

Mechanism-Data Fusion Modeling Method for Aerospace Electromechanical Actuation Systems

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Abstract

High-precision dynamic models are the foundation for performance simulation and advanced control of aerospace electromechanical actuation systems. To address the limitations of pure mechanism models in fully capturing system nonlinearities and uncertainties, as well as the weak physical interpretability of pure data-driven models, this paper proposes a system-level mechanism-data fusion modeling method. First, a high-fidelity mechanism model of a dual-redundancy electromechanical actuation system is constructed using AMESim, and its dynamic response characteristics are verified through simulation. Second, a dual-channel composite loading test platform is built to collect full-factor dynamic data. A long short-term memory network is employed to establish a data-driven compensation model that takes position command, thrust force, and mechanism model displacement as inputs and outputs the displacement residual. The coefficient of determination of the test set reaches 0.9576. Finally, the two models are integrated via a series architecture to form a mechanism-data fusion model. Under three untrained operating conditions (ramp, step, and sine), the root mean square errors of the fusion model are reduced by 76.6%, 90.3%, and 52.2%, respectively, compared with the pure mechanism model, demonstrating a significant improvement in prediction accuracy. This study provides an effective approach for high-confidence modeling of aerospace actuation systems and lays a simulation foundation for subsequent force-fighting analysis and synchronization control research.

Keywords: Electromechanical Actuator; Modeling; Data-driven; Mechanism; Aerospace

1. Introduction

With the continuous development of more-electric/all-electric aircraft technology, electromechanical actuators, as the core actuation units for flight control surfaces, directly affect aircraft handling qualities, safety, and reliability [1]. Establishing high-fidelity system dynamic models not only provides a theoretical basis for performance simulation and state prediction of actuation systems but also offers an efficient simulation environment for the design and verification of advanced control algorithms. This is of great significance for shortening development cycles and reducing test costs [2].

However, constructing models that can accurately reflect the dynamic characteristics of real complex electromechanical systems faces significant challenges. On the one hand, mechanism modeling methods based on multi-domain physical laws can clearly describe the deterministic dynamic processes of a system, possessing clear physical meaning and good extrapolation capability. Nevertheless, the complex uncertainties widely present in real systems—such as nonlinear friction, flexible deformation between components, assembly clearance, time-varying parameters, and unknown external disturbances—are often difficult to fully capture in mechanism models, limiting their predictive accuracy in practical applications [3,4]. On the other hand, purely data-driven "black-box"

modeling methods represented by various deep learning models exhibit strong capability in fitting complex nonlinear relationships [5], but they lack physical interpretability, and their generalization performance heavily depends on the scale and quality of training data. When training data are insufficient or operating conditions fall outside the existing data range, their predictive reliability becomes difficult to guarantee [6,7].

To overcome the limitations of the above two methods, mechanism-data fusion modeling methods have received extensive attention in recent years [8,9]. The core idea is to combine prior physical knowledge with data-driven learning capability, retaining both the physical consistency and extrapolation capability of the mechanism model while using data-driven methods to compensate for unmodeled dynamics [10]. Currently, this method has been successfully applied in fields such as condition monitoring of aviation hydraulic gear pumps [11], performance prediction of aero-engines [12], and online monitoring of cutting tool wear[13].Nevertheless, for complex systems such as aerospace electromechanical actuators that exhibit strong nonlinearity, multi-coupling, and high dynamic characteristics, how to construct an effective mechanism-data fusion model and verify its prediction accuracy under multiple operating conditions remains an urgent research topic.

To this end, this paper focuses on a mechanism-data fusion modeling method for aerospace electromechanical actuation systems, aiming to explore and validate a system-level fusion modeling framework. First, a high-fidelity multi-domain mechanism model encompassing electrical, mechanical, transmission, and load dynamics is constructed. Second, to compensate for the inherent residuals of the mechanism model, a data-driven compensation model is developed using deep learning methods based on dynamic data from a self-built dual-redundancy electromechanical actuator test bench. Finally, the mechanism model and the data-driven model are combined to form a high-precision digital model, which is comprehensively validated using multi-condition experimental data. The proposed fusion model aims to significantly improve the prediction accuracy of system dynamic responses and provide a high-confidence simulation environment for subsequent force-fighting analysis and synchronization control strategy research.

