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Digital Twin Modeling for Smart Injection Molding

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Abstract: In traditional injection molding, each level of the process has its own monitoring and improvement initiatives. But in the upcoming industrial revolution, it is important to establish connections and communication among all stages, as changes in one stage might have an impact on others. To address this issue, digital twins (DTs) are introduced as virtual models that replicate the entire injection molding process. This paper focuses on the data and technology needed to build a DT model for injection molding. Each stage can have its own DT, which are integrated into a comprehensive model of the process. DTs enable the smart automation of production processes and data collection, reducing manual efforts in supervising and controlling production systems. However, implementing DTs is challenging and requires effort for conception and integration with the represented systems. To mitigate this, the current work presents a model for systematic knowledge-based engineering for the DTs of injection molding. This model includes fault detection systems, 3D printing, and system integration to automate development activities. Based on knowledge engineering, data analysis, and data mapping, the proposed DT model allows fault detection, prognostic maintenance, and predictive manufacturing.

Keywords: fault detection; digital twin; system integration; additive manufacturing; injection molding; Industry 4.0

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1. Introduction

Informatic technologies, Artificial Intelligence (AI) methods, and automation remain the pillars of advanced technology that are able to solve many problems in industrial processes. Currently, manufacturing processes are facing different challenges and limitations. The implementation of intelligent systems, adaptation, and smart manufacturing can address some of these issues, like AI for wear monitoring, process optimization, and fault diagnosis [1–4]. The next industrial revolution represents large-scale changes in the current industry. Despite advances in manufacturing technologies, injection molding is one of the most widely used methods for the fabrication of polymeric products. In this paper, a framework of knowledge-based digital twins (DTs) in injection molding is proposed. A DT is a "virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning and reasoning to help decision-making" [5]. The development of DTs for injection molding bridges the gap between the physical and digital realms, underscoring its fundamental value proposition. This initiative seeks to enhance decision-making processes for system stakeholders by leveraging data-driven insights, thereby fostering improved outcomes. Critical to this endeavor is system integration, which facilitates the expression, integration, and management of data and information. This, in turn, supports the creation of a knowledge-based DT, which is essential for advancing the field.

Applications of the DT in the process industry have been reviewed in [6]. The review reveals that the DT has been applied in different domains such as discrete manufacturing, remanufacturing processes, and energy systems, but integrating any new asset or operational change into the existing infrastructure is a major challenge which should be solved for further applications of DTs in injection molding processes. Liau et al. [7] presented the concept of DTs in injection molding, mold design and manufacturing. In this context, they showed the needs of DTs at every stage in the injection molding industry and how they connect with each other to build, operate and enhance the performance at each stage. In this respect, the role of the Internet of Things (IoT) and Cyber-Physical System (CPS) in the DT concept of injection molding was explained, but the researchers emphasized that data acquisition, optimization and prediction analytics model is yet to be solved. An extant study [8] presented a data flow for the smart factorization of the injection molding process. The described framework was expected to increase manufacturing flexibility and reduce defects. The researchers emphasized the necessity for the implementation and validation of their framework in a real case. Recently, in [9], a review on applications of unit-level DTs in the manufacturing industry has been presented.

A review of the recent research works reveals that DTs have been used for various purposes in different industries [10–14]. In a study [15], an approach is presented to facilitate DTs for injection molding. It supports the automation of essential development activities and domain-specific customization based on a model-driven reference architecture in which domain-specific language is considered for CPS to specify events of the physical system. The researchers evaluated the proposed DT of an injection molding machine which controls the machine by optimizing the experiment parameters before the molding process.

In addition, the application of DTs in the process monitoring of micro-injection molding is described in [16]. The main challenge here is finding an appropriate method for continuous monitoring. Hence, a DT was employed as a performance controller that uses process monitoring to evaluate the product with the required quality.

Advanced manufacturing uses not only modern technologies but also information-based and high-tech processes. Utilizing smart solutions like integration systems and smart assistant tools leads to a significant reduction in cost and presents a greater range of capabilities compared to the most currently used methods in traditional processes [17]. For example, in [18,19], AI techniques have been used to optimize the injection molding process. Particularly, in [19], optimization is obtained based on in-mold conditions and explainable AI. The results confirmed a better overall part quality compared to the conventional process optimization approach.

The development of DTs for injection molding represents a pivotal convergence of the physical and digital domains, highlighting its fundamental value proposition. At the heart of this endeavor, DTs are characterized by three essential components: a physical object, its virtual counterpart, and the dynamic connection that facilitates an ongoing exchange between these two elements. This exchange—encompassing data, information, and knowledge—is enabled by cutting-edge technologies such as computer vision, the IoT, system integration, and advanced analytical methods. By leveraging these technologies, the initiative aims to enrich decision-making processes for system stakeholders, offering insights driven by robust data analytics to achieve superior outcomes. System integration emerges as a crucial facet in this context, enabling the effective expression, amalgamation, and management of data and information, thereby laying the groundwork for the evolution of a knowledge-based DT. This strategic integration not only advances the field but also ensures that the potential of DTs in injection molding is fully realized, fostering innovations and improvements in operational efficiency and product quality.

The objective of this study is to develop a DT model that extracts and manages injection molding knowledge. By embedding AI-driven fault detection and an intelligent document management framework within the DT, coupled with the precision of Additive Manufacturing (AM), our approach seeks to create a model inherently capable of predicting, monitoring, and optimizing both product and process performance in real time.

How can a DT model effectively extract and manage knowledge specific to injection molding processes to enhance operational efficiency and product quality, and what is the role of smart technologies in advancing the injection molding sector toward Industry 4.0 standards?

This pivotal question guides our exploration into the mechanisms by which DTs integrate and apply a vast array of operational data to improve the injection-molding process. The discussion will focus on the following:

- The approach for capturing and synthesizing data from multiple sources (e.g, sensors, systems (Enterprise Resource Planing (ERP) and documents) within the injection molding process.
- The impact of integrating AI, specifically Case-Based Reasoning (CBR) and intelligent documentation, on predictive and real-time analytics.
- The role of AM in rapidly prototyping mold designs and making and refining the DT model for greater agility and precision.
- The broader implications of these integrations in steering the injection molding industry toward the innovations promised by Industry 4.0.

The remainder of the paper is organized as follows: in Section 2, basics of injection molding have been briefly described. Section 3 presents a knowledge-based DT in the context of advanced technologies. Details of the proposed DT model for injection molding containing fault detection, AM, and system integration have been explained in Section 4. Finally, Section 5 presents conclusions.

2. Basics of Injection Molding Process

This cyclic process consists of four main stages: filling, packing, cooling, and ejection. In the filling step, the screw moves forward and pushes the molten material into the mold cavity. In the packing or holding stage, the screw keeps the holding pressure, and the mold is filled with material. During this stage, the material cools down, and a little more material is allowed to enter the mold. The created parts must be cooled enough in the cooling step by a coolant flow. Finally, in the ejection stage, the mold is opened, and the created part is ejected. Then, the mold would be closed, and a new cycle begins. A schematic of the injection molding machine and the production cycle of this manufacturing process are shown in Figure 1.

