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Research on Efficient Dynamics Simulation Technology for Artillery Equipment

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1. Introduction

Artillery, as a primary source of firepower on the battlefield, is a complex mechanical system composed of numerous components, and its development process is intricate. In recent years, new modes of warfare have raised cross-generational performance enhancement requirements for weaponry, causing new artillery design schemes to approach their theoretical constraints, making the development process increasingly complex and challenging. Particularly in structural design, the traditional design-simulation-improvement-design-re-simulation process requires a considerable amount of time and is less efficient. To improve artillery development, traditional design methods have been gradually integrated with modern design approaches to enhance development efficiency [1].

Recent research into rapid design methods for artillery equipment includes various approaches, such as introducing parametric design methods, case reasoning techniques, and knowledge reuse technologies. For example, reference [1] proposed a knowledge reuse-based rapid design prototype system for recoiling mechanisms; reference [2] combined case reasoning technology with parametric design methods in recoiling mechanism design to form a template-based rapid design method; and reference [3] conducted research on template-based rapid design technology for artillery barrels. These methods, based on existing design resources, simplify the design process by modifying or reusing models through parameterization, component invocation, and template use, thus improving development efficiency. Reference [4] conducted performance evaluations of the matching between firepower systems and chassis systems based on the fuzzy comprehensive evaluation method. Reference [5] established matching criteria for self-propelled artillery chassis and firepower systems by comprehensively considering the effects of firing vibrations on muzzle disturbance, onboard equipment, and sustained firing. Reference [6] proposed a method for rapid dynamic simulation of artillery and fast matching design of overall parameters by invoking fully parameterized template models. Although these studies on vehicle-gun matching design provide a foundation for modular firepower system design, their research subjects are fixed-configuration single-model equipment, making it difficult to address the matching applicability of modular firepower systems with multiple different chassis platforms simultaneously. Although Reference [7] proposes a modular gun family design method based on knowledge templates, machine learning, and hybrid reasoning strategies, this work does not consider the structural dynamic characteristics of the objects. Furthermore, small arms differ significantly from large-caliber artillery, as they generate far less energy during firing and lack structures such as recoil systems, ramrods, or vehicle suspensions. Consequently, it cannot serve as a sufficiently comprehensive reference for the modular design of artillery equipment.

Meanwhile, research on the concept of digital twins has expanded in recent years from aerospace to fields such as weaponry, naval vessels, and architecture. Particularly in the mechanical engineering domain, its dynamic real-time characteristics have rapidly attracted significant attention from numerous scholars and research institutions. Kapteyn [8] et al. combined a component-based reduced-order model library with Bayesian state estimation to construct a physically and data-fusion-driven digital twin of aircraft structures, enhancing the reliability and accuracy of this approach. Dong Lei [9] et al. from Beihang University systematically outlined key technologies for constructing aircraft digital twins, proposing five core techniques for aircraft structural digital twins while thoroughly examining the current research status and future development directions. Song Xueguan [10-12] et al. from Dalian University of Technology applied virtual-physical integration principles to calculate fluid dynamics for pressure relief valves, optimize material handling parameters, and approximate silicon chip average temperatures using distinct methodologies. Zhou Qi [13] et al. introduced virtual-physical integration into complex equipment optimization design, balancing predictive performance of approximate models against modeling costs.

The development of artillery equipment involves different stages and levels, including overall scheme design, subsystem design, and component design. Among these, the overall scheme design, which needs to be determined in the early stages of development, is extremely important. In current engineering applications and visible public literature, design systems for artillery structure mostly apply to component-level objects like barrels [2], sights [3], recoiling mechanisms [4], and recoil devices [14], with less focus on the application of overall artillery parameters. Therefore, this paper, based on traditional multibody dynamics simulation virtual prototype technology, uses Qt language for secondary development based on RecurDyn simulation software, constructs parametric template models for rapid simulation and solution of design schemes, and combines methods such as artificial neural network approximation modeling, simulation parameter identification based on test data, and multi-level optimization for comprehensive performance optimization, to enhance the rapid simulation and optimization efficiency in the overall scheme design phase of artillery equipment.

