Industrial Metaverse Digital Twin: ISO 23247 Compliant Architecture for AI-Driven Simulation

Alexandre O. Júnior[*][†], José Luis Calvo-Rolle[†][‡], Rui Pires[§], Paulo Leitao[*]
[*] Research Centre in Digitalization and Intelligent Robotics (CeDRI), Laboratório Associado para a
Sustentabilidade e Tecnologia em Regiões de Montanha (SusTEC), Instituto Politécnico de Bragança,
Campus de Santa Apolónia, 5300-253 Bragança, Portugal, Email: {alexandrejunior, pleitao}@ipb.pt
[†]Universidad de La Laguna, Dep. de Ingeniería Informática y de Sistemas, La Laguna, 38204, Tenerife, Spain
[‡]Department of Industrial Engineering, University of A Coruña, CTC, CITIC,
Rúa Mendizábal, s/n, 15403 Ferrol, A Coruña, Spain, E-mail: jlcalvo@udc.es
[§]Volkswagen Autoeuropa, 2954-024 Quinta do Anjo, Portugal, Email: rui1.pires@volkswagen.pt

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***Abstract*—The Industrial Metaverse marks a new stage in Industry 4.0, raising the representation level of Digital Twins (DT) from discrete elements to an interconnected network of assets covering the entire production ecosystem. This paradigm changing reflects advances in enabling technologies such as Artificial Intelligence (AI) and complex what-if simulations. As complexity increases, adopting established industrial standards for implementing DT functionalities becomes imperative to specify guidelines for companies and researchers. This paper proposes a functional architecture for DT implementation in compliance with ISO 23247 standard, aiming to support the development of interoperable and standardized solutions combined within the Industrial Metaverse. The architecture was employed to develop a DT framework for an automotive assembly line, covering the quality inspection process and embedding AI-based mechanisms to leverage the what-if simulation of deviations in structural parameters of the vehicle's body. Experimental results demonstrate the tool's ability to accurately predict outputs for critical quality parameters according to hypothetical measurement scenarios, leveraging the production stakeholders' understanding regarding the correlated impact of deviations at different structural points, and demonstrating the versatility and potential of combining AI strategies for what-if simulations.**

Keywords: Industrial Metaverse, Artificial Intelligence, What-if Simulation, Digital Twin, ISO 23247, Zero Defect Manufacturing

I. INTRODUCTION

The Industrial Metaverse is an emerging paradigm that leverages cutting-edge information and communication technologies, consolidated under Industry 4.0 (I4.0), such as Cyber-Physical Systems (CPS), Internet of Things (IoT), Artificial Intelligence (AI), advanced simulation, and Digital Twins (DT), to establish a more resilient, immersive, sustainable, and human-centred industrial landscape, moving toward the Industry 5.0 vision. These technological enablers can support the development of highly integrated digital-physical environments that cover the entire value chain lifecycle, enabling increased automation and flexibility for the mass production of high-quality customized products [1].

As prominent components of the Industrial Metaverse, DTs must play a broader and more dynamic role in the digitalization of manufacturing ecosystems. They should not be restricted to discrete CPS but rather encompass all industrial assets — such as equipment, environment conditions, processes, personnel, and products — as well as their interactions and complex behaviours. Coupled with real-time IoT connectivity and AI-driven models, these expandable DTs should provide a precise end-to-end digital representation of the manufacturing process [2]. Furthermore, by adopting innovative visualization tools, such as advanced human-machine interfaces (HMI), realistic three-dimensional (3D) models, and augmented, mixed, and virtual reality, Metaverse's DTs can become immersive gateways for decision-makers, allowing the continuous monitoring and diagnosis of the production line [3].

Another aspect is the deployment of DTs to perform simulations under what-if scenarios. This process allows testing and validating distinct production line designs, parameter configurations, and system behaviours [4]. Simulations can leverage the process optimization and prevent failures by autonomously reconfiguring cyber-physical assets through the DT or supporting decision-making backed by recommendation systems and key performance indicators (KPIs). Moreover, embedding AI mechanisms can enhance simulation accuracy, yield more trustworthy recommendations, and reduce evaluation time and resource consumption by filtering out irrelevant scenarios [5].