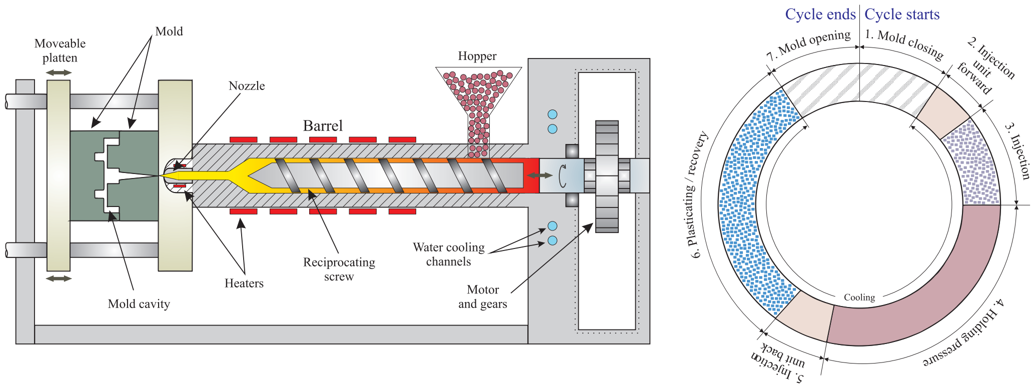

Figure 1. A schematic of injection molding machine and a molding production cycle.

As the injection molding process deals with several fields of engineering and science (e.g., heat transfer, fluid dynamics and polymer science), different techniques have been used to increase the performance and productivity of this manufacturing method [20–22]. Injection molding has a complex cyclic process, and the quality of the products depends on several parameters, such as the raw material, geometry of the part, and accuracy of the machine.

Based on applications of the injection molding process for mass production in many fields, its products have been utilized in different aspects of everyday life. Therefore, smart production and applying innovative technologies in this manufacturing process are essential. In this context, Industry 4.0 can provide opportunities to produce individualized and customized parts with advanced technologies that were never before possible.

3. Knowledge-Based Digital Twin

Applications of information and communication technology have significantly increased compared to past industrial revolutions as a result of world-wide improvements in all industrial manufacturing. Here, we highlight advanced technologies of Industry 4.0 that have been considered in our proposed knowledge-based framework of DT for smart injection molding. They are briefly described in the following subsection.

3.1. Advanced Technologies

The development of DTs dealing with all parameters in the injection molding process can be considered as one of the main challenges in establishing a knowledge-based system. However, there are different obvious sources of data which should be recognized and used. The main techniques of Industry 4.0 are shown in Figure 2.

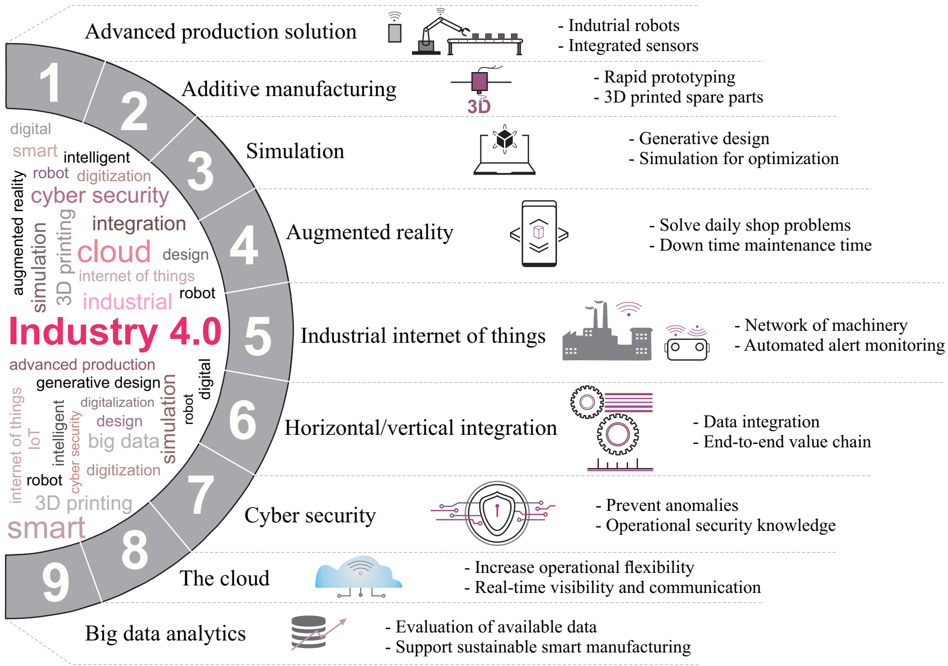

Figure 2. Main pillars of Industry 4.0 in the production process.

Implementing a complete DT contains IoT-enabled sensing methods, smart systems and devices and the CPS, which play an important role in smart factories. For such a development in this manufacturing process, injection molding machines should be upgraded with additively manufactured molds, which is explained in Section 4.2. This required upgrading deals with some challenges because in most companies, traditional machinery is still used based on the hierarchical production planning, which is controlled by a Manufacturing Execution System (MES). Hence, for implementing a successful DT, intelligent system integration solutions are also required for integrating an existing MES/ERP with the new equipment and devices, which is discussed in Section 4.3.

3.2. DT Modeling

Our proposed knowledge-based DT framework is designed to convey how our DT integrates and leverages data, information, and knowledge, aligning with the comprehensive nature of DT systems. It encapsulate the physical object, its virtual counterpart, and the critical connections between the two. These connections are facilitated through advanced technologies such as computer vision, IoT, system integration, and sophisticated AI methods. The main components of DT illustrated in Figure 3 include knowledge exchange and management from diverse sources. This process includes analyzing sensor readings, machine parameters, documents, and production outcomes to create a comprehensive knowledge base. The model uses MES data to optimize mold design and making by AM and 3D printing. It extracts documents and applies this knowledge to optimize real-time process adjustments within ERP and MES systems. In addition, it utilizes machine parameters and sensor readings to minimize defects and predict maintenance needs, thereby enhancing operational efficiency and product quality. Therefore, smart technologies such as AM, advanced sensors, and AI-driven analytics serve as the backbone of the DT model. They provide the critical data and learning capabilities necessary for the model to accurately reflect and improve the physical processes of injection molding.

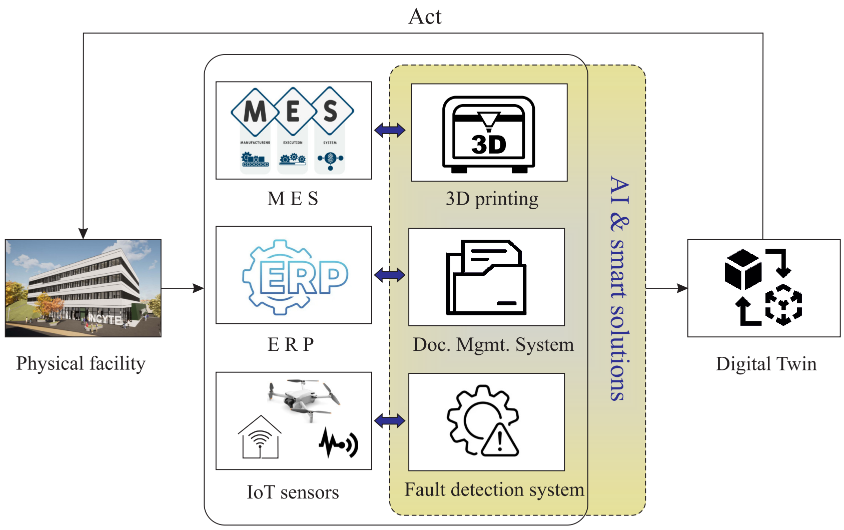

Figure 3. Conceptual diagram of the proposed DT framework.

