Journal of Engineering Mechanics and Machinery (2024)
Clausius Scientific Press, Canada

DOI: 10.23977/jemm.2024.090304
ISSN 2371-9133 Vol. 9 Num. 3

Health Prediction of Integrated Die-Casting Machine Driven by Digital Twin and CNN-LSTM

Lijun Liu[a,*], Yongpeng Cao[b], Yalou Gao[c], Kaixing Liu[d], Yiteng Ma[e]

College of Mechanical and Electrical Engineering, Shaanxi University of Science & Technology, Xi'an, Shaanxi, 710021, China

[a]liulijun@sust.edu.cn, [b]2983427344@qq.com, [c]2533993271@qq.com, [d]220512112@sust.edu.cn, [e]1492393112@qq.com

[*]Corresponding author

Keywords: Integrated die-casting machine, Condition monitoring, Life prediction, Digital twin; CNN-LSTM

Abstract: In order to solve the problem that the health status of the integrated die-casting machine is difficult to control during the operation and maintenance process, a health state prediction method of the integrated die-casting machine driven by the fusion of digital twin and CNN-LSTM was proposed. Firstly, based on the digital twin theory, a digital twin model of condition monitoring of the integrated die-casting machine was constructed to realize the real-time mapping of the real-time status and performance parameters of the integrated die-casting machine and the digital twin. Secondly, based on the CNN-LSTM machine learning algorithm, the life characteristics data of key components of the integrated die-casting machine were mined, and the life prediction model of the key components of the integrated die-casting machine was established, so as to realize the online prediction of the remaining effective life driven by the real-time monitoring data of the twin model. Finally, the effectiveness of the proposed method is verified by constructing an integrated status monitoring and health prediction system for the integrated die-casting machine, which provides a new idea for the intelligent maintenance and management of the integrated die-casting machine.

1. Introduction

With the booming development of new energy vehicle manufacturing, integrated die-casting technology has emerged as a key technology driving the transformation and upgrading of the automotive industry, thanks to its unique advantage of molding multiple components into a large casting in a mold in a single pressing, significantly enhancing production efficiency and reducing production costs. As the core equipment for implementing this technology, the stability and reliability of integrated die-casting machines are directly related to the overall efficiency and product quality of automobile manufacturing [1]. However, integrated die-casting machines feature complex structures and operate in harsh environments (high temperature, high pressure, etc.), making it difficult to monitor their health status. Furthermore, their maintenance relies on manual periodic inspections and post-failure repairs, which are inefficient and difficult to detect potential faults, leading to frequent failures and failing to meet the urgent needs of modern production for efficient and stable equipment operation. Therefore, real-time monitoring of the status of integrated die-casting machines and life prediction of key components have become urgent issues to be addressed.

With the development of intelligent sensors, the Internet of Things (IoT), big data, and artificial intelligence (AI) technologies, digital twin technology, which offers functions such as status visualization, fault diagnosis, and analysis and decision-making, has become a research hotspot in equipment monitoring [2]. Digital twin refers to the creation of a virtual model corresponding to a physical entity using digital technology. This model can reflect the status and behavior of the physical entity in real-time and optimize the design and operation and maintenance management of the physical entity through data analysis, simulation, and other means [3]. In recent years, digital twins have been increasingly applied in equipment status monitoring and life prediction. Santos proposed an interactive digital twin visualization framework for large-scale electromechanical equipment using cloud fusion, providing a method for constructing digital twin models of large-scale electromechanical equipment[4]. Moghadam developed a digital twin-based method for monitoring the remaining useful life of transmission systems[5]. Zhou proposed a motor operating status diagnosis scheme based on digital twins and the Industrial Internet of Things (IIoT) [6]. Pengxing Wu built a visual real-time monitoring solution for discrete digital twin manufacturing workshops and proposed a data- and event-driven virtual-real mapping method[7]. Tao proposed a complex equipment fault prediction and health management system based on digital twin technology, improving prediction accuracy and efficiency through physical-virtual integration[8]. Ren proposed a fault diagnosis method for wind turbine bearings based on digital twins, improving the accuracy and stability of diagnosis[9]. With the gradual development and improvement of deep learning, various neural networks and their extended algorithms have gradually been applied to equipment health prediction. Among them, the CNN-LSTM model combines the advantages of Convolutional Neural Networks (CNNs) in local feature extraction and Long Short-Term Memory (LSTM) networks in time series processing, achieving remarkable results in health prediction. Zhang proposed a model combining CNN, LSTM and attention mechanisms for accurately predicting the remaining useful life of aerospace engines [10]. Cheng proposed a rolling bearing health prediction method based on CNNs and LSTMs and applied this method to health and life prediction of rolling bearings [11]. Zhenyu Zhu proposed a lithium-ion battery health state detection method based on the CNN-LSTM network, achieving lithium-ion battery health state detection by predicting battery capacity [12].

Despite the widespread attention and application of digital twin technology-based equipment health status prediction in the manufacturing field, there is still a lack of in-depth application methods based on digital twin technology for the production process monitoring and status prediction of integrated die-casting machines, which are novel equipment. Therefore, this paper proposes a health status prediction method for integrated die-casting machines based on digital twins and CNN-LSTM. By utilizing digital twin technology, a digital model of the integrated die-casting machine is constructed, enabling real-time monitoring of the machine's status and performance parameters. This not only allows for the timely detection of potential faults, early warning, and maintenance, effectively reducing equipment downtime and enhancing equipment reliability and stability. At the same time, the monitoring data in the twin model can also drive intelligent prediction algorithms to update and predict the remaining useful life of key components in real-time, providing a scientific basis for component replacement, fully extending effective usage time, and reducing component replacement costs.