The successful incorporation of AI techniques into DTs' simulation tools is a crucial step in establishing the Industrial Metaverse as a manufacturing guideline. Recent advancements in AI research, mainly driven by the development of high-end generative and large language models, can, e.g., facilitate the creation of fine-tuned AI simulation models capable of integrating stakeholders' knowledge into the behavioural models of the interconnected chain of manufacturing assets [6], elevating the strategic decision-making level across the industrial sector, covering both upstream and downstream operations. Furthermore, these enhanced simulations will influence the optimization of processes and enable quicker identification of impacts in production, such as operational changes and fault prediction or detection, paving direct pathways to higher productivity, sustainable growth, and the realization of the Zero Defect Manufacturing (ZDM) paradigm [7].

Despite these promising objectives, fully realizing the Industrial Metaverse is a long-term challenge. The current architectures outlined in the literature are in their early design stages, offering wildly divergent definitions, demonstrating that there is still no established conceptual consensus regarding the Metaverse paradigm [8]. Furthermore, they do not yet embrace consolidated reference models and industrial standards for the DT development, such as the Reference Architectural Model Industrie 4.0 (RAMI 4.0) [9] and the ISO 23247 standard [10]. The shortage of real-world applications deployed in the industry also restricts the availability of methodologies and guidelines for embedding AI into the simulation mechanisms. Additionally, ensuring data interoperability across multiple distributed systems in the manufacturing ecosystem remains challenging, exacerbated by the limitations imposed by outdated and legacy information technology (IT) systems [11].

This paper intends to define a supporting architecture for implementing DTs in the Industrial Metaverse context, compliant with the ISO 23247 standard, highlighting the symbiotic incorporation of AI strategies into the DTs functionalities, especially in the simulation components. The proposed architecture has been adopted to implement a DT-based what-if simulation tool for an automotive assembly line's body shop, embedding AI algorithms to model the quality control procedure. This allows decision-makers to explore the impacts on critical assembly points according to the hypothetical variation in the correlated measurement points and quality limits. Furthermore, this approach has the potential to be expanded across the entire assembly line, contributing to the company's broader establishment of the Industrial Metaverse and laying the foundation for developing adaptable strategies applicable to other use cases.

The remainder of the paper is organized as follows: Section II defines an architecture for DT development in the Industrial Metaverse context and aligned with ISO 23247. Section III describes the automotive assembly line case study. Section IV provides an overview of the developed AI-embedded what-if simulation tool to support the quality control process. Section V discusses the preliminary insights and experimental results. Finally, Section VI summarizes the paper by outlining the conclusions and future work.

II. INDUSTRIAL METAVERSE ARCHITECTURE IN COMPLIANCE WITH THE ISO 23247 STANDARD

DTs are at the core of I4.0's digital transformation, and their maturation and expansion are fundamental to realizing the Industrial Metaverse in the coming years, integrating organizations across operational, administrative, and strategic levels [7]. As Metaverse's DT grows in complexity and functionality, following reference architectures like the ISO 23247 and RAMI 4.0 becomes critical to ensure the proper design and integration of DTs in manufacturing. These frameworks provide companies and researchers with structured guidelines, transparent methodologies, and best practices that enhance composability and interoperability, enabling DT solutions tailored to specific manufacturing applications while supporting the formation of cross-company digital value chains [12], [13].

RAMI 4.0 defines a three-axis reference model designed to comprehensively support the digitalization of I4.0 components while ensuring connectivity and interoperability. It encompasses the hierarchical levels of the enterprise's IT and control systems, product lifecycle, and a layered representation of asset properties [9]. RAMI 4.0 can serve as a complementary resource to ISO 23247, which offers more oriented guidelines for the standardized development of DT solutions in manufacturing-specific cases [10]. While the first part of the ISO 23247 series outlines the general requirements for DT development, the second part introduces an entity-based reference architecture with a functional view of the systems and subsystems necessary for DT operation, including their respective applications and components [14].

As ISO 23247 is suitable for implementing digital threads, enabling the development of DTs for several lifecycle stages, the standard has the potential to be adapted and extended to integrate DT ecosystems that can embrace multi-asset lifecycles, thereby responding to the need for the development of standardized frameworks for the Industrial Metaverse [15]. In this context, an extended version of the ISO 23247 entity-based reference model is proposed in Figure 1, covering the novel intrinsic components and functionalities needed by DTs to fulfil the Industrial Metaverse paradigm requirements.