The research focuses on the specific engineering scenario of overall design for large-caliber artillery. Addressing the core challenges of "multiple subsystem coupling, complex dynamic loads, and tight design cycles" in this field, it implements "scenario-based integrated innovation" and "key process improvements" – specifically, through the targeted adaptation and systematic integration of established methodologies (such as parametric modeling and machine learning) from diverse fields, it establishes a specialized technical framework tailored for artillery dynamic simulation and rapid optimization. This fills the gap in existing tools for an "efficient collaborative design-optimization toolchain" during the overall design phase of artillery systems.

2. Traditional Methods for Overall Design of Artillery Based on Dynamics Simulation

The design and manufacturing process of artillery can be divided into five stages, as shown in Fig. 1 [15]: the planning and validation stage of requirements, the research stage for relevant new technologies, the engineering design stage of the equipment, the prototype testing stage, and the final standardization and production stage. During the engineering design stage, the overall scheme design must first determine the overall structural layout of the equipment under various constraints. Following the planning of the overall scheme, the functions, lightweight levels, and stiffness indicators of each subsystem are broken down, and a detailed design is carried out. In recent development work, new types of equipment have highlighted the characteristics of enhanced performance requirements and significantly shortened development cycles. The challenge in current equipment development work is to quickly obtain the optimal overall design scheme.

After the design department completes the design, the geometric model of the assembly is handed over to the simulation department. The simulation department then simplifies the model, defines motion relationships, specifies contact definitions, applies load constraints, etc., to create a simulation model ready for solving, which is a time-consuming process. After the simulation, the design department makes improvements based on the results and repeats the process. Clearly, this process wastes a lot of computational resources.

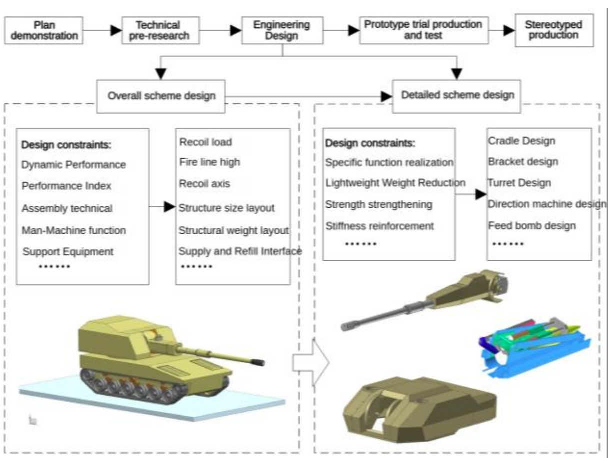


Fig. 1 Design constraints and design objects of artillery in the engineering design stage

3. Agile Simulation Design Method Based on Parametric Template Models

In dynamic simulation, topological structure diagrams are commonly used to illustrate connections between various components in a model. For example, the topological structure and force conditions of a particular type of vehicle-mounted artillery are shown in Fig. 1 [16]. Here, F_{pt} represents the combined force within the chamber between the projectile and the recoil section during firing; N_1, N_2, and N_3 are the support forces exerted by the front, middle, and rear wheels on the ground, respectively; f_1, f_2, and f_3 are frictional forces; N_q and N_z are support forces exerted by the jack and the chock on the ground, respectively; f_q and f_z are frictional forces; H denotes the hinge relationships among various parts, with H_1 representing the plane hinge of the recoil section relative to the cradle part; H_2 is the flexible hinge between the cradle and the turret; H_3 is the flexible hinge between the turret and the chassis; H_4 describes the flexible hinge of the suspension system; H_5 is the flexible hinge connecting the chock and the chassis; and H_0 indicates contact points between the wheels, jack, chock, and the ground. Clearly, the dynamic topological structure diagram of a vehicle-mounted artillery with a "front 1, rear 2" tire layout can be represented as shown in Fig. 2.

