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Metals Production Management 4.0

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Summary

At the age of Industry 4.0 and complex supply chain ecosystems, Production Management Systems (PMS) face a double challenge: first, they need to be re-designed to address increasing requirements for supply chain flexibility and resilience: business process flows and manufacturing strategies need to be more adaptive than ever, and this translates to the production management system. Second, they must incorporate technological developments that came along with the Fourth Industrial Revolution, including dedicated Artificial Intelligence (AI) and data science services, in order to leverage the added value lying in Big Data and support digitally driven manufacturing and quality control processes. Yet, to support such capabilities, production management systems must allow metals producers to model their business processes in workflows and integrate plug-and-play services. They demand collaboration between independent solutions, real-time visibility through embedded analytics, business logic configurability and the possibility of scope extensions via low-code approach. All of these need to be supported by automated deployments, regardless if it is on premise or in the cloud, and seamless upgrades ensuring minimal downtime during upgrade processes. This paper explores the IT infrastructure and business process management functions that a Metals Production Management System 4.0 must provide to support and leverage the promises of the Fourth Industrial Revolution.

Key Words: Industry 4.0; Production Management Systems; Artificial Intelligence; Adaptive Business Flows; Automated Deployment

Introduction

Fast developing trends like the rise of connectivity, data analytics and AI-supported human-machine collaboration are gaining increasing attention and application in the metals industry, from Supply Chain Management to Manufacturing Planning and Execution up to Quality Control. The advantages (and challenges) of service integration inside such a wide ecosystem are presented with few examples, highlighting the crucial role of the PMS software framework to guarantee efficiency and gain value.

From Advanced Planning and Scheduling to Smart Adaptive Supply Chains

Material flow in metals supply chains is being optimized for decades through Advanced Planning & Scheduling (APS) systems. Yet, as illustrated in Figure 1, metals supply chains are facing increasingly complex and volatile ecosystem conditions, resulting among others in less predictable demand patterns and the need to reduce lead times, while maintaining inventories under control, in order to build additional responsiveness. Promoting the speed of both material and information flow is paramount in that respect.

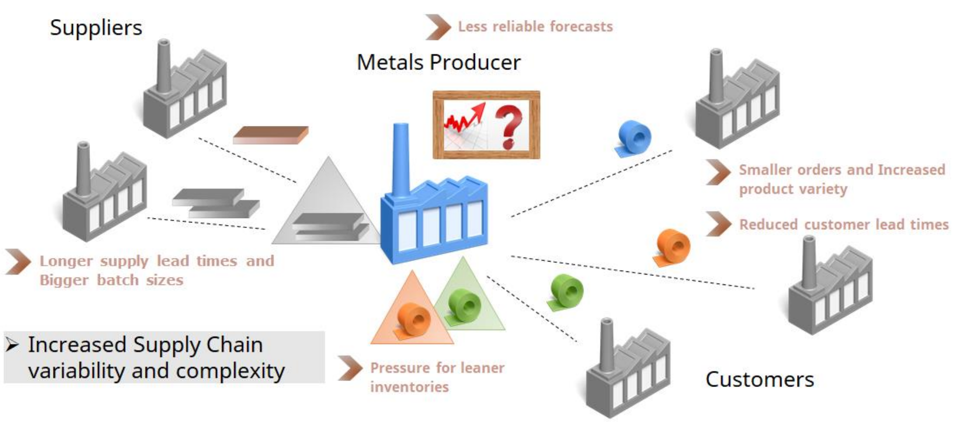

Figure 1: The increasingly volatile and complex ecosystem of metals supply chains

Besides structural supply chain redesign to increase its resilience and flexibility, e.g. through the establishment of decoupling stock buffers, and the adoption of new or hybrid manufacturing strategies, e.g. combining both make-to-stock and make-to-order, one critical element in reducing material flow disruptions is to provide real time visibility to events across the end-to-end supply chain. A second key element is the ability to react as fast and as best as possible.

In other words, supply chains need to increase their levels of transparency and smartness. This is respectively made possible through the digitalization of the end-to-end supply chain and the leveraging of data analytics and business intelligence, both enabled through the availability of new sensing and networking technologies, advances in data science and extended computing power, which came along with the Fourth Industrial Revolution.