The structure of this paper is as follows: Section 2 introduces the mechanism modeling method and simulation verification of the electromechanical actuation system. Section 3 describes the construction of the data-driven compensation model, including the experimental platform, data acquisition, LSTM network architecture, and training result analysis. Section 4 presents the construction and validation results of the mechanism-data fusion model. Section 5 concludes the paper.

2. Mechanism Modeling

2.1 System Description

A dual-redundancy aerospace electromechanical actuation system consists of two electromechanical actuators of identical specifications that jointly drive the same flight control surface. Its structure is shown in Fig. 1. The controller receives the flight control surface position command from the flight control computer and simultaneously collects key feedback signals from the two channels, including the rotational speed signal from the motor resolver and the pushrod linear displacement signal from the displacement sensor at the screw nut. Based on the above feedback information, the controller calculates the drive commands for the two motors, which are output to the two permanent magnet synchronous motors via servo drives, respectively.

The motor output shaft converts high-speed low-torque rotation into low-speed high-torque output through a gearbox, and then converts rotational motion into pushrod linear motion through a ball screw nut pair. The pushrod end is connected to the flight control surface via a universal joint, pushing the surface to rotate about its pivot axis. The displacement difference between the two actuators is superimposed into the respective position loop inputs after synchronization compensation to suppress synchronization errors caused by load differences or parameter perturbations.

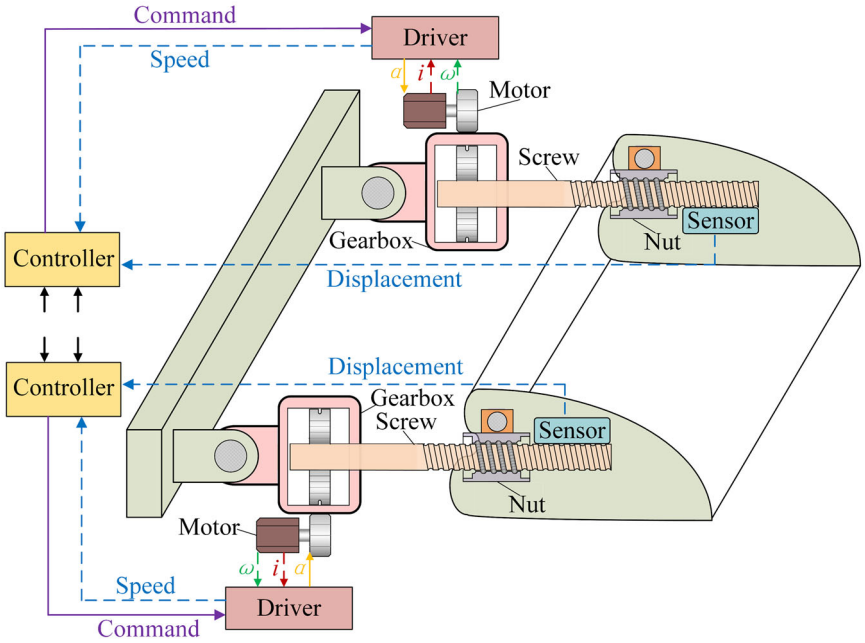


Fig. 1 Structure diagram of the dual-redundancy aerospace electromechanical actuation system

2.2 Simulation and Verification

To verify the correctness of the mechanism modeling and the effectiveness of the synchronization control algorithm, a high-fidelity mechanism model of the dual-redundancy electromechanical actuation system was built on the AMESim software platform, as shown in Fig. 2. The controller adopts a cascade proportional-integral control structure: the position loop feedback comes from the displacement sensor at the screw nut; the velocity loop feedback comes from the resolver signal on the motor output shaft; the current loop is implemented internally by the drive. The displacement difference between the two channels is superimposed into the respective position loop setpoints via a synchronization compensator, forming a synchronization control closed loop. The mechanical part includes the gearbox, the ball screw nut pair, the universal joint, and the flight control surface.

