Série dos Seminários de Acompanhamento à Pesquisa

DEI DEPARTAMENTO DE ENGENHARIA INDUSTRIAL

Número 50 | 03 2023

Artificial Intelligence in data-driven MRO inventory management in times of crisis: a real-world case study of an emerging country

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Apresentação pessoal

- Doutorando em Engenharia de Produção
- Início 2022.1 - 3º Período
- Orientadores: Luiz Felipe Scavarda e Rodrigo Caiado
- Área de concentração: Operações e Negócios em Engenharia
- Linha de pesquisa: Gestão de Operações
- Mestrado em Eng. Produção no DEI – MINTER: Transporte e Logística

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Introduction

- **Operations and Supply Chain Management (OSCM)**: has become increasingly relevant for creating value for an organization (Helo & Hao, 2022).

- The dynamic nature of today's OSCM increasingly demands smart, effective, and fast response tools

- **Industry 4.0 (I4.0) -** digital technologies have revolutionized OSCM

- **Artificial Intelligence (AI) -** its ability to learn from data and support decision making (Liu et al., 2019)

Introduction

AI in OSCM
Sharma et al. (2022)

- Supply chain network design
- Supplier selection
- Sustainable OSCM
- Demand forecasting
- Inventory planning

Introduction

AI in OSCM
Sharma et al. (2022)

Maintenance, repair, and operation (MRO) items

- Supply chain network design
- Supplier selection
- Sustainable OSCM
- Demand forecasting
- Inventory planning

Introduction

Supply chain disruptions

COVID-19 Pandemic

Digital technologies that enable supply chains to be resilient, especially in times of crisis is becoming increasingly evident (Brink et al., 2022).

There is still a dearth of empirical research exploring AI to add value to OSCM (Sharma et al., 2022)

Vidal et al. (2022) propose a framework for data-driven MRO inventory management: FAHP-VIKOR + GA-ANN

Future research:

- Analyzing the impact of COVID-19 on demand behavior
- Implementing a methodology for clustering items of similar behavior

Research question and objective

What is the impact of COVID-19 on the similarity of demand behavior for MRO items and how can combined AI methods contribute to minimizing this impact by forecasting demand in crisis periods?

To present a data-driven methodology to improve inventory management, combining time series clustering methods and hybrid AI models for demand forecasting;

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Methodology

Mixed-method

Scoping review

\+

Case study

Arksey and O'Malley (2005)

Yin (2018)

Case study - Company characterization

Brazilian railroad logistic operator

16,000 SKUs distributed among 12 storage facilities

Spare parts for maintenance

PPE and uniforms

Operation support

Locomotive maintenance
100 SKUs - highest financial consumption

Dataset - the monthly consumption of each SKU

Before COVID-19 in Brazil

26 months (Jan/18 to Feb/20)

After COVID-19 in Brazil

26 months (Mar/20 to Apr/22))

Case study - Framework

1 Time series clustering

To analyze the similarity of the monthly consumption of each SKU, before and after the pandemic

K-means clustering method
- Dynamic Time Warping (DTW) distance technique
- Elbow method

Python language

2 Demand forecast

To forecast demand for the items in each cluster. Randomly one SKU from each cluster was selected for demand prediction

Artificial neural networks with genetic algorithms (GA-ANN)
- 20 months - training and validation (80%/20%)
- 6 months – testing
- GA - optimize ANN hyperparameters

