International Journal of Production Management and Engineering

https://doi.org/10.4995/ijpme.2023.19138
Received: 2023-01-19 Accepted: 2023-07-20

An industry maturity model for implementing Machine Learning operations in manufacturing

Miguel Ángel Mateo-Casalí [*a1], **Francisco Fraile Gil** [a2], **Andrés Boza** [a3], **Artem Nazarenko** [b]

[a] Research Centre on Production Management and Engineering (CIGIP), Universitat Politècnica de València (UPV), Camino de Vera S/N, 46022 Valencia, Spain.
[b] Faculty of Sciences and Technology, Nova University of Lisbon, Monte Caparica, Portugal.
[*a1] *mmateo@cigip.upv.es*, [a2] *ffraile@cigip.upv.es*, [a3] *aboza@omp.upv.es*, [a4] *a.nazarenko@campus.fct.unl.pt*

Abstract:

The next evolutionary technological step in the industry presumes the automation of the elements found within a factory, which can be accomplished through the 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 understand 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.

Key words:

Machine Learning, Manufacturing Execution System, Zero-defect Manufacturing, Manufacturing Operations, CMM, ISA-95, MLOps.

1. Introduction

Over four decades ago, Phillip Crosby coined the concept of "zero defects", a vision that thanks to the rise of Artificial Intelligence (AI) in manufacturing has become achievable (Escobar et al., 2020). AI can be defined as the process by which, using different techniques, machines can be endowed with cognitive capabilities and intellect. Central to this is the concept of machine learning (ML) (El-Naqa et al., 2015), AI can be defined as the process by which, using different techniques, machines can be endowed with cognitive capabilities and intellect. Central to this is the concept of machine learning (ML) (Frank et al., 2019). ML is one of the most essential concepts for Industry 4.0, which aims to provide analytical data modelling and outcome prediction (Frank et al., 2019). ML uses algorithms that receive and analyse data in real time to predict output values within an acceptable range. As new data arrives and is introduced, these algorithms "learn" and optimise their output to improve performance and increase their "intelligence" over time (Ongsulee, 2014). Machine Learning (ML) is a key tool in the implementation of Zero Defects Manufacturing (ZDM) (Psarommatis et al., 2020).

ZDM is a strategy followed to minimise, mitigate or eliminate failures and defects during the production process (Serrano-Ruiz et al., 2021). It is based on the evidence that they will always exist and will eventually affect production and its output, but recognising that (i) faults and defects can be detected and minimised more quickly online; (ii) any production output that deviates from specification should not be allowed to pass to the next step in the value chain or, eventually, to an end customer (Lindström et al., 2020). However, through the implementation of ML, the prediction and early detection of potential failures and defects in the

To cite this article: Mateo-Casalí, M.A., Fraile Gil, F., Boza, A., & Nazarenko, A. (2023). An industry maturity model for implementing Machine Learning operations in manufacturing. *International Journal of Production Management and Engineering, 11*(2), 179-186. https://doi.org/10.4995/ijpme.2023.19138

production process is made possible. Through the analysis of large amounts of data, ML can identify patterns and trends that are difficult to detect with the naked eye, and thus improve the quality of the final product. In addition, ML can be used to optimise the production process by identifying factors that can negatively affect product quality and implementing solutions to prevent their occurrence.

The implementation of ML in ZDM production can be further optimised through the integration of MLOps, which enables efficient lifecycle management of the model and its implementation in production in real time (Calvin, 1983). This means that the ML model can be constantly updated and improved, ensuring the best possible quality of the final product. Conventional manufacturing facilities often have a manufacturing execution system (MES) that enables automated production beyond the automatic control of individual pieces of equipment (Jürgen, 2007). MES systems can be integrated with MLOps to ensure that the ML model is efficiently implemented in production and quickly adapts to changes in data and the production environment. In this way, the quality of the final product can be improved, and the time and costs associated with producing errors and defects can be reduced.