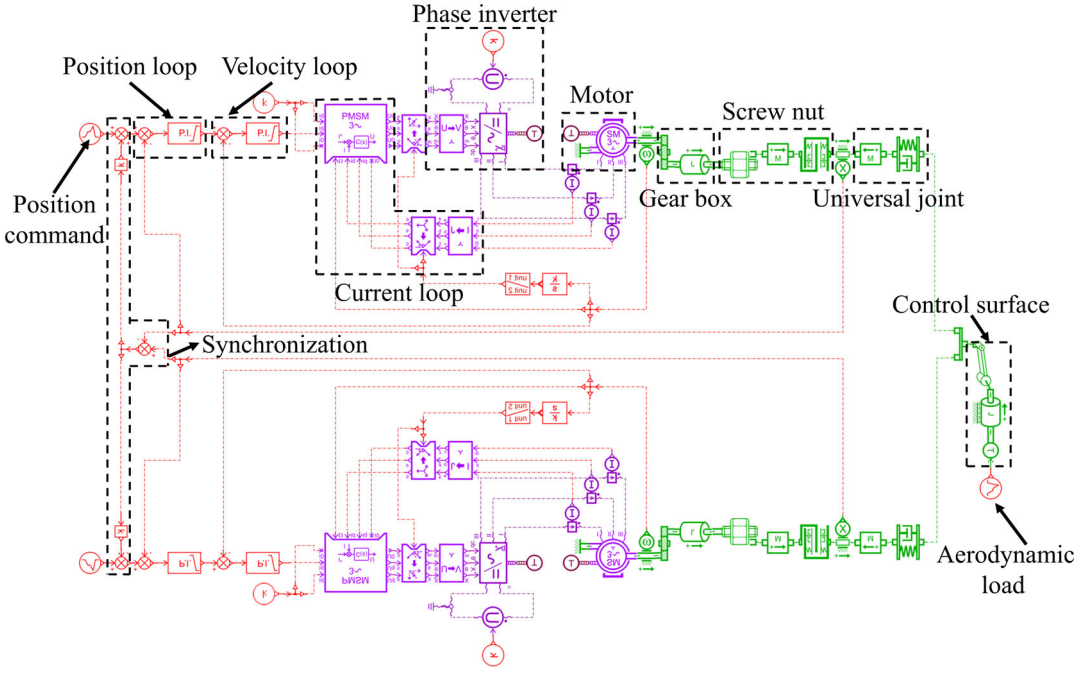
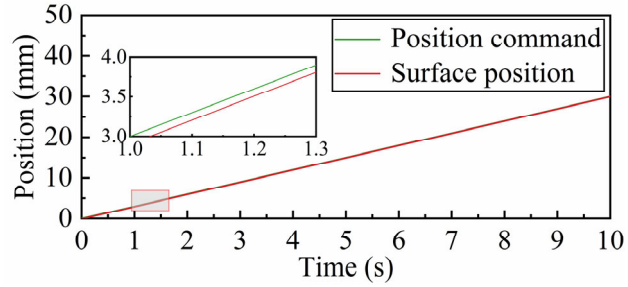
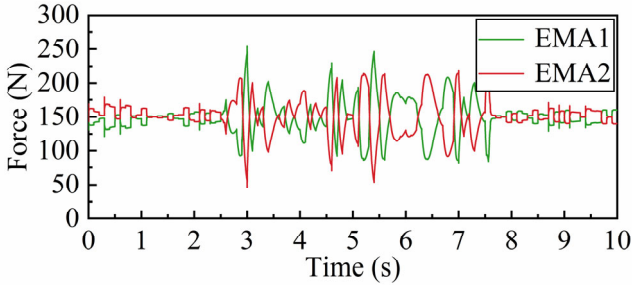


Fig. 2 Mechanism model of the dual-redundancy aerospace electromechanical actuation system based on AMESim

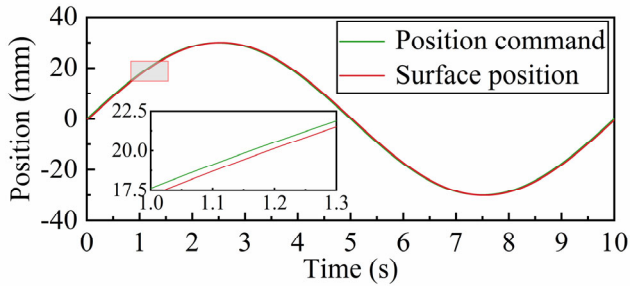
To test the dynamic response characteristics and synchronization control capability of the model, a random load disturbance with an amplitude of 100 N was applied to the pushrod end of the EMA1 channel, and simulation experiments were performed for ramp commands and sine commands, respectively. The simulation results are shown in Fig. 3.



