.

[6] Sun, H. (2023). Optimizing manufacturing scheduling with genetic algorithm and LSTM neural networks, *International Journal of Simulation Modelling*, Vol. 22, No. 3, 508-519, doi: 10.2507/IJSIMM22-3-CO13.

[7] Yildiz, İ., Saygin, A., Çolak, S. Abut, F. (2023). Development of a neural network algorithm for estimating the makespan in jobshop production scheduling, *Tehnički Vjesnik–Technical Gazette*, Vol. 30, No. 4, 1257-1264, doi: 10.17559/TV-20220818161430.

[8] Schindlerova, V., Marcik, J., Cada, R., Sajdlerova, I. (2024). Analysis of non-conforming production in an engineering company, *Tehnički Vjesnik–Technical Gazette,* Vol. 31, No. 1, 296-302, doi: 10.17559/TV-20230907000920.

[9] Kliment, M., Trebuna, P., Pekarcikova, M., Straka, M., Trojan, J., Duda, R. (2020). Production efficiency evaluation and products' quality improvement using simulation, *International Journal of Simulation Modelling*, Vol. 19, No. 3, 470-481, doi: 10.2507/IJSIMM19-3-528.

[10] Liang, S., Chen, C., Wu, D., Chen, L., Wu, Q., Gu, T.T. (2024). An ensemble learning method for the fault multi-classification of smart meters, *Tehnički Vjesnik–Technical Gazette*, Vol. 31, No. 5, 1514-1522, doi: 10.17559/TV-20230417000543.

[11] Yin, B., Wei, X., Wang, J., Xiong, N., Gu, K. (2019). An industrial dynamic skyline based similarity joins for multi-dimensional big data applications, *IEEE Transactions on Industrial Informatics*, Vol. 16, No. 4, 2520-2532, doi: 10.1109/TII.2019.2933534.

[12] Rosin, F., Forget, P., Lamouri, S., Pellerin, R. (2021). Impact of Industry 4.0 on decision-making in an operational context, *Advances in Production Engineering & Management*, Vol. 16, No. 4, 500-514, doi: 10.14743/apem2021.4.416.

[13] Jolliffe, I. (2002). Principal component analysis and factor analysis, In: *Principal component analysis. springer series in statistics,* Springer, New York, USA, 150-166, doi: 10.1007/0-387-22440-8_7.

[14] Cox, M., Cox, T. (2008). Multidimensional scaling, In: *Handbook of data visualization, Springer handbooks of computational statistics,* Springer*,* Berlin, Germany, 316-341, doi: 10.1007/978-3-540-33037-0_14.

[15] Wang, Z., Han, D., Li, M., Liu, H., Cui, M. (2022). The abnormal traffic detection scheme based on PCA and SSH, *Connection Science*, Vol. 34, No. 1, 1201-1220, doi: 10.1080/09540091.2022.2051434.

[16] Jiang, L., Jiang, H., Wang, H.H. (2020). Soft computing model using cluster-PCA in port model for throughput forecasting, *Soft Computing*, Vol. 24, No. 7, 14167-14177, doi: 10.1007/s00500-020-04786-y.

[17] Ye, M., Ji, C., Chen, H., Lei, L., Lu, H., Qian, Y. (2020). Residual deep PCA-based feature extraction for hyperspectral image classification, *Neural Computing and Applications*, Vol. 32, No. 7, 14287-14300, doi: 10.1007/s00521-019-04503-3.

[18] Dong, M., Yu, H., Zhang, L., Sui, Y., Zhao, R. (2023). A PCA-smo based hybrid classification model for predictions in precision agriculture, *Tehnički Vjesnik–Technical Gazette*, Vol. 30, No. 5, 1652-1660, doi: 10.17559/TV-20230530000682.

[19] Huber, R., Ramoser, H., Mayer, K., Penz, H., Rubik, M. (2005). Classification of coins using an eigenspace approach, *Pattern Recognition Letters*, Vol. 26, No. 1, 61-75, doi: 10.1016/j.patrec.2004.09.006.

[20] Shawe-Taylor, J., Cristianini, N. (2004). *Kernel methods for pattern analysis,* Cambridge University Press, London, UK, doi: 10.1017/CBO9780511809682.

[21] Schölkopf, B., Smola, A., Müller, K.-R. (1998). Nonlinear component analysis as a kernel eigenvalue problem, *Neural Computation*, Vol. 10, No. 5, 1299-1319, doi: 10.10.1162/089976698300017467.

[22] Kim, K.I., Jung, K., Kim, H.J. (2002). Face recognition using kernel principal component analysis, *IEEE Signal Processing Letters*, Vol. 9, No. 2, 40-42, doi: 10.1109/97.991133.

[23] Lima, A., Zen, H., Nankaku, Y., Miyajima, C., Tokuda, K., Kitamura. T. (2004). On the use of kernel PCA for feature extraction in speech recognition, *IEICE TransactionS on Information and Systems*, Vol. E87-D, No. 12, 2802-2811.

[24] Hoffmann, H. (2007). Kernel PCA for novelty detection, *Pattern Recognition*, Vol. 40, No. 3, 863-874, doi: 10.1016/j.patcog.2006.07.009.

[25] Van der Maaten, L., Hinton, G. (2008). Visualizing data using t-SNE, *Journal of Machine Learning Research*, Vol. 9, 2579-2605.

[26] Mcinnes, L., Healy, J. Saul, N., Großberger, L. (2018). UMAP: Uniform manifold approximation and projection for dimension reduction, *The Journal of Open Source Software*, Vol. 3, No. 29, Article No. 861, doi: 10.21105/joss.00861.