The *observable manufacturing elements layer* includes all essential physical assets within the industrial ecosystem, encompassing operational equipment, raw materials, processes (e.g., assembly, inspection, and maintenance), infrastructure facilities, environment conditions, supporting documents, personnel at different operational and management levels, and the complete product lifecycle. As the Metaverse expands to an end-to-end view of the industrial ecosystem, the supply chain and logistics digitalization becomes imperative to embrace aspects outside the industry boundaries besides multi-company relationships. Other factors, such as market data and consumer feedback, can influence the design of new products and the provision of support based on usage history. In addition, digitalizing the environmental footprint can foster industries' sustainable development and reduce environmental impact. Also, the representation of digital infrastructures can improve production chain management and guarantee better reliability and security for the continuous operation of the DT network.

The incorporation of the manufacturing elements into the *Industrial Metaverse framework* is established by the *device communication entity*. In this entity, the *data collection sub-entity*, mainly supported by IoT technologies, retrieves data from assets and performs its pre-processing by identifying the required information by the DT applications. Inside the Metaverse, AI-supported feedback and knowledge-gathering functionality can collect valuable insights from decision-makers input to refine and assist production processes. The *device control sub-entity* identifies the asset to be managed and performs its proper actuation and control according to the DT's response. With the interconnection of numerous systems and devices within the Metaverse, an orchestrator backed by AI and simulation can manage and synchronize their control, enabling streamlined and efficient distributed operations.

The *DT entity* hosts the entire collection of the industrial

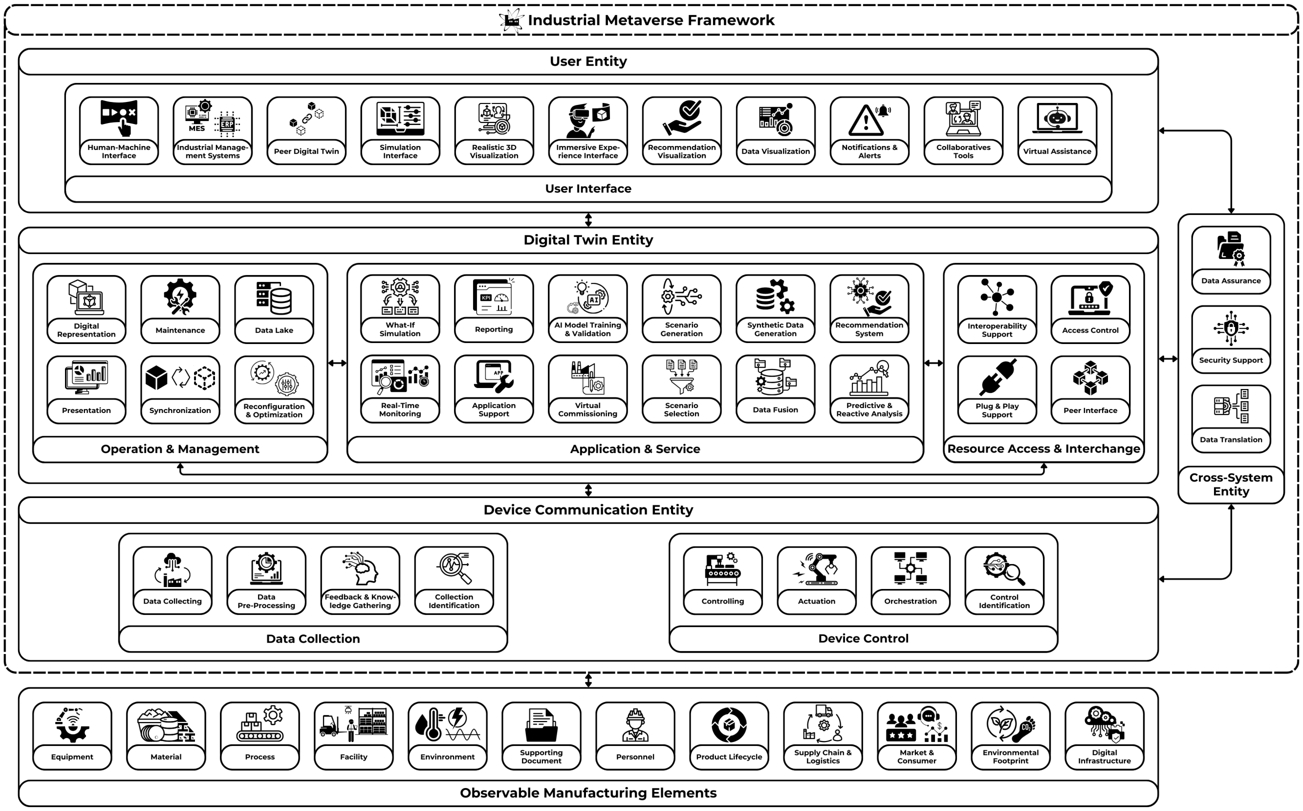


Figure 1. Supporting architecture for DTs implementation within the Industrial Metaverse in compliance with the ISO 23247 standard.