2. Health Prediction framework of Integrated Die-Casting Machine

This paper proposes a framework for predicting the health status of integrated die-casting machines based on the fusion of digital twin and CNN-LSTM technology. The framework mainly consists of four steps: data acquisition, twin model construction, condition monitoring, and life prediction, as shown in Figure 1. Various sensors are installed on the integrated die-casting machine to perceive and collect real-time operational status information. Digital twin technology is utilized to construct a virtual model in virtual space that corresponds to the physical integrated die-casting machine, reflecting its operational status and changes in performance parameters in real-time. By comparing and analyzing the real-time operational data of the integrated die-casting machine with standard parameters and empirical rules in the knowledge base using the real-time collected data and the twin model, the framework can perceive and push notifications about potential issues with the machine. By constructing a prediction model based on the CNN-LSTM algorithm and combining it with real-time data driving from the twin model, the remaining useful life of key components of the integrated die-casting machine can be updated in real-time. The detailed steps are introduced as follows:

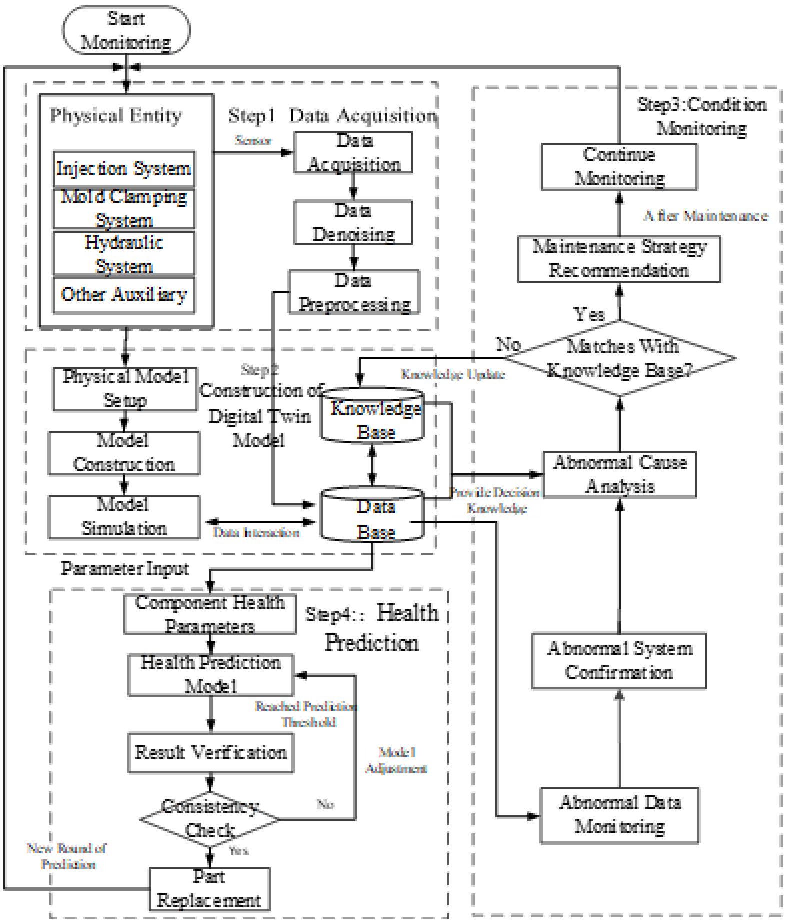

Figure 1: Health Prediction framework of Integrated Die-Casting Machine Driven by Digital Twin and CNN-LSTM

Step 1: Data Acquisition for Integrated Die-Casting Machines.

Firstly, based on the operational logic and functional characteristics of the integrated die-casting machine, it is divided into systems such as the injection system, mold clamping system, hydraulic system, and auxiliary functional systems such as cooling, lubrication, and material feeding. Secondly, monitoring locations and corresponding sensors are determined according to the monitoring requirements of each functional system. Then, data acquisition equipment is installed, a data acquisition system is established, and the sampling frequency is configured to achieve efficient data acquisition from the integrated die-casting machine. Finally, the collected data is preprocessed through methods such as noise reduction, cleaning, and format conversion, and then transmitted to the database.

Step 2: Construction of the Digital Twin Model for Integrated Die-Casting Machines.

Firstly, a three-dimensional geometric model is established based on basic information such as the known component sizes, shapes, and positional relationships of the physical integrated die-casting machine. Secondly, based on the geometric model and actual physical monitoring parameters, physical attributes are assigned to each component of the integrated die-casting machine to simulate its real performance parameters. Then, behavioral modeling and rule definition are carried out according to the working principles and operational specifications of the integrated die-casting machine to simulate its dynamic behavior. Finally, the geometric, physical, behavioral, and rule models are integrated into a digital twin platform, and through real-time data connection and interaction technology, real-time synchronization and interaction with the physical integrated die-casting machine are achieved.

Step 3: Condition Monitoring of Integrated Die-Casting Machine Systems.

Firstly, a condition monitoring index system is established to determine key parameter threshold monitoring indicators, and the digital twin model is used to realize real-time monitoring of the status parameters of the integrated die-casting machine, enabling early warning of abnormal parameters. Secondly, based on a similarity matching algorithm, abnormal monitoring parameters are matched with the fault knowledge base to quickly identify the location and cause of the abnormality. Based on the matching results, combined with solutions and expert experience in the knowledge base, intelligent reasoning is conducted to provide decision recommendations for maintenance personnel. Finally, through the development of a visual monitoring system, the operating status, monitoring indicators, abnormal diagnosis, remaining life, and other condition monitoring content of the integrated die-casting machine are presented in an intuitive interface, helping operations and maintenance personnel quickly grasp the health status of the machine.

Step 4: Effective Health Prediction of Key Components of Integrated Die-Casting Machines.

