Maturity Model for Analysis of Machine Learning Operations in Industry

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Abstract. The next evolutionary technological step in the industry presumes the automation of the elements found within a factory, which can be accomplished through extensive introduction of automatons, computers and Internet of Things (IoT) components. All this seeks to streamline, improve, and increase production at the lowest possible cost and avoid any failure in the creation of the product, following a strategy called "Zero Defect Manufacturing". Machine Learning Operations (MLOps) provide a ML-based solution to this challenge, promoting the automation of all product-relevant steps, from development to deployment. When integrating different machine learning models within manufacturing operations, it is necessary to have a good understanding of what functionality is needed and what is expected. This article presents a maturity model that can help companies identify and map their current level of implementation of machine learning models.

Keywords: Machine learning · Manufacturing execution system · Zero-defect manufacturing · Manufacturing operations · CMM · ISA-95 · MLops

1 Introduction

More than four decades ago, Phillip Crosby coined the concept of zero defects. It was just a vision at that time, but the rise of Artificial Intelligence (AI) in manufacturing has made it achievable [1]. AI can be defined as the process by which, by means of different techniques, cognitive skills can be generated and thus endow machines with intelligence. To achieve this, AI must be provided with the ability to learn tasks, which is where the concept of machine learning (ML) comes in [2]. ML is one of the most important concepts for Industry 4.0 that aims to provide analytical data modelling and outcome prediction [3]. ML uses computer algorithms that receive and analyse real-time data to predict output values within an acceptable range. As new data come in and are introduced, these algorithms "learn" and optimise their output to improve performance

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and enhance their "intelligence" over time [4]. ML can also be focused on finding patterns in data that are seemingly difficult to forecast and supporting the implementation of zero defects manufacturing (ZDM) concept [5]. ZDM is a strategy followed to minimize, mitigate, or eliminate failures and defects during the production process [6]. It is based on the evidence that they will always exist and will eventually affect production and its output, but recognizing that (i) faults and defects can be detected and minimized more quickly online; (ii) any production output that deviates from specifications should not be allowed to pass to the next step in the value chain or, eventually, to an end customer; (iii) any production output that deviates from specifications should not be allowed to pass to the next step in the value chain or, eventually, to an end customer [7]. The ZDM concept can be used in any manufacturing environment that seeks to reduce costs and increase the quality of its products [8]. Conventional manufacturing facilities are equipped with a manufacturing execution system (MES) to enable automated production beyond automatic control of individual pieces of equipment [9]. This article will propose a maturity model to measure the state of ZDM readiness within a company. This model or approach addresses both tactical aspects, at the horizontal level, and operational aspects, at the vertical level. All of this is based on the Zero Defects philosophy, such as the optimisation of the production chain through MLOps, avoiding errors in the final product. This paper will provide the definition and details of the proposed model consisting of vertical and horizontal axis.

2 Vertical Axis

The use of information technologies has generated software development needs in manufacturing companies. This phenomenon is known as Computer Integrated Manufacturing (CIM). CIM is a philosophy of approaching an integrated organisation of the factory and its management [10]. The CIM standard is divided into 5 levels [11]: (i) first level is formed by the industrial processes and their machinery; (ii) second level defines the integration between the physical part and the control systems; (iii) third level corresponds to the interaction between man and the production chain; (iv) fourth level where the measurements are stored; (v) fifth level where the human management by means of tools, such as ERPs, happens.

When integrating different machine learning models within manufacturing operations, it is necessary to have a good understanding of what functionality is needed and what is expected. If this integration is in the requirements that reside in the manufacturing operations domain, the standard that can be used is provided by "International Society of Automation" (ISA-95) [13], especially Part 3 of this standard. ISA-95 is based upon the hierarchical structure presented in the "The Purdue Enterprise Reference Architecture (PERA)". This standard separates the functionality of the enterprise by dividing it into three layers (Fig. 1): Planning or level 4 (top layer with business and logistics information), Execution or level 2 (middle layer with manufacturing operations and control information) and Control (inner layer with the rest of the CIM levels) [11].

