PROJECT

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AUGMANITY
AUGMENTED HUMANITY
PPS2

WORK

A Data-Driven Platform to Support Lean Implementation and Decision-Making under the I4.0 Paradigm

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INTRODUCTION

Thanks to the I4.0 breakthrough, these days, companies handle substantial amounts of data related to their businesses. This data, if thoughtfully explored, may provide relevant information to decision-makers for process optimisation/ improvement to increase competitiveness and overall savings. However, the rapid rise in the companies' ability to collect data, hasn't been matched by the ability to support, filter and manage it effectively to extract such information. Thus, continuous improvement people (which may start in the shop-floor engineer up to the entire lean/quality department) would greatly benefit from a data-driven platform (DDP) that is able to receive, transform and process real-time data from machines to workers and apply innovative and automatic algorithms to obtain robust first (or even second) level root cause analysis (RCA). The big purpose of such platform is to explore and make the most out of the industrial datasets gathered everyday in each company, and to provide to decision-makers helpful information about their industrial processes, where other methodologies failed to find further conclusions.

QUESTIONS AND ISSUES TO SOLVE

Q1: What are the benefits of the DDP for Continuous Improvement or Quality Assurance teams?

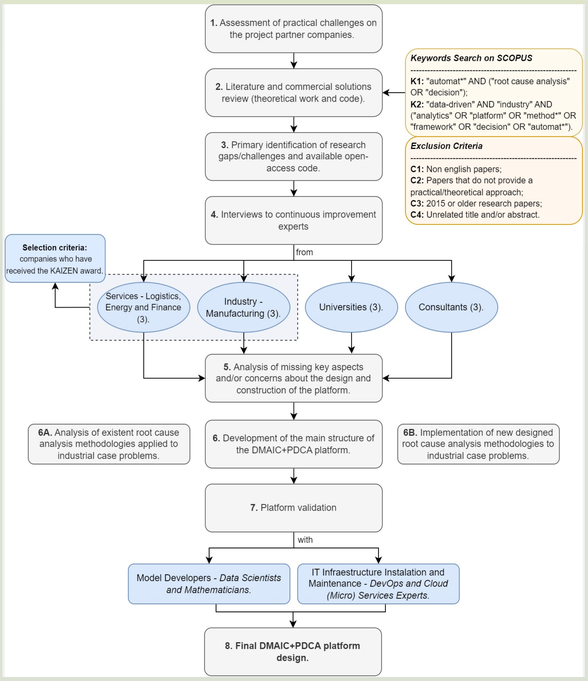
Q2: What is the skeletal structure of the DDP to maximize the integration with I4.0 technologies?

Q3: What set of (detailed) steps should it follow?

Q4: How large can be the domain of application to different industrial processes?

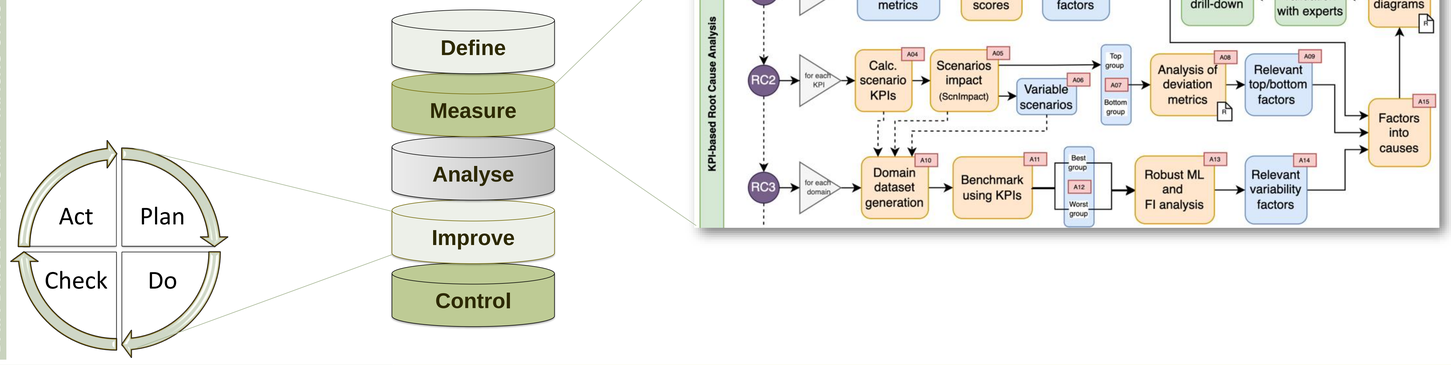
Q5: What are the minimum requirements companies must fulfil to obtain relevant results?

