AI and Digital Twin Driven Closed-Loop Thermal Inspection

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Abstract
The Zero Defects, Zero Waste (ZDZW) project, funded by Horizon Europe programme, proposes to develop digitally enhanced non-destructive inspection solutions to improve production efficiency and support sustainable manufacturing for European factories. One of the aims of Zero Defects, Zero Waste project, is to implement interoperable and decoupled services. Non-destructive inspection systems using **thermal** images captured by **infrared** cameras become the most efficient systems which are used to detect the defects and anomalies in the industrial processes such as thermoforming, welding, heat-sealing, chemicals, plastics, etc. In this paper thermoforming process is analyzed in scope of Non-Destructive Thermal Inspection. Consequently, using advanced artificial intelligence techniques and Digital Twin models for in-line monitoring, real-time control of production processes, waste and defects can be reduced in thermoforming production processes in a passive manner without destructive methods. This paper proposes a closed loop non-destructive inspection solution which is inter-linked and interoperable with digital twin.

Keywords
Thermal Inspection, Digital Twin, Enterprise Interoperability, Artificial Intelligence, Computer Vision, Non-Destructive Inspection, Zero-Defect Manufacturing, Heat Transfer, Finite Element Analysis

1. Introduction

The concept of digitalization is rising in the factories, with Industry 4.0. An important step for digital transformation is the smart integration of manufacturing and inspection processes. This could be achieved through enabled live assessment of the products' health [1]. Manufacturing companies require advanced product improvements to reduce their energy consumption while preventing defects [2]. Zero Defect and Zero Waste (ZDZW) Horizon Europe project, funded by European Union, aims to develop non-destructive inspection thermal applications that will work interoperable in production lines to reduce defect and waste.

Among multiple production processes that operate with thermal energy (heat) such as welding, coating and injection, thermoforming is a widely used polymer shaping operation. Considering the latest developments in Artificial Intelligence (AI) and digital twin technologies can be leveraged to optimize the thermoforming lines. The plastic sheets used in thermoforming production lines during

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heating and forming may be scrapped for different reasons. At this point, thermal inspection suite monitors the surface of polymer sheet provides thermal data with AI to digital twin. This approach eliminates the lack of interoperable work in production lines. Pre-determination of possible scrap formation during production by using thermal inspection suite is important in terms of early preventive system. Then, applying optimization with digital twin in the thermoforming line reduces defects of plastic sheets and downtime in the thermoforming line. In this paper, we propose a system architecture that can work independently and interoperable, thus integrating into the Zero Defect Zero Waste (ZDZW) platform.

2. Concept

Digital Twin is a replica of a unit for virtual testing and optimization purposes. Thermal digital twin of thermoforming process is a system which has thermal dynamics behavior of a heating system and its response. With the help of a digital twin, it is possible to predict thermal patterns to obtain a certain temperature distribution on a heated part. A thermoforming machine has hundreds of heating cells on the top and bottom of the furnace as shown in Figure 1. It is a challenging task to set the heating powers of these cells to obtain a desired temperature pattern on the heated (plastic) sheet. Therefore, there is a relationship between measured temperature pattern in two-dimension (2D) and quality of the product. Also, the optimization of temperature plays a crucial role in the thermoforming process to prevent scraps i.e. local melting of the plastic material due to excessive heating or fractures during the molding phase.

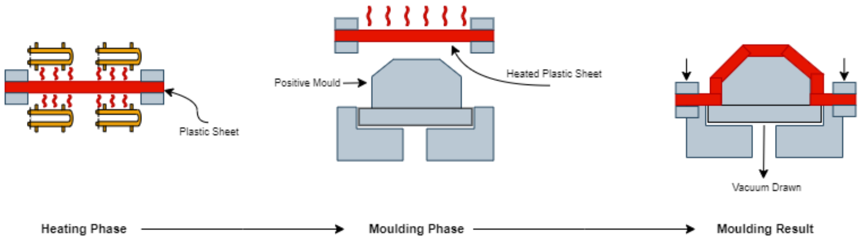

Figure 1: The diagram of thermoforming heating phase.