This paper proposes a maturity model to measure the readiness for the introduction of Machine Learning Models. This model or approach addresses both the tactical aspects at the horizontal level and the operational elements at the vertical level. It is based on the Zero Defects philosophy, such as optimising the production chain through MLOps and avoiding errors in the final product

2. Analysis of the implementation status of machine learning within the industry

The increasing use of Machine Learning (ML) models in industry has made it imperative to validate the correctness of these models before implementing them. One effective way to achieve this is to follow the software development life cycle (SDLC) when developing ML models. The SDLC is a structured approach to software development that consists of several phases, including requirements analysis, design, development, testing, implementation, and maintenance. Following the SDLC ensures that the model is reliable, robust, and delivers the expected performance.

The first step in implementing an ML model is to define the purpose of the model and set performance objectives. This is achieved by conducting a thorough requirements analysis. The purpose of the model should align with the business goals and objectives. For instance, a company may aim to develop a model that can predict the success of an ML project based on several factors, such as team size, budget, and problem complexity. The performance objectives should be measurable, specific, achievable, and relevant to the business goals.

The next step is to design the model. This involves selecting a suitable dataset and defining the model's architecture. The dataset should include all the relevant data required to train the model. For instance, a dataset that includes information on more than 100 Machine Learning projects conducted in the company over the past five years, including the size of the team, the budget, the problem to be addressed, and the outcome of the project (success or failure), can be used. The data should be cleaned and normalized to remove missing or outlier values. The model's architecture should also be selected, for instance, a logistic regression model can be chosen to predict the success or failure of a project. The development phase involves training and fitting the model using appropriate optimization and validation techniques. The selected dataset is used to train the model. The model's hyperparameters are fitted using cross-validation, and the configuration that provides the best performance on the training dataset is selected. This ensures that the model is optimized for accuracy, precision, and recall.

The next step is to evaluate the model's performance using an independent test dataset and appropriate validation techniques to assess its reliability and robustness. The goal is to achieve a specific performance metric such as an accuracy rate of 85% or better in predicting the success or failure of an ML project. The model's ability to generalize to new data is assessed using a 10-group cross-validation technique. An A/B test can also be performed to compare the model's performance with that of a simpler reference model. Once the model has been validated, it can be deployed in production and monitored for performance. The model should be integrated into the project management system and easily accessible to project leaders. Monitoring should be done using metrics such as accuracy rate and mean square error. This ensures that the model is delivering the expected performance and is still relevant to the business goals.

Finally, the model should be periodically reviewed and updated to ensure that it remains accurate and relevant. This may include updating the dataset used to train the model with more recent data, optimizing the model's hyperparameters, or adding new features. This ensures that the model continues to meet the business requirements and performance objectives. For the development of the maturity model, it is essential to follow a careful process and use appropriate validation techniques to ensure that a model that analyses the state of Machine Learning implementation in the industry is reliable and accurate. This includes defining the purpose of the model and setting performance goals, selecting, and preparing a suitable dataset, training, and tuning the model, evaluating the model's performance, validating its reliability and robustness, deploying the model in production, and monitoring its performance, and periodically updating the model to ensure that it remains relevant and accurate.

By following this process through the use of appropriate validation techniques, it can be ensured that the model will provide accurate and valuable results to support decision making in the industry. On the other hand, it is necessary to define the different points at which machine learning models are to be presented and which categories need to be considered when analysing this maturity model. Machine learning models can be presented at different points in a maturity model, depending on the goals and objectives of the industry. Some potential points:

- **Data collection and management**: Machine learning models can be used to improve the collection and management of data by automating data cleaning, validation, and annotation processes.
- **Predictive maintenance**: Machine learning models can predict when equipment is likely to fail, allowing for proactive maintenance and reducing downtime.
- **Quality control:** Machine learning models can be used to improve the accuracy and efficiency of quality control processes by identifying defects in real time.
- **Supply chain optimisation:** Machine learning models can be used to optimise logistics and inventory management by predicting demand and identifying bottlenecks in the supply chain.
- **Autonomous systems:** Machine learning models can be used to develop fully autonomous systems, such as robots and drones, that can perform tasks without human intervention.

3. Development of the Maturity Model

An industry maturity model for implementing machine learning operations in manufacturing is to assess and measure the readiness of a company or industry to adopt and take full advantage of machine learning in its manufacturing processes. These models provide a structured framework to identify the necessary capabilities, assess the gaps and establish a clear path for the successful implementation of machine learning in the manufacturing context.

