Uporaba umetne inteligence v procesu operativnega planiranja, primer Domel

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Povzetek Predstavljamo primer dobre prakse uporabe umetne inteligence (UI) pri razporejanju delovnih nalogov v proizvodnji Domel. UI lahko predvideva prihodnjo realizacijo proizvodnih naročil in svoje napovedovalne algoritme prilagodi tako, da se bolje ujemajo s prihodnjim dejanskim stanjem proizvodnje. Hkrati se uči tudi optimalnih razporeditev in jih vključuje v oblikovanje optimalnega razporeda proizvodnih nalogov na strojih. Primer dobre prakse spada na področje uporabe novih tehnologij v proizvodnji in logistiki.

Ključne besede: proizvodnja, umetna inteligenca, planiranje, predvidevanje, razporejanje

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THE USE OF ARTIFICIAL INTELLIGENCE IN THE OPERATIONAL PLANNING PROCESS, THE CASE OF DOMEL

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Abstract We present an example of good practice of the use of artificial intelligence (AI) in the allocation of production orders in Domel production. AI can predict the future realization of production orders and adjust its predictive algorithms to better match the future actual state of production. At the same time, it also learns optimal sequences and integrates them into the design of the optimal schedule of production orders on machines. An example of good practice is related to the use of new technologies in production and logistics.

Keywords: production, artificial intelligence, planning, prediction, scheduling

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1 Introduction

We are introducing a good practice example of using AI in the production order scheduling process in Domel's production. It fits in the 6th stage of the maturity model on the path to Industry 4.0 (Figure 1). AI can predict future production order realization and it can adapt its predictive algorithms to match the future state of production (Hartley at al. 2019).

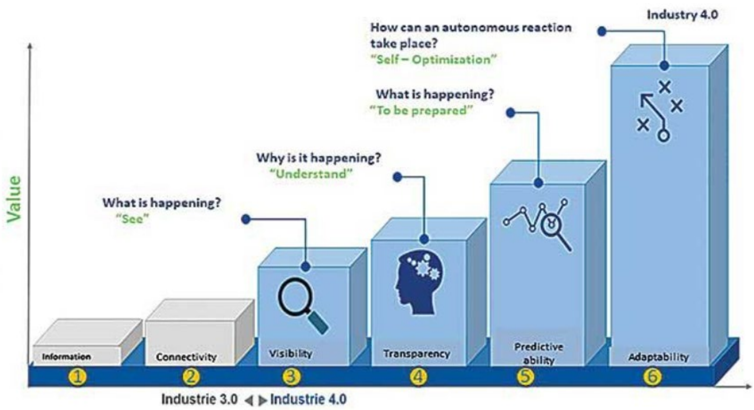

Figure 1: Stages in Industry 4.0. development path
(Source: RWTH Aachen, 2022)

Artificial intelligence (AI) is an important technology that supports the production planning process in supply chain management (Cavadid at al., 2019). Production planning aims to achieve a reliable, responsive, and flexible supply of customers at minimum cost and with high utilisation of the production resources used (Toorajipour at al. 2021).

Because of the complex and mutually exclusive objectives, there are many parameters of uncertainty in the process of operational production planning (Zang at al., 2019): what happens if the material is late, if a work tool fails, if the customer changes demand, if we receive defective materials, if our employees fall ill, if the technical documentation for a new start-of-production is late, and what will be the consequences of the uncertainty, for example, over- or under-stocking, increased labour costs, unreturned work tools.

We have many data in the business and production information systems about such events and their consequences. And where there is data, AI offers us opportunities to make better decisions based on the knowledge identified from the data (Tao at al., 2019). That allows the production planning process to be less sensitive (more robust) to unfavourable events of business.

2 The Context of AI in the system of production planning

The consistency and efficiency of internal supply chain in manufacturing company depends on the production planning function, which maintains the balance between demand, production and supplied materials (Jakobs at al., 2018). Due to the difference between the required delivery times to customers, which are usually much shorter than the time required to transform material into finished product or to deliver the materials from the supplier to the manufacturing company, the planning function mainly operates in an environment of unreliable data (Brown, 2020).

Another variable is the reaction time needed to adjust material and production resources to changing demands. Many resources can be adjusted relatively quickly, e.g., the allocation of work to an additional existing machine, while other resources have a long adjustment time, e.g., the integration and training of new workers.