In this paper, the proposed knowledge base includes data gathering and mapping to develop a real-time system by predicting and detecting failure earlier and performing properly, which is illustrated in Figure 4. This knowledge-based framework plays a significant role for realizing the virtual production. As can be seen, each smart production line contains physical and digital assets like equipment, IoT, CPS, and sensors. Physical systems are using the data generated from sensors and smart systems and devices (enterprise, operational and environmental data) to make decisions in the manufacturing execution system. Sensors allow bidirectional data communication in real time between a physical system and a virtual system using integration technology. This data communication needs integration technologies and methods (e.g., API and interfaces). In this regard, DTs were introduced to create new values by linking the virtual production stage with real production. This is enabled by system integration solutions with the combination of operation technology and information technology, which is also shown in executive and virtual layers. Making the right decisions in real-time processes is the main advantage of the DT in injection molding manufacturing that is achievable by connecting the devices/equipment to the network and using knowledge engineering/data analysis based on smart system integration solutions.

In virtual production, different machine learning models could be built with the gathered data from the knowledge engineering component. The first will be built on the data from in-mold sensors, and it would be correlated with a dataset of defective parts. This will greatly enhance the production, because it allows an early detection of defective pieces. In addition, the plan is to build a model to enhance the molding process directly, for which retrieval of the molding parameters is required. In this way, the related and authorized operators can perform the operation in each single machine and access the interconnected systems and sub-systems from different departments, e.g., manufacturing, procurement, warehousing, transportation and logistics.

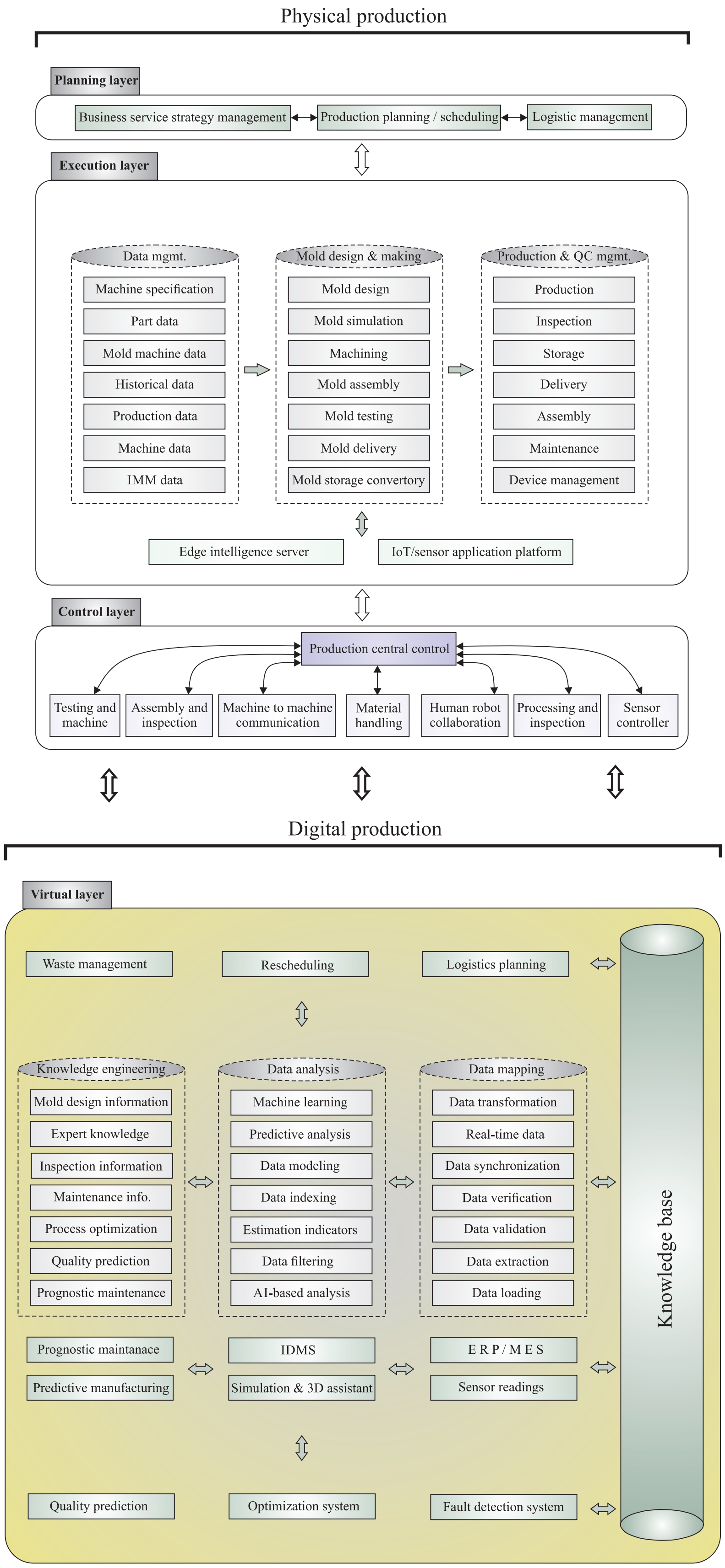

Figure 4. Knowledge-based framework of DT model for smart injection molding.

In addition, the effective use of data and information improves quality, optimizes the manufacturing processes (faster and more efficient) and reduces the costs. Moreover, there are also other benefits: predictive analytics and fault detection, global standardization to make sure about alignment in all facilities, remote monitoring and control for managing the production process and light-out manufacturing. Therefore, machines can start to gather data by enabling them with sensors and smart systems. In this way, machines can communicate with each other, and by delivering the information in real time, operators can use the fault detection systems and find out their problems directly. By machinery communication and sharing data with each other, they adapt their own settings (parameters). It is also useful for ensuring that the process is error-free and stable, and on the other hand, reducing costs and being more energy efficient, because when a machine is not processing plastic, it can be on standby until another machine tells it to turn again. Smart devices can also communicate with operators by providing different reports about the status of the machine, production and maintenance.

For end-to-end integration systems, a full suite of intelligent connectors should be designed and developed. Implementing a robust system integration involves complex processes, and considering some aspects like user-friendly interfaces and less complexity in configurations needs further investigation. In this regard, smart devices, intelligent systems and required interfaces facilitate the whole process by vertical and horizontal system integration solutions. Since injection molding has been widely used for the production of parts with complex geometry and high precision, it is crucial to set appropriate values of process parameters at the beginning of the manufacturing process. Here, we employed the Case-Based Reasoning (CBR) approach in a knowledge-based fault detection system in an Injection Molding Machine (IMM), which is discussed in Section 4.1.