ISA 95 Part 3 focuses on activities within manufacturing operations; this part specifies a generic activity model that applies to different types of manufacturing operations

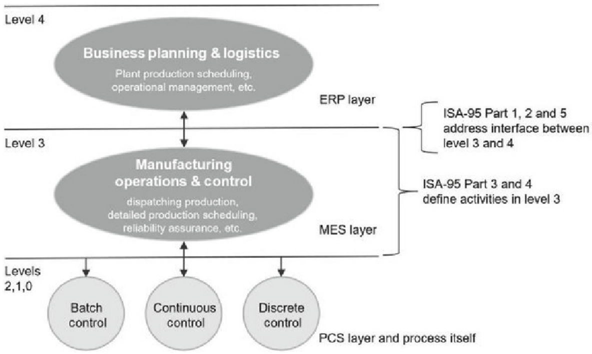

Fig. 1. ISA-95 functional hierarchy model [12].

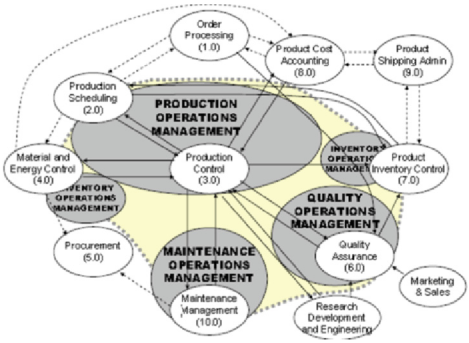

Fig. 2. Production management activities according to ISA 95 standard [12].

[14] (Fig. 2). These manufacturing operations management activities are those that coordinate personnel, material, and equipment in the conversion of raw material into components or finished products and include activities that can be carried out by human effort, equipment or information systems controlled by scheduling, usage, capacity, definition, history, and resource status [14]. Considering these levels of activities, we try to group them into 5 categories, which will form the levels to be measured in our maturity model:

- **Management of production operations** defines the functions associated with the operations of a factory, such as product definition management, production resource management, data collection, etc.
- **Management of maintenance operations;** those activities that ensure the availability of personnel, equipment, or tools for manufacturing operations.
- **Management of laboratory operations** are the set of activities related to quality measurement and reporting (both quality operations and quality operations management).
- **Management of materials handling and storage** are the set of activities that manage the inventory of products and materials.

- **Support activities**, including security, information, configuration, documentation, compliance, and incident/deviation management.

3 Horizontal Axis

The Capability Maturity Model Integration (CMMI) presents a model for the appraisal of an organisation's processes, developed by Carnegie-Mellon University (USA) in 1986 for software implementation processes [15]. It consists of a set of key practices in processes that are grouped into five "maturity levels". [16] Thus, a company or organisation that complies with all the practices intrinsic to the corresponding level and the levels below is considered to have reached that level of maturity. These levels are: Initial, Repeatable, Defined, Managed and Optimised. This CMM model allows progress assessment as maturity levels advance. To conform with each level, several conditions must be fulfilled. These are identified by the satisfaction or dissatisfaction of several clear and measurable objectives. The description of the horizontal axis levels is provided below:

i. **Initial.** This is the starting point of any company or organisation, as it has no ML process or strategy in place. ML development processes are not designed and implemented within an architecture or have no structure at all. On the other hand, the ML processes in the organisation are not standardised and lack a correct management approach.
ii. **Repeatable.** At this point, the company, or organisation, has an idea of what ML is and has established a scope for its implementation. However, at this point the company does not have sufficient data to apply ML and the ML development architecture is centralised and only applied for independent processes. In summary, the company has taken the first steps to implement ML.
iii. **Defined.** The company has a defined plan and architecture for implementing ML. On the other hand, it has data to train the models. The company has a department or assigned workers that are focused on implementing and improving ML. The integration of ML processes within the company has been automated and monitoring and tracking tools have been included. In summary, the company has implemented and has some experience in implementing ML.
iv. **Managed.** At this point the company/organisation has already implemented different ML strategies, which have been properly configured and are constantly analysed. All the company's ML models are highly integrated with the company's subsystems. Moreover, it clouds solutions are the part of a ML development strategy facilitating distributed computing. Thus, the company at this level can be considered advanced in the industrial ML implementation and will be one step away from being able to generate ML-related standards.
v. **Optimisation.** At this point, the company or organisation has implemented a complete ML strategy, has strong support and monitoring of all models, within a well-defined architecture. The company's products and services are regularly updated with the help of ML to improve their value.