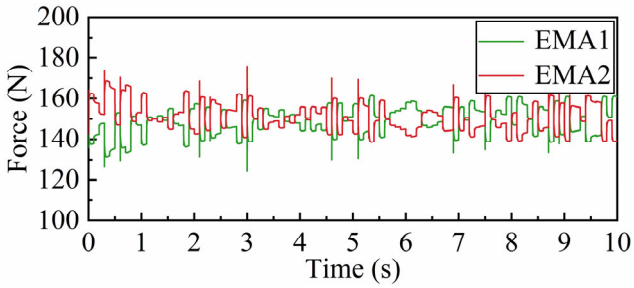
(a) Displacement tracking curves under ramp command



(b) Force-fighting curves under ramp command



(c) Displacement tracking curves under sine command



(d) Force-fighting curves under sine command

Fig. 3 Simulation results of the mechanism model

In Fig. 3(a), the ramp command has a slope of 3 mm/s and an amplitude from 0 to 30 mm. The actual displacements of both actuators closely follow the command signal. The maximum tracking error of the two actuators is 0.11 mm. This small error indicates that under slow ramp input, the cascade PID control and the synchronization compensator can coordinate the motion of the two channels well, and the instantaneous deviation caused by the load disturbance is quickly suppressed. Fig. 3(b) shows the difference in output thrust forces of the two actuators, i.e., force fighting. During the load disturbance application, the peak force fighting is 207.7 N. Such a significant peak mainly stems from the inconsistent dynamic responses of the two channels during sudden random load changes: EMA1 directly bears the disturbance and its controller needs a short time to adjust the output, while EMA2 senses the disturbance indirectly through the synchronization compensator. The transient responses of the two channels have a phase difference, resulting in a large internal force conflict. Although the peak is high, this does not affect the displacement tracking performance of the two actuators, indicating that the synchronization compensator can effectively suppress the asynchronization caused by the disturbance.

Fig. 3(c) shows the displacement tracking curves under a sine command with amplitude 30 mm and frequency 0.1 Hz. The maximum tracking error of the two channels is 0.58 mm. Compared with the ramp command, the tracking error under the sine command is significantly larger. This is because sinusoidal motion requires the system to continuously accelerate and decelerate, and the periodic variations of inertia and friction make it difficult to completely eliminate the steady-state error of the position loop. Fig. 3(d) shows that the peak force fighting under the sine command is approximately 51.7 N. This value is much smaller than the 207.7 N under ramp random disturbance, indicating that the system's force-fighting response to the same load disturbance is significantly weaker in sinusoidal motion than in ramp motion.

The simulation results demonstrate that the constructed mechanism model can correctly reflect the

kinematic and dynamic characteristics of the dual-redundancy actuation system, providing a reliable benchmark model for subsequent data-driven compensation.

3. Data-Driven Modeling

Although the mechanism model captures the main dynamics of the system, residuals still exist between its predicted values and the actual measured values of the physical entity, which originate from unmodeled high-order dynamics, time-varying parameters, and nonlinear friction uncertainties [14]. To compensate for these residuals, this section establishes a data-driven model focusing on learning the complex dynamics that the mechanism model fails to characterize. By adding the data-driven compensation term to the output of the mechanism model, a significant improvement in prediction accuracy is expected.

3.1 Experimental Platform and Data Acquisition

To provide training data for the data-driven model and validate the effectiveness of the proposed modeling method, a fully functional comprehensive test platform for the actuation system was constructed. Its architecture is shown in Fig. 4. The platform uses a Speedgoat real-time target machine as the control core. All sensors and servo drives are connected via I/O boards, forming a hardware-in-the-loop test environment. On the software side, MATLAB/Simulink is used for code generation, and a self-developed host computer is used for algorithm deployment, online parameter tuning, command transmission, and real-time monitoring and recording of status data. The host computer interacts with the Speedgoat in real time via the CANopen protocol, forming a closed-loop development and testing process.