Another part of the concept is the thermal inspection suite that thermoforming solution which monitors thermal images of heated and formed plastic sheets during thermoforming process. It is an edge-based solution and has closed-loop communication with Digital Twin. The calibration of Digital Twin can be done with measured temperature pattern via thermal inspection suite. For this reason, the processing and transfer of thermal data received from the line in the factory plays a critical role in the production line. The digital twin model integrates real-time production data from the sensors located in the production line to the simulation data [2]. In addition to the data from the sensors, AI driven thermal inspection suite will share the real time thermal profile data which is collecting data from thermal cameras and detected anomaly information of the plastic sheet.

It is important to detect anomalies and defects without human intervention. Artificial intelligence is used for this purpose, as well as for signal processing, data analysis and image evaluation, because it can adapt flexibly to changing conditions and make decisions like humans. In addition, Artificial Intelligence encompasses a wide range of algorithms and principles of operation, including machine learning and its subgroups such as deep learning [3]. The detected quality issues can be taught to an AI system to match digital twin predictions and quality issues.

The aim of the Zero Defect, Zero Waste Project is to implement the solution it offers by communicating and collaborating with the two different concepts mentioned above as seen in Figure 2. Detailed information on how the method mentioned in the concept is implemented in an interoperable way is given in the section 4. Architecture.

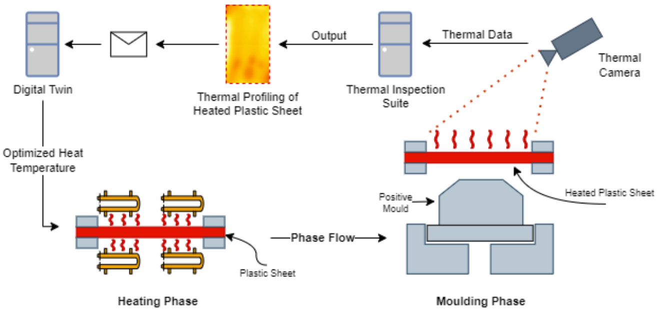

Figure 2: Overall concept of AI and Digital Twin Driven Closed-Loop Thermal Inspection

3. Methodology

As demonstrated in previous studies, it is necessary to validate and calibrate the heat transfer simulation results for the heating process by considering the temperature distribution of the sheet [4]. The real-time input parameters used in the digital twin simulation are listed in **Error! Reference source not found.**. Heat Transfer equations are employed to create the computational core of the Digital Twin. Finite Element Analysis is the key ingredient to estimate the thermal behavior of the thermoformed plastic sheet [4]. Critical parameters including heating array setup, cycle time, material and geometric properties of the sheet are integrated within the context of the Digital Twin.

Temperature predictions on the surface of the plastic sheet can be calculated with Heat Transfer equations. Conductive and Radiative Heat Transfer modes represent the dominant modes of thermal behaviors. Transient Conduction equation in three-dimensions is represented with:

$$\frac{\partial T}{\partial t} = \alpha \left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2} \right), \ \alpha = \frac{k}{\rho C_p} \qquad (1,2)$$

In this equation, Temperature is denoted with T and Thermal Diffusivity is denoted by a. Left hand side of the Conduction equation capture the time dependency while right hand side is to model the diffusion of temperature field with the body of the part. Thermal diffusivity depends on thermal conductivity (k), material density (r) and the Specific Heat Coefficient Cp [5]. In a similar fashion, radiative heat transfer has its own set of equations. Rate of change of heat transfer between to surfaces [5] are defined with:

$$\dot{Q} = \frac{\sigma (T_1^4 - T_2^4)}{\frac{1-\epsilon_1}{A_1 \epsilon_1} + \frac{1}{A_1 F_{1\to 2}} + \frac{1-\epsilon_2}{A_2 \epsilon_2}} \qquad (3)$$

T, as before denotes the Temperature where e is the emissivity of the surface, s is the Stefan Boltzmann coefficient, A is the surface area and $F_{1\text{-->}2}$ is the view factor between surface 1 and 2. Emissivity is the ability of the surface to emit energy. View factor is a value which defines the position and orientation of two surfaces against each other. In a problem with multiple surfaces, view-factors are pre-calculated with special integrals [5]. In this work, CalculiX is used to estimate the temperature predictions [6]. In a Thermoforming machine, a heating array is used to control the heating on the surface of the plastic sheet. A typical heating array (also depicted in Figure 2, heating phase) is given below and resulting Temperature profile is shared below:

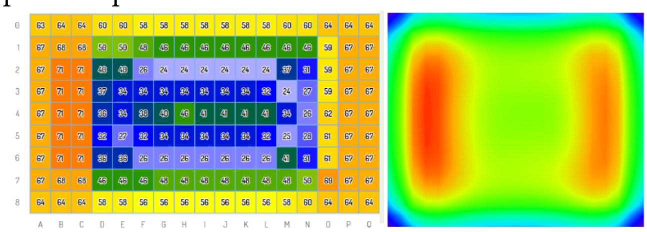

Figure 3: Heater Array (on the left), Temperature Estimation on plastic sheet (on the right)

The numbers on the cells show the percentage (%) of the heater Watt output, 0% meaning no heat input where 100% fully activated cell. Since each array element has its own set value, view factors in Equation 3 are calculated separately. Once the simulation is completed, Temperature distribution Figure 3 can be estimated. During the heating process, the system measures the temperature of the sheet from a single point where the calibration of the simulation results is not reliable from this single point [4]. Therefore, a thermal inspection suite is required between the heating and molding phase. To complete the setup of Digital Twin, a comparison is made on the Thermal Analysis against the Thermal Camera output and the differences between the prediction and real measurements are calculated on the surface. Using minimization algorithms, based on Gradient Descent, the heating array output is calibrated, consequently computational core of Digital Twin is adjusted uniquely for the Thermoforming machine.

Table 1: Process Parameters used in Digital Twin Simulation

Thermoforming Phase	**Input Data**	**Source of Data**
Pre-Heating Phase	Temperature distribution on the plastic sheet	Thermal Camera
Heating Phase	Local Temperatures on the plastic sheet	Thermal Camera
Molding Phase	Temperature distribution on molding result	Stereo Camera and Thermal Camera

4. Architecture

The traditional approach is to have a common database and a monolithic structure. However, these traditional methods cause the problems of lack of scalability and lack of interoperability in the industrial environment. Data collecting, processing, and analyzing parts are combined on a machine in the monolith structure. As stated in the methodology section, data needs to be collected from different parts of the thermoforming machine. Therefore, it is important that the services must be distributed. In the following section 4.1. System Architecture, the distributed service-oriented architecture is explained in detail.

4.1. System Architecture

Our proposed architecture is based on a microservice structure. The solutions need to be integrated to The Zero Defect Zero Waste Platform as an application. The platform is orchestrating via Kubernetes. Each developed application must be interoperable and decoupled.

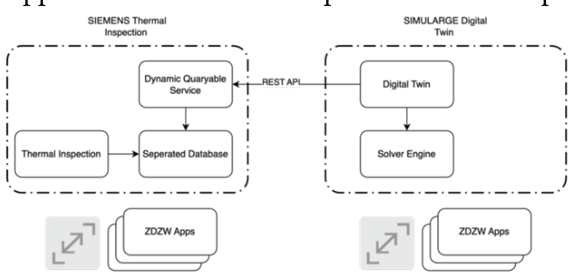

Figure 4: The interoperable architecture of proposed solution.

The thermal inspection service proposed includes a microservice module for dynamic query and analysis as shown in Figure 4, which provides the digital twin with flexible analysis capabilities, even without a common database structure. One of the main advantages of the thermal inspection service's data transmission is through a dynamic, queryable REST-API microservice. This allows for scalability and interoperability.

The thermal inspection suite and digital twin solutions are completely decoupled and communicate using standard communication protocols such as the Open API specification. In this way, the thermal inspection suite will be able to scale and work interoperable by orchestrating independently from the digital twin solution.

The distributed architecture proposed enables the separation of data collection, data processing, and analysis. This separation allows for more efficient and effective handling of data. In this way, data processing part which is explained in subsection 4.2. AI Inference Architecture can be placed another machine or location.

4.2. AI Inference Architecture

The approach which we proposed contains also artificial intelligence services. The services are supporting thermal inspection suite for detecting anomalies on the polymer sheet. Thermal data obtained from the thermal camera is pre-processed in image capturing functions of backend service for building AI Inspection models. The trained artificial intelligence model is served via Triton Inference Server which is installed on GPU-based machine in the factory [7]. The NVIDIA Triton Inference Server is an open-source software that enables users to send inference requests from any framework to any CPU- or GPU-based platform [8].