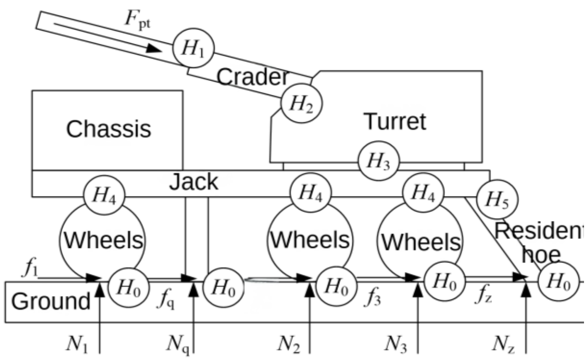


Fig. 2 Topological structure diagram of a vehicle-mounted artillery

3.1. Overall concept of the IAOD system

Different artillery systems can analyze load transfer characteristics based on similar typical structural features, enabling the use of the same model to describe parametric structural dynamic characteristics for various objects [17]. The IAOD (Intelligent Artillery Overall Design) system is an auxiliary tool for agile artillery design, developed as a secondary extension of the RecurDyn multi-body dynamics simulation software. Its overall concept is illustrated in Fig. 3. The system creates fully parametric dynamics simulation models for different types of artillery and stores them as template models. When performing overall validation of a new model, the corresponding template model of the same artillery type can be directly retrieved from the

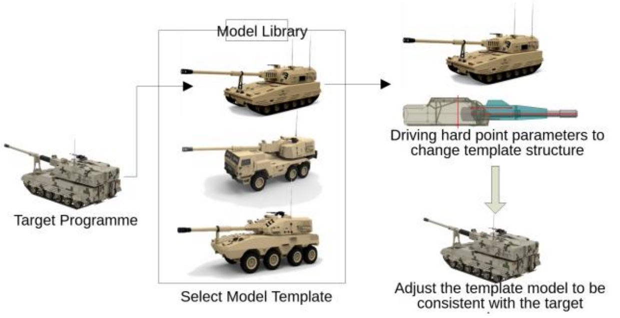


Fig. 3 The overall concept of agile design based on a parameterized template model

model library, and adjustments to structural design parameters enable rapid construction of the dynamics simulation model.

3.2. Technical characteristics of IAOD

The overall structure of the IAOD system is shown in Fig. 4. From the user's perspective, the IAOD system offers a wizard-style interface, allowing users to complete the design and optimization of artillery by entering parameter values according to the schematic diagram. At the logical level, the system is divided into simulation modules, optimization modules, and post-processing modules. In the simulation module, high-efficiency creation of models and dynamics calculations is achieved using template models and overall design parameters, with the option to perform parameter identification using real data for uncertain parameters.

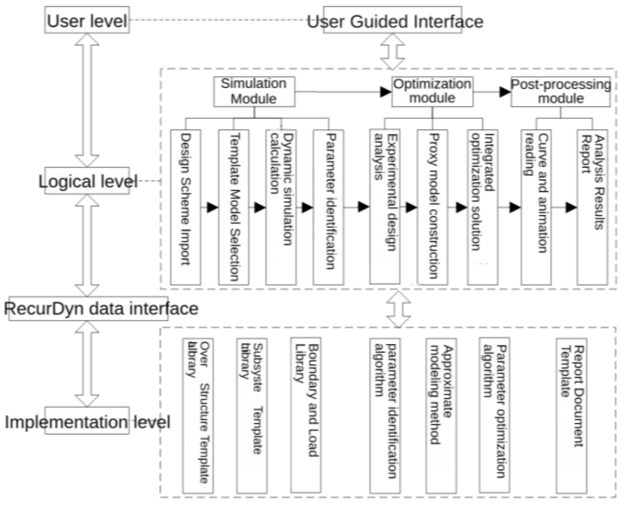


Fig. 4 Schematic diagram of the overall structure of the IAOD system

In the optimization module, users can select experimental design methods and algorithms as needed, with the simulation module invoked for iterative calculations to optimize overall equipment parameters, and high-precision surrogate models constructed. In the post-processing module, simulation results can be analyzed via curves and animations, and directly integrated into document templates to generate reports. At the IAOD execution level, the secondary system interacts with RecurDyn through data interfaces for calling and reading data, requiring the establishment of various template model libraries, approximation modeling techniques, optimization algorithms, and report templates.

4. Implementation of Key System Functions

The IAOD system must achieve three key functionalities in the modeling and simulation process: full parametric drive of the model, application of shooting loads, and optimal parameter matching methods. The following sections detail the implementation of these functionalities.

4.1. Full parametric drive of the model

During the overall design phase of the equipment, design parameters can be categorized into three types: overall structural parameters, component feature parameters, and boundary and operating condition parameters.

