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Implementation of Digital Twin and Deep Learning for Process Monitoring: Case Study in Injection Molding Manufacturing

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Abstract **-** This study explores the implementation of artificial intelligence for process monitoring within smart factories, particularly under the Factory 4.0 paradigm. It proposes an approach centered on a data-centric model for digital twins, enhanced by the application of deep learning methodologies utilizing LSTM models to forecast the melt cushion parameter—a crucial indicator of process stability in injection molding. The methodical framework unfolds in stages, beginning with the proposition of the digital twin architecture, followed by the deployment of LSTM networks trained on historical datasets. Following training, the model integrates smoothly into the digital twin ecosystem to provide predictive analytics and decision-making support. In the experimental phase, a hybrid strategy is adopted, combining edge and cloud computing for data acquisition and simulation. Core elements of the methodology include architecture validation, establishment of communication protocols, creation of offline model conditions, integration of the digital twin without disruption, and utilization of edge computing for real-time predictive analysis during simulations. This approach offers a comprehensive solution to the challenges of process monitoring in smart factories, facilitating enhanced operational efficiency and performance optimization.

Keywords**:** *Digital Twin, Injection Molding Process, Melt Cushion Parameter, LSTM Model, Deep Learning*

1. Introduction

In the dynamic landscape of Industry 4.0, the fusion of Internet of Things (IoT) technologies with advanced digital concepts has given rise to the Smart Industry paradigm [1]. At the heart of this revolution lies the concept of Digital Twins, offering a virtual mirror of physical systems for real-time monitoring, analysis, and optimization [2]. This article embarks on an exploration of the transformative impact of Digital Twins in the realm of injection molding, elucidating its benefits, challenges, and innovative applications.

Implementing Digital Twins in injection molding holds immense promise, offering a myriad of benefits. By leveraging real-time data analytics, manufacturers can optimize process parameters, enhance product quality, minimize downtime, and reduce costs [3]. However, realizing these benefits necessitates overcoming significant challenges.

Primary among the challenges is the accurate representation of intricate physical systems within the virtual domain. Modern approaches employ sophisticated modeling techniques and data-driven algorithms to bridge this gap effectively. Furthermore, integrating Digital Twin solutions with the diverse IoT infrastructure, including edge computing and cloud management, presents present a significant challenge [4].

This article offers a substantial contribution to the field, encapsulated in three primary points:

- Innovative Digital Twin Architecture: It introduces a novel architecture for digital twins tailored specifically for injection molding processes. This architecture serves as a foundation for effective process monitoring and control.
- Deep Learning-Based Prediction Model: The integration of a deep learning model, particularly utilizing LSTM networks, represents a significant advancement. By training on offline data, this model facilitates the accurate prediction of critical parameters, such as the melt cushion parameter, enhancing process stability.
- Hybrid Edge-Cloud Computing Approach: The adoption of a hybrid approach, combining edge and cloud computing, marks a departure from traditional methodologies. This approach optimizes data acquisition and simulation, ensuring efficient real-time monitoring and decision-making capabilities within the manufacturing environment.

The paper is structured into three main sections. Firstly, it outlines the overarching concept of digital twins and their various layers within the realm of injection molding. Secondly, it discusses the implementation of an LSTM model, detailing its training offline using real datasets. Finally, it presents proposed experiments leveraging edge computing and cloud resources.

2. Scope of study and literature review

2.1. Basic overview of Injection molding process

The Injection molding is an industrial technique, involves injecting plastic material into a mold cavity under high pressure, which can range from hundreds to thousands of bars [5]. Once injected, the plastic cools and solidifies within the mold cavity, taking the shape of the mold and producing a specific plastic product [6]. Figure 1 illustrates the five main stages of the standard production cycle.

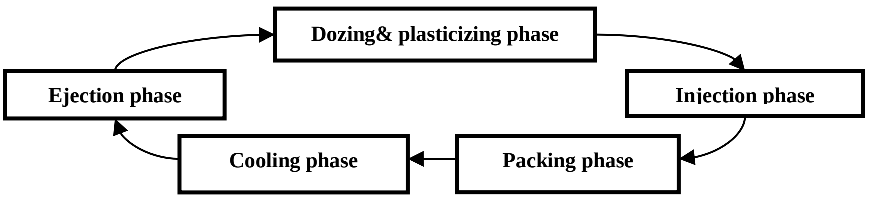

Fig. 1: Main steps of injection molding process.