Firstly, the key components of each system are identified, and historical characteristic parameters related to component life degradation are screened from the database using the Pearson correlation coefficient method. Secondly, the life prediction model for key components of the integrated die-casting machine is constructed based on the CNN-LSTM algorithm, and the prediction model is trained using historical characteristics in the database. Finally, based on real-time data driving from the twin database, real-time updates of the prediction results for the remaining effective life of key components of the integrated die-casting machine are achieved.

3. A Health Prediction Method for Integrated Die-Casting Machines Based on the Fusion of Digital Twin and CNN-LSTM

3.1. Construction of a Digital Twin Model for Integrated Die-Casting Machines

The digital twin model for the integrated die-casting machine outlined in this text is introduced as follows: Firstly, based on the design drawings and measured data of various components of the integrated die-casting machine, three-dimensional modeling technology is utilized to create unit-level shape and size models. The relative positions between components are constrained through assembly relationships, thereby restoring the geometric model of the integrated die-casting machine.

Secondly, sensor technology is employed to collect real-time dynamic physical parameters of the integrated die-casting machine. Through three-dimensional visualization technology, a virtual model is constructed. Sensor data is transmitted to the virtual model in real-time via data interfaces and communication protocols, enabling data synchronization and mapping between the virtual model and the physical entity. Thirdly, based on the behavioral responses generated by the physical entity during the die-casting process, an event-driven finite state transition model for the integrated die-casting machine is constructed. This enables the die-casting twin to possess response mechanisms and state transition capabilities. Lastly, based on the standard operating specifications and anomaly monitoring requirements of the integrated die-casting machine, a rule model is constructed through a combination of machine learning and rule engine technologies. This achieves real-time monitoring and feedback of abnormal states of the integrated die-casting machine. By digitally representing the integrated die-casting machine in four dimensions: geometry, physics, behavior, and rules, a comprehensive and realistic digital twin model is constructed. Figure 2 illustrates the four-dimensional model of the digital twin for the integrated die-casting machine.

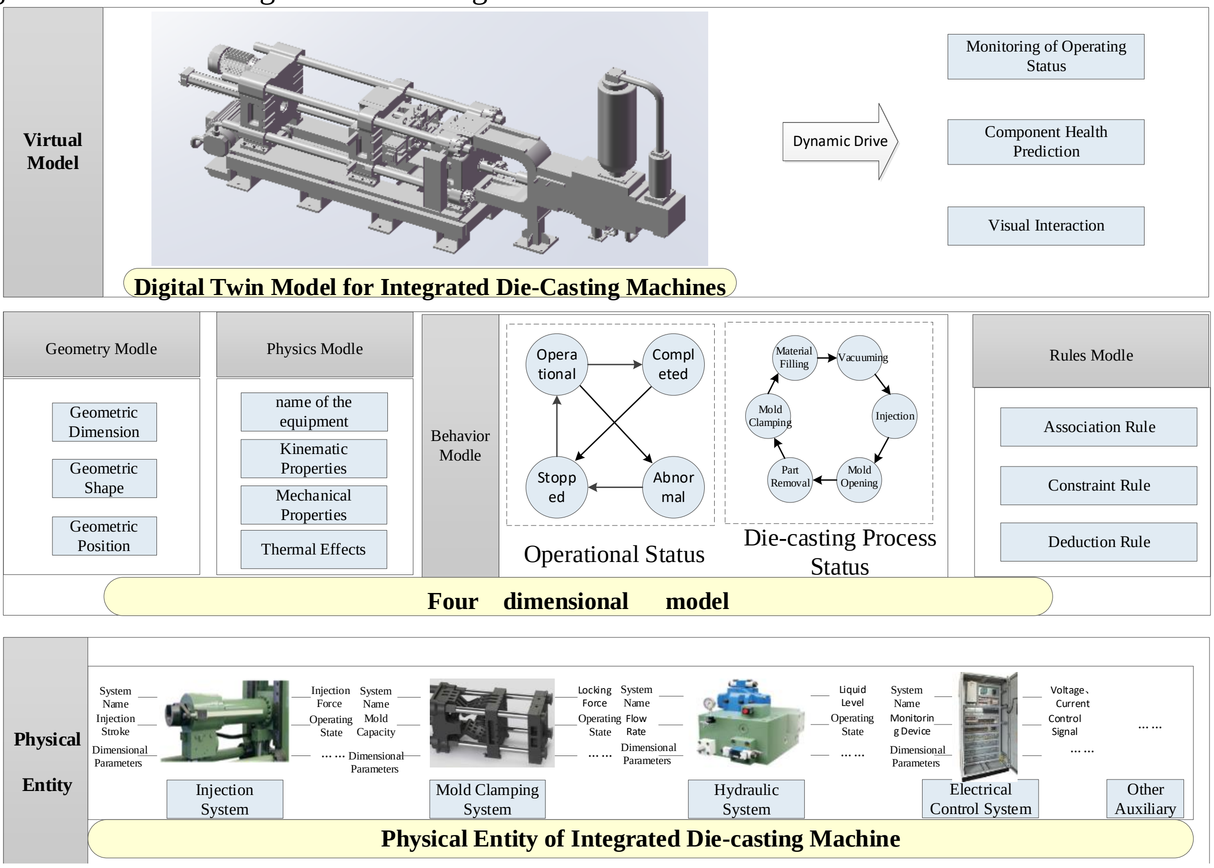

Figure 2: A four-dimensional model of Integrated Die-Casting Machine

The digital twin model of the integrated die-casting machine (DCDTM) is described as:

$$TLDTM = \{GA, PP, BR, SR\} \tag{1}$$

where:
GA (Geometric Attribute) represents the Geometry Modle.
PP (Physical Parameters) represents the Physics Modle.
BR (Behavior Respond) represents the Behavior model.
SR (Simulation Rule) represents the Rules Modle.
Geometry Model Construction Formula:

$$GA = \{GD, GS, GPO\} \tag{2}$$

Where:
GD represents geometric dimensions.