Component Feature Parameters: These include the mass, inertia, and counterweights of individual components.

Boundary and Operating Condition Parameters: These include soil boundaries, firing angles, simulation time, etc., and can be directly set in component attributes or calculation formulas.

Overall Structural Parameters: These describe the spatial relative positions of different components in the equipment and are used to construct parametric models. Fig. 5 illustrates some of the overall structural parameters for a tracked large-caliber self-propelled artillery. In this model, the center of the seat ring is taken as the origin O of the global coordinate system. The main structural parameters for the upper structure include the horizontal distance L_{MS} and vertical distance H_{MS} of the turret's center of mass M_s relative to the origin O, the horizontal distance M_O and vertical distance H_O of the axle center O' relative to the origin O, and the relative distance L_{MH} of the recoil section's center of mass M_H relative to the axle center O'.

For the chassis, the main structural parameters include the horizontal distance L_{MD} and vertical distance H_{MD} of the chassis's center of mass M_D relative to the origin O, the horizontal distance L_{OF} and vertical distance H_F of the driving wheel center F relative to the origin O and the ground, the horizontal distance L_{OR} and vertical distance H_R

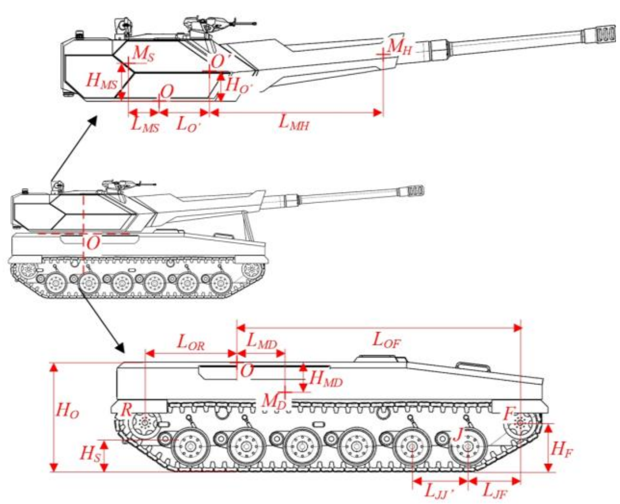


Fig. 5 Partial overall structural parameters of a tracked large caliber self-propelled artillery

of the idler wheel center relative to the origin O and the ground, and the horizontal distance L_{JF} between the center of the idler wheel J and the driving wheel center F, as well as the distance L_{JJ} between different idler wheel centers. In the software, these parameters are input to the corresponding positions as shown in the Fig. 5 to drive the template model to implement structural changes.

In the dynamics simulation model, full parametric modeling can be achieved by setting the global and local coordinates of the assembly components. Starting from the center of the seat ring, components are grouped sequentially upwards and downwards according to the assembly order: the turret and chassis are at the first level, the cradle, chock, and driving system are at the second level, and the barrel and components within the driving system are at the third level, and so forth. During dynamics modeling, the assembly position of each component relative to its parent component is set as the origin of that component's coordinates, and the installation position relative to child components is represented by parameters. These parameters are used in the overall design of the equipment.

4.2. Application of shooting loads

In the IAOD system, three methods for applying loads are provided, depending on the design phase and research conditions: approximation based on momentum theorem, load curve application, and load application based on recoil structure design.

4.2.1. Approximation based on the momentum theorem

During the overall design phase, detailed structures and parameters may not be available. Sometimes, it's necessary to estimate the firing stability of the cannon without the recoil force loads and the recoil mechanism structure. In such cases, the total impulse III applied to the cannon can be approximated as [18]:

$$I = \alpha \cdot \beta \cdot m_{shell} \cdot v_{shell} \,, \quad (1)$$

where: α is the conversion coefficient considering the high-explosive propellant, typically 1.2; β is the conversion coefficient considering the muzzle flame gas effect, typically 1.35; m_{shell} is the mass of the shell, and v_{shell} is the muzzle velocity of the shell. The value of I can be estimated from the range and power indicators given during the verification phase. For estimating the firing process of the equipment, the total impulse of the shell, the chamber force impulse, and the recoil resistance impulse are considered equal:

$$\alpha \cdot \beta \cdot m_{shell} \cdot v_{shell} = F_{chamber} \cdot t_{chamber} = F_{recoil} \cdot t_{recoil} \,, \quad (2)$$

where: $F_{chamber}$ is the equivalent force of the chamber force, a constant value; $t_{chamber}$ is the duration of the chamber force; F_{recoil} is the equivalent force of the recoil resistance, a constant value; t_{recoil} is the duration of the recoil resistance. Therefore, I can be used as an approximate load applied to the installation point of the recoil mechanism in the model for estimation purposes.