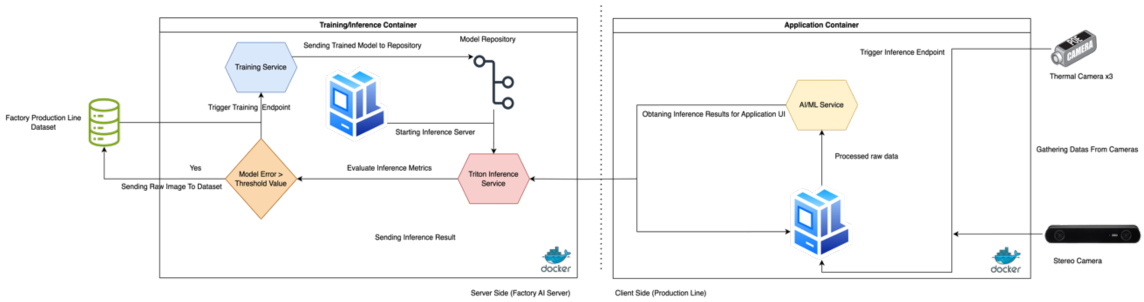

Figure 5: AI Inference Server Architecture

In the industrial thermoforming machine, it is expensive to locate GPU-based platform on every production line. Triton Inference Server serves the artificial intelligence model in a device-agnostic way [8]. Therefore, the CPU-based and low-cost clients can be able to inference with artificial intelligence model in distributed environment. With this proposed solution, the production line devices can send an inference request to the Triton Inference server and receive the output, regardless of the system architecture. **Error! Reference source not found.** shows that our distributed system allows for flexible placement of edge-based and low-cost instances to collect data from cameras. As explained in the 4. Architecture, the monolithic structure is coupled, requiring each unit to implement its own artificial intelligence inference part with a GPU-based instance. This results in the need for multiple GPU-based instances for each analyzing phase as mentioned **Error! Reference source not found.**. Our approach minimizes costs by utilizing a single GPU server.

Table 2: Deployment resources of proposed solution

System Setup	Deployed GPU-based Instance	Deployed Edge-Based Low-Cost Instance
Without AI Inference Server	3	0
With AI Inference Server	1	3

5. Conclusion

This paper presents an interlinked and interoperable system architecture solution for non-destructive AI thermal inspection and digital twin. The architecture has been designed in the process from taking the image from the thermal camera to returning the temperature value of the digital twin. With the great advantage provided by the dynamic and queryable REST-API microservice structure, the data transfer of the thermal inspection service provides scalability and interoperability. Based on the specified methodology, the monolithic structure was not preferred because it requires obtaining and collecting data from various parts of the thermoforming machines. Our proposed solution decreases the GPU-based instance requirement for each inspection phase.

The system is specifically designed for thermoforming machines. Regarding future work, it can be configured for other industrial manufacturing machines.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

[1] Ghanbary Kalajahi, E.; Mahboubkhah, M.; Barari, A.: Skin Imaging: A Digital Twin for Geometric Deviations on Manufactured Surfaces. Appl. Sci, 2023, 13, 12971, https://doi.org/10.3390/app132312971

[2] Turan, E. et al: Sustainable Computing: Informatics and Systems 35 (2022) 100655

[3] Kuric I, Klarák J, Bulej V, Sága M, Kandera M, Hajdučík A, Tucki K. Approach to Automated Visual Inspection of Objects Based on Artificial Intelligence. Applied Sciences. 2022; 12(2):864. https://doi.org/10.3390/app12020864

[4] Zienkiewicz O, Taylor R, Zhu JZ (2013) The Finite Element Method: Its basis and Fundamentals, 7th edn. Butterworth-Heinemann, Oxford

[5] Incropera, F.P., DeWitt, D.P., Bergman T.L., Lavine, A.S. (2006) Fundamentals of Heat and Mass Transfer, 6th edn. John Wiley & Sons, New Jersey

[6] Dhondt, G., 2004, The Finite Element Method for Three-Dimensional Thermomechanical Applications, Wiley

[7] "Triton Inference Server," [Online]. Available: https://github.com/triton-inference-server/server.

[8] Savard, C., Manganelli, N., Holzman, B., Gray, L., Perloff, A., Pedro, K., ... & Ulmer, K. (2023). Optimizing High Throughput Inference on Graph Neural Networks at Shared Computing Facilities with the NVIDIA Triton Inference Server. *arXiv preprint arXiv:2312.06838.*

[9] IKERLAN S. COOP, "Non-Destructive Inspection Services for Digitally Enhanced Zero Waste Manufacturing," 4 September 2022. [Online]. Available: https://cordis.europa.eu/project/id/101057404.