Molds and clamps which are traditionally made by steel also can be fabricated by AM, which is explained in Section 4.2. Utilizing AM for the fabrication of molds and clamps not only reduces costs and saves time but also is beneficial for the production of geometrically complex molds and avoids damage to the parts which are in contact with additively manufactured clamps. Product complexity has a crucial effect on the design time, which is improved based on the production of molds by AM, as we discussed in [23].

A DT for the knowledge-based injection molding process consists of three main components:

- IMM, AM, and the ERP/IDMS model.

IMM represents the injection molding machine model. It takes into account the machine's setting parameters and sensor parameters to simulate and replicate the behavior and performance of the physical injection molding machine in the DT. AM represents the additive manufacturing model. It incorporates the quality parameters and design and redesign parameters to capture the AM processes involved in producing molds and clamps using AM technology within the DT. ERP represents the enterprise resource planning model. This component integrates the production parameters and document parameters to manage and optimize the overall production process. It includes activities such as scheduling, resource allocation, and documentation within the DT. By combining these three models, the DT system forms a comprehensive representation of the injection molding process. It enables real-time monitoring, fault detection, and decision support. The connectivity between the physical production and the DT is facilitated by IoT-enabled sensing systems. These systems intermittently collect data from the physical process and continuously update the DT, allowing for monitoring, analysis, and optimization of the injection molding process. To facilitate a deeper understanding of the DT model, here is the algorithm we designed to systematically update the virtual model, ensuring its continuous alignment with the physical process (see Algorithm 1). It operates in five key steps:

1. Initialization: The algorithm begins with the existing state of the virtual model, denoted as $V_{model}^{(t)}$, which represents the most current validated state of the injection molding process.
2. Knowledge Extraction: Using a function f, the algorithm processes various types of input data—such as sensor data (S_{data}), process data (P_{data}), 3D printing mold

data (M_{3D}), material data (Mat_{data}), and machine setting parameters (MS_{params})—to extract relevant knowledge (K_{ext}). This knowledge encapsulates critical insights about the current state of the molding process.

3. Model Update Computation: An update function ΔV takes the extracted knowledge along with technology updates (T_{update}) and insights from the IDMS ($IDMS_{data}$) to calculate the necessary updates to the virtual model. This computation reflects changes in the physical process that need to be mirrored in the digital realm to maintain the DT's accuracy.
4. Virtual Model Update: The virtual model is updated to a new state, $V_{model}^{(t+1)}$, by integrating the computed updates. This step ensures that the virtual model remains a faithful and updated replica of the physical injection molding process.
5. Output: The final step returns the updated virtual model, $V_{model}^{(t+1)}$, which is now ready for further analysis, simulation, and optimization to support improved decision making and operational efficiency.

Overall, this algorithm is a systematic method for integrating diverse data into a coherent model that supports the optimization of injection molding operations. It illustrates the iterative nature of maintaining a DT, where data are continuously used to refine and enhance the virtual representation of the manufacturing process.

Algorithm 1 Update Virtual Model for Injection Molding DT

Input: Sensor data (S_{data}),
Process data (P_{data}),
3D printing mold data (M_{3D}),
Material data (Mat_{data}),
Machine setting parameters (MS_{params}),
Technology updates (T_{update}),
IDMS data ($IDMS_{data}$)

Output: Updated virtual model ($V_{model}^{(t+1)}$)

procedure UPDATEVIRTUALMODEL ($V_{model}^{(t)}$)
▷ Start with the current state of the virtual model

$K_{ext} \leftarrow f(S_{data}, P_{data}, M_{3D}, Mat_{data}, MS_{params})$
▷ Extract Knowledge

$V_{update} \leftarrow \Delta V(K_{ext}, T_{update}, IDMS_{data})$
▷ Compute Model Update

$V_{model}^{(t+1)} \leftarrow V_{model}^{(t)} + V_{update}$
▷ Update Virtual Model

return $V_{model}^{(t+1)}$

end procedure

Combining the elements of operational optimization and fault detection, here is a comprehensive example of how the algorithm facilitates a knowledge-based DT model in the context of injection molding:

Imagine an injection molding company that specializes in plastic components. The company employs the proposed DT model to monitor and optimize its injection molding machines.

1. Initialization of the Virtual Model:

- The process begins with the current state of the DT model ($V_{model}^{(t)}$), representing the operational status of an injection molding machine.

2. Knowledge Extraction:

- Sensors on the machine gather real-time data (S_{data}) on temperature, pressure, and cycle times.
- Process data (P_{data}) provide insights into production efficiency, material usage, and operational trends.
- The machine's recent design changes, facilitated by Additive Manufacturing (M_{3D}), are incorporated into the DT to reflect updated mold configurations.
- Material data (Mat_{data}) detail the properties of plastics used, influencing processing parameters.
- Machine setting parameters (MS_{params}) and updates from new technologies (T_{update}) are integrated to keep the model current.
- The system synthesizes these data (K_{ext}) to form a comprehensive understanding of the machine's performance and potential improvements.

3. Compute Model Update:

- Given the clarification on the role of the IDMS focusing on managing documents like invoices and delivery notes to integrate ERP functions, and the emphasis on material properties monitoring and machine performance through the fault detection system, the algorithm calculates necessary model adjustments (ΔV) based on the extracted knowledge, considering insights from the Intelligent Document Management System ($IDMS_{data}$).

4. Update Virtual Model and Fault Detection:

- The DT model ($V_{model}^{(t+1)}$) is updated, reflecting the latest operational state.

Concurrently, a Case-based Fault Detection System (CFDS) analyzes the data to identify potential faults. If patterns similar to historical faults are detected, it triggers an alert for preemptive action.

5. Proactive Operational and Fault Management:

The updated DT model enables optimized machine settings for enhanced production efficiency and product quality.

Upon fault detection, the DT suggests immediate corrective measures, such as maintenance or process adjustments, preventing downtime and maintaining product consistency.

In a practical scenario, the DT model identifies a trend of increasing injection pressure, hinting at possible wear in the mold. Before this wear leads to product defects or machine downtime, maintenance is scheduled based on the DT's recommendation, ensuring continuous, efficient production.

In parallel, the CFDS flags an irregularity in the cooling system's performance, which is reminiscent of a previous fault scenario. The DT, referencing the historical data, advises checking the cooling system for potential blockages or failures. Maintenance personnel act swiftly, resolving the issue before it affects production.

Through this comprehensive approach, the DT model not only maintains an accurate real-time reflection of the injection molding process but also empowers the company with data-driven insights for operational excellence and proactive fault management. This example illustrates the algorithm's role in enhancing the DT's functionality, thereby advancing the injection molding sector toward the innovative standards of Industry 4.0.

4. Illustration of the Proposed Modeling

In this section, we illustrate the performance and applicability of the proposed DT framework for knowledge-based injection molding processes. More specifically, we present the results for the use cases defined in the following subsection. Three use cases are considered, and we explored further aspects of smart injection molding (see Figure 5).