4.2.2. Load curve application

The use of total impulse loading often results in significant errors. The load curve application is currently the most commonly used method in dynamic simulations. For example, the chamber force and recoil resistance load curves for a large caliber cannon are shown in Fig. 6. These loads are numerically solved based on the firepower system's design equations. In the simulation model, the chamber force is applied to the bottom surface of the barrel, and the recoil resistance load is applied to the recoil system. If a similar firepower system design is available for reference in the overall design, this method of load application should be used.

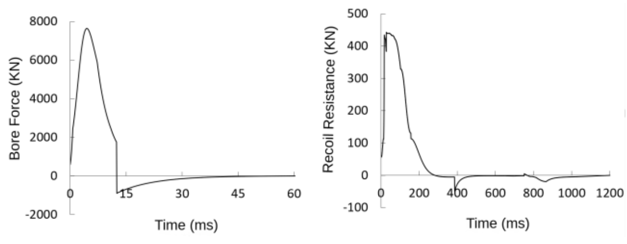


Fig. 6 Chamber pressure curve and recoil resistance curve of a large caliber cannon: a – the chamber force curves for a large caliber cannon, b – recoil resistance load curves for a large caliber cannon

4.2.3. Load application based on recoil structure design

When calculating the load curve, it is assumed that the ear axis center remains stationary, there is no energy exchange between the firepower system and the outside world, and the applied load is a force-time curve that is not affected by recoil displacement and recoil velocity. Therefore, when the stability of the artillery is good, the simulation method using curve loading has a smaller error, but when there is significant slippage or shaking of the artillery, the error will significantly increase.

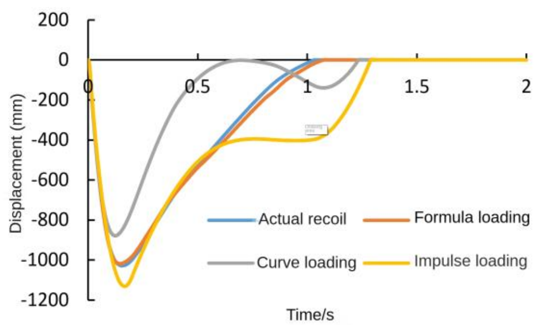


Fig. 7 Simulation results of recoil displacement of a large caliber artillery with different loading methods (0° firing angle without stationary hoe support)

The dynamic simulation of a certain model of large caliber artillery was carried out, and the recoil displacement obtained by solving different loading methods is shown in Fig. 7. Obviously, using numerical methods to settle load curves cannot guarantee simulation accuracy, and directly loading them with design formulas yields the highest simulation accuracy.

For the template model, the formulas for recoil force and recuperator force are directly incorporated. Currently, large caliber cannons commonly use liquid-gas recuperators and control rod recoil brakes. According to cannon design theory, the recoil resistance F_R is:

$$F_R = F_{zt} + F_f + F_T - m_h g \sin\varphi , \quad (3)$$

where: F_{zt} is the hydraulic resistance of the recoil brake, F_f is the recuperator force, F_T is the frictional force, and $m_h g \sin\varphi$ is the gravitational component of the recoil section. The hydraulic resistance formula during the recoil process is:

$$F_{zt} = \left(1+v_{zt}\right)\frac{k_1\rho}{2}\left[\frac{\left(A_0 - A_p\right)^3}{a_x^2} + \frac{K_2}{K_1}\frac{A_{fj}^3}{A_1^2}\right]v^2 , \quad (4)$$

where: v_{zt} is the equivalent friction coefficient of the recoil brake, A_0 is the working area of the brake piston during recoil, A_p is the control ring orifice area, K_1 and K_2 are hydraulic resistance coefficients for main and bypass flows, A_{fj} is the working area of the recuperator control, A_1 is the minimum cross-sectional area of the bypass, ρ is the density of the recoil fluid, a_x is the orifice area (which varies with the hydraulic rod's stroke), and v is the recoil speed.