element's digital copies, along with services and applications required for the DT's functioning. The *operation and management sub-entity* contains digital representation models that translate the asset's characteristics and dynamically reflect its status and behaviour through synchronization functionalities. The data collected from the assets are stored in data lakes and can be visualized alongside the asset's digital representation model through the presentation function. The maintenance function ensures the DT's optimal operation by monitoring results and identifying and repairing anomalies. In addition, the reconfiguration and optimization function adjusts and fine-tunes the DT's performance. The *access and resource exchange sub-entity* controls access to the DT's functionalities, guaranteeing data security. Besides, the peer interface provides a means to interface the set of DTs in the Metaverse framework, guaranteeing interoperability support for data among the different entities and subsystems and plug-and-play support for the connection of manufacturing DTs.

The DT's functional components are clustered in the *application and service sub-entity*, which provides application support for developing and deploying open and closed-loop functionalities for reactive and predictive analysis, as well as real-time monitoring. The Metaverse's incorporation of AI and simulation capabilities further benefits and expands these applications, particularly if they are combined. A key example is the what-if component that employs AI mechanisms to refine simulation accuracy and assist in generating and selecting relevant scenarios of potential operational conditions. These simulations can also support other tools, such as virtual commissioning and synthetic data generation. The data fusion function can merge synthetic and actual asset data, populating the data lake with high-quality data essential for AI model training and validation. These models accurately portray the asset's characteristics and support other DT applications. Based on simulation and data analytics results, the reporting and recommendation system components generate reports and recommend actions to users.

The *user interface sub-entity*, defined by ISO 23247, includes HMI mechanisms, industrial management systems for planning and controlling operations, and peer DT functionalities for coordinating the interconnected network of the assets' DTs. To promote the user's immersion in the Industrial Metaverse, applications, e.g., dynamic simulation interfaces and realistic 3D visualizations of the industrial ecosystem and its elements are crucial, which can be further enhanced by immersive experience interfaces that take advantage of virtual and augmented reality technologies. Tools that provide robust data visualization capabilities, along with notifications and alerts, are imperative to keep users informed through analytical monitoring. Furthermore, the recommendation visualization and virtual assistance can be achieved due to the incorporation of AI algorithms to understand the manufacturing process through analytics and simulation outcomes. Besides, the inclusion of collaborative tools, e.g., integrated communication, codesign and development platforms in this entity can enhance collaborative work between multiple users and stakeholders.

Finally, the *cross-system entity* provides common functionalities for the other entities, such as data assurance to ensure data integrity and surveillance, security support for handling the framework authentification, confidentiality and authorization levels, and data translation to guarantee interoperability, syntax adaptation and semantic awareness.

III. AUTOMOTIVE ASSEMBLY LINE CASE STUDY

Several complex stages are involved in automotive production, from the engineering and design process of vehicles, pressings and stampings of parts to the assembly, painting, quality control and final assembly procedures. Creating a whole automotive ecosystem within the Industrial Metaverse is highly challenging, as it demands the digitalization of all the interconnected elements across these different stages. Aiming to establish initial guidelines for creating a Metaverse in compliance with the proposed ISO 23247-based architecture, this paper adopts a part of the quality control process in an automotive assembly line's body shop as a case study.

Figure 2 illustrates the sequential layout of the automotive body shop, organized into three distinct stages for assembly and inspection. Each assembly stage is managed by multiple automated stations dedicated to the vehicle's framing, doors and tailgates assembly. After completing each assembly stage, the vehicle is inspected at a station equipped with robotic triangulation laser systems. These sensors measure several geometric parameters to verify the vehicle's structural compliance with defined dimensional tolerances along the X, Y, and Z axes, or gap and flush parameters to ensure spacing and alignment between adjacent components.