RapidMiner

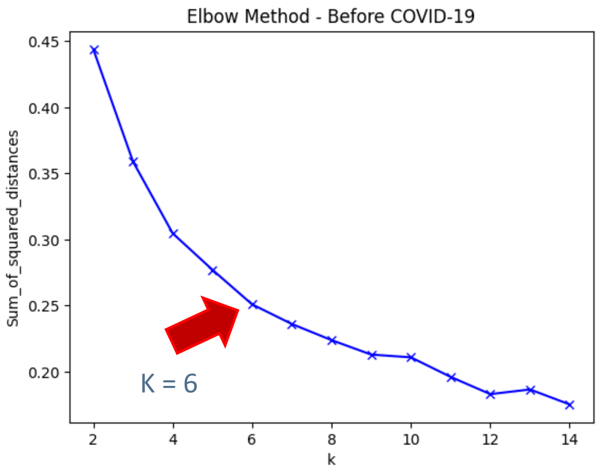
Time series clustering

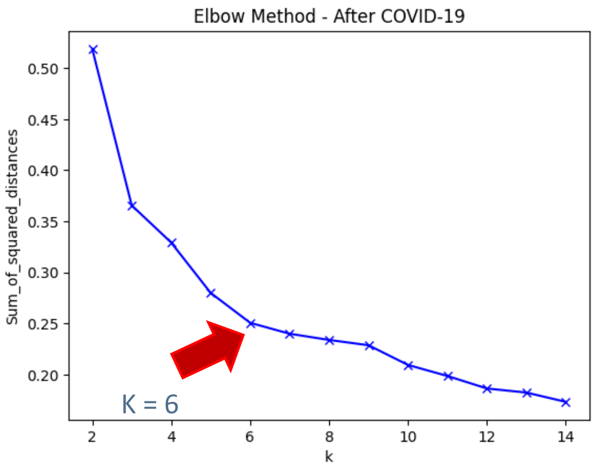
Preprocessing

Moving Average - 6 months
Smooth the demand behavior curve, eliminating outliers

MinMax Normalization