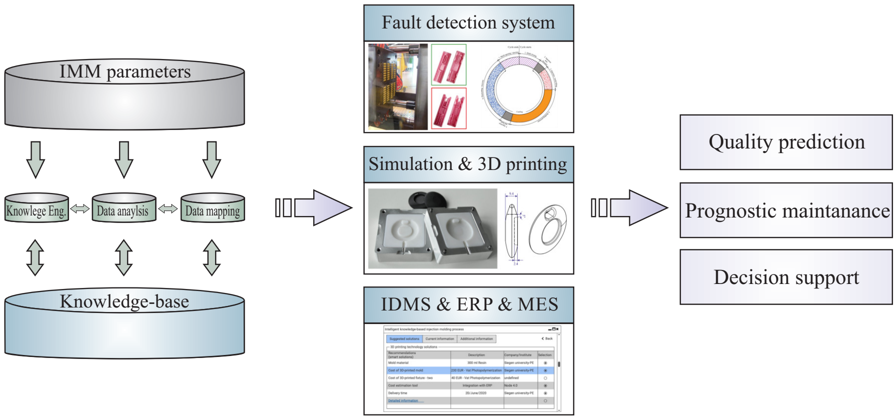

Figure 5. Schematic overview of the proposed DT modeling.

4.1. Faults Detection

The integration of the automated fault detection system with a knowledge-based DT enhances its capabilities. DT serves as a virtual representation of the physical injection molding process, facilitating not only real-time synchronization (by ensuring data collected from the physical system is mirrored in the DT) as well as real-time monitoring and analysis but also predictive modeling by leveraging the DT for simulating various scenarios and predicting the outcomes of potential adjustments, thereby optimizing the molding process and preemptively addressing issues before they escalate.

The establishment of an automated fault detection system involves five key steps:

1. Sensor Integration: Equipping the injection molding machines with sensors to collect relevant operational data.
2. System Calibration: Setting baseline parameters and performance metrics based on historical data to enable accurate anomaly detection.
3. Case Base Development: Designing and developing case base and similarity measurements/algorithms to identify patterns and predict faults based on the collected data.
4. Testing and Validation: Conducting trials to test the system's accuracy and reliability in detecting faults and predicting failures, using a specific case, such as dripper production, as a pilot area for implementation.
5. Integration with DT: Embedding the fault detection system within the DT framework to facilitate continuous monitoring, analysis, and optimization of the injection molding process.

In the production line, various faults can occur. The implemented CBR system is designed to detect these faults by analyzing the relationships between different parameters in the injection molding process. The knowledge-based system comprises four key components: (a) identification of features in the injection molding process, (b) computation of feature values using their fuzzy weights and rule generation, (c) development of a case database and presentation of relevant cases, and (d) matching cases and diagnosing faults. CBR is an artificial intelligence approach that focuses on representing and manipulating knowledge by leveraging successful solutions from previous problems. The membership function has three parameters, $a, b, c \in U$, with $a < b < c$ which can be presented as (a, b, c), and this is defined as follows:

$$\mu(x) = \begin{cases} \frac{x-a}{b-a} & \text{if} \quad a \leq x < b \\ \frac{x-c}{b-c} & \text{if} \quad b \leq x \leq c \\ 0 & \text{else} \end{cases} \tag{1}$$

These functions allow for the determination of fuzzy concrete features as structures of crisp concrete features and in turn, the defuzzification. We have utilized the weighted mean method to calculate the crisp value:

$$Crisp(\tilde{f}) = \frac{a + 2 \times b + c}{4} \quad (2)$$

Based on Equation (2), the weights are calculated as follows:

$$w_{f_i} = \sum_{j=1}^{m} FO_{f_i} \times Crisp(\tilde{\mu}_{f_i}^{Relationship}(PR_{ji})) \quad (3)$$

where w_{f_i} is the fuzzy weight for the *ith* feature, FO_{f_i} is the occurrence weight of the *ith* feature and $\tilde{\mu}_{f_j}^{Relationship}(PR_{ji})$ is the crisp value for the relationship of the *jth* parameter and the relevant feature (i). Previous solutions can serve as potential solutions for new problems. In our work, described in [24,25], we applied CBR to develop an intelligent fault detection system specifically tailored for an injection molding production line. IMM consists of several essential components, including the plasticating unit, hydraulic unit, mold, and clamping unit. Each of these units comprises various elements such as a screw, heating bands, and cooling system. When implementing the knowledge-based system, based on the domain expert consideration, we focused on 19 specific features categorized into five groups: temperature, pressure, time, speed, and size. Figure 6 shows different types of features in the injection molding process, which built our case base.

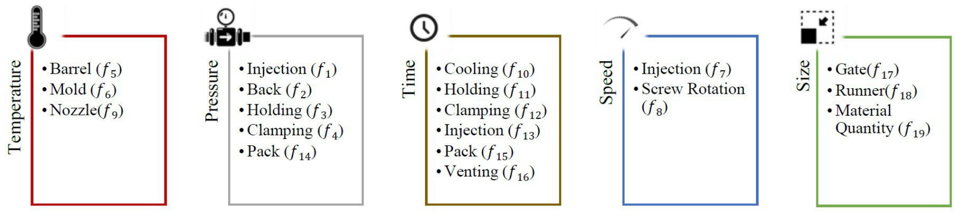

Figure 6. Identified features of process parameters in injection molding machine.

The initial step in case retrieval involves case indexing and determining the weights assigned to each feature. In this study, we identified five fuzzy sets (very weak, weak, medium, strong, and very strong) for classifying the effect and relationship between process parameters and a combination of quality control, part, and mold parameters. To calculate the relationship between each feature in the injection molding process, we utilized a fuzzy inference system. This system takes related parameters as inputs and generates a membership function output that represents the level of relationship [24]. In a specific example discussed in reference [25], we implemented a fuzzy CBR system to address the production line of drippers at Semnan Polyethylene Pipe and Fitting Co. in Iran [26]. Drippers are components used in irrigation tapes made by polyethylene (PE) material to ensure efficient water consumption. They are designed and produced with different flow paths which prepared different discharge rates (e.g., 1.1, 1.3, 1.5, 2.1 and 3.8 L per hour at a water pressure of 1 bar). In the first phase of drippers production, the PE material is fed to the machine and by a rotating screw. The material is then melted by conduction from the heating units that are installed in the barrel. This molten materials are transmitted to the tip of the screw. The second phase includes filling, packing, cooling and ejection, which is similar to the injection molding of other components. The total cycle time of the dripper production is fourteen seconds. The production of drippers can be affected by various improper molding conditions, which can result in faulty drippers. Figure 7 shows the mold of the studied drippers, which is installed on the mold injection machine. Moreover, faulty and perfect drippers are shown in Figure 7. As can be seen, when a dripper is manufactured with a fault, the discharge rate is completely altered, rendering it unusable. In our study, we specifically focused on identifying and addressing 21 unsuitable molding conditions that could occur during the production process of drippers. By applying the fuzzy CBR system, we aimed to utilize past experiences and knowledge to diagnose and rectify these unsuitable molding conditions. This approach allowed us to leverage previous successful solutions and adapt them to new problems or faults encountered in the production line of drippers.