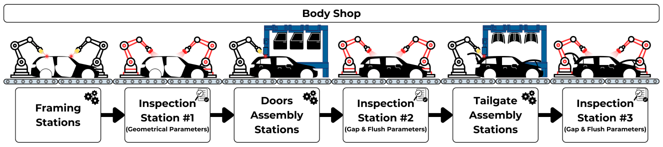


Figure 2. Sequential layout of work and quality inspection stations on the automotive body shop.

During each inspection phase, numerous measurement points throughout the vehicle's structure are evaluated to confirm the proper assembly and identify any need for adjustments or rework. For this purpose, measurement criteria previously established during the vehicle's engineering and testing phases are applied, categorized as follows:

- *Lower Specification Limit (LS)* and *Upper Specification Limit (US)*: Define the minimum and maximum acceptable values for a measurement point according to the vehicle specifications.
- *Lower Tolerance Limit (LT)* and *Upper Tolerance Limit (UT)*: Specify a narrower range within the specification limits, enhancing reliability in parameter quality.
- *Lower Rejection Limit (LR)* and *Upper Rejection Limit (UR):* Sets a slightly wider boundary outside the specification limits, where any value beyond these limits is deemed unacceptable and must be corrected.

For the quality evaluation of the assembly process, some specific structural points are classified as critical due to their significant impact on the vehicle's overall quality. Assuring their compliance within the defined inspection limits is even more essential for ensuring the vehicle's aesthetics and structural integrity since, due to the mutual correlation between critical and non-critical points, slight deviations in a determined point can influence the occurrence of more significant misalignments in other areas. The leverage of AI-driven models for what-if simulation tools can offer to quality analysts and production supervisors means to explore hypothetical assembly scenarios with distinct measurement inputs. By simulating the potential impact of correlated measurements on critical points, these tools can provide valuable insights concerning deviations in the assembly process and even how the very measurement limits of one point can affect another, enabling the identification of optimal inspection thresholds.

IV. AI-EMBEDDED WHAT-IF SIMULATION TOOL IMPLEMENTATION WITHIN INDUSTRIAL METAVERSE

In order to explore the impact on the vehicle quality inspection process at critical structural points through the selection of hypothetical values for the measurement points, a framework based on the proposed architecture was implemented. Figure 3 shows the relevant subsystems of the generic architecture that were selected and adapted to incorporate AI-based strategies in simulation for the case study, serving as a proof-of-concept implementation of the proposed architecture in Section II.

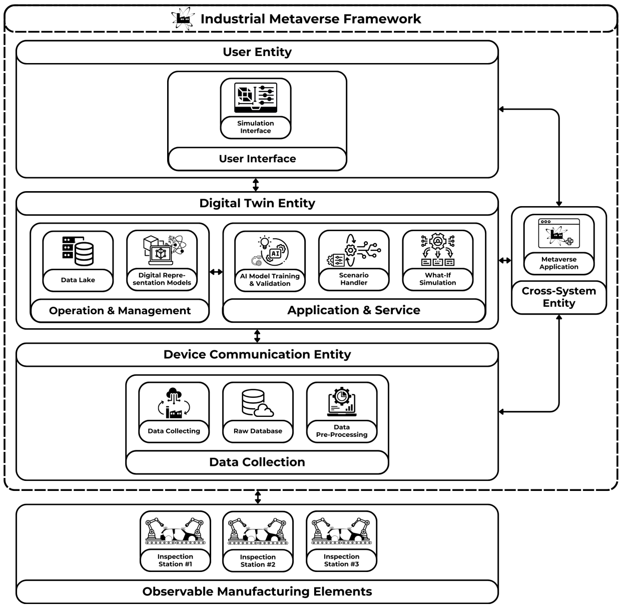


Figure 3. Implementation of the Industrial Metaverse framework for what-if simulation within the body shop's quality control process.

Briefly, the *observable manufacturing elements layer* represents the body shop's inspection station. The *device communication entity* manages data relating to the measurements performed by the inspection stations, where the data are collected and stored in a raw database on a server of the automotive company. The data then undergoes a pre-processing process to extract the information needed for the simulation and to generate the assets' descriptive AI models. Once processed, the data is stored in a data lake managed by the *operation and management sub-entity*, which makes the information accessible to other modules. This entity also hosts the models that represent the inspection assets.