Therefore, the classical model of hierarchical planning for manufacturing companies (Günther, 2005) contains a variety of methods and techniques, which differ depending on the object of planning and the length of the planning horizon. The hierarchical levels of planning (Figure 2) use more or less aggregated data from the past (business statistics), data about the current situation and data about future requirements. A thicker arrow means more aggregated data.

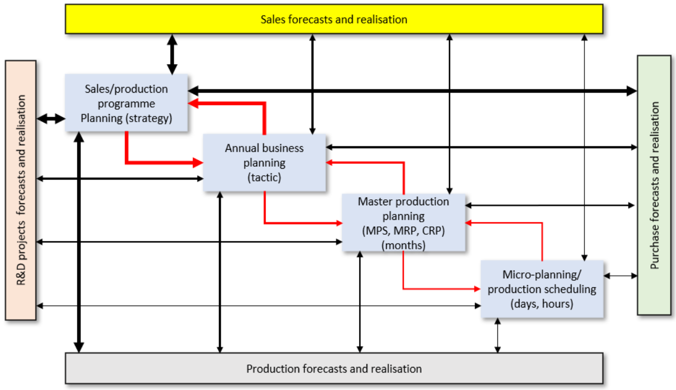

Figure 2: Simplified classical hierarchical production planning process
(Source: Roblek, 2022)

The focus of good practice example is on micro-planning. Micro-planning or production scheduling process is the lowest hierarchical level of planning in manufacturing firms. By checking the material supplied (and variances), the production already realized (and variances), the sales demand already covered (and variances), and the testing of new products (and variances), the cost-effective production is controlled with the sequence of production orders that is optimal and materially covered in a given time, both from the production floor view (maximum efficiency) and the entire internal chain view (low inventories, few delays).

In principle, we can say that in the micro-planning process a wrong decision has relatively little consequence, but a single delay in the arrival of one material by few days means playing out *n* possible new schedules to enable production to achieve the target production efficiency. This topic of planning in manufacturing firms is part of Advanced Planning and Scheduling information systems (APS).

3 Using the method of business process re-engineering

3.1 As-Is process

Following the existing procedure to improve planning process, we had to define the most accurate production master data in ERP, based on which our ERP roughly scheduled the production orders to order the necessary materials. Then, the data was transferred to the APS, where advanced algorithms determined the optimal work schedule in the production at the micro level. In the next step, manufacturing execution system (MES) used this schedule as a desired sequence of production orders. Then, the workers approximately followed the proposed schedule due to various real-life events that were not included in the ERP master data. Then, the actual data was returned from MES to the ERP system, where the analysts identified the reasons of the main variances between ERP and actual data and, if necessary, the planner corrected the master data in the ERP system for a more accurate calculation of plan in the future repetitions of micro-planning process. Anomaly: the master data in the ERP is basically the data used for a price calculation ("sold" to the customer). So, it was necessary for technologists to additionally create adjusted versions of master data intended for APS system only to plan more realistic schedules.

3.1 To-Be process

Conceptually, AI can be considered the most advanced technology integrated in the APS systems. It also replaces the role of data stored in ERP systems. With the use of AI, the importance of accurate master data in ERP for planning purposes to match the current capability of the production process is decreasing. Master data is still recorded in the ERP and "sold" to the customer via target labour and material costs. These are targets values that are not met usually at the start-of-production (SOP) phase of production. APS system equipped with AI technology has no data for the first production iteration (trial batch). It takes the master data from the ERP system. After first few production runs, APS with AI uses actual MES data and starts with the preparation of its own "master" data. Then it activates the learning process and considers the impact of extraordinary events, outages, etc. With the new iteration of planning process, AI creates a plan based on the adjusted master data, and it considers a mass of other relevant factors from the MES statistics. The micro-production plans are much more realistic.

4 Case study: Domel

4.1 AI solution user

The case is based on a large Slovenian company Domel (Domel, 2023) with a wide product range: from end-user products to products intended as assemblies for integration into complex products. Domel is a development supplier of sophisticated electric motor drive solutions and components based on its innovative technologies. The company has several production facilities in Slovenia and abroad. It is a dominant player in international global supply chains, with customers across the globe.