GS represents the geometric shape.

GP represents the geometric position.

The geometric model intuitively reflects the external outline and internal structure of an integrated die-casting machine. By obtaining the geometric shape and geometric dimension parameters from the design drawings and measured data of the machine's components, a 3D model of each part is constructed using a parametric modeling approach in 3D modeling software. The assembly function in the modeling software is then used to determine the geometric relationship between the parts.

Physics Model Construction Formula:

$$PP = \{MP, TP, KP\} \tag{3}$$

Where:

MC represents mechanical properties.

TB represents thermal effects.

KP represents Kinematic Properties.

The physical model reflects the dynamic changes in the important physical attributes of the integrated die-casting machine and its components. Mechanical properties such as clamping force, ejector force, and injection force are collected through pressure sensors. Thermal properties such as mold temperature, ambient temperature, cooling water temperature, hydraulic oil temperature, and molten material temperature are collected through temperature sensors. Kinematic properties such as displacement, speed, acceleration, and vibration during the operation of the components are collected through displacement sensors. These sensors work together to comprehensively monitor the physical parameter changes of the integrated die-casting machine.

Behavior Model Construction Formula:

$$BR = \{MSS, PE, AR\} \tag{4}$$

Where:

MSS represents the transient characteristics status set.

PE represents the driving event.

AR represents the action response.

The behavioral model reflects the dynamic changes of the integrated die-casting machine's functions under the joint influence of external environmental disturbances, control commands, and operational mechanisms. The finite state machine defines the driving events that trigger transitions between various working states, die-casting process states, and trigger states of the twin model. The integrated die-casting machine includes four basic operating states: running, abnormal, completed, and stopped, as well as process states such as clamping, material filling, vacuuming, and injection. Event-driven programming is used to realize the transition between die-casting states and execute motion trajectories, speed, acceleration, and other action responses under corresponding events. The finite state machine, event-driven programming, and geometric-physical models work together to enable the die-casting twin to have a response mechanism and state transition capability.

Rules Model Construction Formula:

$$SR = \{AR, CR, DR\} \tag{5}$$

Where:

AR represents association rules.

CR represents constraint rules.

DR represents deduction rules.

The rule model involves various constraints and deduction rules in the operation process of the integrated die-casting machine, ensuring stable, safe, and reliable operation. Based on the physical characteristics of the die-casting process and the safety standards of the equipment, constraint rules are defined, such as the early warning range of dynamic parameters and the sequential operation of functional components. Association rules are extracted from fault phenomena, causes, and solutions based on expert diagnostic experience and fault case knowledge, and a fault knowledge base is established to store fault diagnostic association rules in a structured format. Neural network algorithms are applied to train and learn historical data of the integrated die-casting machine, extracting data change patterns and realizing the deduction and prediction of potential faults.

3.2. Construction of a Remaining Useful Life Prediction Model for Integrated Die-Casting Machines Based on CNN-LSTM

This paper optimizes the traditional LSTM life prediction algorithm to construct a life prediction model for key components of the integrated die-casting machine. The input parameters are the feature parameters related to the prediction of the injection head's lifespan, and the output is the remaining useful life (RUL) of the injection head, with the useful life represented by health status. The construction process of the injection head life prediction method is shown in Figure 3, and the main content includes the acquisition of injection head life characterization parameters, data normalization processing, the construction of a CNN-LSTM network, hyperparameters based on Bayesian methods, model training, and model performance testing.

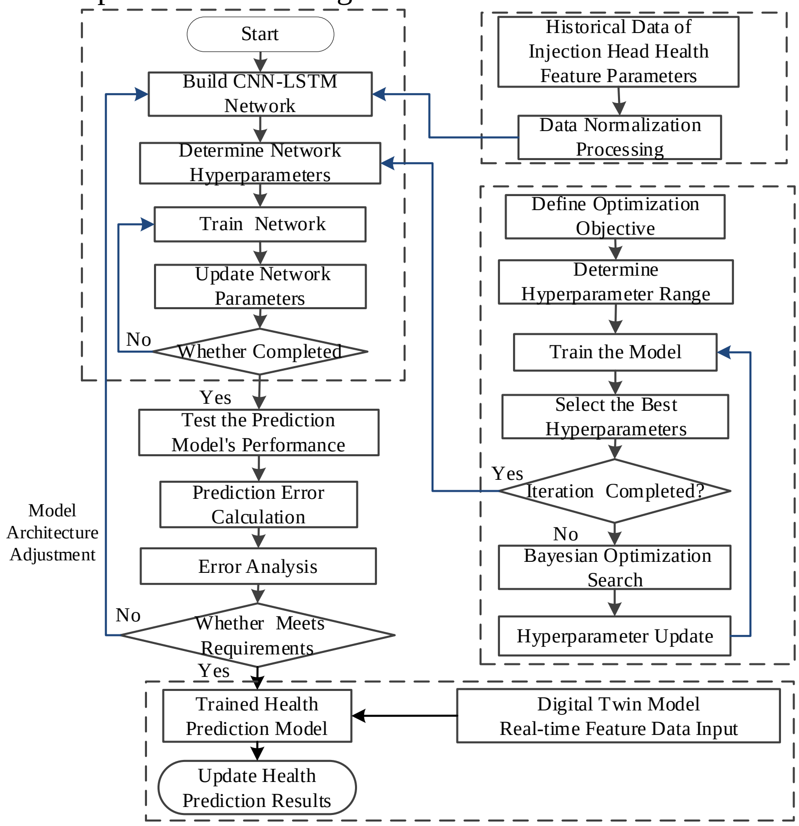

Figure 3: Block diagram of Bayes-optimized CNN-LSTM life prediction

3.2.1. Acquisition of Injection Head Life Characterization Parameters for Integrated Die-Casting Machine

Historical data of the injection head life prediction feature parameters, preprocessed through the database in the digital twin model, are obtained. Due to the inconsistency of units and scales among different feature parameters, the input data is normalized. The maximum-minimum normalization method is used to normalize each feature value, so that the normalized x_i values fall within the range of [0, 1].

$$x_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{6}$$

Where:

x_i— The data value corresponding to each input feature.

x_{min} — The minimum value of the data for each failure influencing factor.

x_{max} — The maximum value of the data for each failure influencing factor.

