ISSN: 2472-3703 DOI: 10.6911/WSRJ.202609_12(9).0018

Digital Twin of Three-Sided CNC Punching System for Automotive U-Shaped Longitudinal Beams: Modeling Research

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Abstract

This paper develops a digital twin (DT)-based intelligent computer numerical control (CNC) punching system applied to automotive U-shaped longitudinal beams to enhance the intelligent level, operation stability and machining efficiency of equipment. A high-fidelity DT model is established by means of three-dimensional(3D) modeling, multi-body dynamic simulation, and real-time data interaction between physical equipment and virtual space. Combined with fault tree analysis and machine learning algorithms, the model can realize equipment health state monitoring, fault early warning and remaining useful life prediction. Experimental verification shows that the punching efficiency of the system is increased by more than 30%.

Keywords

Computer numerical control; Punching system; U-shaped longitudinal beams; Digital twin technology.

1. INTRODUCTION

Driven by technological progress and market demands, the automotive manufacturing industry is undergoing a transformation from traditional production to intelligent manufacturing. The traditional frame forming technologies have been evolving toward high-efficiency, high-precision, and flexible production. Longitudinal beams are the main load-bearing parts of vehicle frames, and their performance directly determines the safety and stability of ladder-type frames and central-beam frames. CNC punching system provides an efficient digital processing scheme for longitudinal beam hole machining. In the process of long-term continuous operation, aging, performance degradation of key components, and external interference factors, may lead to malfunctions of the entire equipment. In order to solve the above problems, this paper constructs a technical framework combining DT technology and reliability analysis.

DT is a virtual representation driven by physical models, sensor data, and operational history. It can accurately simulate the punching process in a virtual space, optimize processes in advance and prevent production errors. Therefore, the application of DT technology in the three-sided CNC punching system of automotive U-shaped longitudinal beams has important practical engineering value.

In recent years, DT has been increasingly applied to precision manufacturing of large-scale components. Anwer et al. and Michael et al. reviewed fundamental DT concepts, methods, and engineering-design applications [1, 2]. Tian et al. combined deep learning with FEM for

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deformation and seepage analysis of high earth-rock dams [3]. In studies on the fault diagnosis and prognostics, Chen et al. used a Time-Series Dense Encoder surrogate within a multi-step MPC framework for real-time decision-making [4], Yu et al. [5] and Cui et al. [6] developed DT-driven diagnostic methods, respectively for non-contact IFD (98.34% average accuracy) and quantitative bearing-fault severity assessment from raw waveforms. Ma et al. reviewed DT-inspired IFD and RUL prediction [7]. Sun et al. [8] and Cao et al. [9] further proposed knowledge-embedded and tool-health DTs for multi-tool wear prediction and CNC predictive maintenance. For thermal-error and machine-tool monitoring, Weng et al. reviewed data-driven and DT-based thermal error compensation [10], whereas Sun et al. combined C#, ANSYS, and MATLAB for in-situ monitoring of thermally induced volumetric errors with over 95% accuracy [11]. Other studies [12–19] similarly apply DT to CNC machine tools and precision manufacturing. Although considerable progress has been achieved in DT-driven precision manufacturing, few researches pay attention to three-sided punching equipment for automotive U-shaped longitudinal beams. This research fills this gap.

This paper is organized as follows. In Section 2 the related technical information including overall technical route, fault analysis and identification(Section 2.1), construction of DT model(Section 2.2), model verification and optimization(Section 2.3), and mechanical structure modeling(Section 2.4) are presented. Finally, conclusions are drawn in Section 3.

2. DT MODELING

The overall technical route is shown in Figure 1.

2.1. Fault Analysis and Identification

Historical fault records, operation manuals, design drawings and other technical documents are collected and analyzed to identify the main fault factors such as material fatigue, mechanical wear and overload operation. Meanwhile, combined with the feedback of on-site operators, the cause of the fault is further analyzed. Failure Mode and Effects Analysis and Fault Tree Analysis are adopted to clarify fault types(such as punch fracture, die damage and transmission system fault, etc.) and their possible impacts. System performance under different fault conditions is tested and quantitatively analyzed. The above results lay a foundation for the subsequent construction and optimization of the DT model.

2.2. Construction of DT Model

Based on fault analysis results, high-precision 3D digital models are established using professional modeling software and algorithms. CAD/CAE softwares(e.g., SolidWorks and ANSYS) are adopted to construct high-fidelity 3D models, which can realize mechanical structure simulation and multi-body dynamic analysis. The model covers key components such as punch, die, transmission mechanism and feeding device, and ensures that the geometric size of each component is consistent with the physical entities. The geometric shape, material characteristics and operating parameters are set in accordance with the actual working conditions. In addition, multi-body dynamics software ADAMS is utilized to simulate relative motions and interaction forces among components and capture the dynamic behavioral characteristics of the whole system, which are critical for understanding the actual operational states of the equipment during production.