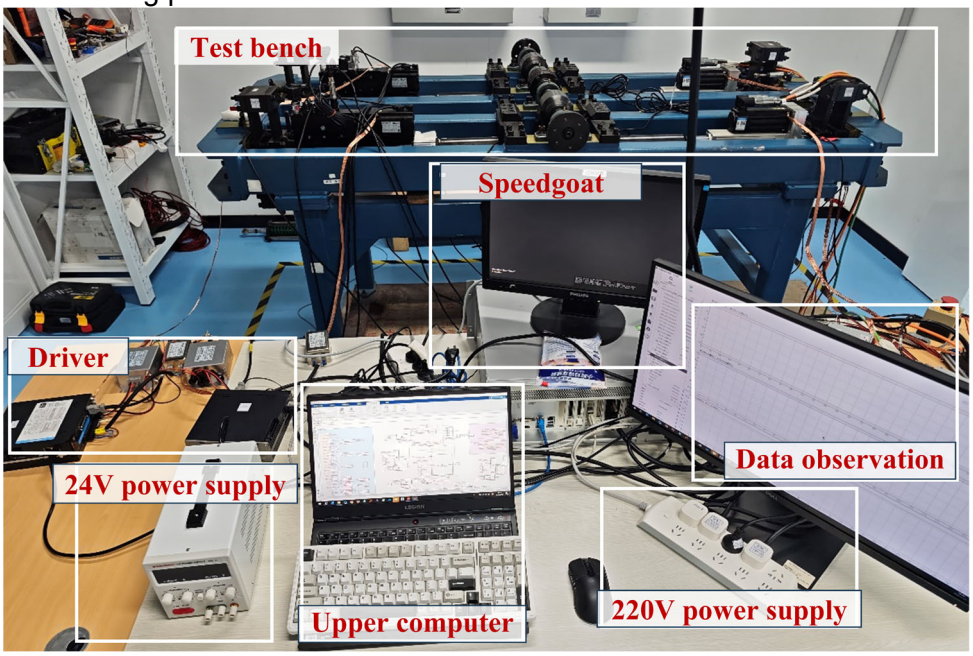


Fig. 4 Comprehensive test platform for the actuation system

The actuation test bench is shown in Fig. 5. Its mechanical main structure adopts a dual-channel composite loading configuration. Each channel consists of one electromechanical actuator as the driving unit and one electro-hydrostatic actuator as the load simulation unit. They are connected via a mechanical rocker arm, forming an independent drive-load pair. The two channels are mechanically coupled via a clutch. When the clutch is engaged, cooperative or competitive scenarios in dual-redundancy control surface actuation can be simulated; when the clutch is disengaged, the two channels operate completely independently, facilitating single-channel characteristic tests. This platform provides a physical basis for studying synchronization control and force-fighting problems under different connection states.

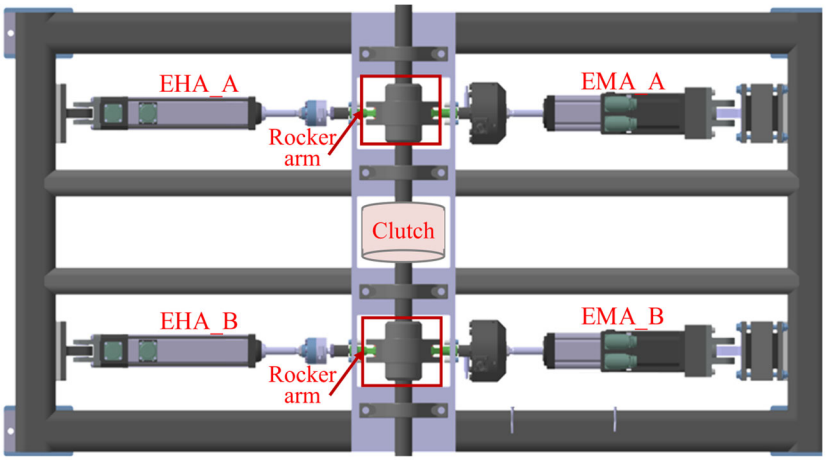


Fig. 5 Actuation test bench

The data acquisition object is a single electromechanical actuator. The acquired signals include the position command signal, the actual output displacement of the actuator, and the actuator thrust force. The sampling frequency is 100 Hz, and the sampling duration for each test group is 10 s, yielding 1000 data points. A full-factor design is adopted, covering typical operating modes of aerospace actuators. There are 30 groups of ramp commands with slopes from -30 mm/s to 30 mm/s in steps of 2 mm/s; 30 groups of step commands with amplitudes from -30 mm to 30 mm in steps of 2 mm; and 36 groups of sine commands combining 6 amplitude levels (5, 10, 15, 20, 25, 30 mm) and 6 frequency levels (0.05, 0.10, 0.15, 0.20, 0.25, 0.30 Hz). A total of 96 test groups are performed. For each group, the position command, actual displacement, thrust force, and mechanism model predicted displacement are recorded. The mechanical stroke limit of the actuator is ±30 mm, and all tests are completed within the safe stroke.