The training of these AI models occurs within the *application and service sub-entity*, where the historical vehicle measurement data is first utilized to generate a correlation matrix comprising the different inspection points. This matrix helps to identify relationships between critical and non-critical points, guiding the selection of variables for model building. Then, an implemented engine with the support of the Scikit-Learn [16] library is applied to generate linear regression models for the critical points. Note that this model, alongside the random forest model employed in a later step of the system implementation, were selected due to their suitability for multivariate systems, which does not exclude adopting other AI models. In this process, each critical point is treated as a dependent variable, while points with high or moderate correlation with the critical point act as the independent variables for the model's training.

The engine performs a fine-tuning process by systematically testing several combinations of independent variables to optimize the model's precision. This step ensures the avoidance of overfitting caused by highly correlated variables or underperformance due to weakly correlated inputs. Moreover, the engine generates random forest models for the critical points as they can capture non-linear relationships between variables, supporting measurement points where strong linear correlations are not observed. During the model validation phase, the engine evaluates both regression and random forest models, selecting the one with the highest predictive accuracy for each critical measurement point.

The scenario handler orchestrates the configuration of the input parameters for the independent variables based on the user's entries and the selection of the desired critical point. Once the scenario is set, the what-if simulation tool employs the AI model to predict the output value for the selected critical point. This predicted value is subsequently analyzed against the predefined measurement criteria, informing the user whether it falls within or out of the specification, tolerance, or rejection thresholds, considering the precision of the models and its estimated error or uncertainty. Finally, for establishing the *user entity*, a simulation interface was developed using the Dearpygui library, enabling the user to select the critical points for the what-if simulation, setting the input values for the correlated points, and visualizing the prediction and analysis results considering the measurement criteria.

V. EXPERIMENTAL VALIDATION AND DISCUSSION

The framing inspection station was selected for the initial experimental validation of the Industrial Metaverse framework due to its high number of highly correlated measurement points identified by the correlation matrix. Since the framing inspection station is at the initial assembly stage, only dimensional values are measured since only welding operations on the vehicle body have been carried out, and there are no parts attached to the gap and flush measurements. Data from over 137,000 cars produced over a 10-month period and stored in the raw database were selected to construct the training database. This dataset was pre-processed to exclude irrelevant features and points that were not consistently measured. Approximately 285 measurement points were identified, of which around 80 are critical to the quality process.

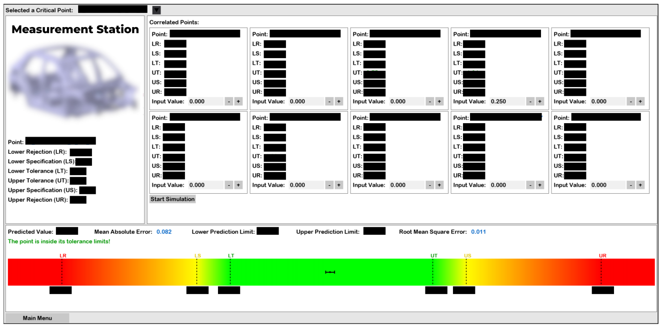
The critical points' linear regression and random forest models were generated through the model training engine. After testing, a maximum limit of up to 15 independent variables was set to fine-tune the models. Of the 80 critical points, 64 models were selected for the simulation tool, as their estimated mean absolute error (MAE) was below 0.1 mm (a threshold chosen to ensure that estimation errors do not significantly impact the quality process). Of the selected models, 61 were linear regression models, while 3 were random forest models corresponding to critical points with weaker linear correlations.

Data from approximately 47,000 vehicles produced over a 4-month period were used for the preliminary validation of the models and simulation mechanisms. Table I presents the metrics obtained during these tests, including the coefficient of determination (R^2), MAE, and root mean square error (RMSE). The models were applied to predict the values of the critical points according to their respective correlated points. The models achieved high accuracy, with an average R^2 of 0.96, and their errors remained within the established 0.1 mm threshold. This level of accuracy ensures the reliability of the hypothetical simulation tool, increasing production supervisors' confidence in its use.

Table I
METRICS RESULTING FROM THE SIMULATION TEST WITH THE MODELS.