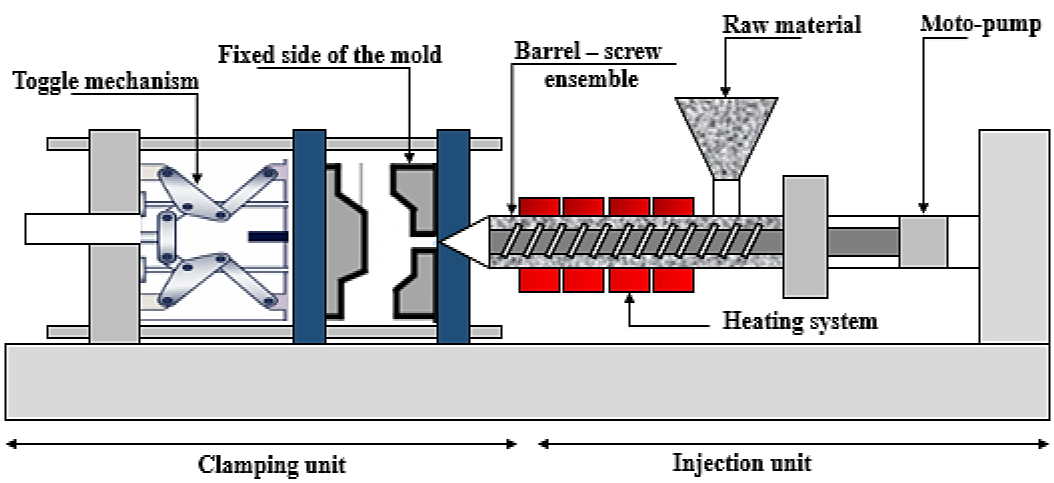

Fig. 2: Structural Overview of an Injection Molding Machine

To carry out the manufacturing process, injection molding is employed, utilizing a machine that comprises several components as indicated on the figure 2. These include a hopper for feeding the raw plastic material, a heating unit consisting of a barrel, screw, and heating resistances to melt the material, and an injection unit responsible for injecting the molten material into the mold cavity. Additionally, the machine features a clamping unit to securely hold the mold halves together during the injection and cooling phases [7]. Furthermore, the machine is equipped with controls to regulate temperature, pressure, and other parameters, ensuring the production of high-quality parts. The clamping Unit [8] is responsible for holding the fixed and the moved side of the mold together under pressure during the injection and cooling process. It consists of a mold, which is mounted on a fixed platen, and a movable platen which is connected typically to a hydraulic system. The clamping unit plays a crucial role in maintaining the mold closed during injection, ensuring the precision and quality of the molded parts. In contrast, the Injection Unit involves a screw mechanism that pushes the molten material through a heated barrel and into the mold under high pressure [9].

2.2. Digital twin concept

Digital Twin plays a crucial role in the Fourth Industrial Revolution by integrating information technology with operational technology, thereby linking the preparatory production stage with real production to create new value [10]. The Digital Twin concept model comprises three main components [11] as indicated on figure 3: Physical products in real space, virtual products in virtual space, and the data and information connections between these physical and virtual spaces. Essentially, a Digital Twin is a digital replication of a real physical production system. It is used for system optimization, monitoring, diagnostics, and prognostics by integrating artificial intelligence, machine learning, and software analytics with large volumes of data from physical systems. The Digital Twin model comprises five essential components: sensors and physical assets from the physical system, integration technology, data, analytics, and responsive actions [12]. The data encompasses enterprise, operational, and environmental information collected by sensors distributed throughout the physical system. These sensors facilitate real-time, bidirectional communication between the physical and virtual systems via integration technology, which includes communication interfaces. The Digital Twin then utilizes analytics techniques to process the data for defined purposes, providing responsive actions based on simulation results to the physical assets.