3.2 LSTM Topology Architecture

The input features of the data-driven model are a three-dimensional vector comprising the position command signal, the real-time thrust force of the actuator, and the displacement predicted by the mechanism model. The output target is the residual between the mechanism model predicted displacement and the true displacement. This sequence has significant temporal correlation, making it suitable for time-series neural networks that can capture long-term dependencies. As a classic time-series neural network, the long short-term memory network is an improved form of recurrent neural network. Through the ingenious design of input gates, forget gates, output gates, and memory cells, the LSTM effectively avoids the vanishing gradient and exploding gradient problems of traditional RNNs, making it particularly suitable for modeling systems with dynamic memory characteristics [15].

Fig. 6 shows the topology of the LSTM. The input layer contains 3 nodes, the LSTM layer contains 64 nodes, the fully connected layer contains 64 nodes, the dropout rate of the dropout layer is 0.15, and the output layer contains 1 node.

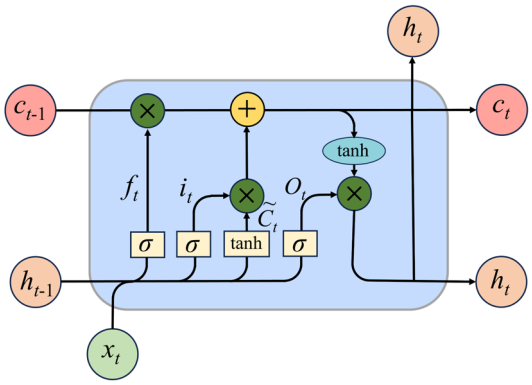
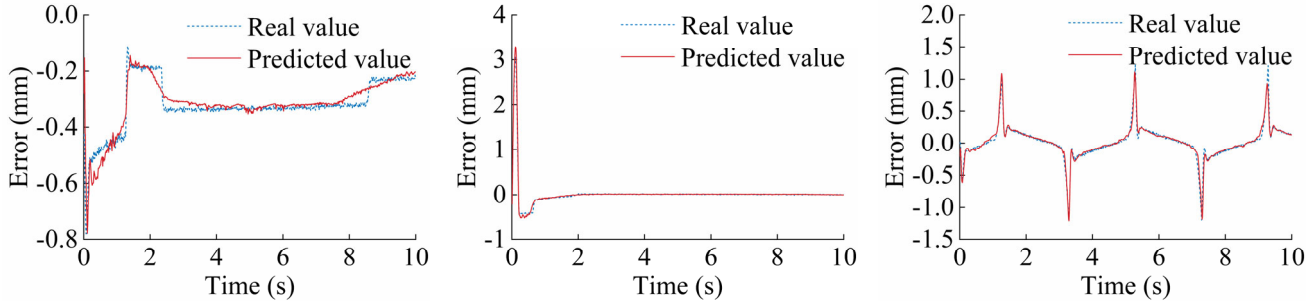


Fig. 6 Topology of the LSTM

3.3 Training Result Analysis

The data are divided into training set, validation set, and test set in a ratio of 7:1.5:1.5. The model training uses the following hyperparameters: maximum number of epochs 800, initial learning rate 0.015 with a piecewise decay strategy (multiplying the learning rate by 0.7 every 100 epochs), mean squared error as the loss function, and batch size of 22.

On the independent test set, the R^2 of the trained LSTM model reaches 0.9576, indicating that the predicted residuals have high accuracy in approximating the true residuals. Fig. 7 shows the fitting results for randomly selected ramp, step, and sine commands in the test set.



(a) Ramp command (b) Step command (c) Sine command

Fig. 7 Fitting results for arbitrary sequences in the test set

In Fig. 7(a), under the ramp command, the residuals exhibit noticeable fluctuations in the early stage (0-2 s) and the late stage (8-10 s) of the prediction time, and the model shows relatively large prediction errors before and after these fluctuations. The LSTM model learns the overall trend of the residuals but still has some prediction deviation in the regions where fluctuations occur.