Analyze the behavior of time series over time and not their absolute numbers, putting the data in the same unit of measurement

Clusters Number: Elbow Method





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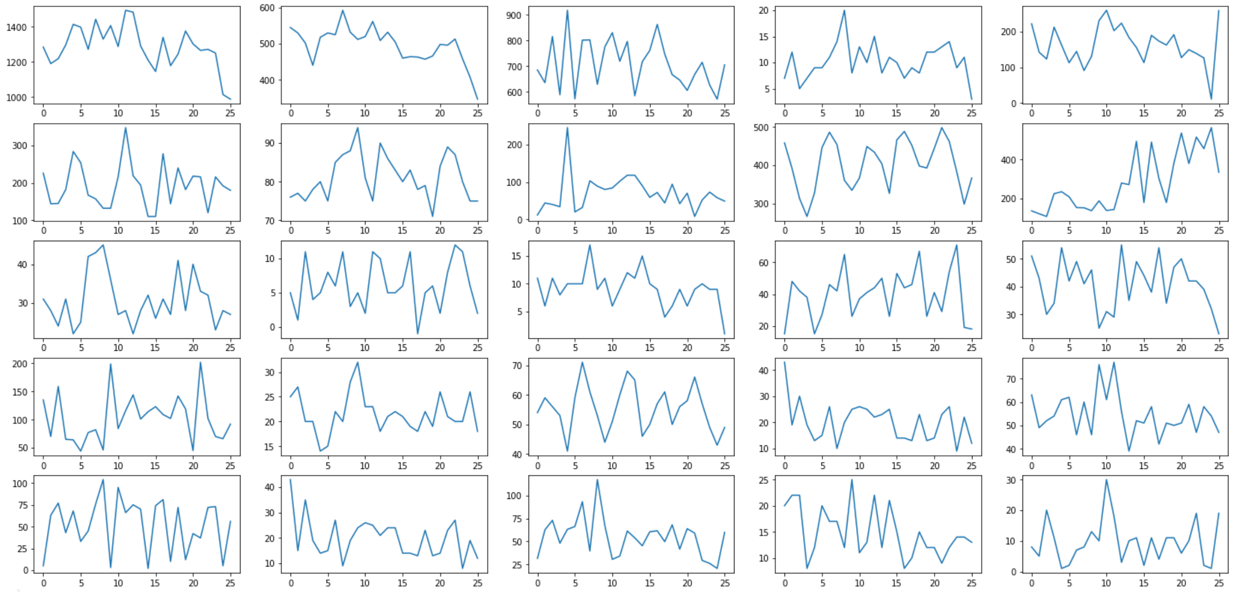
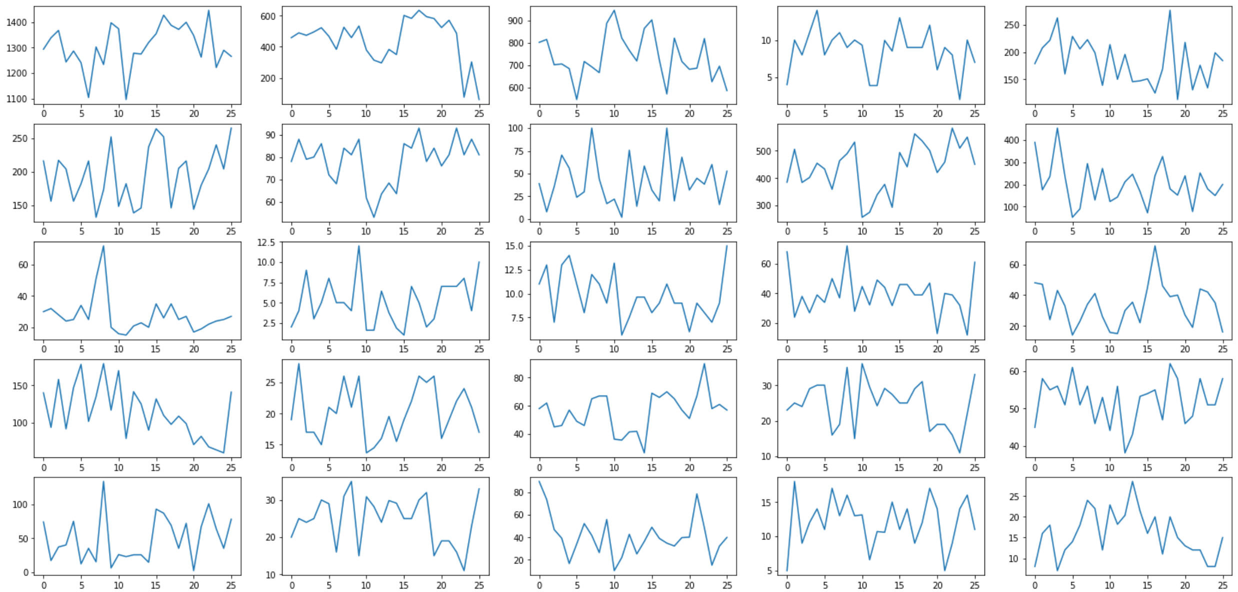
Dataset