3.2.2. Construction of Injection Head Life Prediction Model Based on CNN-LSTM

In order to fully explore the multi-dimensional life characteristics of the injection head and improve the accuracy of life prediction, this paper combines the feature learning capability of CNN networks with the ability of LSTM networks to handle data dependencies. A multi-feature life prediction network model based on CNN-LSTM is proposed. The network model is shown in Figure 4.

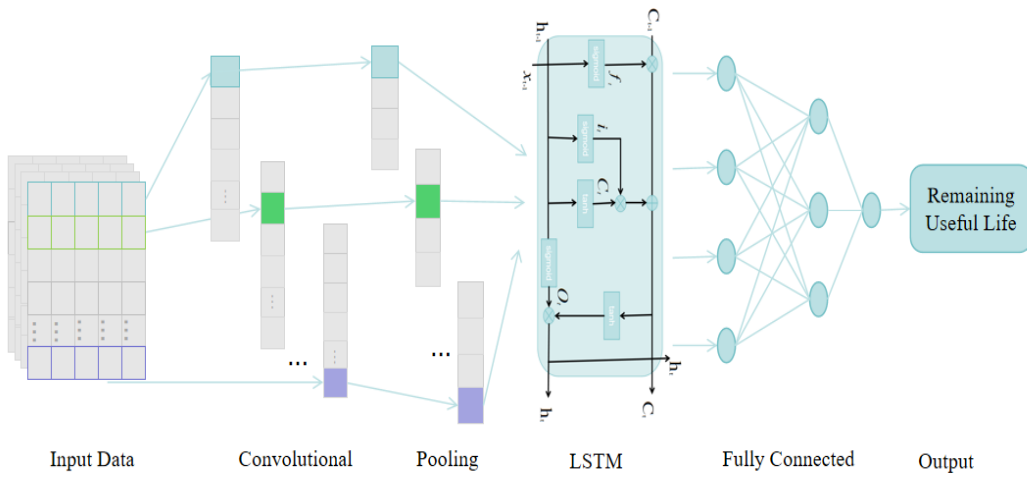

Figure 4: Health prediction network model

The construction process of the injection head prediction model based on CNN-biLSTM is as follows:

First, the processed feature data for injection head life prediction is input into the model. Then, the convolutional layers extract local features from the data, and the pooling layers reduce the dimensionality to lessen the computational load. Afterward, bidirectional LSTM (biLSTM) is constructed based on equations (7-12) to capture the dependencies between the data during the degradation process of the injection head life features, thereby improving prediction accuracy. Finally, in the fully connected layer, the comprehensive information of the injection head life from biLSTM is fused to output accurate predictions of the injection head's effective life.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{7}$$

$$i_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_i\right) \tag{8}$$

$$\hat{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{9}$$

$$C_t = f_t.C_{t-1} + i_t \cdot \hat{C}_t \tag{10}$$

$$O_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_o\right) \tag{11}$$

$$h_t = O_t \cdot \tanh(C_t) \tag{12}$$

3.2.3. Hyperparameter Optimization Based on Bayesian Methods

To improve the efficiency and accuracy of parameter tuning, Bayesian optimization is applied to the CNN-LSTM network model. The learning rate, L2 regularization coefficient, and the number of neurons in the LSTM layer, which are three important hyperparameters, are optimized. A broad strategy is used to set the parameter ranges for optimization. Random sampling within the range of hyperparameters provides an initial estimate for the surrogate model based on Gaussian processes. The average absolute error (MAE) from the training results, as shown in Equation (13), is used as the objective function for the current hyperparameters. The objective function value (MAE) is calculated under the current hyperparameters, and the acquisition function is used to select the next set of hyperparameters for the next round of evaluation. This process continues until the preset number of iterations is reached, and the optimal hyperparameter combination is returned for input into the CNN-LSTM injection head life prediction model.

$$X_{MAE} = \frac{1}{N}\sum_{i=1}^{n}|y_i - \bar{y}_i| \tag{13}$$

3.2.4. Model Training

Adam combines the advantages of momentum and adaptive learning rate adjustment. Compared to common gradient descent algorithms, it is more efficient in terms of convergence speed and has moderate memory usage. Therefore, the Adam optimization algorithm is used to train the network model, updating the model's weights and biases to improve the accuracy of the life prediction model.

3.2.5. Model Performance Testing

To validate the accuracy of the constructed injection head life prediction model, the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are selected to evaluate the life prediction results. The corresponding evaluation formulas are shown in Equations (14), (15), and (16):

$$X_{MAE} = \frac{1}{N}\sum_{i=1}^{n}|y_i - \bar{y}_i| \tag{14}$$

$$X_{RMES} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{15}$$

$$X_{MAPE} = \frac{1}{N}\sum_{i=1}^{n}\frac{|y_i - \bar{y}_i|}{y_i} \tag{16}$$

3.2.6. Update of Health Prediction Results

The process of updating the injection head prediction model results is as follows: First, real-time feature parameters related to life prediction are obtained through the digital twin model. Next, a data transfer interface is created to transmit the real-time feature parameters as key inputs to the trained life prediction model. Then, an automated model operation process is established to dynamically update the life prediction results. Maintenance personnel use the life prediction results to develop a maintenance plan for the injection head, reducing production interruptions caused by injection head wear and, in turn, improving production efficiency.

