Predictive ERP

White Paper

INTELLIGENT ENTERPRISE OPERATIONS MANAGEMENT

PREDICTIVE ERP – The Enterprise Operations AI Platform presents itself as the brain and heart of the Industry 4.0.

EXECUTIVE SUMMARY

The I4.0 paradigms can lead to improvements in efficiency and in customer satisfaction. However, taking advantage from IoT technologies, AI algorithms and Information Systems through all the company levels is a big challenge. Notably, trying to coordinate distinct backbone systems to deal with different types of data and optimize the decision making is a complex task. In this document, we introduced the Enterprise Operations AI Platform, which helps to manage such complexity and accelerates the transformation to adopt I4.0 paradigms. By integrating the three major information layers (the Smart Factory, the Digital Thread and the Value Chain Management) to orchestrate the company operations, the Enterprise Operations AI Platform presents itself as the **brain and heart of the I4.0**.
This Enterprise Operations AI Platform is represented by the Predictive ERP, a solution meant to intelligently control and execute the PLM, MES and ERP systems. To create a model of the company and adapt to a dynamic environment, the Predictive ERP uses both Parametric Simulation models, which are based on a PPR approach and Predictive Analytics models, based on Machine Learning. This allows the Predictive ERP to respond to unexpected events, disruptive changes and new operations.
Finally, we show how the Predictive ERP can deal with volume, velocity, veracity and variety in data, to generate added value. Particularly, two elements are to be highlighted: firstly, the cloud computing and AI services provided by Azure will help to deal with data velocity, volume and veracity. Secondly, the Predictive ERP capabilities allow it to integrate data from different sources, which tackles the variety challenge in big data.

BACKGROUND ON INTELLIGENT ENTERPRISE OPERATIONS MANAGEMENT

Manufacturing is getting smarter: sensors, wireless technologies and intelligent algorithms are transforming it (Kusiak, 2017). In this transformation, data is the key enabler as it contains the knowledge to improve production processes and trains Artificial Intelligence (AI) algorithms. For instance, studies estimate that by 2020, there will be between 25 to 50 billion connected devices, generating data in the range of exabytes (Mahdavinejad et al., 2018; Tiwari, Wee, & Daryanto, 2018). Data has even been compared to oil in terms of value (The Economist, 2017). Research has shown that 82% of the companies using technologies related to the Industry 4.0 (I4.0) had improved their efficiency. Additionally, 45% of the companies have identified an improvement of the customer satisfaction (Wang, Ma, Zhang, Gao, & Wu, 2018). Despite all the benefits, most of the companies do not know what to do with their data and they are far from fully extract knowledge from it to improve their products and processes (Kusiak, 2017). This is mainly caused by limitations such as issues when collecting data from heterogeneous sources, lack of scalability in terms of storage and data management and problems to link the physical and digital world (Tao, Qi, Liu, & Kusiak, 2018).

This article aims to explain a brand-new solution:
The Predictive ERP. Its role is to intelligently perform operations management at all the levels of the company under the context of the I4.0. Furthermore, its objective is to fill the previously mentioned gaps in order to fully benefit from I4.0 data and technologies. Before addressing the Predictive ERP, it is important to settle some background concerning the I4.0. At the beginning in 2011, it was difficult to identify which system was the **heart** of the I4.0. It was mostly a competition between what we call the company **backbone systems** to take the lead: The Product Lifecycle Management (PLM), Enterprise Resource Planning (ERP) and the Manufacturing Execution System (MES). There were no constructive relationships between these backbone systems. Nonetheless, trends in the I4.0 paradigm propose that to take advantage of data in order to manage the company's operations, there should be a unique system. Such unique system would be the **brain and heart** of the company's operations, managing them to have in-time delivery, better quality and minimal cost. AI techniques embedded in systems could provide a way to create that unique system. From this point, we will define this system as the Enterprise

Operations AI Platform. Also, to guide our discussions, this article will be guided by four main questions related to the Enterprise Operations AI Platform:

- **What is the essence of an Enterprise Operations AI Platform?**
- **Which are the necessary steps to achieve such a system?**
- **Which is the role of AI in the Enterprise Operations AI Platform?**
- **Which are the capabilities of the Enterprise Operations AI Platform?**

The remainder of this document will try to answer the aforementioned questions. The first question will define the concept of Enterprise Operations AI Platform as well as information layers. The second question will deal with the requirements to implement such system and will explain its functioning. The third question will give further detail about the functioning of the system in order to justify the use of AI. The fourth question will explain how the Enterprise Operations AI Platform is able to tackle the challenges proposed by modern Big Data in manufacturing.

SHAPING THE FUTURE OF MANUFACTURING: ANSWERING QUESTIONS ABOUT THE ENTERPRISE OPERATIONS AI PLATFORM

► What is the essence of an Enterprise Operations AI Platform?

According to Leiva (2018), I4.0 has three major information layers: The Smart Factory, the Digital Thread and the Value Chain Management. These layers are themselves composed by sub layers enabling their functioning:

1. **The Smart Factory:** optimizes the flow of products through production processes and orchestrates the allocation of resources. This layer encompasses five sub layers: Business Intelligence, connected enterprise system, operations management; Smart Apps, Controllers, OT-IT Bridges; and Smart Machines, sensors, tooling, workforce.
2. **The Digital Thread:** It encompasses the creation of work instructions for automated production and the verification process. For instance, instructions for 3D printing, machining and the verification against engineering specifications. This layer is composed by the three sub layers: Specifications management, operations management and service management.
3. **The Value Chain Management:** It delivers real-time data from production processes to other business management functions and orchestrates activities into the supply chain to make sure that materials, parts and subassemblies arrive at the right place at the right time. It encompasses the five sub layers: Customer management, compliance management, operations management, resource management and supplier management.