To do this, we must first define the values to be taken into account for the measurements, both on the vertical and horizontal axes. The combination of these axes should allow a complete and structured evaluation of the maturity of the implementation of machine learning in manufacturing. The vertical axes will focus on the key functional areas, while the horizontal axes will reflect the maturity levels of machine learning implementation. By using this structure, the maturity model provides a clear and consistent framework for assessing and measuring progress in the implementation of machine learning in manufacturing and allows areas for improvement to be identified and specific targets to be set at each maturity level.

3.1. 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 (Fox et al., 1993). The CIM standard is divided into five levels (Unver, 2013):

- **First level** is formed by the industrial process, machinery, and human resources.
- **Second level** is formed by Integrating physical components and basic control systems like PLCs and sensors.

- **Third level** consists of Interaction between humans and the production chain, including operator monitors (HMI) and SCADA systems for computer-based monitoring and management.
- **Fourth level** consists of a database that stores data from the plant and MES (Manufacturing Execution System), which acts as an interface between the intelligence of the company and the production processes.
- **Level five** is found in the business brain, which includes tools for managing inventory, billing, and logistics using ERP systems.

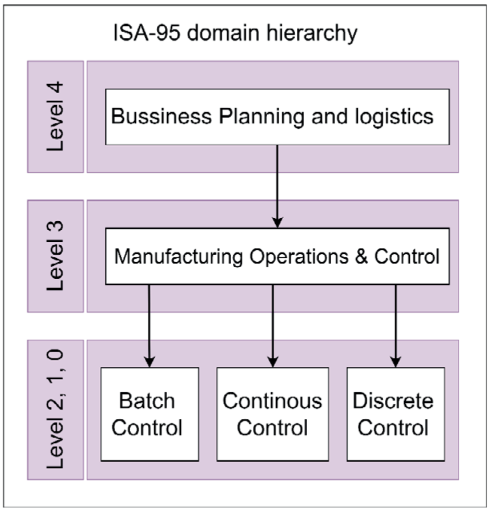

Figure 1. ISA-95 Domain Hierarchy.

When integrating different machine learning models within manufacturing operations, it is necessary to understand 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 the "International Society of Automation" (ISA-95) (Junín et al., 2016), especially Part 3 of this standard. ISA-95, derived from the CIM model, aims to establish a clear connection between control and business functions. The goal is to minimise errors and costs associated with implementation, ensuring an efficient and secure exchange of information (Junín et al., 2016). This standard organises the functionality of a company into three layers. The top layer, called Planning, encompasses all business and logistics information and corresponds to level 4 of CIM. The middle layer, Execution, integrates all manufacturing and control operations and is located at level 3 of CIM. The bottom layer, Control, encompasses the remaining levels of CIM (Figure 1). ISA-95 is based upon the hierarchical structure presented in the "Purdue Enterprise Reference Architecture (PERA)". This standard separates the functionality of the enterprise by dividing it into three layers: 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) (Unver, 2013).

The concept of Manufacturing Execution System (MES) was established in 1992 in Boston by AMR Research Inc. as the level of execution for manufacturing activities, which, as seen in the ISA-95 model, falls between the control systems of the production chain and the company (Jürgen, 2007). 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 (Finkelstein, 1992). 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 (Finkelstein, 1992). Considering these levels of activities, we try to group them into five categories, which will form the levels to be measured in our maturity model:

i. **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.

ii. **Management of maintenance operations;** those activities that ensure the availability of personnel, equipment, or tools for manufacturing operations.

iii. **Management of laboratory operations** is the set of activities related to quality measurement and reporting (both quality operations and quality operations management).

iv. **Management of materials handling and storage** is the set of activities that manage the inventory of products and materials.

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

3.2. 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 (Galan et al., 2021). It consists of a set of key practices in processes that are grouped into five "maturity levels". (Finkelstein, 1992) 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. 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 needs more data to apply ML, and the ML development architecture is centralised and only used 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 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 appropriately configured and are constantly analysed. All the company's ML models are highly integrated with the company's subsystems. Moreover, cloud solutions are part of a ML development strategy facilitating distributed computing. Thus, the company at this level can be considered advanced in 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 and 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 reason for choosing the CMMI model is its well-defined structure, which outlines the capabilities, characteristics, and potential of a company at each maturity level. The five-scale CMMI maturity levels provide a generic model to start with, which has been readapted to ensure compliance and coherence with the previously defined domains. A comprehensive maturity assessment is required to provide a transparent view of a company's current level, including strengths and weaknesses. This approach enables the identification of the AS-IS situation of all dimensions analysed, allowing for the definition of the starting point for further improvement.