In Fig. 7(b), under the step command, an error peak of 3.3 mm occurs at the instant of the command step, but the error quickly approaches zero after 0.7 s. Throughout the prediction cycle, the model predictions show no oscillation or steady-state error. The peak error in the step response originates from the simplified treatment of inertia and friction in the mechanism model, while the LSTM successfully learns the transient compensation law under step excitation through training and can correct the residual to near-zero in a short time.

In Fig. 7(c), under the sine command, the residual exhibits periodic fluctuations with an amplitude of approximately ±1 mm. The model accurately captures the phase and amplitude of the peaks and troughs. This is because the system dynamics under sine commands are highly repetitive, allowing the LSTM network to fully utilize information from historical cycles to predict the residual of the current cycle, thereby achieving almost lag-free precise compensation.

The above results demonstrate that the LSTM network successfully learns the dynamic evolution law of the mechanism model residuals under various time-varying commands, providing a high-precision data-driven module for subsequent fusion compensation.

4. Validation of the Mechanism-Data Fusion Model

Compensating the displacement output of the mechanism model using the LSTM-based data model constitutes the mechanism-data fusion model. The architecture of the fusion model is shown in Fig. 8. The core advantage of this architecture is that the mechanism model provides a physically reasonable baseline trajectory, while the LSTM model predicts and corrects the residual between the baseline trajectory and the true trajectory in real time. The two complement each other, maintaining physical interpretability while improving prediction accuracy under complex operating conditions.

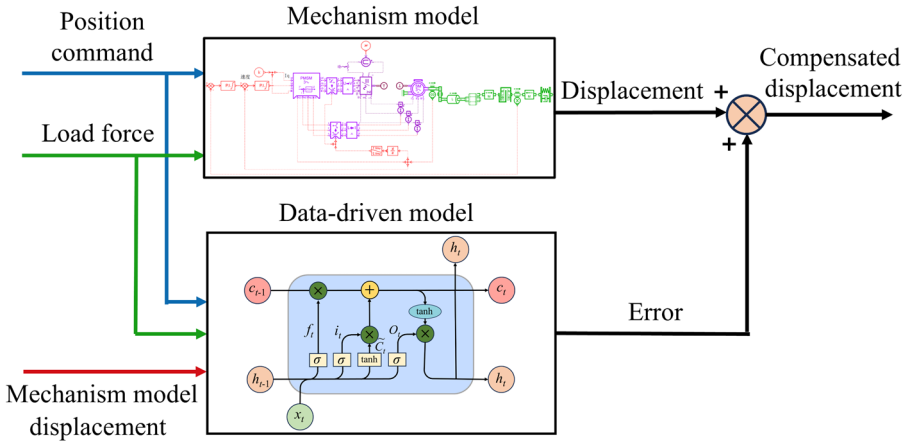
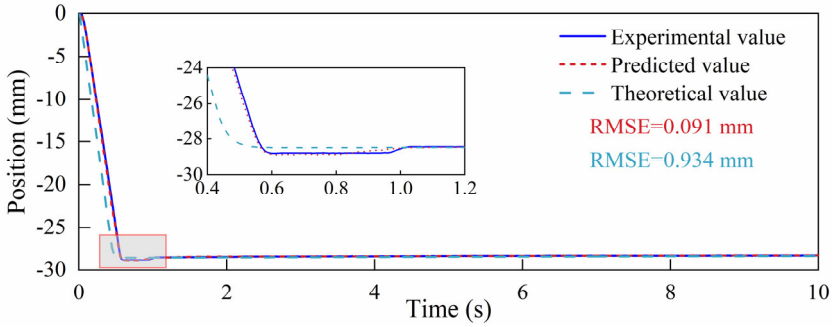
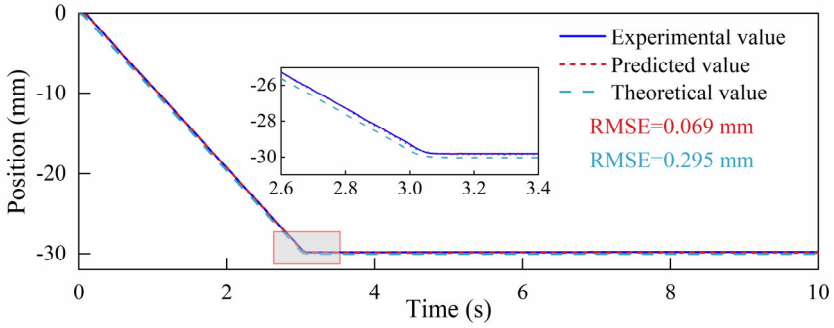