The three layers are coordinated by their own Operations Management sub layer. In such manner, to collaborate, share and manage all key aspects of manufacturing operations, these three layers must be integrated. This is the role of the Enterprise Operations AI Platform: it is threaded to them through their Operations management sub layer. Figure 1 depicts the relationship between the Enterprise Operations AI Platform and the three information layers.

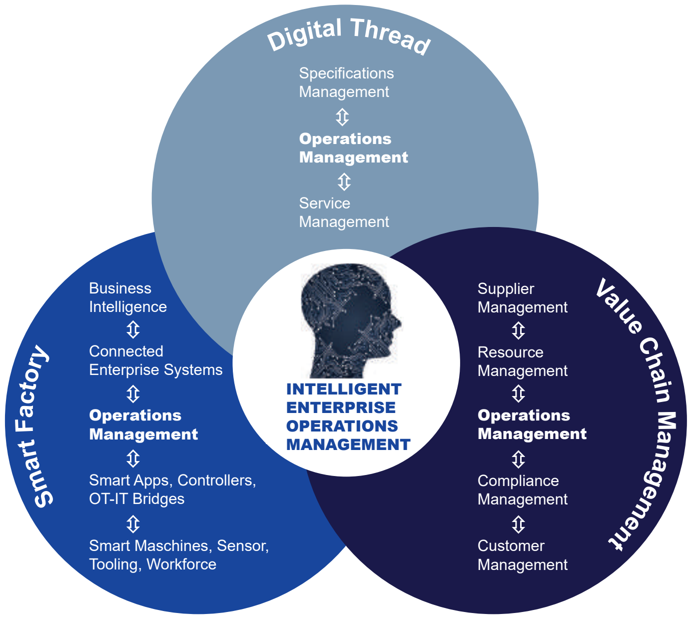

Figure 1. Link between the Enterprise Operations AI Platform and the information layers

As stated before, this integration is done at the level of the Operations management sub layer. This assures that all the needs from each layer are satisfied, enabling an End-to-End (E2E) continuity and correctly managing all the intermediate deliverables such as drawings, purchase orders, productions schedules, etc. Figure 2 represents this integration through the Operations management sub layer.

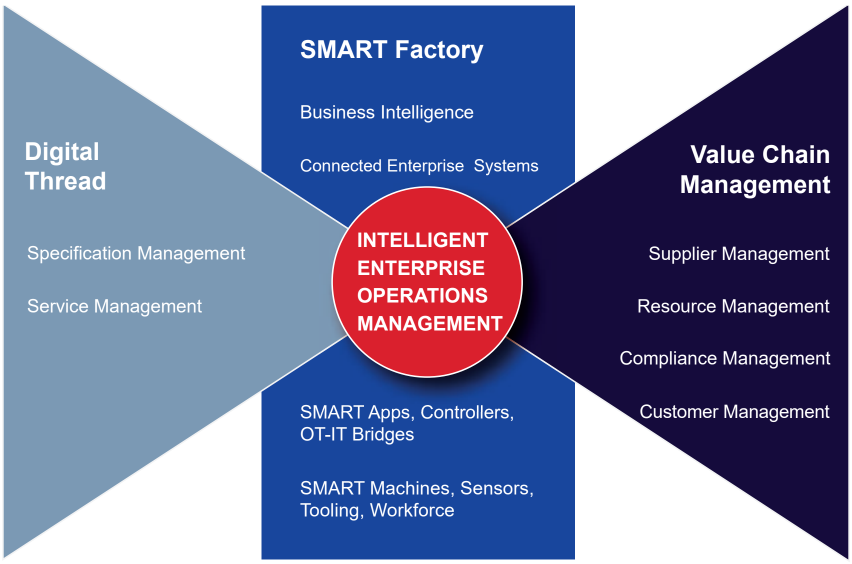

Figure 2. Integration of the three layers through the Operations Management sub layer

To answer the first question, it is possible to conclude that the essence of the Enterprise Operations AI Platform is to be the integrator that intelligently analyses and chooses the data from the enterprise's backbone systems, to collect meaningful data. Subsequently, this data is used to automatically optimize the production process following three objectives: in-time delivery, quality and cost. Furthermore, under the I4.0 paradigm, this optimization is characterized to be done in real time and to self-adapt to the environment dynamics. This allows the platform to intelligently retrieve meaningful data from the Data Lake through AI algorithms and expert rules. After the data retrieval, the Enterprise Operations AI Platform triggers optimization processes in the PLM, ERP and MES.