The CMM model establishes a measure of progress as maturity levels advance. To pass each level, several process areas must be accomplished. That are identified by the satisfaction or dissatisfaction from several clear and quantifiable goals. These goals are known in the CMM documentation by the acronym KPA, which stands for Key Process Area. Each KPA identifies a set of interrelated activities and practices, that when carried out collectively, allow the fundamental goals of the process to be achieved.

4 Maturity Model

The measurement matrix (Table 1) is used to determine the status of machine learning implementation at the different levels of activities within the manufacturing operations and will be the basis for identifying all the steps needed to move from the traditional factory to an automated one. As mentioned above, we will use the CMI model as a basis, establishing five levels of scale, to specify its status within the factory. This snapshot will be the means for the user to identify the necessary steps to adopt the use of machine learning models in a smooth and stepwise manner. In this way, the matrix provides a brief and clear form of the current state and desired conditions, showing different alternatives.

Table 1. Maturity model

	Initial	Repeatable	Defined	Managed	Optimised
Management of production operations	There is no control of production operations	Control of production operations has begun to be established	The company has a defined plan and architecture for implementing ML in production operations management	It has included cloud solutions, such as cloud computing, for better integration and use of MLOps	A full MLOps strategy has been implemented and everything is managed automatically
Management of maintenance operations	There is no monitoring or control of maintenance operations	Data collection has started to try to control maintenance operations	An ML has been developed for degradation analysis of parts, to predict their changeover and cumulative effect	The company or organisation has already implemented different MLOps strategies to manage storage operations	A full MLOps strategy has been implemented to manage warehousing operations automatically

(*continued*)

Table 1. (*continued*)

	Initial	Repeatable	Defined	Managed	Optimised
Management of laboratory operations	There is no quality control operation	Quality starts to be an important point for product development	The organisation has ML quality control measures in place that are implemented in accordance with industry standards and best practices	Models have been introduced to analyse appropriate configurations to measure quality and are constantly monitored	ML is used to control all elements of quality in the company automatically
Management of materials handling and storage	There is no control of the warehouse or procurement of materials	Basic warehouse control tools have been introduced and a history of data is kept	The integration of ML processes within the company has been defined and material monitoring and tracking tools have been included within the company	Models have been introduced that manage information on storage and existing materials. The model is trained to give warnings of material procurement	The company's products and services are regularly updated with the help of MLOps to improve its warehousing control automatically
Support activities	There are no standards in place to assist operations management	The preparation of materials to manage, explain and help workers has been considered	The company has a department or assigned workers focused on implementing and improving ML	The company at this level can be considered advanced in the industry and will be one step away from being able to generate standards	The company has strong support and monitoring of all models, within a well-defined architecture. It is a reference in the sector and can support other companies

5 Practical Application

To define the level of implementation of machine learning models in industry, a questionnaire will be developed according to each of the characteristics listed in the matrix

(Table 1). A company will be able to say that it has a level of implementation, if it fulfils all the questions positively referred to on the horizontal axis. It will not be able to move up a level without having positively completed all the questions associated with the previous level. This result of the matrix provides the integrators of learning models in manufacturing operations with an overview of the implementation status of the models (Table 2) and will allow them to know where they need to improve. Following the analysis of the current state of the implementation of learning models within the factory. Our maturity model would return a report with the points to be improved in order to reach better levels within this maturity model.

Table 2. Example of a measurement matrix

	Initial	Repeatable	Defined	Managed	Optimised
M1		x			
M2		x			
M3			x		
M4		x			
M5				x	

6 Conclusions

Throughout this article, a proposal for a Machine Learning Maturity assessment model covering various levels of activities within the manufacturing operations aspects has been made. To this end, a maturity model has been developed using the CMM background for the ML implementation stage analysis in relation to the activities that take place in the manufacturing operations management system addressed by ISA-95. It allows obtaining an image of the state of a factory at a specific moment within the digital transformation process to the automation. This matrix will be used to measure the implementation of machine learning models in the Zero-Defect Manufacturing Platform (ZDMP) or Industrial Data Services for Quality Control in Smart Manufacturing (i4Q) projects, which have several solutions that deploy algorithms as a service (AaaS) and encourage the use of machine learning models.

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