Fig. 8 Architecture of the mechanism-data fusion model

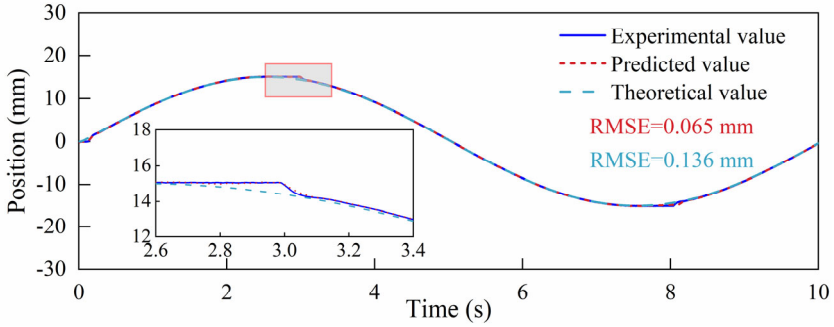
To comprehensively evaluate the effectiveness of the fusion model, three typical test conditions not involved in model training were selected for verification: a ramp command with a slope of -10 mm/s, a step command with an amplitude of -28 mm, and a sine command with an amplitude of 16 mm and a frequency of 0.1 Hz. Fig. 9 shows the experimental validation results.



(a) Ramp command



(b) Step command



(c) Sine command

Fig. 9 Experimental validation results of the mechanism-data fusion model

It can be seen from Fig. 9 that when the experimental values exhibit fluctuations and deviations, the fitting accuracy of the fusion model is significantly better than that of the pure mechanism model. Under the three test conditions (ramp, step, and sine), the RMSE of the fusion model is reduced to 0.069 mm, 0.091 mm, and 0.065 mm, respectively, which are 76.6%, 90.3%, and 52.2% lower than those of the pure mechanism model. Under the ramp condition, the main error of the mechanism model originates from nonlinear friction variations in the constant-speed segment. By learning the residual pattern from historical data, the LSTM effectively compensates for this systematic deviation, reducing the RMSE from 0.295 mm to 0.069 mm. Under the step condition, the error of the mechanism model mainly comes from transient overshoot and oscillation. Benefiting from its strong capability in modeling temporal dependencies, the LSTM accurately predicts the overshoot peak and decay process, achieving the most significant compensation effect with an error reduction of 90.3%. Under the sine condition, the error of the mechanism model is relatively small and periodic. Although the LSTM further reduces the residual, the improvement is limited (52.2%), which is consistent with the intuitive logic that a more accurate baseline leaves less room for compensation.

In summary, the proposed mechanism-data fusion model significantly improves the prediction accuracy and provides a high-confidence digital simulation environment for subsequent force-fighting analysis and synchronization control strategy research.

5. Conclusion

This paper systematically investigates a mechanism-data fusion modeling method for aerospace electromechanical actuation systems. The main conclusions are as follows.

(1) A high-fidelity mechanism model of the dual-redundancy electromechanical actuation system is constructed based on AMESim. Simulation verification shows that after applying a 100 N load disturbance, the maximum position tracking error of the mechanism model is 0.58 mm and the peak force fighting is 207.7 N. The model correctly reflects the kinematic and dynamic behavior of the system and validates the effectiveness of the synchronization control algorithm in the mechanism model, providing a reliable benchmark for data-driven compensation.

(2) A dual-channel composite loading test platform is built, and 96 groups of full-factor dynamic data containing typical commands such as ramp, step, and sine are collected. Based on these data, an LSTM network is constructed that takes the position command, actuator thrust force, and mechanism model displacement as inputs and outputs the displacement residual. The test set R^2 reaches 0.9576, and the model accurately fits the temporal patterns of residual variations under various commands, demonstrating that LSTM can effectively learn the unmodeled dynamics of the mechanism model.

(3) The data-driven compensation model and the mechanism model are fused via a series architecture to form a unified mechanism-data fusion model. Under three independent test conditions, the RMSE of the fusion model is reduced by 76.6%, 90.3%, and 52.2%, respectively, compared with the pure mechanism model. The fusion model significantly improves the prediction accuracy of system dynamic responses and provides a high-confidence digital environment for simulation studies of subsequent force-fighting analysis and synchronization control strategies.

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