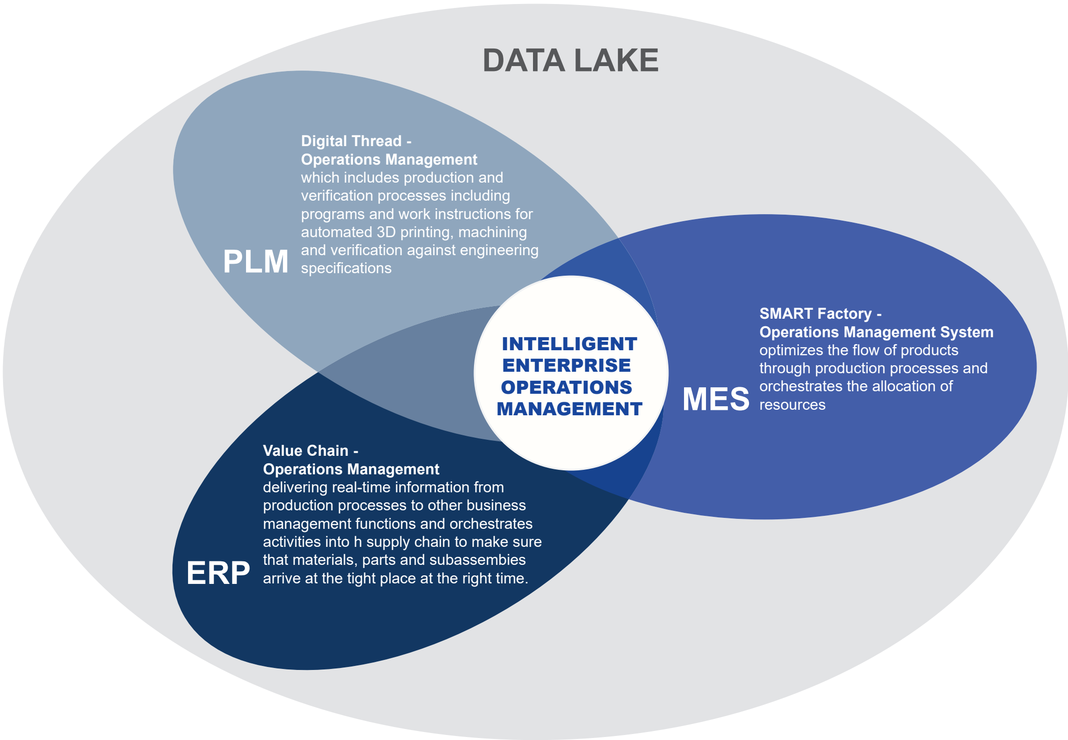

Figure 3. The Predictive ERP: Integrator of the backbone systems

Figure 3 shows the three backbone systems integrated by the Enterprise Operations AI Platform: The Predictive ERP. From this point, the terms Enterprise Operations AI Platform and Predictive ERP are used interchangeably.

► Which are the necessary steps to achieve such system?

In this question, two main topics are discussed: the requirements to implement the Predictive ERP and the logic behind its functioning.

Predictive ERP requirements

Regarding the three information dimensions, they are currently managed by independent backbone systems such as PLM, ERP and MES. Nevertheless, exchanges between these three systems are full of redundant and irrelevant data. Therefore, the industrial need lies in a platform able to integrate the minimum necessary data from these backbone systems as well as real time operations data to create a unique enterprise operations model. Afterwards, this data is analysed by intelligent algorithms that will command other execution systems. However, how to create such system? To define this, four clusters of requirements have been identified:

- **AI Platform's success factors:**
  - Identification of the meaningful data from each backbone system and real time data to feed the AI algorithms
  - Intelligent data pre-processing
  - Unique solution proposal for modelling with AI
  - Technical insights for data modelling and AI algorithm management
  - Scalability in terms of capacity, connectivity and data management
- **AI Platform's key architecture elements:**
  - Integrated solution platform with no data exchange between data bases
  - Full technology alignment between modelling and algorithm
  - Full cloud service compliance for scalability and integration
- **AI Platform's key capabilities:**
  - Parametric enterprise operation modelling
  - Simulation, sequencing, scheduling, balancing and task allocation algorithm integration
  - Activity scheduling sharing and control

- **AI Platform's key data model elements:**
  - Detailed and parametrised Product, Process and Resources (PPR) model
  - Capacity, skill and resource availability
  - Material availability
  - Real time operations status
  - Order status

These four clusters are meant to guide the creation and development of the Predictive ERP.

How will the Predictive ERP work?

In a company fulfilling the previously mentioned requirements, the Enterprise Operations AI Platform would act as the core system orchestrating the other backbone activities. Such system is presented as the Predictive ERP. Figure 4 depicts the role of the Predictive ERP in among the main backbone systems. As shown in figure 4, the Predictive ERP integrates the model definition and model execution stages. It will use data from the PLM in order to optimize the different deliverables of the ERP system. Subsequently, the MES system will provide the required feedback to generate Strategic continuous improvements through the Data Lake. Finally, the Predictive ERP will ensure this exchanges to adapt the production process to the environment dynamics.