Metric	Minimum value	Maximum value	Average	Std. deviation
R^2	0.785	0.999	0.969	0.032
MAE	0.002	0.099	0.031	0.004
RMSE	1.64×10^{-5}	0.015	0.003	0.004

Figure 4 depicts the simulation interface for the framing station. Users can select one of the critical points for this assembly stage through a drop-down menu, displaying the measurement criteria limits for the selected point and its correlated points. A field allows the manual setting of an input value for the simulation scenario for each independent variable. The bottom window displays the simulation results, including the predicted value, the model's estimated error, and its confidence interval. A gradient bar indicates whether the value falls within the tolerance (green), specification (green-yellow), rejection (yellow-orange-red) or beyond the rejection limits (red), thus portraying the impact of the hypothetical measurements for which selected critical point.



Selected a Critical Point: [redacted]

Point: [redacted]
Lower Rejection (LR): [redacted]
Lower Specification (LS): [redacted]
Lower Tolerance (LT): [redacted]
Upper Tolerance (UT): [redacted]
Upper Specification (US): [redacted]
Upper Rejection (UR): [redacted]

Point: [redacted]
LR: [redacted]
LS: [redacted]
LT: [redacted]
UT: [redacted]
US: [redacted]
UR: [redacted]
Input Value: 0.000

Point: [redacted]
LR: [redacted]
LS: [redacted]
LT: [redacted]
UT: [redacted]
US: [redacted]
UR: [redacted]
Input Value: 0.000

Point: [redacted]
LR: [redacted]
LS: [redacted]
LT: [redacted]
UT: [redacted]
US: [redacted]
UR: [redacted]
Input Value: 0.000

Point: [redacted]
LR: [redacted]
LS: [redacted]
LT: [redacted]
UT: [redacted]
US: [redacted]
UR: [redacted]
Input Value: 0.250

Point: [redacted]
LR: [redacted]
LS: [redacted]
LT: [redacted]
UT: [redacted]
US: [redacted]
UR: [redacted]
Input Value: 0.000

Point: [redacted]
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Predicted Value: [redacted]
Mean Absolute Error: 0.082
Lower Prediction Limit: [redacted]
Upper Prediction Limit: [redacted]
Root Mean Square Error: 0.011

The point is inside its tolerance limits!

[redacted] [redacted] [redacted] [redacted] [redacted] [redacted]

Figure 4. What-if simulation interface for the framing station. *(Note: Point's have been blurred to maintain the privacy of the company's data.)*

Although the framework has undergone preliminary validation, it remains in the prototyping stage, with modifications being made based on production supervisors' feedback. While the linear regression and random forest models have demonstrated strong performance for the multivariate system, exploring more advanced AI mechanisms will be essential for representing points with weaker correlations and expanding the modelling to subsequent assemble stages and stations.

Nevertheless, embedding AI mechanisms into the what-if simulation tool has enabled highly accurate predictions for critical points, providing stakeholders with valuable insights and KPIs regarding the effects of hypothetical measurements on correlated points, which will enhance the decision-making process. Additionally, AI can be leveraged to support the implementation of other modules within the proposed architecture, such as the development of recommendation systems, the deployment of advanced real-time data analytics tools, and efficient data flow management for the digitalization of the manufacturing ecosystem. These advancements will enhance the framework's capabilities, enabling it to address more complex scenarios and fostering interoperability in alignment with ISO 23247 and the development of ZDM applications.

VI. CONCLUSIONS AND FUTURE WORK

As the DT concept evolves alongside the emergence of the Industrial Metaverse, the need for architectures that incorporate industry-established standards for DTs becomes increasingly compulsory. This paper has proposed an ISO 23247-compliant architecture for DT design, addressing the specific demands of the Industrial Metaverse. This architecture was applied to an automotive assembly line case study, encompassing the quality inspection process and AI-driven what-if simulations to study the impact of measurement values on the vehicle's critical structural points. Experimental tests demonstrated that the simulation application delivers accurate predictions, helping stakeholders understand how measurement deviations influence the assembly process.

Future work will focus on expanding the simulation tool's functionalities, incorporating more advanced AI models to better represent the correlations between the measurement points and simulate their impacts on other critical and non-critical points. Additional assembly stages will also be integrated, enabling the framework to assess the assembly process throughout its lifecycle, thus supporting its adoption as a ZDM strategy for the defect prevention. Other functionalities will also be explored, particularly in the *DT* and *user entities*, further enhancing the user experience and advancing the Industrial Metaverse framework's potential.

ACKNOWLEDGMENTS

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