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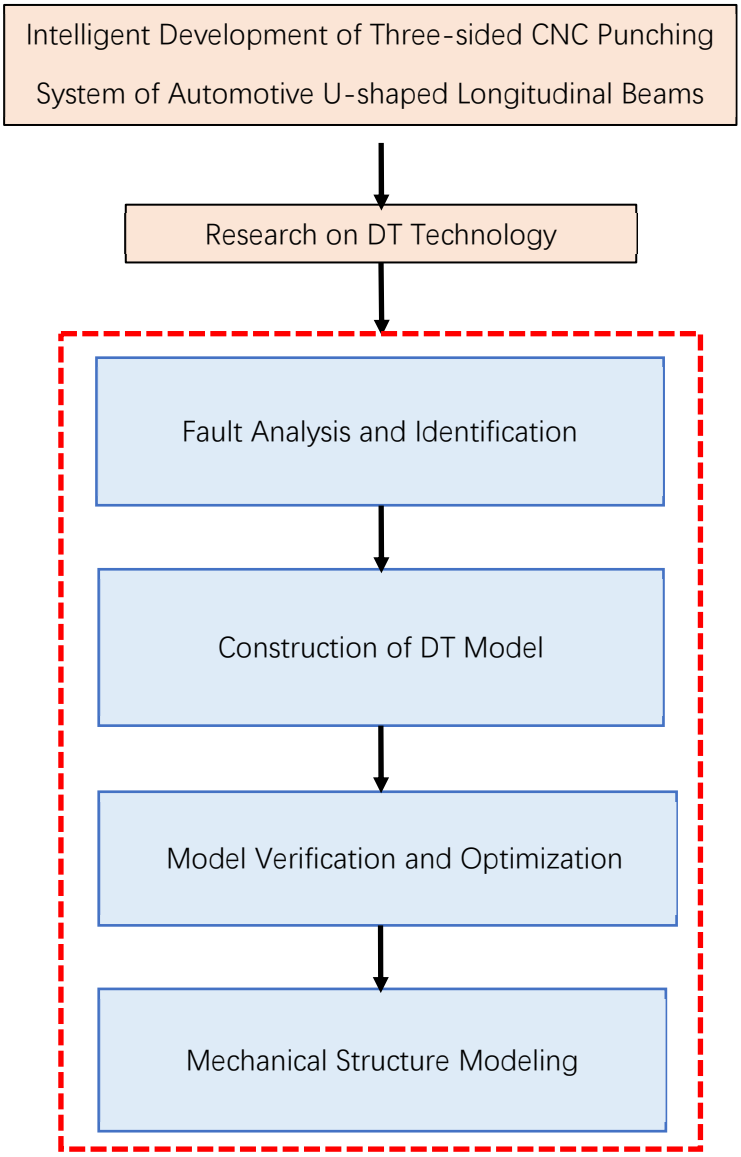


Figure 1. Technology route of DT modeling for three-sided CNC punching system for automotive U-shaped longitudinal beams

2.3. Model Verification and Optimization

Temperature, vibration, stress and displacement sensors are arranged at key positions of the equipment to collect real-time data. These data can not only find potential risks in advance, but also provide the basis for model calibration. The industrial internet of things technology is used to upload the collected data to the cloud platform for analysis and processing. Data security and integrity are guaranteed in the transmission process.

Support vector machines, neural networks and other machine learning methods are used to process real-time data and extract effective characteristic information to guide the iterative correction of the DT model. Through continuous optimization, the virtual model is highly consistent with the physical equipment. The real-time data is imported into the DT model, and the accuracy of the model is verified by comparing the deviation between the simulation outputs and the actual operation states. The model parameters are adjusted to reduce the error and improve the fitting effect. At the same time, the new data is continuously collected to optimize the model structure and algorithm.

Based on the verified DT model, the life prediction method suitable for longitudinal beam punching system are studied by considering the working environment, operating frequency and

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other factors.In addition, the RUL prediction method based on DT is proposed to realize equipment health monitoring and predictive maintenance.

2.4. Mechanical Structure Modeling

Mechanical structure modeling is built by combining SolidWorks parametric design and ANSYS SpaceClaim geometry repair function. The local stress is calculated based on Hertz contact theory

$$\sigma_{max} = 0.418\sqrt{\frac{FE^*}{RL}},$$

where E*, R, and L are equivalent elastic modulus, punch radius, and contact length, respectively. In addition, the multi-body dynamic model is established by Lagrange equation:

$$\frac{d}{dt}\left(\frac{\partial T}{\partial q_i}\right) - \frac{\partial T}{\partial q_i} + \frac{\partial V}{\partial q_i} = Q_i,$$

where T, V, and q_i are kinetic energy, potential energy, and the generalized coordinate, respectively. The modeling parameters are analyzed, and the model is adjusted and optimized according to the actual motion characteristics of the equipment.

3. CONCLUSIONS

In this study, the DT technology is applied to realize equipment health monitoring, fault identification of three-sided CNC punching system for automotive U-shaped longitudinal beams, and formulate scientific and rational preventive maintenance scheduling. This approach can not only reduce production cost, extend equipment service life, but also improve the adaptability of equipment to variable production demands and overall production efficiency. It was experimentally validated that the punching efficiency of the upgraded system increased by more than 30%.

In addition, a multi-body dynamic model covering mechanical structural dynamics, stamping plastic deformation theory, and thermo-mechanical coupling effects is constructed. The accurate coupling mechanism among different physical processes is revealed, so that the DT model can truly reflect the complex physical behavior in the punching process and realize high-precision simulation and prediction.

ACKNOWLEDGMENTS

This work was supported by the Shandong Province Science and Technology SME Capability Innovation and Enhancement Program (Grant No. 2025TSGCCZZB0068).

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