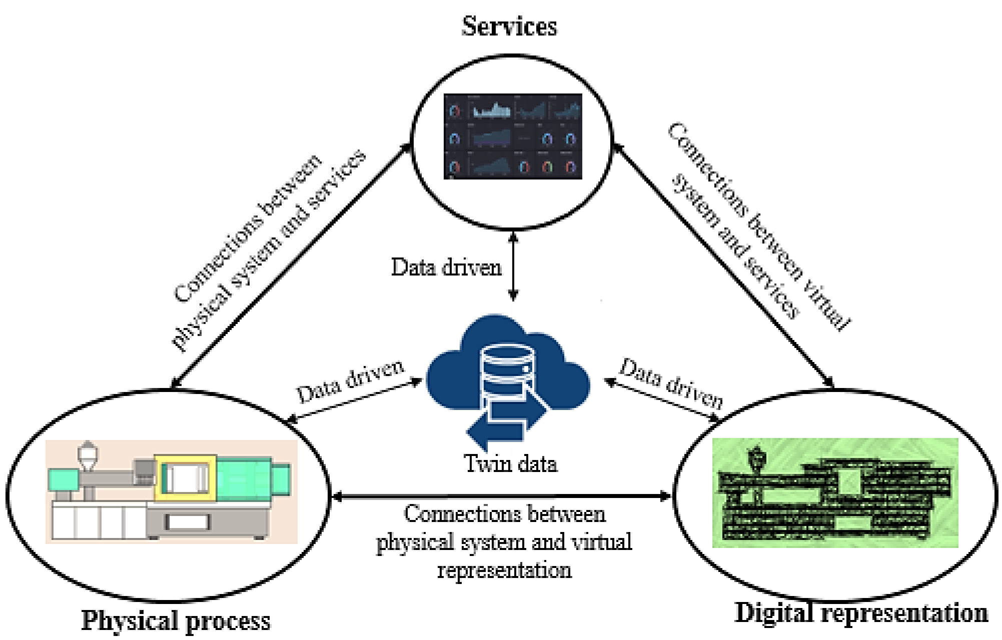

Fig. 3: The five dimensions of Digital Twin framework

A Digital Twin makes the operations of individual machines and interconnected systems visible to authorized personnel in areas like manufacturing, procurement, and logistics [13]. It allows manufacturers to monitor system performance through the manufacturing execution system. Using analytics techniques such as what-if and predictive analysis, a Digital Twin simulates real-time conditions and predicts future states, enabling manufacturers to visualize processes, compare options, and collaborate across different sections

2.3. Long short term memory

LSTM (Long Short-Term Memory) is proposed to enhance the short-term memory capacity of recurrent neural networks (RNNs) by incorporating long-term memory states, commonly referred to as cell states [14]. Figure 4 illustrates the structure of an LSTM cell, which comprises input, output, and forget gates. Initially, the LSTM cell initiates with a forget gate, tasked with either retaining or discarding the prior cell state information, c_{t-1}. he decision to forget or retain information is determined by processing the input data, x_t, and the previous hidden state, h_{t-1}, through a sigmoid activation function, yielding an output value, f_t, is between [0,1], as shown in formula (1) and (2).

$$f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f) \tag{1}$$

$$\sigma(x) = \frac{e^x}{e^x + 1} \tag{2}$$

Where W stands for the weight matrices of the gates, and *b* represents the bias vectors.

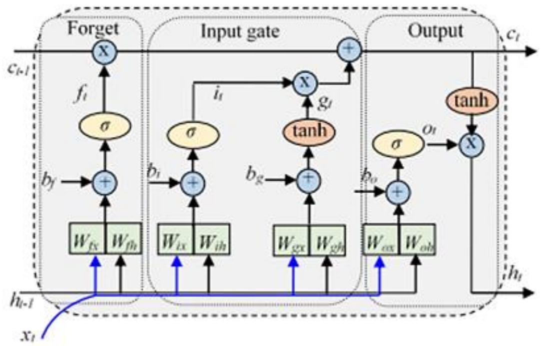

Fig. 4: Internal structure of LSTM cell [15]

Following this, the input gate initiates the generation of a new memory state, *gt*, by feeding *xt* and *ht-1* into the *tanh* activation function, as in (3) and (4). Simultaneously, the input gate determines which portions of the candidate memory state will be retained, creating an input state, *it*, as in (5). Next, the updated state of the memory cell, ct, is archived as indicated in equation (6)

$$g_t = tanh(W_{gx}x_t + W_{gh}h_{t-1} + b_g) \tag{3}$$

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{4}$$

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i) \tag{5}$$

$$g(t) + f(t) \tag{6}$$

Ultimately, the updated hidden state is generated by the output gate. *ht*, derived from the newly updated memory cell state and the output state, *ot*, as in (7) and (8)