4. Case Study

This paper takes the body structural component molding die-casting machine from an automotive parts manufacturing plant in Shaanxi as the research subject. Through real-time data collection and processing, combined with digital twin modeling technology, a digital twin mapping model of the integrated die-casting machine is constructed. Based on the digital twin mapping model, real-time monitoring of abnormal state parameters and life prediction of key components are achieved through data mining and predictive analysis techniques. A visual interface is developed to display the results of state monitoring and life prediction in real time. Using the life characteristic data collected during the life degradation process of the injection head in the injection system as an example, the accuracy of the life prediction method is analyzed to validate the accuracy and practicality of the proposed health status prediction method for the integrated die-casting machine based on digital twin technology.

4.1. Data Acquisition and Processing for Integrated Die-Casting Machines

The schematic diagram of the dynamic data collection process in the digital twin model of the integrated die-casting machine is shown in Figure 5. Dynamic parameters from various functional systems during the production process are collected through sensors installed on the integrated die-casting machine. These data are transmitted via the TCP/IP communication protocol, establishing interconnectivity between the local server and the software virtual server, enabling the collection and transmission of complex data in the physical space. The collected data are uploaded to the twin data storage platform through an industrial router. By deploying 5G networks and PHP databases, real-time data access and persistent data storage are achieved [13]. Through this process, dynamic data from the integrated die-casting machine are collected, and through preprocessing steps such as data denoising, cleaning, and transformation, the data are converted into simulation-driven data that can directly drive the digital twin model for simulation. The data are finally stored in the database, making it easy for the integrated die-casting machine to call directly from the dynamic mapping.

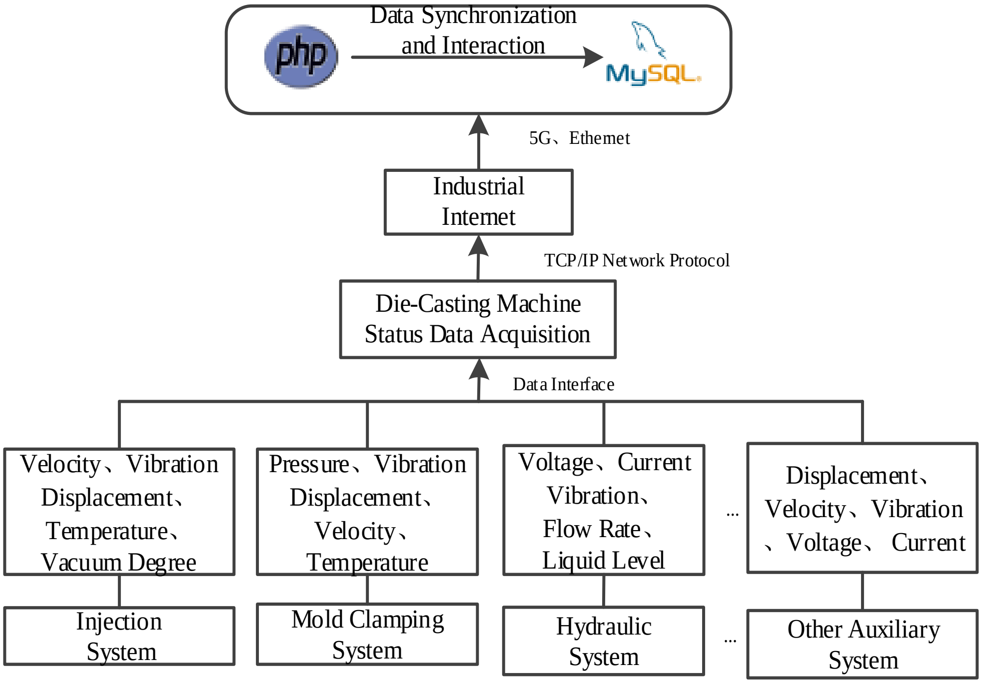

Figure 5: Schematic diagram of data acquisition

4.2. Construction of Data Twin Model for Integrated Die-Casting Machines

The integrated die-casting machine is a small vertical cold-chamber die-casting machine from a certain brand. In the construction of the four-dimensional twin model, the process is as follows: First, 3D modeling software such as CREO is used to create 3D models of various components of the integrated die-casting machine, including the injection system, clamping system, and hydraulic system. By assembling the models and adding constraints between the components, the accurate geometric shape of the integrated die-casting machine is presented. Next, the 3D model is imported into Unity3D simulation software, where the physical properties of the components in the simulation model are set. Through communication interfaces, the real-time data collected by sensors is transmitted to the simulation model, enabling real-time updates of the physical parameters of the integrated die-casting machine.

Then, the behavior of the integrated die-casting machine under the joint influence of abnormal disturbances, external inputs, and internal commands is described. A finite state machine model is used to model the behavior of the integrated die-casting machine, enabling precise control of its behavior. Finally, a rule engine is used to define various abnormal phenomena and judgment rules, constructing the associations and constraint rules for the abnormal parameter warning and fault identification of the integrated die-casting machine. Machine learning algorithms are used to train component degradation feature data to build life prediction and deduction rules. The rule engine and intelligent algorithms complement each other to achieve abnormal parameter warnings, abnormal cause analysis, and component life prediction for the integrated die-casting machine. The details of the integrated die-casting machine twin model, constructed from the four dimensions of geometry, physics, behavior, and rules, are shown in Table 1.