The recuperator force during the recoil process is:

$$F_{zt} = \frac{k_1\rho}{2}\frac{A_{of}^3}{a_x^2}u^2 , \quad (5)$$

where: A_{of} is the working area of the brake piston during recuperation, and u is the piston relative speed. The hydraulic resistance of the recuperator during recuperation is:

$$F_{fjjz} = \frac{k_2\rho}{2}A_{fj}\left(\frac{A_{fj}+a_f}{a_f}\right)^2 u^2 , \quad (6)$$

where a_f is the orifice area of the recuperator's fluid flow. The recuperator force is given by:

$$F_f = \left(1+v_{fj}\right)F_{f0}\left(\frac{V_0}{V_0 - A_f x}\right)^n , \quad (7)$$

where: v_{fj} is the equivalent friction coefficient of the recuperator, F_{f0} is the initial recuperator force, A_f is the working area of the recuperator piston, V_0 is the initial volume of the recuperator gas, x is the recoil displacement, and n is the gas polytropic index, generally taken as 1.3.

If the current design includes detailed parameters for the recoil mechanism, this loading method should be used.

4.3. Construction method for the surrogate model of artillery overall parameters

Surrogate models use approximate functions that can be solved mathematically in place of complex dynamic models, simplifying the problem and thus improving solution efficiency [19]. Commonly used surrogate models in engineering include polynomial response surface models, Kriging models, radial basis function models, and artificial neural network models. Recently, with the rapid development of artificial intelligence and machine learning technologies, artificial neural networks have become the most commonly used method for constructing surrogate models of complex mechanical systems.

The overall design of a cannon involves a large number of parameters, which poses challenges for convergence and solution of the surrogate model. Moreover, during the firing process, the load transfer is influenced by all subsystem design schemes, so a surrogate model cannot be constructed for each subsystem individually without considering the influence of other subsystems. To address this issue, the IAOD system adopts a sparse single-hidden-layer neural netwok structure. The construction process is as follows:

1. Construct a Standard Fully Connected Single-Hidden-Layer Neural Network: The input layer consists of all input parameters, grouped by subsystem (e.g., firepower subsystem, loading subsystem, driving subsystem). The output layer includes all simulation output results.

2. Initialize Weights and Biases Using Extreme Learning Machine (ELM) [20]: The ELM method allows for the single-step computation of the Moore-Penrose generalized inverse matrix of the hidden layer output matrix, resulting in a neural network based on empirical risk minimization. However, ELM can lead to overfitting, so further sparse processing is required.

3. Train Using Dropout Method: Randomly divide all sample data into $2m$ groups, where m is the number of training-testing cycles. Use the first group to sequentially train each subsystem with the dropout method, which randomly deactivates neurons in the hidden layer for that subsystem while keeping neurons for other subsystems active.

4. Second Training of Subsystems: Train each subsystem a second time using the second group of samples from the $2m$ groups. During training, perform unstructured pruning to further simplify weight values, resulting in a sparse connection state for that subsystem.

5. Repeat Training for Other Subsystems: Apply the training process described in steps 3 and 4 to the remaining subsystems, using the first and second groups of samples, respectively, for training.

6. Final Testing and Adjustment: After completing the first round of training, use the third and fourth groups of samples to test errors for each subsystem. If the accuracy does not meet the requirements, continue training with new data according to the previous steps until the model accuracy is satisfactory. The result is a converged and easy-to-use sparse network structure.

Latin hypercube sampling for surrogate model; to meet optimal sample space randomness and fallibility, the Latin hypercube sampling approach is used to generate the inputs, and then nonlinear dynamics simulations are performed to obtain the outputs. The two hundred independent samples are enough to guarantee the accuracy of the constructed surrogate model in this paper.