Of particular interest is the increasing possibility of close collaboration between human agents, e.g. a scheduler or a yard operator, and smart autonomous agents, as illustrated in Figure 2. These are small pieces of software focused on a very specific set of problems – e.g. checking material availability for a transport order, or adjusting a pre-released schedule – and which can make independent local decisions and notify human agents or even other smart agents working together to solve larger problems by communicating together in “Multi-Agent Systems” (MAS). As mentioned previously, such agents can be incorporated as part of business process workflows and can also be enhanced through AI in order to detect changes in their environment, learn from the impact of decisions and adapt their behavior correspondingly.

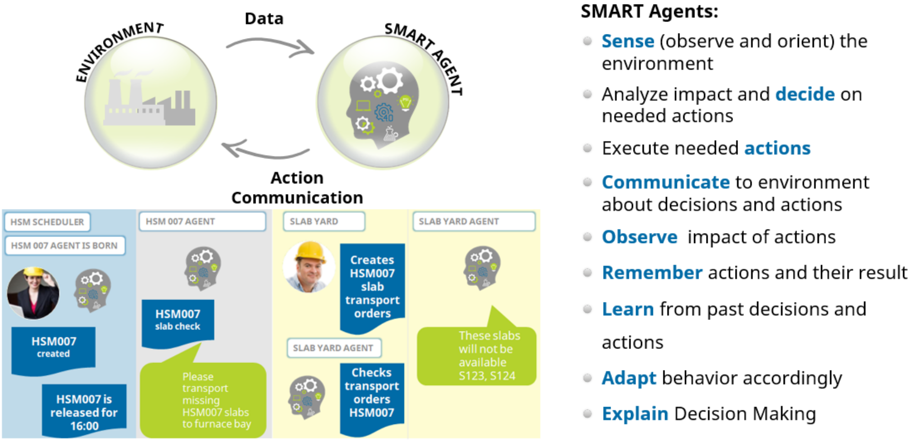

Figure 2: The increasingly volatile and complex ecosystem of metals supply chains

From automation to AI-enhanced quality control

Automation is the foundation of Industry 4.0. In an automatized manufacturing framework, a big amount of data is generated, collected, exchanged and enriched, also across several production lines or sites.

This data can be considered as an ever-increasing, “raw” source of knowledge about the production process. To leverage the potential hidden in the data and harvest additional knowledge, the principle of complementarity applies: the relationship between technology and human creativity enhance the value of each other [1].

Artificial Intelligence (AI), and Machine Learning (ML) in particular, is here the technology of choice. Thanks to increased computational power, Machine Learning algorithms can elaborate big amount of data at rapid rate and discover various types of correlations and insights without being specially trained within a specific business domain.

To enable the complementary interaction with human knowledge, so-called Explainable Artificial Intelligence (XAI) or White-Box AI has emerged in the past years. XAI aims at offering ML models that provide an explanation for their results to domain experts in the application area. As illustrated in Figure 3, an explainable model results by the interaction between different areas of expertise that correspond also to the interaction between different entities: the ML technology, the data scientist and the domain expert. In practical contexts, the results obtained by a White-Box ML model are made visually accessible and “explainable” using features issued by the domain experts, which are therefore easier to understand by the same experts than other type of feature representation, which are transformations of input data [2].

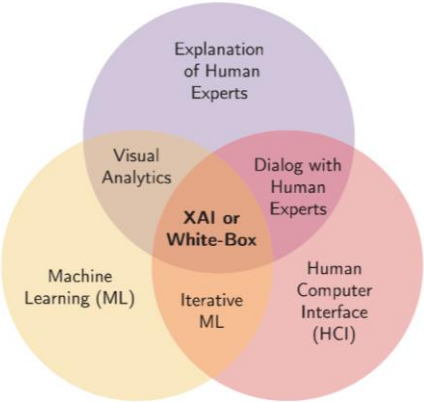

Figure 3: A graphic illustrating the interaction of the different areas forming the XAI model [2]

This way, the domain experts can interact ("converse") with the data scientists on a common ground and support them in the iterative process of training and improving the model's predictive performance. This human interaction has to be considered crucial in order to obtain sound models that deserve the trust of the domain experts whose work is expected to be supported by the ML models. Trustworthy models can be deployed as a service for the Quality Management System (QMS) with the aim of making old and new knowledge systematically ("24/7") operational.

One of the most promising application of ML models in Quality Management is their integration into Reactive Quality Control at the utmost early stage. A Machine Learning model can be trained on historical data featuring quality characteristics to be controlled and process data along the entire production route that might be relevant for the characteristics' outcome.
If after training and validation the model reaches a trustworthy ability to predict quality characteristics or the risk of their deviation from a desired outcome, the model can be deployed for operational quality control of semi-finished products. To perform the prediction at an intermediate production stage, the model will be fed with as-is process data for the upstream production steps and with expected process data for the pending downstream production steps. The "expected" data can be often derived from the process instructions contained in the original Production Order as setting values for the Level 2 automation (so called PDI, Process Data Input).