4.2 AI solution provider

Qlector (Qlector, 2022) is developing artificial intelligence-based solutions for manufacturing, logistics and other industries powered by Qlector LEAP AI Platform. Several team members pursue active research and help with mentoring of PhD students working on novel methods from different areas of AI. The team members published original research articles from the areas of machine learning, data mining, text mining, information retrieval, network analysis and the semantic web.

4.3 Project of implementing AI

In 2019, the company Domel was started with its business strategy for 2020 to 2025, and it identified the digitalisation of processes as one of its strategic activities (SA). Then it started with the mapping of its processes and interrelationships to ensure the coverage of all end-to-end (E2E) main and related processes.

The company then identified 440 pain points across all processes, from business to manufacturing; these challenges were preventing the company from achieving the planned business results set for 2025. Then it recognized 33 projects in different areas and aggregated them according to their common characteristics into 10 coherent digitalisation projects for the foreseen period.

Following the presented process, 10% of the identified process pain points referred to the requirement "A balanced production schedule (fewer order delays, higher capacity utilisation, more even capacity utilisation, with fewer changeover times, lower semi-finished inventories) is obtained in real time". The business addressed response with the project "Deployment of artificial intelligence to predict and build optimal production schedules". The first pre-project activities involved detailed mapping of operational planning and production processes, defining platform and integration requirements (to the Domel ERP, MES), researching the maturity of available AI solutions and providers on the market, and carrying out control calculations of the investment.

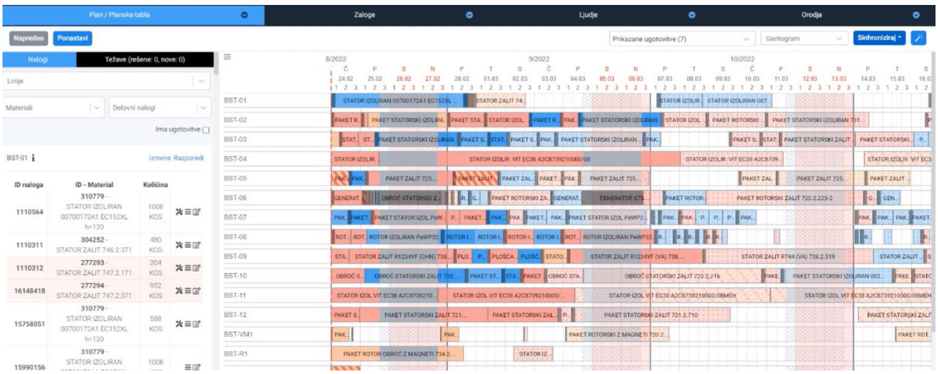

Figure 3: AI Leap computer interface for the planner
(Source: Roblek, 2022)

Then Domel activated a project of implementing AI Leap (Figure 3) on the pilot production site, with activities: Integration of AI solution (3 months), the learning phase of AI and validation (6 months), functional testing on the "beta" system and customization of Domel special requirements (3 months), and “Go live” (planning with Leap, creating user-friendly interfaces).

4.4 AI solution Leap

The operational planner uses the AI solution Leap in the process of production scheduling. The AI helps planners:

- To consider uncertainties in the data ("stars" in figure 4) when developing (predicting) realistic production schedules (automation of production prediction),
- To propose an optimal solution for production schedule, not the first possible solution (automation of optimal scheduling),
- To automatically check routine controls (RPA – robot process automation) like material coverage, and customers' due dates, when developing/simulating different sequences of production orders.