Table 1: Details of the 4D twins of the Integrated Die-Casting Machine

Dimension	Composition	Content
Geometry Modle	Geometric Dimension, Geometric Shape,Geometric Position	Injection System:Injection Head,Injection Chamber,Injection Rod,Accumulator
		Clamping System: Mold Plate,Guiding Mechanism,Toggle Mechanism
		Hydraulic System: Hydraulic Pump,Hydraulic Valve,Oil Circuit,Oil Tank
		Auxiliary System: Robotic Arm,Spraying Device,Cooling Water Pump
Physics Modle	Thermodynamic Properties	Mold Temperature,Ambient Temperature, Cooling Water Flow Rate,Hydraulic Oil Temperature
	Mechanical Properties	Clamping Force,Mold Opening Force,Injection Force,Forging Pressure
	Kinematic Properties	Injection Speed,Injection Acceleration,Injection Rod Vibration
Behavior Modle	Operational Status	Operational,Completed,Stopped,Abnormal Material Filling,Vacuuming,Injection,Mold Opening,Part Removal,Mold Clamping
	Process Status	Operating Commands:Start,Stop,Adjust Parameters Trigger Events:Abnormal Event,Node Status,Production Task Completion
	Action	Mold Opening and Closing Action,Injection Head Movement, Molten Material Replenishment,Abnormal Response
Rules Modle	Parameter Warning	Flow Rate,Liquid Level,Temperature Pressure etal. Parameter Range Monitoring,Trend Warning
	Fault Diagnosis	Analyze the changes in abnormal parameters and their

		occurrence locations, and identify system failure conditions.
	Health Prediction	Prediction of replacement cycles for key components such as the injection head and hydraulic pump.

4.3. Verification of Health Prediction Method

Due to the complexity of the integrated die-casting machine as a whole and the uncertainty of actual working conditions, life prediction for the entire equipment remains a high challenge in both technical implementation and prediction accuracy. Therefore, predicting the life of key components individually allows for more precise correlation analysis of the life characterization parameters during the degradation process of specific components. Taking the injection head as an example, life prediction for the key components of the integrated die-casting machine is carried out. The relevant data for the remaining life of the injection head is obtained from the monitoring system's database. The life characteristics of the injection head include injection force (KN), injection speed (m/s), corresponding die cavity external monitoring temperature $(°C)$, vibration acceleration of the injection rod during the injection process (mm/s^2), injection time per cycle (s), and the number of injections (n), among other information. The life characteristics of the injection head are shown in Table 2.

Table 2: Characteristic parameters of the life of the injection head

Characteristic parameters Number	Characteristic parameters Description	Unit
1	Injection Force	KN
2	Injection Speed	m/s
3	Injection Chamber Temperature	$°C$
4	Injection Rod Vibration	mm/s^2
5	Injection Time	s
6	Injection Count	n

Using the equidistant sampling method, 320 sets of characteristic data for the injection head of the integrated die-casting machine during different life stages are selected from June 2023 to June 2024. Among these, 240 sets are used as training data and 80 sets are used as test data, with the data randomly divided. The training data set is used to construct the life prediction model, and the test data set is sequentially input into the CNN-LSTM life prediction model. The obtained life prediction results are shown in Figure 6. As seen from Figure 6, the MAE of the life prediction model for the injection head of the integrated die-casting machine proposed in this paper is 3.127%, the RMSE is 4.005%, and the MAPE is 0.083%. The predicted results are nearly identical to the actual values. This model demonstrates good performance in life prediction for the injection head of the integrated die-casting machine and is expected to be extended to life prediction for other key components in the future.

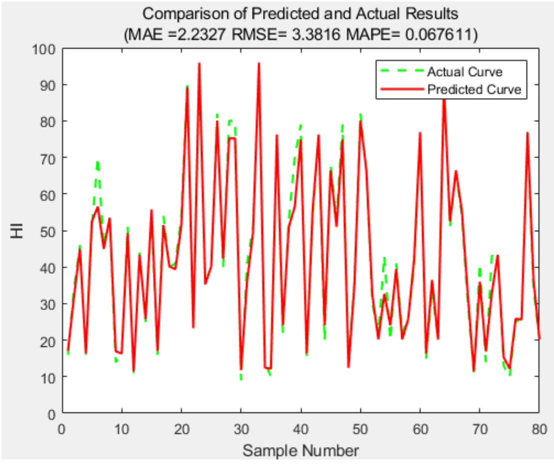

Figure 6: Comparison of the predicted value with the true value of the CNN-LSTM life prediction model

4.4. Visualization of Condition Monitoring and Health Prediction for Integrated Die-Casting Machines

Combining data visualization-related web technologies [14], a visualization dashboard layout is designed to display real-time production data collected by sensors on a large screen. In the visualization model, first, real-time visual display of the physical entity's status and action changes is achieved through the digital twin model and real-time driving technology. In the entity status monitoring, the integrated die-casting machine is divided into systems such as the hydraulic system, mechanical structure, electrical control system, and auxiliary functional equipment, with relevant parameters of each system monitored separately. Next, the monitoring data is matched with the fault knowledge base to provide early warning alerts for abnormal states, accurately locate the abnormal positions, quickly identify the causes of the issues, and assist maintenance personnel in making effective decisions. Finally, the life characteristic parameters of key components are used as data inputs to drive the CNN-LSTM-based life prediction model, which updates the remaining useful life (RUL) prediction results of key components in real time. When the predicted results fall below a certain threshold, the components are replaced in time to avoid quality degradation in die-casting products and reduce losses. On the visualization application interface, the parameter status of various systems and the remaining life of key components of the integrated die-casting machine are displayed in real-time on the large screen. The health status and remaining life interface of the integrated die-casting machine is shown in Figure 7.