[27] Tenenbaum, J.B., de Silva, V., Langford, J.C. (2000). A global geometric framework for nonlinear dimensionality reduction, *Science*, Vol. 290, No. 5500, 2319-2323, doi: 10.1126/science.290.5500.2319.

[28] Halder, R., Fidkowski, K.J., Maki, K.J. (2024). An adaptive sampling algorithm for reduced-order models using isomap, *International Journal for Numerical Methods in Engineering*, Vol. 125, No. 8, Article No. e7427, doi: 10.1002/nme.7427.

[29] Lu, W., Shi, C., Fu, H., Xu, Y. (2023). Research on transformer fault diagnosis based on ISOMAP and IChOA-ISSVM, *IET Electric Power Applications*, Vol. 17, No. 6, 773-787, doi: 10.1049/elp2.12302.

[30] Li, M., Yang, J.H., Xu, J.W., Yang, D.B. (2009). Trend analysis method via manifold evolution in high dimensional space for state of machinery equipment, *Journal of Mechanical Engineering*, Vol. 45, No. 2, 213-218.

[31] Reddy, C.S., Reddy, M.R. (2024). Nonlinear difference subspace method of motor imagery EEG classification in brain-computer interface, *Digital Signal Processing*, Vol. 155, Article No. 104720, doi: 10.1016/j.dsp.2024.104720.

[32] Mohammed, M.A.A., Szabó, N.P., Szűcs, P. (2025). High-resolution characterization of complex groundwater systems using wireline logs analyzed with machine learning classifiers and isometric mapping techniques, *Modeling Earth Systems and Environment*, Vol. 11, Article No. 85, doi: 10.1007/s40808-024-02263-1.

APEM journal
Advances in Production Engineering & Management
Letnik 20 | Številka 1 | Marec 2025 | Strani 87–98
https://doi.org/10.14743/apem2025.1.529
ISSN 1854-6250
Spletna stran: apem-journal.org
Izvirni znanstveni članek

Izboljšanje kakovosti izdelkov za letalsko industrijo z metodo ISOMAP za prepoznavanje ključnih dejavnikov

Shen, D.Y.[a,b], Liu, N.Z.[a,*], Liu, W.[b], Wang, Z.[b]

[a]College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, Nanjing, P.R. China
[b]Beijing System Design Institute of the Electro-mechanic Engineering, Beijing, P.R. China

POVZETEK

Nelinearna in visoko-dimenzionalna narava dejavnikov, ki vplivajo na kakovost proizvodnje izdelkov za letalsko industrijo, predstavlja glavno težavo pri zagotavljanju kakovosti v tem sektorju. Za določitev vplivnih dejavnikov, ki vplivajo na kakovost izdelkov, je smiselno izvesti zmanjšanje dimenzionalnosti na zbranih vzorcih, preden se ti nadalje obdelajo. V tem delu je uporabljen algoritem izometričnega preslikavanja značilk (ISOMAP) s pretočnim učenjem (angl. stream learning) za izvedbo nelinearnega zmanjšanja dimenzionalnosti podatkov. To omogoča izračun korelacijskih koeficientov med glavnimi komponentami po zmanjšanju dimenzionalnosti in izvirnimi vplivnimi dejavniki, določitev njihovih povezav ter razvrstitev glavnih komponent glede na stopnjo vpliva. Eksperimentalni rezultati kažejo, da algoritem omogoča izvedbo korelacijske analize 17 dejavnikov, ki vplivajo na kakovost proizvodnje izdelkov za letalsko industrijo, ter analizo 13 glavnih dejavnikov. Med slednjimi so po padajočem vrstnem redu vpliva: ustreznost merilnih metod, ustreznost zasnove merilnih točk, obraba orodja, stopnja normaliziranosti opreme, stopnja zastarelosti opreme, ustreznost zasnove programa, stopnja napak v materialu, ustreznost zasnove tehnološke poti, ustreznost zasnove priprav, strokovna usposobljenost osebja, raven izkušenj osebja, delovno stanje osebja in standardiziranost delovanja. Algoritem ISOMAP je bil uporabljen za zmanjšanje dimenzionalnosti teh 13 dejavnikov, s čimer je bilo oblikovanih in razvrščenih šest glavnih komponent vpliva. Na ta način se odpravijo odvečni dejavniki, poudarijo glavni vplivni dejavniki in razkrijejo notranja razmerja v podatkih. Sklepi raziskave z analizo podatkov omogočajo pravočasno preprečevanje morebitnih težav s kakovostjo v proizvodnji izdelkov za letalsko industrijo. Za izboljšanje kakovosti proizvodnje izdelkov za letalsko industrijo je priporočljivo, da se kjer koli je to mogoče, uporabljajo standardizirane avtomatizirane merilne metode, poleg tega pa je priporočljivo okrepiti redno vzdrževanje obdelovalnih strojev in opreme, da se zagotovi njihovo brezhibno stanje.

PODATKI O ČLANKU

Ključne besede:
Izdelki za letalsko industrijo;
Kakovost proizvodnje;
ISOMAP;
Nelinearno zmanjšanje dimenzionalnosti;
Okvir 5M1E;
Korelacijska analiza;
Nadzor kakovosti

**Kontaktna oseba:*
liunz_tx@163.com
(Liu, N.Z.)

Zgodovina članka:
Prejet 28. oktobra 2024
Popravljen 8. aprila 2025
Sprejet 21. aprila 2025