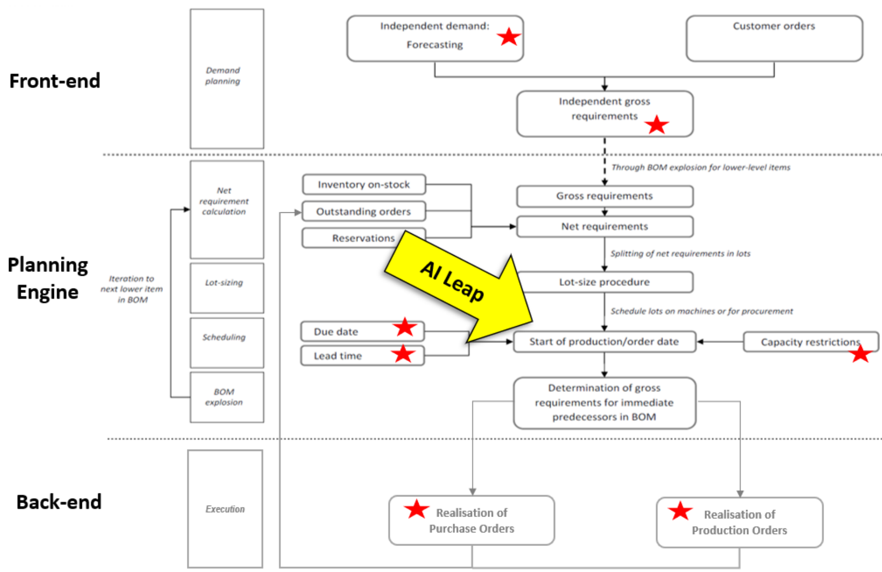

Figure 4: The process of production planning with AI Leap

5 Results

Too little time (September 2022) has elapsed since the implementation of AI technology in Domel to be able to exclude the effects of the implementation phase or the impact of the transition to the new planning process from the interpretation of measurements. We are currently seeing (not yet statistically significant):

- Improved production capacity utilisation and reliability of supply,
- Increased production productivity and lower production costs,

- Faster adaptability of production to last minute changes,
- Improving the use of productive resources and market opportunities,
- Improved resilience on uncertainties and disturbances,
- Reduction of production planning costs and delivery times,
- Increased competitive advantage.
-

Table 1: The conditions needed for the practice to be successful

Conditions to be resolved before implementing AI	
Strategic planning	Choose a systematic approach that precisely addresses the achievement of the desired objectives in the company and in the planning process itself, Choose an AI solution that fits the characteristics of your production and operational planning process. Evaluate solution on KPIs that measure improvement of the planning process (not KPIs for the selection of the most advanced AI technology), Make an agreement with the solution provider where the payments are linked to direct and indirect benefits.
Information infrastructure	Ensure stable hardware and network infrastructure at the shop floor level before deployment.
Compatibility of information systems	Ensure full vertical and horizontal integration and compatibility between all existing IS used in the planning and execution processes, Select an AI solution on a platform that is compatible with ERP and MES.
Conditions to be resolved during AI implementation	
Data availability	Ensure access to a large amount of production traffic data from the production process. Ensure that data of the current situation at the execution level are accurate.
Data management	Remove users from the creation of production traffic data (avoid creating data manually).

5.1 Measurement of AI success in production scheduling process

Area of Artificial Intelligence - KPIs:

- Accuracy in predicting production times,
- Accuracy of forecasting free capacity,
- Accuracy of predicting delays,
- Accuracy of intermediate stocks predictions.

Area of creating optimal schedule - KPIs:

- Schedule with fewer order delays: Leap vs planner,
- Schedule with higher machine utilisation: Leap vs planner,
- Schedule with a more even daily machine utilisation: Leap vs planner,
- Schedule with fewer changeover times: Leap vs planner,
- Schedule with lower stocks of semi-finished/finished products: Leap vs planner.

6 Conclusions

The expected impact (long-term influence) on the production planning process is a 50% reduction of today's planner's work by 2025. Planners will be freed from routine work, with more focus on knowledge-intensive challenges that AI cannot solve, like analysing poor AI predictions and scenario selection (AI mentoring).

The company can encounter the following challenges in applying the AI solution:

- Functional challenges in the simulation of optimal schedules identified and solved e.g., added functionality of saving of parameters/constraints configurations to run simulations in named groups: configuration for basic optimisation, configuration for optimisation under special circumstances,
- Challenges from hidden technical and software bugs, e.g., Incomplete data transfer from APS to ERP and vice versa, or failure of the connection between ERP, APS with AI and MES,

- Human errors, e.g., Planner mistakenly reassigns "all" production orders (outside AI planning horizon) and saving in ERP,
- Conflict situations within the APS with AI, e.g., multiple planners simultaneously schedule tasks and save the result. The danger is that they change each other's plan, especially when optimising internal workshops separately.

From the change management view, it is best to involve planners and production managers at the start of the project to build their confidence in the quality of the automated schedules and the new role of AI. It is important to detail the planning process, its specifics, and the strategic and operational objectives before the implementation project. It is also important to present the current quality of the available data and the level of automation of the data capture from the production process to potential solution providers before the project begins.

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