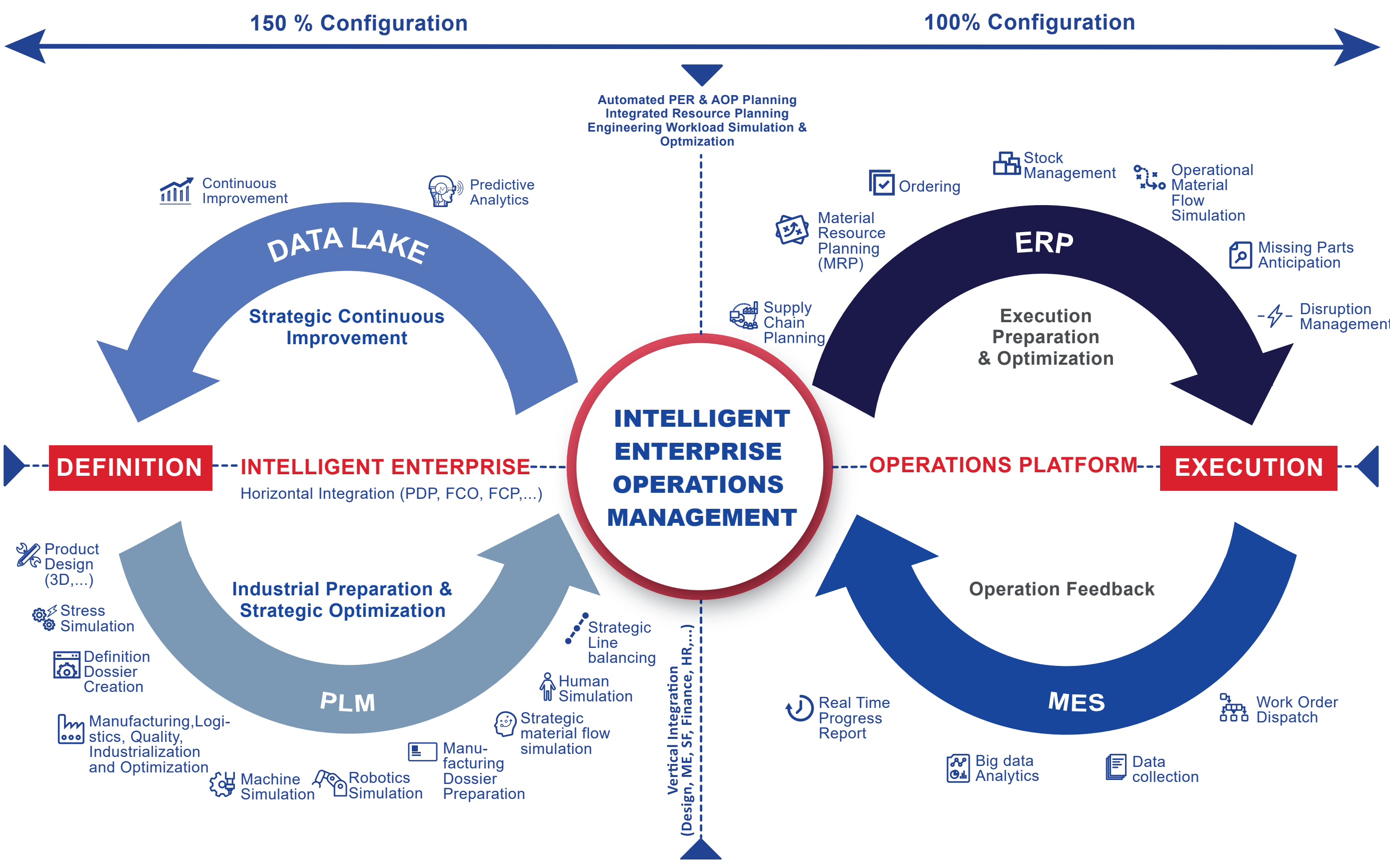

Figure 4. Interaction between the Predictive ERP and the backbone systems

In order to make dynamic adjustments and to be context aware, the Predictive ERP must have access to a model of the company's environment. However, which is the best way to model a company? Should we use deterministic parametric modelling or stochastic models? The answer is both. The Predictive ERP will switch between two base models: A Parametric Simulation model (PPR based) and a Predictive Analytics model (Machine Learning based). The former is characterized by having logic parametric constraints to make decisions, while the latter will learn relationships from data to guide its actions. In such way, the Predictive ERP will benefit from both parametric and AI-based models, the choice of which model to use will depend of their prediction maturity. The next section will explain the reasoning behind this logic.

► Which is the role of AI in the Enterprise Operations AI Platform?

Coupling the Parametric Simulation and Predictive Analytics model

To assist intelligent decision making, latest developments on AI create models and derive rules from historical data. Nevertheless, data modelling through AI has two base prerequisites: data volume and veracity. The former is related to the amount of data, which must be statistically enough while the latter concerns the trustworthiness and quality of the data (Zhou, Pan, Wang, & Vasilakos, 2017). Automated processes fulfil these two prerequisites as they present high levels of maturity and reproducibility. Nonetheless, when manual work is to be performed or a change in the production process is done, the two prerequisites are not met. For instance, manual work introduces a high degree of variability, which negatively affects veracity. However, a system proposed as the core of all the company dimensions must be able to make the right decisions, even when the process' data is not reliable or abundant. Therefore, the Predictive ERP must adaptatively switch between the Parametric Simulation and Predictive Analytics model. In such manner, when either new operations or disruptive changes are introduced, the Predictive ERP will use the Parametric Simulation model as baseline, as it provides good practices derived from the company's expertise. However, when there is enough reliable data to adequately train Machine Learning algorithms to reach a better level of prediction maturity and quality, the Predictive ERP will switch to the Predictive Analytics model. Figure 5 depicts this process.