The CMMI model is a proven approach that helps companies to identify their process maturity levels in a structured manner. By adopting this model, companies can identify their strengths and weaknesses, as well as areas that require improvement. The model provides a framework for continuous improvement, ensuring that companies can move towards higher levels of maturity over time. A comprehensive maturity assessment can help companies to identify their current process maturity levels in a transparent way. By conducting such an assessment, companies can gain a clear understanding of their strengths and weaknesses and identify areas that require improvement. This approach enables companies to define a starting point for further improvement, and to develop a roadmap for achieving higher levels of maturity.

As we can see, the CMM model defines a measure of progress through the advancement of maturity levels. To reach each level, several process areas must be achieved. These areas are identified by the satisfaction or dissatisfaction of clear and measurable objectives, known in the CMM documentation as Key Process Areas (KPAs).

Each KPA identifies a set of related activities and practices that, when executed together, achieve the fundamental objectives of the process. To create our maturity model, we will use the Capability Maturity Model Integration (CMMI), an evolution of the CMM that was introduced in 2001. In this way, we will develop a matrix that can measure the Analysis of Machine Learning Operations in the Industry

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. It 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 to establish 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. This way, the matrix provides a brief and clear form of the current state and desired conditions, showing different alternatives.

5. Validation and Use of the Maturity Model

Considering the development of the maturity model, the next step would be to verify that the model is consistent and applicable to the real world. For this purpose, the following examples will be applied:

- **Data analysis:** We used an online questionnaire to collect information from a sample of companies in our sector on their use and adoption of Machine Learning. We then used data analytics tools to examine emerging trends and patterns in companies' responses and finally assess the state of Machine Learning implementation.

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 complete 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 the 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 complete MLOps strategy has been implemented to manage warehousing operations automatically.
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.	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 have 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.

- **Case study analysis:** We would look for a case study of a company that has successfully implemented and used Machine Learning. We analyse how they have implemented and the results they have obtained. We use these case studies to improve our maturity model that analyses the state of Machine Learning implementation".
- **Expert assessment:** We would gather a panel of Machine Learning experts from different companies within the industry and ask them to assess the current state of Machine Learning implementation using our maturity model. We use their opinions and assessments to complement and enrich our model.
- **Process analysis:** We would examine the critical processes of implementing Machine Learning in a company's operations and evaluate their efficiency and effectiveness. We identify areas of improvement and process changes to improve the implementation and use of Machine Learning.

Considering the scope of this article, to define the level of implementation of machine learning models in the industry, a questionnaire will be drawn up according to each of the characteristics listed in the matrix (Table 1). A company can be said to have a level of implementation if it positively fulfils all the questions 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 matrix result provides the integrators of learning models in manufacturing operations with an overview of the state of implementation of the models (Table 2). It will allow them to know where they need to improve.

Table 2. Example of a Measurement Matrix.

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

Following the analysis of the current state of the implementation of learning models in the factory. Our maturity model will be able to answer questions such as:

- What types of problems or challenges is the company trying to address using Machine Learning in [production operations, maintenance operations, laboratory operations, materials management or support activities]?
- What processes or activities in [production, maintenance, laboratory, materials management or support activities] are being automated or improved through the use of Machine Learning?
- What impact has the use of Machine Learning had on the efficiency and productivity of [production operations, maintenance operations, laboratory operations, materials management or support activities]?
- How are the results of using Machine Learning in [production operations, maintenance operations, laboratory operations, materials management or support activities] being measured and evaluated?

These responses will provide a basis for suggesting improvements or next steps to further improve the implementation of machine learning models in an industry's operations.

6. Conclusions and future work

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 concerning the activities 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 automation.