$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o) \tag{7}$$

$$h_t = tanh(c_t) \odot o_t \tag{8}$$

2.4. Related works

Numerous studies, including Y. Liau et al. (2018) [16], have introduced frameworks for applying the Digital Twin concept to the injection molding process, from mold making to final production. Traditionally, mold design, mold making, and the injection process have been managed separately. However, to thrive in the current industrial revolution, these stages must be interconnected, enabling real-time communication and adjustments. The Digital Twin creates a virtual model that interacts bidirectionally with the physical process, enhancing efficiency, quality, and responsiveness by leveraging real-time data and predictive analytics. Zhiyong Wang et al. (2021) [17] explored the Digital Twin technology in the injection molding industry. They described an integrated industrial Internet architecture involving intelligent equipment, production lines, and factories. The study focused on key technologies like injection molding control systems and MES-based management, establishing a smart factory architecture. Its feasibility was verified through industrial applications, and prospects for an intelligent manufacturing cloud platform were discussed. Sara Nasiri et al. (2024) [18] focused on Digital Twin (DT) modeling for smart injection molding, emphasizing the need for interconnected stages in the process. They detailed the technology required to build DTs for each stage, enabling automation and data collection. Their approach includes fault detection, 3D printing, and system integration for predictive manufacturing. F. J. Lacueva-Perez et al. (2012) [19] introduced a cloud-based Digital Twin for injection molding. It employs AI to control process parameters and predict part quality in real time. Validated in industrial settings, his approach successfully detects faulty products but faces challenges with traditional Cloud-centric IoT approaches, such as network issues and high data transfer costs. Pascal Bibow et al. (2020) [20] developed a model-driven approach for Digital Twins (DTs) in injection molding, automating processes and data collection. Their method supports customizations and streamlines development using a reference architecture. They evaluated this approach with an injection molding machine DT, optimizing parameters between cycles to improve efficiency. Overall, their approach enhances machine use by systematically engineering reactive DTs. Based on the literature review, two main gaps were identified:

- Limited research has focused on implementing LSTM prediction for process stability linked with Digital Twins.
- There is a scarcity of studies that have utilized Digital Twins to analyze melt cushion parameters.

These gaps have motivated our paper to address these shortcomings in the existing literature.

3. Implementation and methodology

3.1. Methodology

The proposed approach in the figure 5 leverages the Digital Twin concept and an LSTM network to predict process stability, focusing on the Melt Cushion Parameter in injection molding. The physical system emits real-time data, which is extracted and sent to the cloud via edge computing. Communication uses OPC UA (Open Platform Communications Unified Architecture) between the injection molding machine and the edge, and MQTT (Message Queuing Telemetry Transport) between the edge and the cloud. Data is stored and processed in a local cloud system, offering services such as historical data access and model configuration updates. A digital shadow preprocesses real-time data and feeds it into a trained LSTM model to predict future states. Based on these predictions, the system suggests potential actions to adjust or stop the machine, which are then validated by an adjuster before implementation. In this concept, we are focusing only on proposing actions for recommendation to the adjuster, who validates the actions before any implementation on the physical system. This integrated approach aims to enhance the stability and quality of the injection molding process through advanced monitoring and predictive analytics, focusing on actionable recommendations rather than automatic adjustments.