Network structure of surrogate model: The multilayer feedforward neural network was used to learn and approximate the nonlinear relationship between features and responses. The leaky ReLU and Linear functions are selected as the activation of the hidden and the output layers, respectively, the dropout ratio is set to 0.36, and three hidden layers are selected with numbers of 50, 35, and 20. The

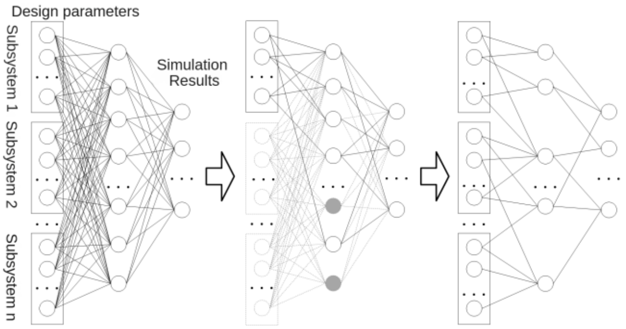


Fig. 8 Sparse neural network structure process for constructing surrogate models of cannon design parameters

initial learning rate is set to 0.05 and varies exponentially with the number of epochs until 0.01. Cross-validation and the regularization technique are applied to avoid overfitting and enhance generalization. The mini-batch stochastic gradient descent method is used to train the network. And the loss function is defined as the root mean squared error between simulated and testing responses.

In evaluation of surrogate model, the indicators for measuring the accuracy of the constructed surrogate model are:

1. Coefficient of determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n_e} \left(y^i - \hat{y}^i \right)^2}{\sum_{i=1}^{n_e} \left(y^i - \bar{y} \right)^2}, \tag{8}$$

2. Root mean squared error (RMSE)

$$R_{MSE} = \sqrt{\frac{\sum_{i=1}^{n_e} \left(y^i - \hat{y}^i \right)^2}{n_e}}, \tag{9}$$

3. Mean absolute error (EMAE)

$$R_{MAE} = \frac{\sum_{i=1}^{n_e} \left| y^i - \hat{y}^i \right|}{n_e}, \tag{10}$$

4. Relative root mean squared error (RRMSE)

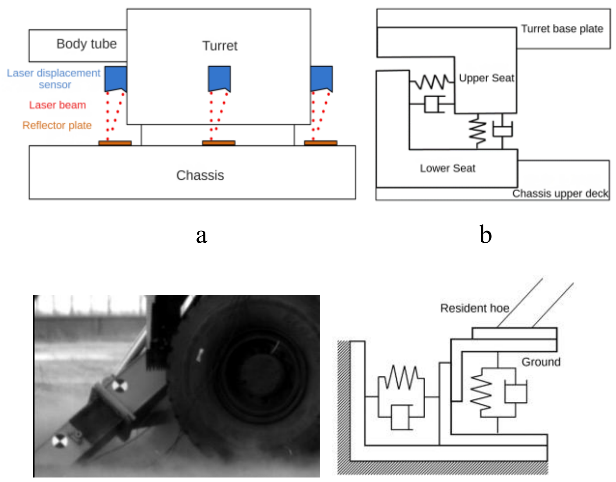
$$RR_{MSE} = \sqrt{\frac{\sum_{i=1}^{n_e} \left(y^i - \hat{y}^i \right)^2}{n_e}} \Bigg/ \bar{y}, \tag{11}$$

where: n_e is the number of testing samples, y^i is the actual response of the i-th sample, $\hat{y}^i$ is the computed response by the surrogate model of the i-th sample, and $\bar{y}$ is the mean actual response of all testing samples.

4.4. Equivalent and parameter identification of boundaries and interfaces

The interfaces and ground support conditions of large caliber cannons have a significant impact on their stability analysis results [21], with these factors exhibiting complex nonlinear characteristics that are difficult to account for in a comprehensive equipment analysis.

To simplify these complex constitutive relationships, linear models can be used. For instance, Fig. 9 illustrates linearized models for the rocking of the seat ring interface and the soil support on the stabilizer, which can improve the accuracy of multi-body models [22].



c d

Fig. 9 The linear equivalence of the dynamic model under the influence of the joint of the seat ring and the hoe and the soil boundary: a – seat ring oscillation test, b – simplified model of seat ring line elasticity, c – displacement test of the stationary hoe, d – simplified model of soil linear elasticity

However, in these equivalent models, parameters such as stiffness, damping, and friction coefficients are challenging to determine. Additionally, parameters influencing simulation accuracy, such as the connecting stiffness of the track links in tracked artillery, pre-tension forces, and tire forces in wheeled artillery, are also difficult to obtain. To address this, parameter identification can be performed using similar equipment that has undergone firing tests to determine these parameters and improve simulation accuracy.