The next step we should take to validate our maturity model would be the possibility of using it to analyse the state of implementation of machine learning models in a real case study. At this point, we will have to consider categories such as:

- **Automation**: How much of the process is automated, and what is the level of human involvement?
- **Data-driven decision making**: How much of the process is based on data and analytics?
- **Interoperability**: How well do the different systems and devices work together?
- **Real-time processing**: How quickly are decisions made and actions were taken?
- **Flexibility**: How easily can the system adapt to changing needs and new technologies?

- **Connectivity**: How well is the system connected to the Internet and other devices?
- **Cybersecurity**: How well is the system protected against cyber threats?
- **Human-machine interaction:** How well do the human and machine elements work together?
- **Human-centered design:** How well is the system designed to meet the needs and preferences of its human users?

These categories can help to identify the areas where machine learning models can be most effectively introduced and applied. On the other hand, we will also see it being used in different European projects, such as Zero-Defect Manufacturing Platform (ZDMP) or Industrial Data Services for Quality Control in Smart Manufacturing (i4Q) projects. These projects feature different algorithmic solutions and computational intelligence through cloud-based platforms offering Algorithms-as-a-Service (AaaS).

Acknowledgements

The research leading to these results received funding from the European Union H2020 programs with grant agreements No. 825631, "Zero-Defect Manufacturing Platform (ZDMP)" and No. 958205 ", Industrial Data Services for Quality Control in Smart Manufacturing (i4Q)".

References

Escobar, C., Arinez, J., & Morales-Menéndez, R. (2020). Process-Monitoring-for-Quality-A Step Forward in the Zero Defects Vision. *SAE Technical Papers*, 2020-April, April, 1–8. https://doi.org/10.4271/2020-01-1302

Naqa, I., Li, R., & Murphy, M. J. (Eds.). (2015). Machine Learning in Radiation Oncology. Springer International Publishing. https://doi.org/10.1007/978-3-319-18305-3

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics, 210*(September 2018), 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004

Ongsulee, P. (2017). Artificial intelligence, machine learning and deep learning. *Fifteenth International Conference on ICT and Knowledge Engineering*, 1–6. https://doi.org/10.1109/ICTKE.2017.8259629

Psarommatis, F., Prouvost, S., May, G., & Kiritsis, D. (2020). Product Quality Improvement Policies in Industry 4.0: Characteristics, Enabling Factors, Barriers, and Evolution Toward Zero Defect Manufacturing. *Frontiers in Computer Science, 2*(August), 1–15. https://doi.org/10.3389/fcomp.2020.00026

Serrano-Ruiz, J. C., Mula, J., & Poler, R. (2021). Smart manufacturing scheduling: A literature review. *Journal of Manufacturing Systems, 61*, 265–287. https://doi.org/10.1016/j.jmsy.2021.09.011

Lindström, J., Kyösti, P., Birk, W., & Lejon, E. (2020). An initial model for zero defect manufacturing. *Applied Sciences (Switzerland), 10*(13). https://doi.org/10.3390/app10134570

Calvin, T. W. (1983). Quality Control Techniques for 'Zero Defects'. *Technical Paper - Society of Manufacturing Engineers, C*(3), 323–328. https://doi.org/10.1016/0026-2714(84)90075-1

Jürgen, K. (2007). Manufacturing Execution System - MES.

Fox, M. S., Chionglo, J. F., & Barbuceanu, M. (1993). The Integrated Supply Chain Management Project. Retrieved from https://www.researchgate.net/publication/239033756_The_Integrated_Supply_Chain_Management_Project

Unver, H. O. (2013). An ISA-95-based manufacturing intelligence system in support of lean initiatives. International *Journal of Advanced Manufacturing Technology, 65*(5–8), 853–866. https://doi.org/10.1007/s00170-012-4223-z

Junín Durán de Leon, A., Cruz Rentería, J. R., Muñoz Zamora, G., García-Alva, S., Gutiérrez-torres, L., & Sánchez Hernández, Z. (2016). Desarrollo de Software basado en el estándar ISA-95.

Finkelstein, A. (1992). A Software Process Immaturity Model, *ACM SIGSOFT Software Engineering Notes, 17*(4), 22–23. https://doi.org/10.1145/141874.141878

Galan Manuel, J., de la fuente, S., Alonso de Armiño, C., & Alcalde Delgado, R. (2021). *15th International Conference on Industrial Engineering and Industrial Management*. Retrieved from https://pressbooks.pub/cioxxv