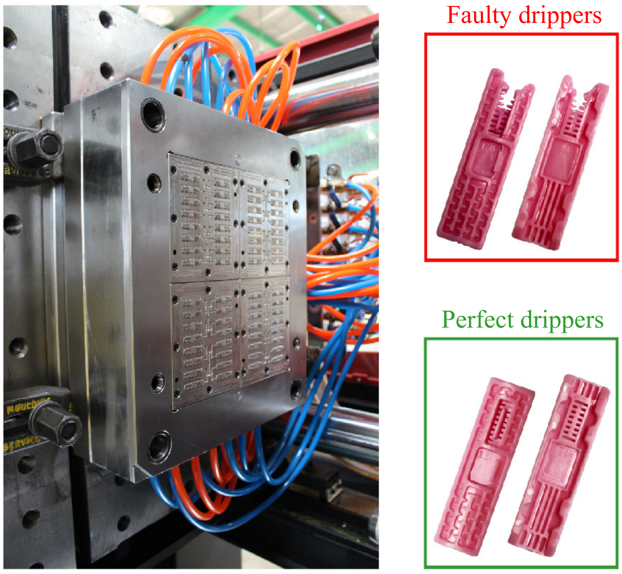

Figure 7. Mold of the drippers (**left**), faulty and perfect fabricated drippers (**right**).

After defining all features and parameters for each fault, we have calculated their significant weights of fault occurrence. Therefore, the proposed case base is created based on all faults, its cause and effect rules, attributes, and their weights. It should be noted that the case base of the dripper contains all attributes which are essential for detecting faults in this product. As utilizing an appropriate similarity measurement is a crucial issue in the procedure of case retrieval, we used a local/global similarity approach in our fault detection system, which is explained in [27]. Based on the results obtained from our study, the proposed system demonstrates promising potential for the preliminary fault diagnosis of molded drippers. The accuracy of the proposed system by using the fuzzy retrieval process for the occurring faults is increased from 17% to 50% in comparison with the default system, and the total accuracy of fault detection is 80% in the studied dripper's production line. The technique employed in this research can be further expanded and applied within the context of Industry 4.0 for the fault diagnosis of various other products.

In today's manufacturing environment, emissions reduction and energy conservation are critical challenges. By utilizing various intelligent systems, the product's overall energy consumption can be decreased. In this context, CBR can be employed to reduce the production time of high-quality products and accordingly reducing the cost. Moreover, using advanced technologies such as AM can be considered as a method to save energy.

By leveraging the knowledge-based approach and utilizing data-driven techniques, the system can effectively analyze and identify faults in the manufacturing process. This extends its applicability beyond the specific case of dripper production and opens avenues for implementation in different industrial domains. The system's adaptability and scalability make it a valuable tool for fault diagnosis in the broader context of Industry 4.0, where advanced technologies and interconnected systems play a vital role in optimizing production and quality control processes.

In addition, different kinds of sensors are developed for detecting in-mold process parameters, whereby temperature and pressure are the two most important parameters of these processes. In addition to these parameters, there are other factors which are important to monitor viscosity, warpage and shrinkage [28]. Beyond these fundamental parameters, the ability to monitor viscosity, warpage, and shrinkage within the mold cavity offers a comprehensive overview of the molding process, allowing for unparalleled precision and control.

Temperature sensors are utilized to monitor the thermal profile of both the molten plastic and the mold itself, ensuring that the material properties are maintained at optimal levels for flow and solidification. Pressure sensors, placed within the mold cavity, track the pressure exerted by the molten plastic, offering insights into the effectiveness of the injection process and the potential for defects in the final product.

The data collected by the sensors are not merely informational, but serve as a foundation for actionable insights that drive process optimization. Enriching these data with additional semantics, like fault tags, is crucial for generating self-contained, independent data streams without excessive resource use. We have developed a knowledge base that acts as a data lake, where metadata and stream data are integrated through an extract-load process and stored for future access. Data pipelines are then established to filter (based on fault tags) and supply the required data for fault detection. Refer to Listings 1 and 2 for examples of pressure and temperature sensor readings and their annotated counterparts. Temperature and pressure data are analyzed in real time, which allow to maintain process stability. Sensors measuring viscosity provide critical feedback on the material's flow characteristics, enabling the fine-tuning of heating and cooling cycles to accommodate different materials or product designs. Warpage and shrinkage sensors alert operators to dimensional deviations, facilitating immediate corrective actions to mitigate these issues.

Listing 1. Example of temperature/pressure sensor reading.


```
{
   "Sensor_ID": "TempSensor_10",
    "Reading": {
        "Temperature_C": 23.7,
        "Timestamp": "2024-03-29T12:00:00Z"
    }
    "Sensor_ID": "PressSensor_10",
    "Reading": {
        "Pressure_Bar": 45.5,
        "Timestamp": "2024-03-29T12:00:00Z"
    }
}
```


Listing 2. Annotated temperature/pressure sensor reading.


```
{
    "Sensor_ID": "TempSensor_10",
    "Reading": {
        "Temperature_C": 15.5,
        "Timestamp": "2024-03-29T12:05:00Z"
    },
    "Metadata": {
       "Sensor_Type": "Thermocouple",
       "Location": "Injection␣Molding␣Unit␣10"
    },
    "Fault_Detection": {
        "Status": "Incompleted␣Part_Fault-05",
        "Code": "F05"
    }
"Sensor_ID": "PresSensor_10",
    "Reading": {
        "Pressure_Bar": 23.5,
        "Timestamp": "2024-03-29T12:05:00Z"
    },
    "Metadata": {
       "Sensor_Type": "Strain␣Gauge",
       "Location": "Injection␣Molding␣Unit␣10"
    },
    "Fault_Detection": {
        "Status": "Incomplete␣Part_Fault␣05",
        "Code": "F05"
    }
}
```

The integration of sensor technology into injection molding processes represents a significant leap toward achieving "smart" manufacturing objectives. By enabling the real-time monitoring and control of critical process parameters, manufacturers can achieve higher levels of product quality, reduce waste, and enhance production efficiency. The ability to collect and analyze data from the mold cavity transforms the injection molding process from a largely reactive operation to a proactive, data-driven endeavor. This shift not only improves operational outcomes but also fosters a culture of continuous improvement and innovation within the manufacturing sector.

4.2. Additive Manufacturing

Molds play a crucial role in the quality and accuracy of injection-molded components. The mold shapes the molten material into the desired geometry, and several parts can be fabricated in each cycle by utilizing multi-cavity injection molds. The design and fabrication of a mold and its different components represents a highly technical and complex process. Traditional molds are fabricated by several process chains containing design steps, material selection, machining, assembly, and quality control. In most cases, the molds used in injection molding are made from metals such as steel or aluminium, and in general, more complex injection-molded products require more complex molds. Various traditional manufacturing processes should be used to fabricate different parts of the molds (e.g., cavity plates, ejector pins, and support plates). Although injection molding is an appropriate technique for large-scale production, traditional manufacturing processes have a prohibitively high cost and long lead time. Indeed, in traditional mold fabrication methods, complexity, high cost, and difficulties are inherent. AM, which also known as 3D printing, provides a time- and cost-efficient solution.

All 3D-printed molds can be produced by available 3D printers in the market, which can be used in both desktop and industrial molding machines. In this context, 3D-printed molds can be quickly tested and validated. They can be utilized for the fabrication of pre-production parts and even manufacture end-use parts in low volumes with limited equipment and training. In fact, fabricating 3D-printed molds reduced costs, labor, and time compared to machining aluminum molds.