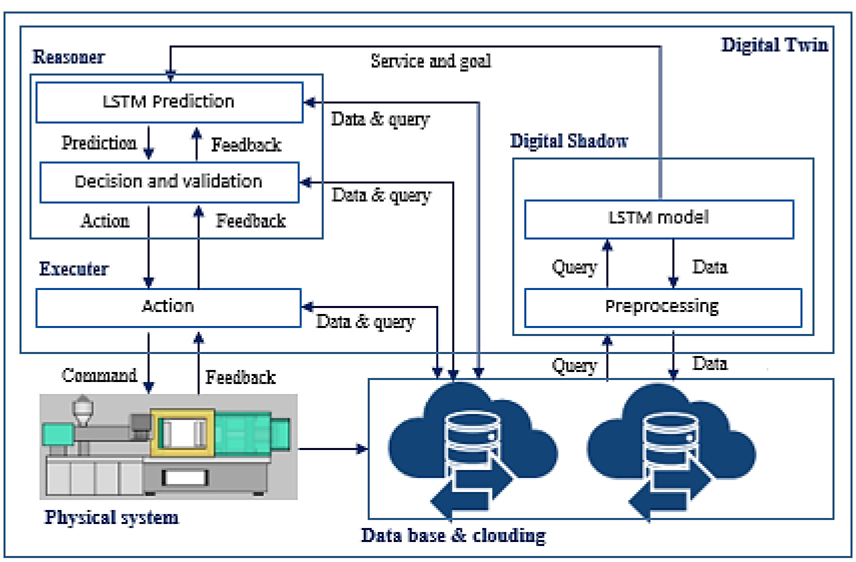

Fig. 5: Architectural Framework of the Proposed Digital Twin Concept

3.2. Simulation

To simulate the working process of the digital twin, we used two edge computers with Raspberry Pi; one as the server and two communication protocols (OPC-UA and MQTT). The first edge computer is configured to emulate an injection molding process, fed with real data from an actual injection molding machine. This computer simulates the operation by sending data to the second edge computer. The second edge computer is responsible for transmitting the collected data to the cloud. In the cloud, the LSM model is trained and makes predictions, providing the next Melt Cushion value. This prediction allows the adjuster to make any necessary configurations and monitor the stability of the process. The simulation architecture is illustrated on the fig 6.

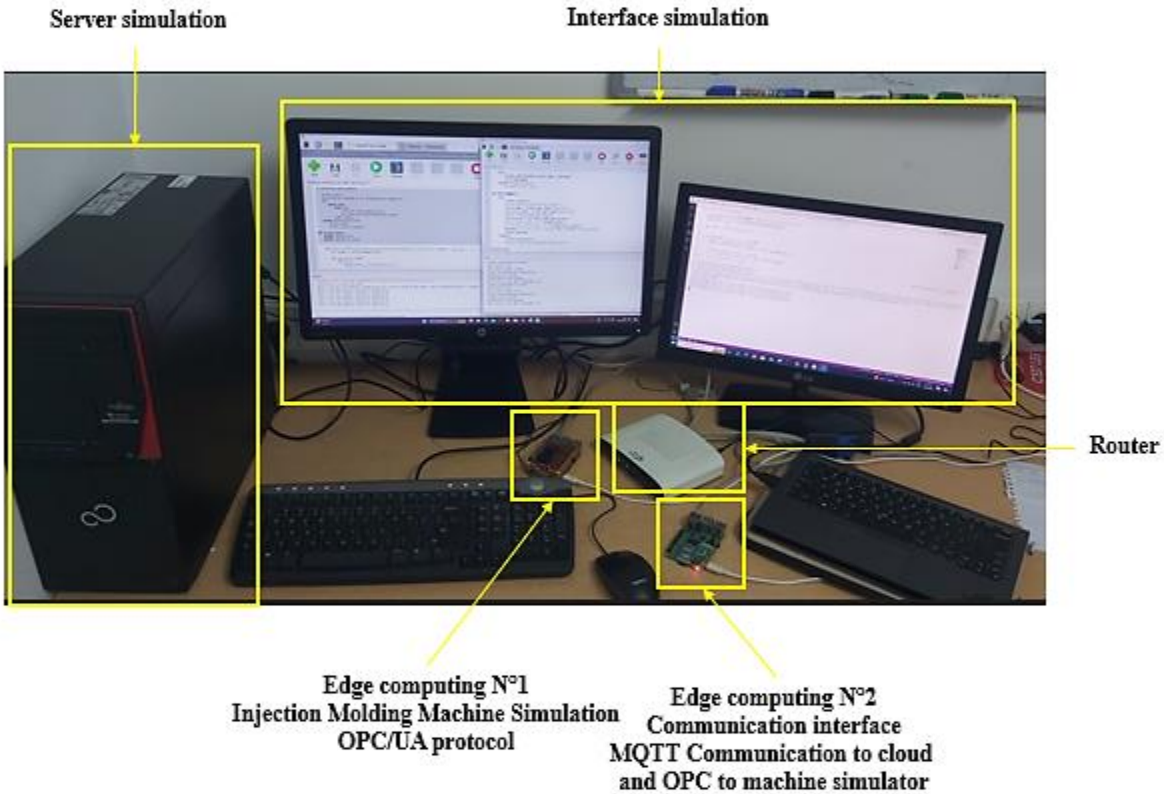

Fig. 6: Key Components of the Simulation Architecture

4. Result and discussion

During the simulation, 6000 observations of the Melt cushion parameter were gathered from a real injection molding machine, specifically an Arburg GMBH machine with a capacity of 150T. These data were then transferred to the initial computing edge, which emulates the operation of the actual press. The data transmission occurs in accordance with the real production cycle, which spans 32 seconds. At the end of each 32-second cycle, the initial edge forwards the collected values to the secondary edge, acting as an intermediary between the injection molding process and the cloud infrastructure. The cloud environment houses an LSTM model along with real-time data acquired from the machine. Prior to integration into the digital shadow system, the LSTM model underwent training using 20% of the dataset in offline mode to enable predictive capabilities. Table 1 illustrates the training and tuning phases of the model, highlighting the superior performance achieved in Tune 4 compared to other configurations.