For example, the model for predicting tensile strength of a cold rolled micro-alloyed galvanized coil might require the Chemical Composition and data from the Hot Rolling step as well as data from the Cold Rolling, Annealing and Temper Rolling.
A prediction that is performed after Hot Rolling of a specific slab will then use the collected as-is data of its chemical composition and hot rolling process and derive from the production order the downstream data, assuming that the downstream production steps will fulfill the instructions (the "recipe") described in the Production Order.

After each production step, the prediction provides a measure of the risk of a deviation in the final quality characteristics. The risk might be a consequence of a clear deviation in the upstream process or even of an “unfortunate” combination of parameters that otherwise fulfill the requirements defined for them singularly. Referring to the example above, a “rather high” coiling temperature might pose a risk if combined with a “rather soft” chemical composition, even if no single parameter is violating its own target range.

In case of high-risk prediction, a prescriptive ML model can be used to react: in form of an optimization of the downstream production parameters in order to counterbalance the “unfortunate” situation detected or the recommendation of additional actions, from re-work until de-allocation.
Referring to the example of the cold rolled galvanized coil, the instruction might affect the Annealing Temperature or the Skin Pass Reduction. Figure 4 visually summarizes the described predictive and prescriptive Quality Control loop.

Figure 4: Schematic of Predictive and Prescriptive Quality Control using ML models

While the creation of trustful ML predictive and prescriptive models is the result of the collaboration of data scientist using XAI with domain experts, making the models operational (and so leveraging their potential in an industrial environment) is the task of a modern Quality Management System. The QMS 4.0 infrastructure has to

- Interface the ML models and trigger them at configurable production steps
- Deliver correct and reliable input data to the ML models
- Provide the evaluation of the Prediction
- Trigger the Prescription ML model and evaluate its response
- Update the Production Order instructions with the Prescription (in terms of process settings and possibly production route) for single material units
- Interface Scheduling in order to avoid conflicts due to the Prescription

It is apparent, that a high degree of collaboration matched with the openness to external solution is required, along with a high degree of configurability and real-time (but also historical) visibility of the adaptions performed by the predictive-prescriptive Quality Control.

The building blocks of Production Management System 4.0 (PMS)

Every business has unique requirements that may not be fully met by a standard PMS. To address this, a configurable PMS that can be tailored to meet the specific needs of a business is necessary.

Business workflows are an effective way to configure a PMS without the need to alter its source code. They enable the division of complex tasks into modules where each module is designed to perform a specific function and can be combined with other modules to form a larger and complex workflow. By dividing tasks into smaller modules, it becomes easier to manage and modify the system, as the business needs change. Users can accomplish a wide range of functions within the PMS with the help of business workflows. The following example explains it well.

It is highly probable that a standard workflow in a product needs some adjustments. The needs could vary from adding a new task, modifying the parameters of an existing task to cover more conditions, adding a human task in the process etc. To accommodate such on-the-go modification of a workflow, a modeling tool can be utilized.

Use case: escalation handling during Order Promising

Let us take a closer look at the order promising process as supported by a dedicated Due Date Quoting (DDQ) planning engine, as illustrated in Figure 5. DDQ is a system that helps provide reliable due date quotes to incoming orders considering various factors such as production capacity, order volume, possible production routes etc.

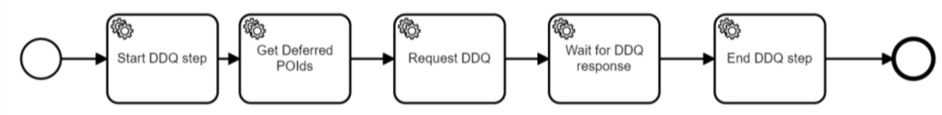

Figure 5: DDQ Business process modelling

The process typically runs as an automated background service, yet there could be scenarios where a human intervention is required in the process, e.g. for escalation handling. The business workflow illustrated in Figure 6 below depicts how a user task can be added in an existing workflow to accommodate above scenarios.

The newly added human task can be monitored in the Admin Console (Figure 7). Business process modeling not only promotes machine-to-machine interaction but also machine to human interaction as seen here.

Business workflows not only make our complex, business processes convenient but also empowers the end-users by offering them the flexibility to modify things with a low code approach.