METHODOLOGY



SOLUTION

DATA-DRIVEN PLATFORM – MACRO STRUCTURE

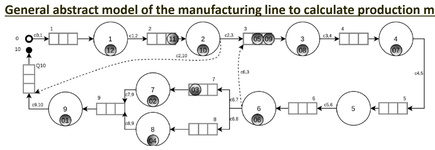


INDUSTRIAL CASE APPLICATIONS

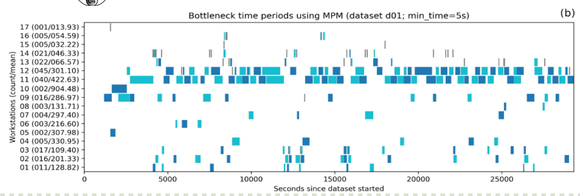
BOTTLENECK DETECTION WITH MINIMAL INFORMATION

1. A data-driven model for bottleneck detection in manufacturing lines was built based on **minimal information** retrieved from a manufacturing execution system (MES), for companies initiating their digitalization process (requiring the smallest hardware investment). A general abstract model of a production line is proposed, a Queue Directed Graph (QDG). The QDG model is able to represent any kind of job-shop with a discrete production environment and to calculate production metrics. Industrial case application in a manufacturing line at Bosch Thermotechnology.

General abstract model of the manufacturing line to calculate production metrics:



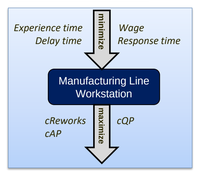
Graphical result:



ROOT CAUSE ANALYSIS OF BOTTLENECKS AND REWORKS

2. Multi-directional efficiency analysis (MEA) is used for **root cause analysis** of product reworks and bottleneck occurrence in a manufacturing line. The analysis is based on four worker-related parameters: experience time, wage, delay time and response time. The approach allows to identify individual inefficiencies per tuple worker/working shift and to cluster them according to similar inefficiency parameters. Industrial case application in a manufacturing line at Bosch Thermotechnology.

Per (worker, work shift):



Optimization problem:

Problem $P_i^e(z,\bar{n})$:
$\min \alpha_{in}(\bar{n})$ *such that*
$\sum_n \lambda_n x_{in}(n) \le \alpha_{in}(\bar{n}),$
$\sum_n \lambda_n x_i(n) \le x_i(\bar{n}),\ i \in [I],\ i \ne m,$
$\sum_n \lambda_n y_i(n) \le y_i(\bar{n}),\ i \in [J],$

Problem $P_j^f(z,\bar{n})$:
$\max \beta_j(\bar{n})$ *such that*
$\sum_n \lambda_n x_i(n) \le x_i(\bar{n}),\ i \in [I],$
$\sum_n \lambda_n y_i(n) \le \beta_j(\bar{n}),\ i \in [J],$
$\sum_n \lambda_n y_i(n) \le y_i(\bar{n}),\ i \in [J],\ i \ne j,$

Problem $P^{rl}(\alpha,\beta,z,\bar{n})$:
$\max \gamma(\bar{n})$ *such that*
$\sum_n \lambda_n x_i(n) \le x_i(\bar{n}) - \gamma(\bar{n}) x_i(\bar{n}) - \alpha_i^*(\bar{n})),\ i \in [M],$
$\sum_n \lambda_n x_i(n) \le x_i(\bar{n}),\ i \in [I] \setminus [m],$
$\sum_n \lambda_n y_i(n) \ge y_i(\bar{n}) + \gamma(\bar{n})(\beta_i^*(\bar{n}) - y_i(\bar{n})),\ i \in [L],$

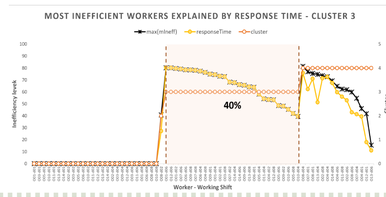
For the input $i \in [I]$ the contribution in the unit $z(\bar{n})$ is given by $\mathrm{mEff}_i(n) = \dfrac{x_i(n) - \gamma(n)(x_i(n) - \alpha_i^*(n))}{x_i(n)} \forall [DI](i).$

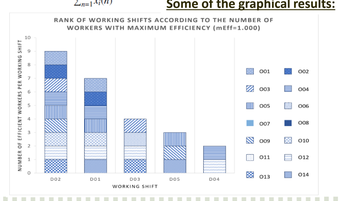
For the outputs $j \in [J]$ the contribution is given by $\mathrm{mEff}_j(n) = \dfrac{y_j(n)}{y_j(n) + \gamma(n)(\beta_j^*(n) - y_j(n))}.$

For a given dataset $z = \{z(n)\}_{n \in N}$ the inefficiency index for each given input index $i \in [I]$ and tuple $n \in N$ is given by

$$\mathrm{mIneff}_i(n) = \frac{\sum_{n=1}^{N} \gamma(n)(x_i(n) - \alpha_i^*(n))}{\sum_{n=1}^{N} x_i(n)}.$$

Some of the graphical results:





DATA-DRIVEN PDCA PROTOCOL

3. Presentation of a data-driven version of the well-known PDCA cycle for continuous improvement within a general class of problems represented by key performance indicators (KPI). Such class is wide enough to accommodate several real problems but still has a controlled level of complexity that allows defining a general data-driven protocol that covers all the (sub)steps of the cycle. A brief example of one of the steps of the protocol is given with real data from a company that adopts many of the new Industry 4.0 technologies.