The table 1 outlines the hyperparameters and performance metrics of LSTM models across different tuning iterations. In all iterations, the model comprised of two LSTM layers. In Tune1, Tune2, and Tune3, each LSTM layer consisted of 50 units, while in Tune4, the second layer had 100 units. The optimizer utilized across all iterations was Adam, except for

Tune4, where SGD was employed. Various activation functions were tested, with Relu being used in Tune1, Tune3, and Tune4, and tangh in Tune2. Epoch numbers varied across the iterations, with Tune2 utilizing 50 epochs while others utilized 100 epochs. Batch sizes also varied, with Tune1 employing a batch size of 8, Tune2 a batch size of 1, and Tune4 and Tune4 both utilizing a batch size of 32. Regarding model performance, R2 values indicate the goodness of fit, with higher values indicating better performance. Across the training and test sets, R2 values ranged from approximately 0.0575 to 0.7796. Mean Squared Error (MSE) and Mean Absolute Error (MAE) were also assessed. Lower values of MSE and MAE are indicative of better model performance. Throughout the tuning process, there were fluctuations in these metrics, suggesting varying degrees of model accuracy across different hyperparameter configurations.

The main findings of this research can be summarized as follows:

- Utilizing an LSTM model to model the function of injection molding, enabling prediction of the Melt cushion parameter.
- Development of a Digital Twin architecture, facilitating simulation of real communication between the physical and virtual system.
- Integration of the trained LSTM model into the Digital Twin setup, enabling real-time predictions based on data acquired from the physical computing edge.

These findings highlight the efficacy of Digital Twin technology in injection molding. By linking the virtual and physical worlds, Digital Twins enable predictive insights and performance optimization for the injection process. This facilitates proactive adjustments and enhancements, leading to improved operational efficiency.

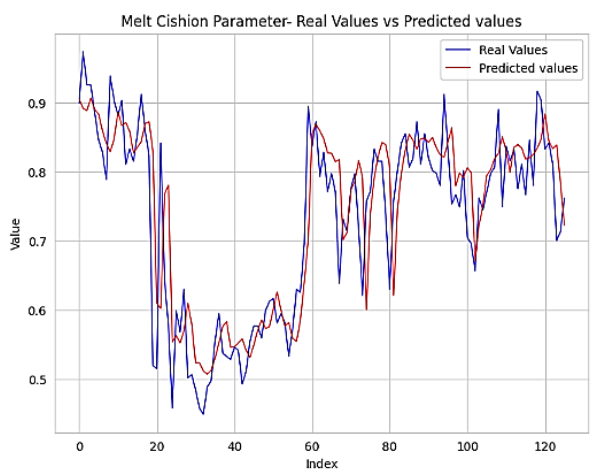

Table 1: LSTM Model Hyperparameters Tuning

Parameter and hyper parameter	Tune1	Tune2	Tune3	Tune4
Number of LSTM layers	2	2	2	2
Number of LSTM unit by layer	50	50	50	100
Optimizer	Adam	Adam	Adam	SGD
Activation function	Relu	tangh	Relu	Relu
Epoch number	100	100	50	100
Batch size	8	1	32	32
Training				
R2	0.7394	0.7796	0.6863	0.091
MSE	0.0056	0.0051	0.0071	0.0208
MAE	0.0524	0.0496	0.0583	0.1138
Test				
R2	0.7178	0.7567	0.6812	0.0575
MSE	0.005	0.0040	0.0058	0.0174
MAE	0.050	0.0482	0.0548	0.1072

Fig. 7: Prediction of Melt Cushion (left) and Hyperparameter Optimization (Table1)

5. Conclusion

This paper outlines a framework for Digital Twin implementation in injection molding, covering physical systems, cloud integration, communication, AI with LSTM, and interface access. Simulations demonstrate real-time communication between predictive values and physical systems. However, the paper does not address the final loop of the Digital Twin, which involves executing actions on the physical systems directly from the Digital Twin. This aspect of the research presents a prospective avenue for further exploration, such as the application of optimization models like reinforcement learning or genetic algorithms. Exploring this perspective could open up new avenues for research and development in the future.

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