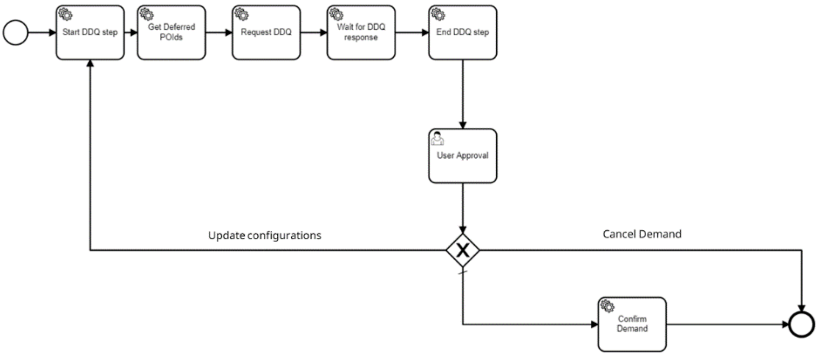

Figure 6: DDQ Business process modelling with added user task

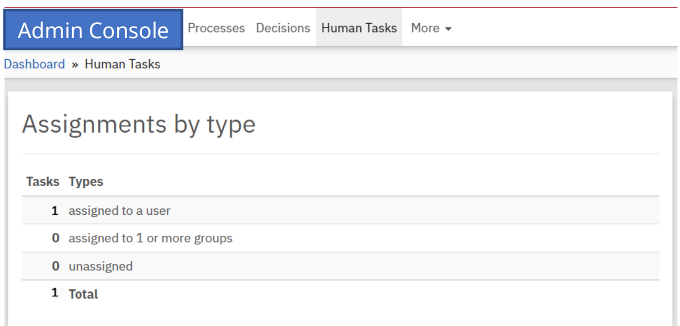

Figure 7: User tasks displayed in the Admin console

Plug & Play Integration

As described above, another requirement of a modern PMS is the capability to integrate with Third Party's applications at customer's end, at best is an effortless "Plug & Play" mode. The applications can register themselves on a so-called "Service Bus" provided by the PMS framework in order to transfer the business data without the need of building direct connections between each application (external and internal). Such a framework shall support cases like:

- An application is interested in just consuming events from a PMS. For example, a label printing service for material just wants to get information about material. Or a ML model wants to generate a prediction based on process data about a material. Such a third party application understands the data model of the PMS, provides the right authorization to listen to the event, and maps the input data to their own data model as desired.
- An application is interested in publishing the events back to the PMS. The application has to publish an event that is understandable by the receiving system. The application needs to know what events are read and consumed so that the events sent are appropriately received and processed by the PMS. For example a prescriptive ML model sending a suggestion for PDIs.

The "Service Bus" is the central hub to learn about all registered applications and offers standardized transport mechanism to connect them with a defined protocol.

Applications that do not follow this protocol originally can be connected via an adapter.

Extending the PMS

In addition to the above modifications, there could be the need to extend a standard PMS. Since it is not easy to implement all the possible business use cases in a standard component, a framework should provide well-defined access points to extend the solution based on project needs. The framework of a PSM 4.0 offers the support for Extensions, allowing system integrators to enhance the scope of a solution according to their needs.
The extensions can be implemented as Static or Dynamic Extensions, giving system users the capability to add project specific requirements either by programming or adding customized attributes at the run-time.

Looking at the future

Production Management Systems are very complex especially when they cover planning, production, quality and logistics. Critical considerations in delivering and maintaining a successful PMS solution comprise among others adequate support during deployment to address the dependencies that only an expert would know about, accommodation of software upgrades in the production environment and no compromise to security.

A disruptive way of delivering a PMS solution is self-service approach. The aim here is to containerize standalone applications or services, deliver them via a secure channel over the internet (an “AppStore”) along with the installation instructions and support the deployment of the containerized applications using Kubernetes. After download and installation of the updated container with improved features, the system detects the new container with an updated version and the service requests will automatically be directed to the updated container.
At its best, shop floor users will be abler to upgrade the applications “on the go” with zero or minimal downtime. This also supports the interworking between two applications, independently from their deployment on premise or in the cloud.

Conclusion

PMS 4.0 has the potential to transform the way production is designed and executed. With the above presented developments, the metals industry can already look forward to low-code configurability via business workflows, extensibility of the system to accommodate smart new services, secure and faster delivery complimented by automated standard installations and minimal downtime upgrades.

References

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