Small example for Protocol's substep 9:

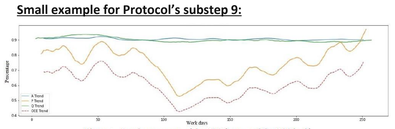


Figure 5 - Trend components of the OEE factors and the OEE itself.

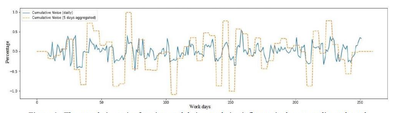


Figure 6 - The cumulative noise functions and their cumulative influence in the seasonality and trend.

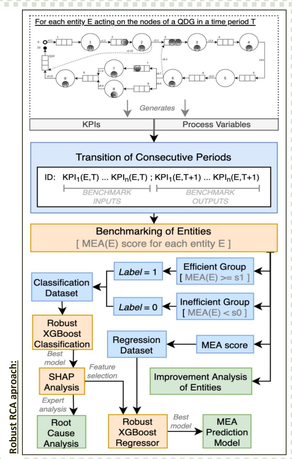
ROOT CAUSE ANALYSIS OF PERFORMANCE VARIATION

4. Presentation of a robust Root-Cause Analysis (RCA) approach to deal with classical methods' sensibility to data perturbations. It is based on: (1) Multi-directional efficiency analysis (MEA) from Operational Research; (2) eXtreme Gradient Boosting (XGBoost) from Machine Learning; (3) Shapley values (SHAP) from Game Theory.

Outcomes: Benchmarking based on performance variation, determination of most relevant process variables that explain the efficient and non-efficient benchmarks, and performance variation prediction of future work sessions. Industrial case application in a crystal and porcelain manufacturing line in Vista Alegre, Portugal.

5. Application of this RCA methodology to a very distinct manufacturing process from Bosch Termotecnologia, in Portugal, to demonstrate the approach's scalability and relevance.

Robust RCA aproach:



ABOUT THE *AUGMANITY HUMANITY PROJECT*

The Augmented Humanity (AH2020) Project is essentially based on 3 main challenges:

1. Emission reductions - improving the efficiency of industrial processes, as well as corresponding emission reductions;

2. Adequacy of production - the development and adequacy of production processes according to the characteristics of the active population;

3. Industry 4.0 - the preparation of human resources for a new industrial reality.

AH2020 – PPS2 (Product, Process and Service)

This work is framed within the PPS2 scope of Big data and predictive analytics for i4.0. The aim is to create interrelated and integrated solutions for problems, currently faced by the industry, related to predictive maintenance, data-driven asset/plant performance optimization, and data-driven quality control by taking advantage of mathematical modelling and recent machine learning techniques that have been proven to be effective in various sectors.

REFERENCES

[1] *A data-driven model with minimal information for bottleneck detection - application at Bosch Thermotechnology.* A. F. Brochado, E. M. Rocha, D. Almeida, A. de Sousa & A. Moura (2022). In International Journal of Management Science and Engineering Management. DOI: 10.1080/17509653.2022.2116121

[2] *Workers Benchmarking Using Multi-Directional Efficiency Analysis in a Manufacturing Production System*. Rocha, Eugénio M., Ângela F. Brochado, and Ana Moura (2022). Procedia Computer Science 200 (January): 1451–60.

[3] *PDCA Protocol to ensure a Data-Driven Approach for Problem-Solving*. Brochado, Ângela F., Rocha, Eugénio M., and Pimentel, Carina (2022). Proceedings of the 12th Annual International Conference on Industrial Engineering and Operations Management, Istanbul, Turkey. DOI: 10.1080/17509653.2022.2116121

[4] *Benchmarking and Prediction of Entities Performance on Manufacturing Processes through MEA, Robust XGBoost and SHAP Analysis*. E. M. Rocha, Â. F. Brochado, B. Rato and J. Meneses (2022). IEEE 27th International Conference on Emerging Technologies and Factory Automation (ETFA), 2022, pp. 1-8.

[5] *Understanding and Predicting Process Performance Variations of a Balanced Manufacturing Line at Bosch*. Brochado, Ângela F., Rocha, Eugénio M., and Pimentel, Carina. (2022): Communications in Computer and Information Science.

SUPPORT

SYSTEMS

NEXEED Bosch Manufacturing Execution System

Python EcoSystem

Business Intelligence System

SBRO INFO

SMART Business Research Observatory

SERVER: ua1m01
PROJECT ID: AH2020
WORKAREA: AH2020.PPS2
USECASE: AH2020.PPS2.U01C

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