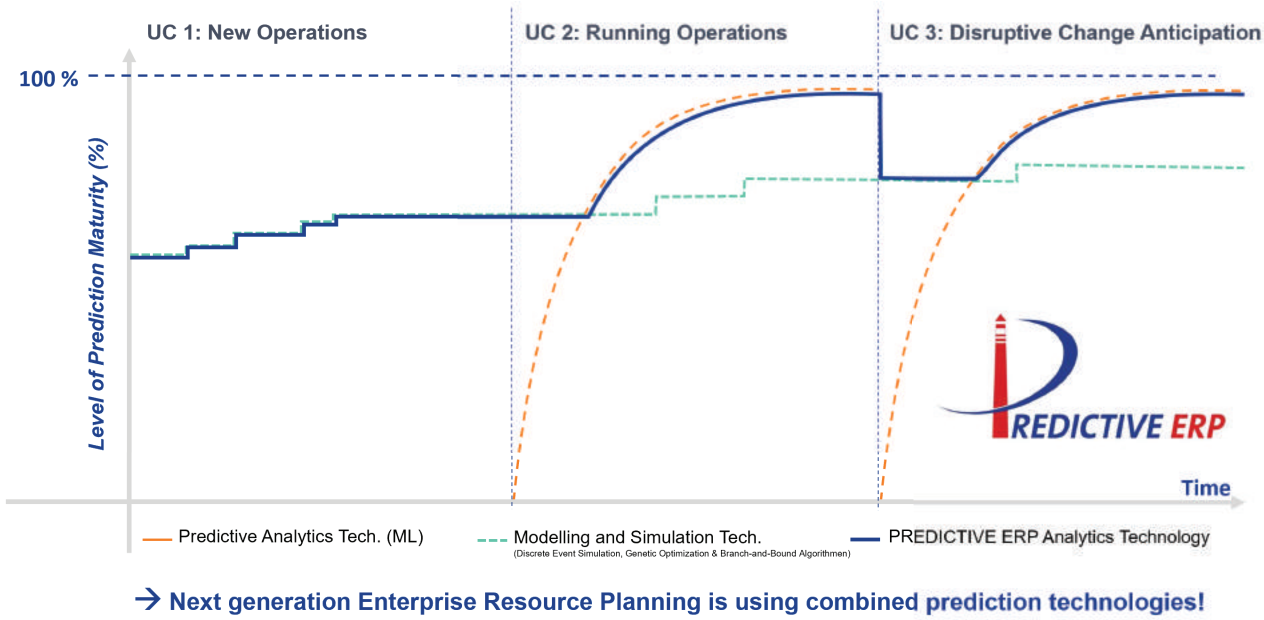

Figure 5. Adaptative functioning of the Predictive ERP

Measuring the prediction maturity

Having explained the Predictive ERP's functioning principle, an important question must be answered: how to measure the prediction maturity? To do so, we propose to use the three fundamental improvement axes for a company: in-time delivery, quality and cost. This is summarized in figure 6.

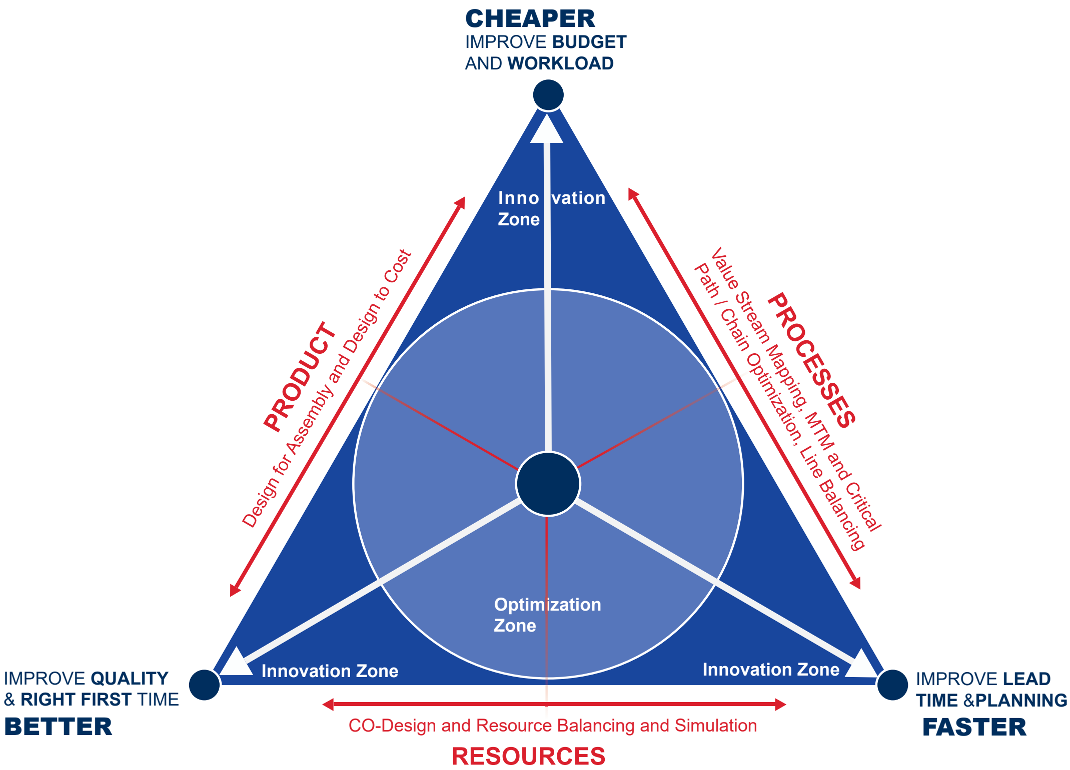

Figure 6. The three fundamental improvement axes

As stated before, the Parametric Simulation model is based on a PPR approach, which includes all the improvement axes. Nevertheless, trying to optimize all three dimensions has proven not to work as there are trade-offs between them. For that reason, it is important to determine a priority axis which will be the measure of the prediction quality for the Simulation Parametric model. After choosing the priority axis, the next step is to identify impacted enterprise model objects and the corresponding improvement method to be applied. Understanding this constraints and objects will allow to put automatic algorithms to make decisions based on simulation and optimization results.

Concerning the Predictive Analytics model, its maturity measure will depend on two main factors: the chosen priority axis for the Simulation Parametric model and the model's complexity. The latter was added to avoid high variance, which negatively affects the prediction quality and inhibits interpretability.

Figure 7, taken from Hastie, Tibshirani, & Friedman (2009, p. 38), represents this issue: the higher the model's complexity, the higher the prediction error in new data (red curve). In such manner, it is capital to minimize the complexity of data model in order to have the Predictive ERP working as efficient and accurate as possible. Therefore, the prediction maturity for Predictive Analytics models will be both measured with respect to the priority axis and the model's complexity.