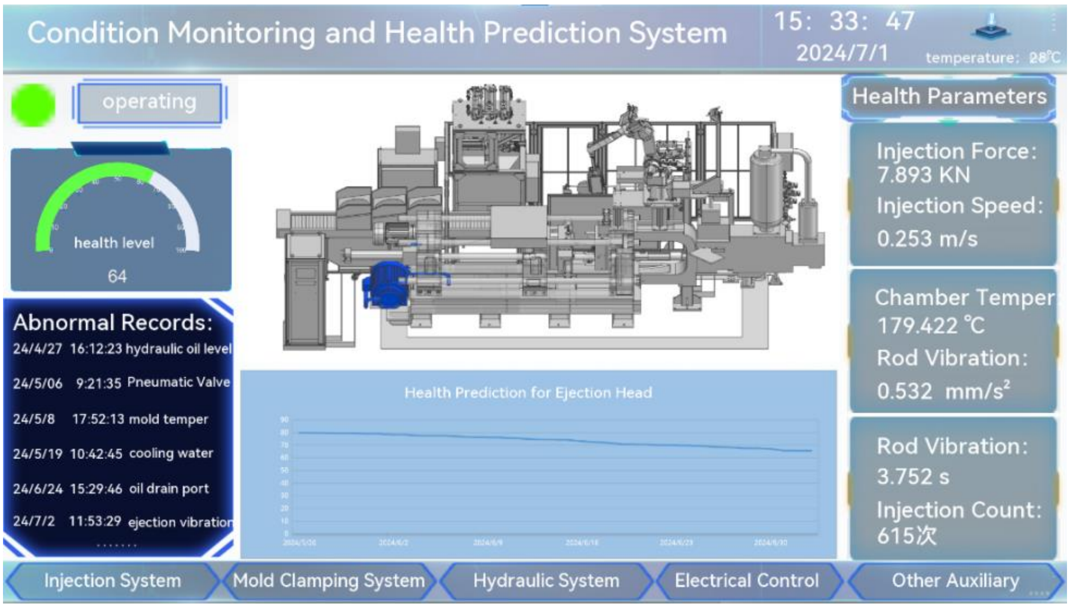

Figure 7: Integrated Die-Casting Machine condition monitoring and health prediction visualization

5. Conclusions

This paper proposes an integrated die-casting machine health condition prediction method based on the fusion of digital twin and CNN-LSTM. By utilizing data acquisition and simulation technologies, a real-time visualization model of the integrated die-casting machine is constructed to comprehensively monitor the status of each system within the machine using real-time data. Taking the core vulnerable component of the integrated die-casting machine, the injection plunger, as an example, the method combines multi-feature data from key components monitored in real-time through the digital twin model with the driving approach of the CNN-LSTM deep learning model to predict and analyze the remaining useful life of the key components. This guidance aids maintenance personnel in conducting preventive maintenance, achieving good results. In terms of research objects, the current focus of life prediction is on the injection plunger in the injection system of the integrated die-casting machine. Subsequent research will extend the life prediction to other key components such as hydraulic pumps and mold plates, based on the life prediction of the injection plunger in the injection system. In terms of research applications, future work will focus on improving monitoring efficiency and early warning capabilities by combining threshold-based early warning with intelligent algorithms.

References

[1] LI Xianzhou. Integrated Die Casting Technologies of Aluminum Alloy [J].Automobile Technology & Materia, 2023(7):17-21.

[2] Riccardo Rosati, Luca Romeo, Gianalberto Cecchini, et al. From knowledge-based to big data analytic model: a novel IoT and machine learning based decision support system for predictive maintenance in Industry 4.0[J]. Journal of Intelligent Manufacturing, 2022, 34(1): 107-121.

[3] Savolainen Jyrki, Urbani Michele. Maintenance optimization for a multi-unit system with digital twin simulation[J]. Journal of Intelligent Manufacturing, 2021, 32(7): 1953-1973.

[4] Jhennifer F. Santos, Bendict K. Tshoombe, Lucas H. B. Santos, et al. Digital Twin-Based Monitoring System of Induction Motors Using IoT Sensors and Thermo-Magnetic Finite Element Analysis.[J]. IEEE Access, 2023, 11: 1682-1693.

[5] Farid K. Moghadam, Amir R. Nejad. Online condition monitoring of floating wind turbines drivetrain by means of digital twin[J], Mechanical systems and signal processing, 2022, 162.

[6] Zhou Yuxi, Tang Jing, Yin Xue, et al. Digital Twins Visualization of Large Electromechanical Equipment[J]. IEEE Journal of Radio Frequency Identification, 2022, 6: 993-997.
[7] Wu Pengxin, Guo Yu, Huang Shaohua, et al. visual real-time monitoring method for discrete manufacturing workshop based on digital twin[J].Computer Integrated Manufacturing Systems, 2021, 27(6) :1605–1616.
[8] Tao Fei, Zhang Meng, Liu Yushan, et al. Digital twin driven prognostics and health management for complex equipment [J]. Cirp Annals-manufacturing Technology, 2018, 67(1): 169-172.
[9] Ren Weixi, Zhang Wenyu, Li Ming, et al. Fault diagnosis of wind turbine bearing based on digital twin.[J].Journal of Projectiles, Rockets, Missiles and Guidance, 2022, 42(03):97-104.
[10] Zhang Jiajin. Prediction of remaining life of aero engine based on attention mechanism and CNN-BiLSTM model [J]. Journal of Electronic Measurement and Instrumentation, 2022, 36(8):231-237.
[11] Cheng Yiwei, Hu Kui, Wu Jun, et al. A convolutional neural network based degradation indicator construction and health prognosis using bidirectional long short-term memory network for rolling bearings[J]. Advanced Engineering Informatics, 2021, 48: 101247.
[12] Zhu Zhenyu, Gao Dexin. A state-of-health detection method for lithium-ion batteries based on CNN-BiLSTM network [J]. Electronic Measurement Technology, 2023, 46(3):128-133.
[13] Liu Shimin, Bao Jinsong, Zheng Pai.A review of digital twin-driven machining: From digitization to intellectualization [J]. Journal of Manufacturing Systems, 2023, 67:361-378.
[14] Niu Jinxin, Sun Wenlei, Liu Guoliang, et al. Research on robot motion simulation and virtual-real synchronized mapping driven by digital twins[J].Modern Manufacturing Engineering, 2024(5):48-55.