As shown in Figure 8, we used 3D printing and fabricated molds of the housing for a chip key (transponder as a key). Figure 8 illustrates 3D-printed molds in aluminium housing and the geometry of the designed chip key. Although 3D-printed molds can be produced by different 3D printing techniques, high-temperature resins are ideal for use in the 3D printing of molds based on the stereolithography method. In fact, not many 3D-printed materials can withstand the repeated pressure; there is a highly glass-filled resin which is an appropriate material for the fabrication of 3D-printed molds. This material is extremely stiff, strong, and heat and chemical resistant, which are necessary properties for an injection mold. Here, we used a Formlabs 3D printer (Form 2) to print the mold, and the build volume of this 3D printer is approximately 145 × 145 × 175 mm (XYZ).

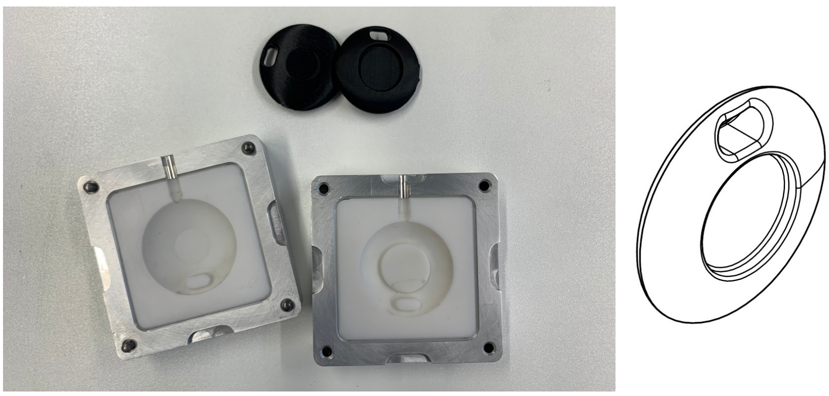

Figure 8. Fabricated 3D-printed mold for production of the chip key.

Although post-processing is needed for a 3D-printed mold produced by stereolithography, the emphasis in this method is on the production of geometrically complex components, which is not possible with conventional manufacturing processes. Since it was necessary to conduct a post-print curing, the printed parts in this study were cured using ultraviolet LED light in various positions and 10 min for each direction to ensure that there is no uncured resin in the 3D-printed mold. It is noteworthy that this post-print curing makes the 3D-printed parts more stable and rigid. Overall, 3D printing provides accurate molds with crisp features and a smooth surface finish that will yield high-quality final molded parts.

Although some print parameters are fixed by 3D printer manufacturer and cannot be modified, we have possibility to use appropriate material to reach the resired result. Some printing details are summarized in Table 1. High-temperature resins are ideal materials for the fabrication of 3D-printed molds based on the stereolithography technique. In the current study, we used Rigid 10K Resin material, which can provide a smooth matte finish with a high resistance to chemicals and heat. In fact, for 3D-printed molds, we need components that can withstand high temperatures and pressures and must not bend, break, or deflect.

Table 1. Printing process parameters on fabrication of 3D-printed mold.

Parameters	Values	Parameters	Values
Printing duration	11 h	Material	Rigid 10 K Resin
Infill density	100%	Layer height	50 micron
Build angle	45°	Support touchpoint size	0.5 mm

In the knowledge-based recommender system, user requirements are extracted at the first step. Consequently, the initial results are displayed based on the applicable advanced technologies of Industry 4.0. If more parameters are needed, the user should provide more details. It is worth noting that entering more parameters can lead to narrower results being suggested to the user. At the final step, appropriate solutions that address user need would be chosen and recommended as proposed solutions. The GUI for the data acquisition is illustrated in Figure 9, which is divided into different parts to extract parameters from the existing traditional production processes (e.g., 3D printing, virtual training, and generative design). As illustrated, the material, quantity, and dimensions of the final part must be entered to order a 3D-printed mold. In addition, according to the required time and cost estimations, certain parameters (e.g., printing speed) can be defined.

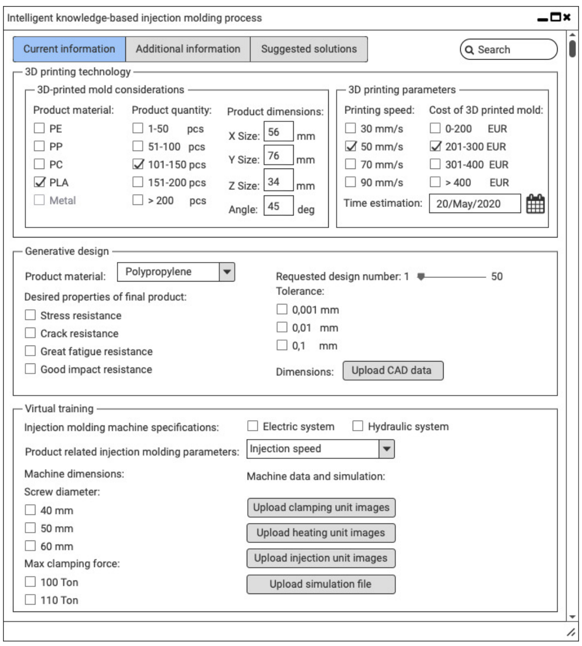

Figure 9. Design parameter of 3D printing [23].

4.3. Horizontal and Vertical System Integration

In a production process, horizontal and vertical integration refers to well-integrated processes. As existing systems are not integrated completely, in Industry 4.0, solving communications disparities is considered by a full integration via establishing a meta-network. In detail, horizontal integration refers to the integration at the production-floor level, and vertical integration deals with coordination of the production floor with higher-level processes. This integration can occur at different levels (e.g., supply chain, production facilities, quality assurance). System integration enables tools and devices of the IoT and the Industry 4.0 platform for efficient communication between sub-systems that produce measurable results. Considering the produced amount of data and offering the possibility of using them for making operational and business decisions are the main outcomes of the IoT. When utilizing the Industry 4.0 platform and the interconnected smart manufacturing, horizontal and vertical system integration, it is important to make sure that first, the machinery, IoT devices and engineering processes work together smoothly and continuously and then at higher organizational levels by using production data makes decisions, respectively. Horizontal and vertical system integration aspects in the injection molding processes could be outlined as follows:

- Networking between production sites.
- Integration of the user into the processes.
- Information exchange throughout the entire value-added process.
- Intelligent system communication in different departments.
- Networking within the company from the production to the field level.
- IT systems communicate at all levels.

Due to the need to share data and functionalities among several systems, the technical issues of information systems integration have become more and more complex. One of the main objectives is focusing on the integration problems in the context of ERP systems [29–31]. An ERP system automates business processes to make the organization more efficient and provides better visibility into those processes [32]. For obtaining the full complement of ERP benefits, organizations have to integrate all the other systems, sub-systems and applications with their ERP system. Therefore, having an elegant ERP system requires a concrete ERP deployment plan and strategy, which provides proper connectors to integrate data and information across all of the processes. A sufficient ERP system increases efficiency, has a modular approach and gives a desired decision support with distributed monitoring, control and computing processes. But, still there is a risk in selecting one system to complete the whole process without difficulty regarding its integration with other systems. Here, the proposed system is developed for the integration between the ERP system and Document Management System (DMS) in the smart injection molding process (fully automatic integration of documents, e.g., delivery receipts and invoices to desired ERP systems). This solution is module based, and admins can configure the system based on their requirements. These requirements include defining and selecting the document types, key values and related keys on the DMS side as well as selecting an ERP system, document types, required keys and the related items and interface on the ERP side. In Figure 10, the flowchart of the proposed system is illustrated.