Before COVID-19



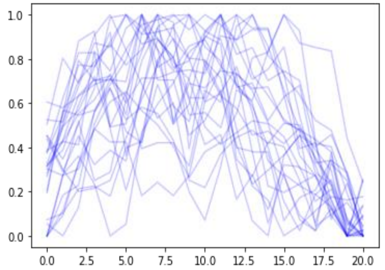
After COVID-19



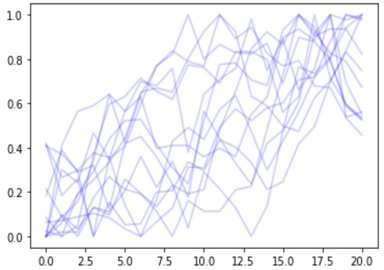
Results: Time series clustering

Before COVID-19

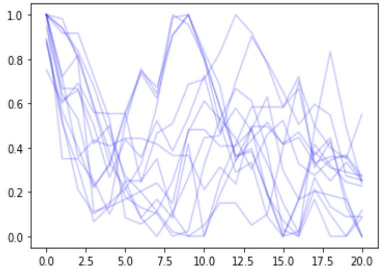
Cluster 0



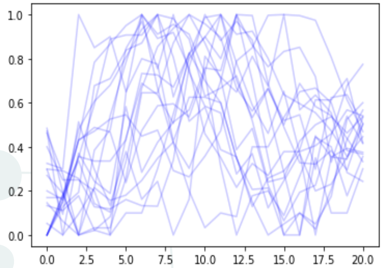
Cluster 1



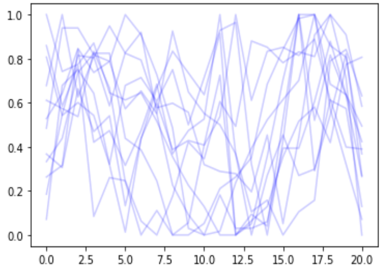
Cluster 2



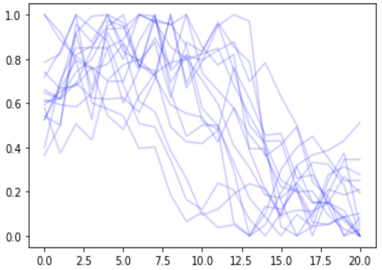
Cluster 3



Cluster 4

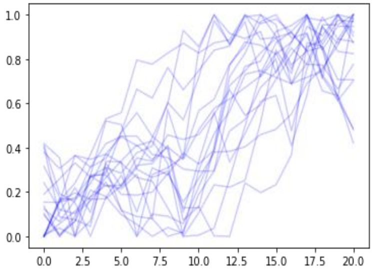


Cluster 5

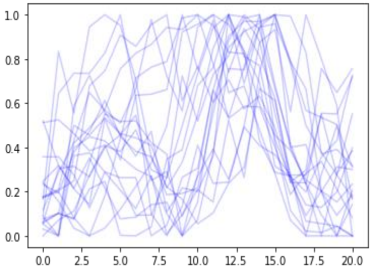


After COVID-19

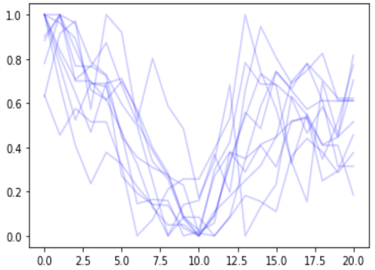
Cluster 0



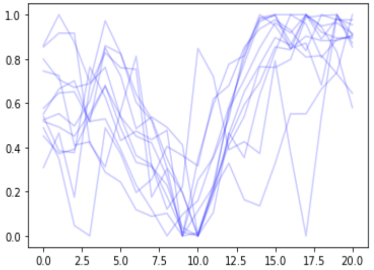
Cluster 1



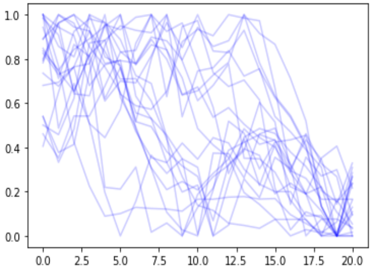
Cluster 2



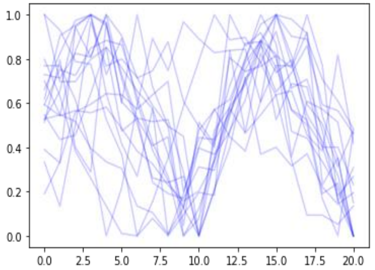
Cluster 3



Cluster 4



Cluster 5



Discussions: Time series clustering

- Only 31% of the items remained in the same cluster in both databases;
- This result makes evident how much the post-pandemic period influenced the demand for the company's MRO items;
- There were no major changes in the quantity of items in each cluster before and after COVID-19, meaning that in general the pandemic did not influence the standardization of demand.

Results: Demand forecast

Performance Measures - Validation and Test Basis

Cluster	Basis 1 - Before COVID-19		Basis 2 - After COVID-19	
	Validation	Test	Validation	Test
Cluster 0	3.4%	10.2%	3.5%	5.1%
Cluster 1	17.5%	37.6%	14.4%	30.7%
Cluster 2	2.4%	8.9%	21.3%	26.8%
Cluster 3	2.6%	12.3%	1.5%	13.3%
Cluster 4	8.3%	17.4%	5.4%	10.4%
Cluster 5	7.5%	7.2%	5.5%	9.0%

Discussions: Demand forecast

- High variability of the results, with the best result being 1.5% and the worst at 37.6%, making it evident how much this performance can vary according to the behavior of the data being predicted, varying considerably between each Cluster;

- The average results of the models before and after COVID-19 did not vary greatly, even though there was such a significant change in the clusters as identified in the previous step;

- The average MAPE for the validation base before COVID-19 was 6.9% and 8.6% after COVID-19;

- For the test base, the average MAPE evolved from 15.6% to 13.7%;

- This makes it evident how much AI methods can contribute to supply chain resilience, due to their ability to learn quickly from data, allowing conclusions to be drawn from complex problems efficiently.