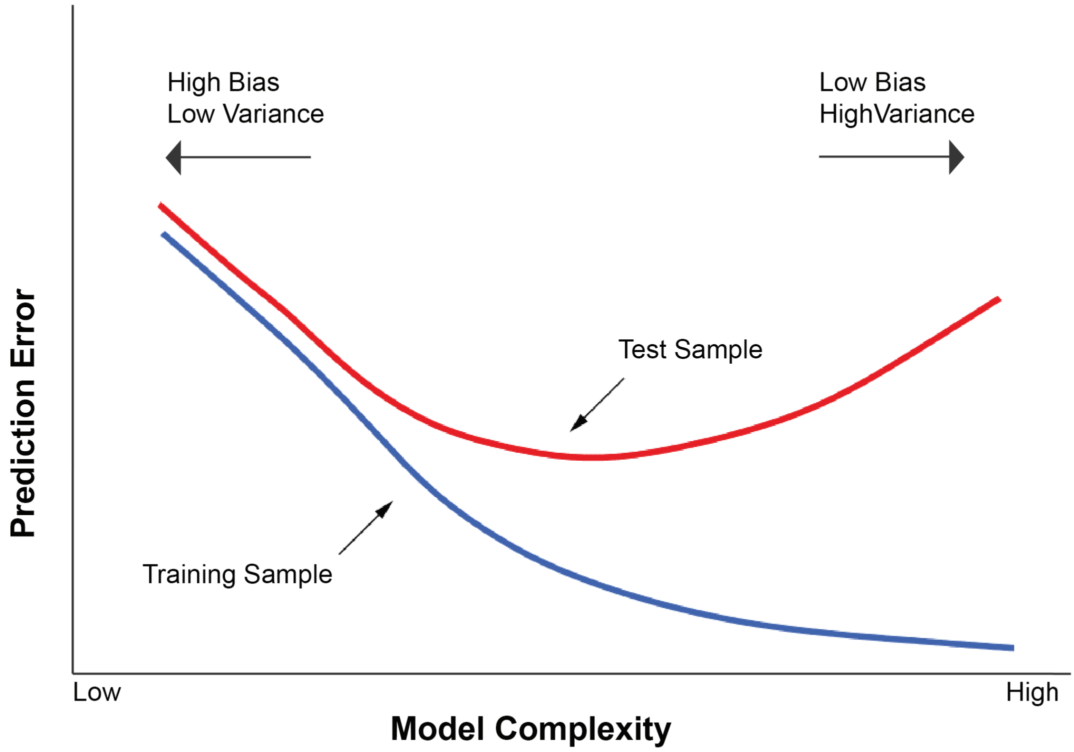

Figure 7. Influence of model's complexity on the prediction error (Hastie et al., 2009, p. 38)

Measuring the prediction maturity

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The functioning of the Predictive Analytics model

The predictive analytics model functioning is represented in figure 8. It consists of a feedback cycle that updates the industrial knowledge base with respect to the shopfloor progress captured through the MES system. Based on the change on this industrial knowledge base, the model parameters adapt to the current state of the production environment. This is represented in figure 8:

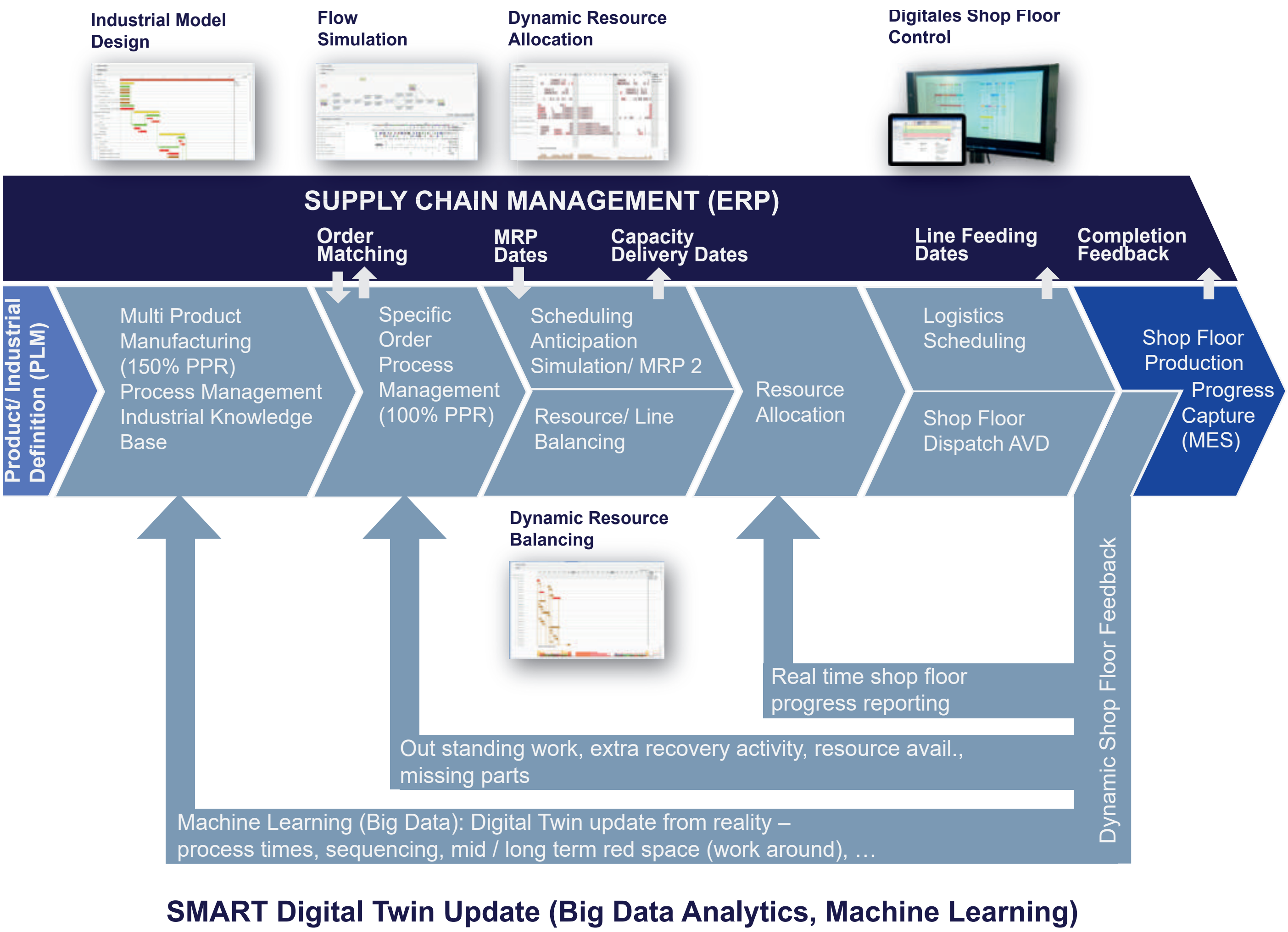

Figure 8. Detailed functioning of the Predictive Analytics model

► Which are the capabilities of the Enterprise Operations AI Platform?