The preliminary objective of the proposed system is digitalizing the paper-based documents (invoices and delivery receipts) and integrating them to the ERP system. Many companies waste their time and cost by digitalizing their processes manually (employees added the information to different systems) or semi-automatically, which slightly decreases the time/cost wasting, but reaping the benefits of a complete full automatic integration solution has not yet taken place.

Figure 11 shows the injection molding and extrusion machines of Semnan Polyethylene Pipe and Fitting Co. (Oldham, UK) [26], where we used manufacturing data for developing the knowledge-based recommender system. The proposed system would be used there to digitize paper-based documents.

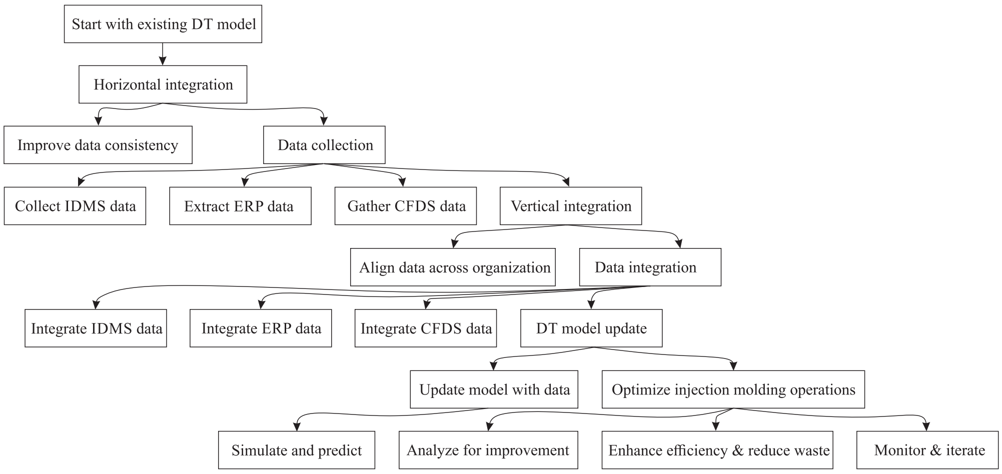

Figure 10. The flowchart of the proposed system.

Figure 11. Injection molding and extrusion machines in Semnan Polyethylene Pipe and Fitting Co.

Today, many companies receive their invoices either by e-mail or post. Based on the work [33], each incoming paper invoice costs approximately 17.60 Euro to the company, while in comparison, a digitalized copy costs only 6.40 Euro until the whole process is completed. The implemented system extracts all relevant data and transfers it to the appropriate software or lets the users manage their invoices/delivery receipt notes with a suitable interface and configurable modules. The comparison of the traditional process and smart solutions is shown in Figure 12. This two-axis chart illustrates the reduction in process cost and time per document by utilizing an intelligent document management system. In this chart, incoming invoices (II) and sending invoices (SI) are compared in manual and full automatically digitalized process management. The integration aspects of the proposed system are outlined below:

- Third-party suppliers and our system for the recording of invoices (e.g., invoices from different service providers).
- API for conversion of different file types. Thus, there are many use cases for which this system can be further developed for other input and output data types.
- Bidirectional integration between text files and AI engine (training and testing).
- ERP system integration: Direct linkage with ERP systems to synchronize financial, operational, and resource management data, allowing for a unified view of business processes and enabling more informed decision making.

- Real-time analytics and dashboard integration: Incorporates real-time data analytics and customizable dashboards, providing stakeholders with immediate insights into operational performance, financial metrics, and other key business indicators.

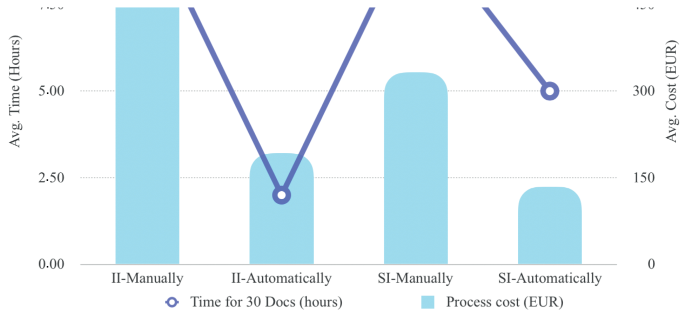

Figure 12. Two-axis charts for comparing time and cost in traditional process and smart solutions.

5. Conclusions

In this paper, we presented a knowledge-based DT for injection molding, which was designed to enhance operational efficiency and product quality through the integration of AI-driven fault detection, intelligent document management, and AM. This DT model uses data from injection molding processes to create systems capable of predicting and optimizing product and process performance in real time. The system integration demonstrates a structured approach to optimizing injection molding operations using a DT model. It starts with assessing the existing DT to identify areas for improvement. Horizontal integration enhances data consistency, while comprehensive data collection gathers key metrics from various systems (IDMS, ERP, and FDS). Vertical integration aligns data across the organization, and data integration brings insights into production efficiency. The digital twin model is updated with these data, enabling it to simulate and predict optimal performance. Finally, the optimized DT model guides process improvements to enhance efficiency, reduce waste, and ensure continuous optimization.

The implementation of our DT model demonstrates how integrating multiple data sources—from sensors to ERP systems—allows for the effective capture and synthesis of injection molding knowledge. This integration supports advanced predictive analytics and real-time monitoring capabilities, substantially improving decision-making and operational processes. For example, our fault detection system, equipped with CBR and based on fuzzy weights, shows an accuracy of 80% in predicting and preventing faults, indicating substantial enhancements in system reliability and process quality.

AM has proven particularly transformative with 3D-printed molds significantly reducing the time required for mold fabrication by up to 77% compared to traditional steel or aluminum molds. Moreover, the use of 3D printing for producing clamps has shown notable advantages in terms of both cost and time savings.

Furthermore, the integration of IoT and advanced fault detection systems within the DT model propels the injection molding sector toward the innovative standards set by Industry 4.0. The system's ability to integrate and digitalize documents and to seamlessly connect with ERP systems further demonstrates substantial cost and time efficiencies, achieving average savings of 62% and 65%, respectively.

As we continue to refine the DT model by incorporating a continuous parameter analysis of new applications and devices, we enhance the knowledge-based rules and solutions within the DT framework. This iterative improvement process ensures that the model remains up to date and increasingly effective in enhancing the operational efficiency of injection molding processes.

In conclusion, the development of this knowledge-based DT model fulfills the objectives set out at the beginning of our study, providing valuable insights and demonstrating the potential of advanced technologies to transform manufacturing processes in the injection molding industry.

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Conflicts of Interest: Sara Nasiri is the founder and CEO of the Company SmartyX GmbH and the first author of this research. The remaining authors declare no commercial or financial relationships that could be construed as a potential conflict of interest, ensuring the integrity and impartiality of this research.

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