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Conclusion

- The results show that the application of AI models in MRO inventory management can bring important conclusions about demand behavior and forecasting performance;
- Mainly in periods of crisis such as the COVID-19 pandemic, which has a direct impact on supply chain disruptions, especially in emerging countries that are not structured to face such situations;
- Its main practical application is in providing supply chain managers with a decision support tool for MRO inventory management, enabling them to achieve the necessary resilience in their supply chains after COVID-19.
- Suggestion for future work:
  - Use other indicators to predict the demand;
  - Replicate the prediction models for the other SKUs in each cluster.

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References

- Brink, S. van den, Kleijn, R., Sprecher, B., Mancheri, N., & Tukker, A. (2022). Resilience in the antimony supply chain. Resources, Conservation and Recycling, 186, 106586. https://doi.org/10.1016/J.RESCONREC.2022.106586
- Caiado, R. G. G., Scavarda, L. F., Gavião, L. O., Ivson, P., Nascimento, D. L. de M., & Garza-Reyes, J. A. (2021). A fuzzy rule-based industry 4.0 maturity model for operations and supply chain management. International Journal of Production Economics, 231. https://doi.org/10.1016/j.ijpe.2020.107883
- Conceiçao, S. V., Da Silva, G. L. C., Lu, D., Nunes, N. T. R., & Pedrosa, G. C. (2015). A demand classification scheme for spare part inventory model subject to stochastic demand and lead time. Production Planning and Control, 26(16), 1318–1331. https://doi.org/10.1080/09537287.2015.1033497
- Helo, P., & Hao, Y. (2022). Artificial intelligence in operations management and supply chain management: an exploratory case study. Production Planning and Control, 33(16), 1573–1590. https://doi.org/10.1080/09537287.2021.1882690
- Liu, H., Liu, Q., & Hu, Y. (2019). Combined method of artificial intelligence regression forecasting models under fluctuating errors. International Journal on Artificial Intelligence Tools, 28(5), 1–16. https://doi.org/10.1142/S0218213019500180
- Muniz, L. R., Conceição, S. V., Rodrigues, L. F., de Freitas Almeida, J. F., & Affonso, T. B. (2021). Spare parts inventory management: a new hybrid approach. International Journal of Logistics Management, 32(1), 40–67. https://doi.org/10.1108/IJLM-12-2019-0361
- Naz, F., Kumar, A., Majumdar, A., & Agrawal, R. (2022). Is artificial intelligence an enabler of supply chain resiliency post COVID-19? An exploratory state-of-the-art review for future research. Operations Management Research, 15(1–2), 378–398. https://doi.org/10.1007/s12063-021-00208-w
- Seyedghorban, Z., Tahernejad, H., Meriton, R., & Graham, G. (2020). Supply chain digitalization: past, present and future. Production Planning and Control, 31(2–3), 96–114. https://doi.org/10.1080/09537287.2019.1631461
- Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., & Munim, Z. H. (2022). The role of artificial intelligence in supply chain management: mapping the territory. International Journal of Production Research, 2022(24), 7527–7550. https://doi.org/10.1080/00207543.2022.2029611
- Vidal, G. H. de P., Caiado, R. G. G., Scavarda, L. F., Ivson, P., & Garza-Reyes, J. A. (2022). Decision support framework for inventory management combining fuzzy multicriteria methods, genetic algorithm, and artificial neural network. Computers & Industrial Engineering, 174, 108777. https://doi.org/10.1016/j.cie.2022.108777
- Wan, X., Britto, R., & Zhou, Z. (2020). International Journal of Production Economics In search of the negative relationship between product variety and inventory turnover. International Journal of Production Economics, 222, 107503. https://doi.org/10.1016/j.ijpe.2019.09.024

Questions