Functional capabilities

To correctly create a system orchestrating all company's operations through the execution of the three information layers, a set of capabilities and data inputs must be provided. This must include scenario modelling, result presentation and live feedback of the constrain model.

In addition, a different set of algorithms in order to address dedicated aspects such as calculation, simulation, optimization and arrangement. Other inputs and outputs of the Predictive ERP are presented in figure 9.

	Analytics	Capacity Planning	Tactical Planning/ Anticipation Simulation	Resource Balancing & Scheduling	Shopfloor Feedback
IMS					
Model Input	**Lean Business Process Analysis and statistical data analytics** + Lean Value Stream Mapping + Lean Business Process Mapping + Machine Learning (Big Data Analytics)	**Business Process and Resource Modelling** + Process PERT with times and resource allocations per product/ project variant + Process lead times on station level + Long term delivery orientated capacity simulation + MTM time integration	**Material Flow Modelling** + Station resource restriction + Detailed shift models + Simulation scenarios + Production schedule + Production allocation line split + Material flow model + Teams & skill availability + Shift scheduling + MRP Scheduling	**Resource Constrain Modelling** + Skill and resource availability matrix + Resource capacity per shift definition + Activity sequence and resource allocation constrain definition + Special process state definition + Distance matrix definition + Optimization priority axis definition	**Work order / skill & resource allocation** + Worker operational progress feedback + Worker operational issues feedback
Internal Processes Output	✓ Business Process Performance Analysis ✓ Predictive Analytics ✓ Operational Performance Analysis	✓ AOP Simulation ✓ Procurement Supplier Seizing ✓ Human Skills and Resource Planning ✓ Machine Capacity Planning ✓ Global Resource Bottle-neck analysis ✓ Storage and stock sizing ✓ Engineering workload and resource planning	✓ Production sequence optimization ✓ Resource demand mid term planning ✓ Bottleneck analysis ✓ Critical path analysis ✓ ERP bottleneck scheduling	✓ Automated resource/ skill balancing optimization ✓ Shopfloor work order scheduling per resource ✓ CVAT assessment analysis ✓ Automated optimized skill/ resource work order allocation ✓ Bottleneck analysis ✓ Critical chain analysis ✓ ERP activity scheduling	✓ Real time issue management and anticipation ✓ Real time production progress feedback and reporting ✓ Shopfloor operation issue management ✓ Automated product history data collection and reporting ✓ Real time production performance reporting ✓ Resource availability data capturing (holidays, etc.)
External Processes Output	• Supply Chain Performance Analysis	• Supplier Parts Delivery Scheduling • Supplier Capacity Planning	• Late delivery anticipatio and internal impact analysis	• Late delivery recovery planning and internal impact planning	• Production progress reporting for customers
	IMA IMD IML VSM	IMV	IMV	IMC	IMO

Figure 9. Functional capabilities of the Predictive ERP

Technical and architectural capabilities

The two main technical and architectural key capabilities will be the system scalability and the data integration from different tools. The system scalability overcomes the challenge of high-volume data generated at high velocity (Zhou et al., 2017), while the data integration deals with the variety of data. Moreover, the intelligent algorithms in the Predictive ERP will be able to identify the minimum data requirements in order to create meaningful and comprehensible models, avoiding high complexity. For instance, using a cloud architecture will enable scalability, while adapting the Predictive ERP to receive data from other sub systems such as the supplier's ERP will enable integration. Figure 10 describes the scalability and data integration key factors.

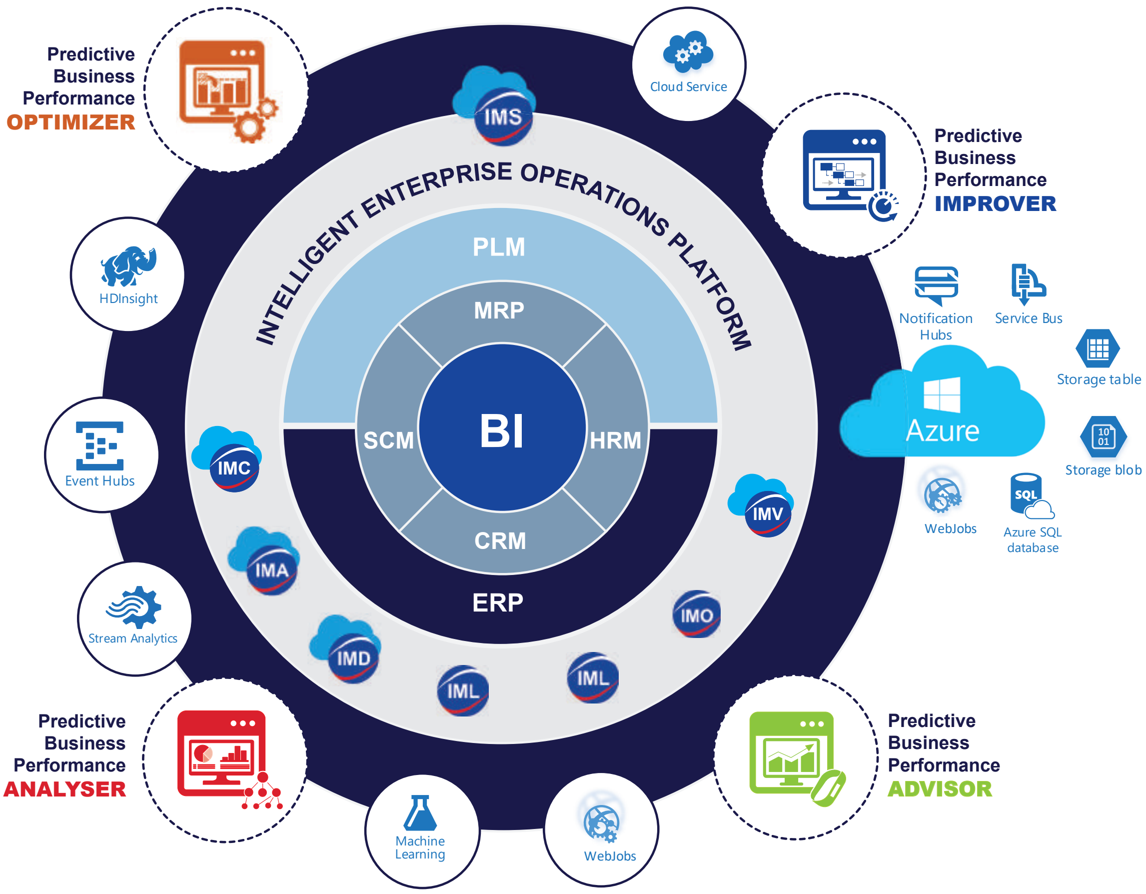

Figure 10. Scalability and data integrator key factors

Finally, to tackle data velocity, it is capital to flexibly and interactively integrate the vertical information chain, from business intelligence to the Internet of Things. Cloud architecture integrating standard services for data streaming and connectors will support this aspect. This is summarized in figure 11.

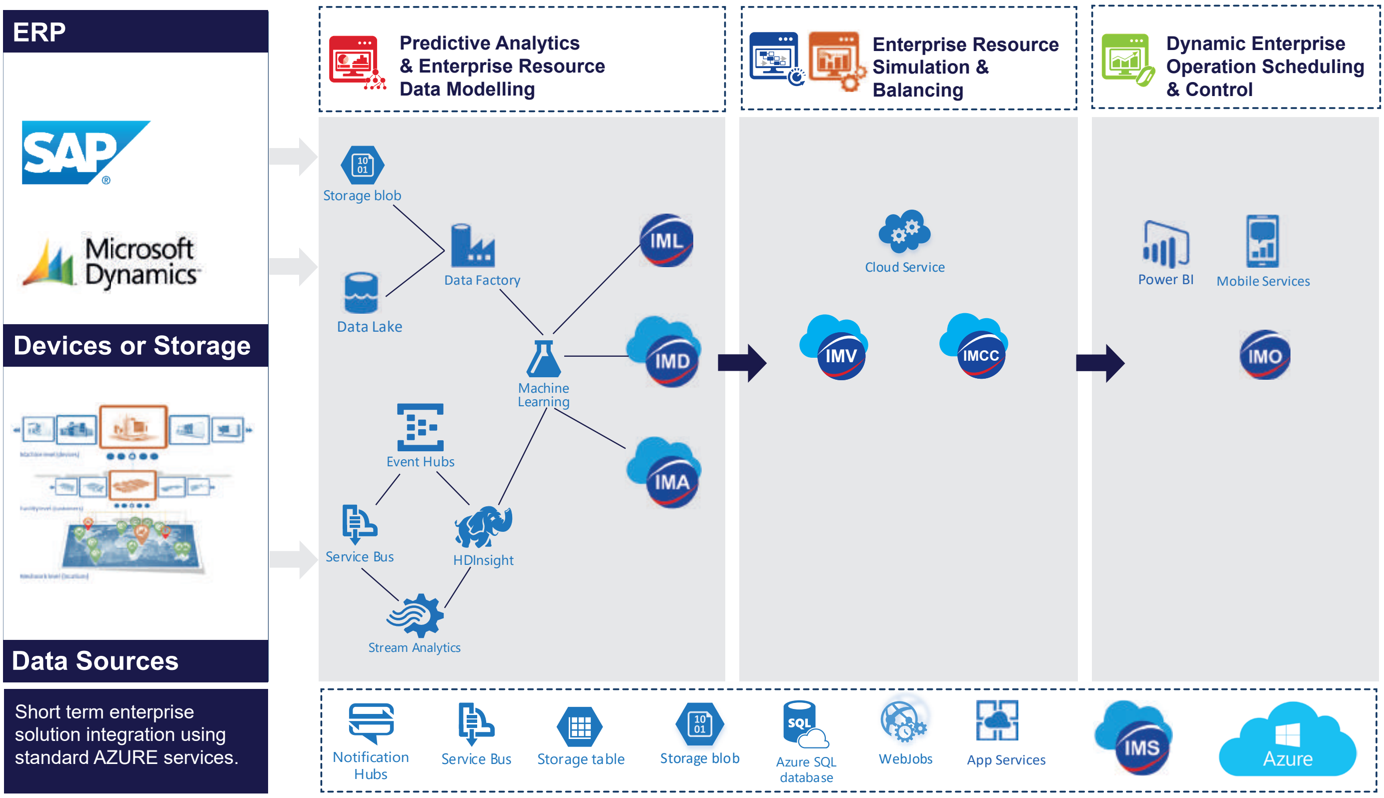

Figure 11. Flexibility of the Predictive ERP and integration of the vertical information chain

In such way, the Predictive ERP will be able to manage data volume, velocity, variety and veracity to generate value (Zhou et al., 2017), placing it an essential tool to tackle big data challenges in I4.0 manufacturing.

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