In the IAOD system, genetic algorithms are used to optimize and solve Eq. (12) for parameter identification:

$$min: f = \sqrt{\frac{\min_{a_1 \cdots a_n} \sum_{i=1}^{N} \sum_{j=1}^{M} k_j \left(\tau_{ji} - \overline{\tau_{ji}} \right)^2}{N}}, \tag{12}$$

where: $a_1 \ldots a_n$ are the parameters to be identified, corresponding to uncertain parameters in the dynamic model; N is the length of discrete output samples, M is the number of outputs, k_j is the weight, τ_{ji} is the simulation output, and $\overline{\tau_{ji}}$ is the test result. The optimized results can be used as reference inputs for the new model.

4.5. Optimal parameter matching design method

Modern warfare demands high-performance requirements for artillery equipment, such as long-range capabilities, lightweight design, and intelligence [23]. Conventional design methods and single-object optimization approaches are increasingly unable to meet these development needs. To address this, the IAOD system provides not only optimization for single design objects but also a multi-level optimization algorithm capable of simultaneous collaborative parameter optimization for multiple objects [24]. This method can perform comprehensive performance optimization for single equipment under multiple operating conditions and optimize universal systems for serialized equipment.

In the IAOD system, a secondary optimization algorithm is used to simultaneously optimize multiple simulation models with the same set of parameters. The structure of this method is shown in Fig. 10, and the specific steps are as follows:

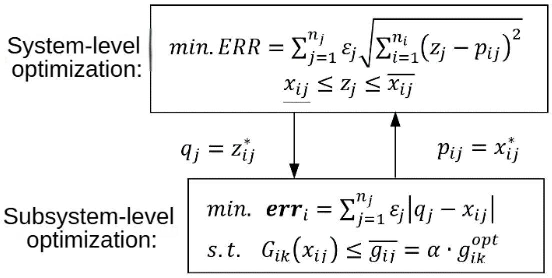


Fig. 10 The algorithm structure of the multi-objective collaborative optimization design method

1. Subsystem-Level Optimization: perform subsystem-level optimization for a single simulation object in the optimization model. Initially, the impact of other subsystems is not considered, and the optimal result g_{ik}^{opt} for the objective function k in subsystem i is obtained.

2. Integrated Optimization Across Multiple Subsystems: when performing comprehensive optimization across multiple subsystems, relax constraints using coefficient α based on the results from subsystem optimization. The optimization objective is:

$$err_i = \sum_{j=1}^{n_j} \varepsilon_j \left| q_j - x_{ij} \right| , \tag{13}$$

where: x_{ij} is the j-th design parameter of subsystem i, q_j is the j-th design parameter value obtained from system-level optimization, treated as a constant in subsystem optimization; and ε_j is the weight of design variable x_{ij}.

3. System-Level Optimization: transfer the results from subsystem-level optimization x_{ij}^* to system-level optimization as constant values p_{ij} for further optimization. The system-level optimization variable is z_j, with constraints based on the parameter definitions. The objective function is:

$$ERR = \sum_{j=1}^{n_j} \varepsilon_j \sqrt{\sum_{i=1}^{n_i} \left(z_j - p_{ij} \right)^2} , \tag{14}$$

4. Iterative Optimization: Iterate between subsystem-level optimization and system-level optimization until the objective function in system-level optimization reaches zero. At this point, the optimization results for each design parameter across all subsystems will be consistent, resulting in the final design scheme [25].

5. Validation of the Surrogate Model

Taking the process of artillery firing as the research object, the firing stability as the scene, the computed responses predicted by the constructed surrogate model are compared with the testing results, validating the accuracy and effectiveness of the surrogate model.

The design inputs and response outputs are listed in Tables 1 and 2.

Table 1

Design inputs of firing stability

Variables	Unit	Range
cross-sectional radius of air cavity	mm	54.6~101.4
piezoresistive coefficient	/	0~15
suspension stiffness	N·mm/rad	1.68e7~3.12e7
suspension damping	N·mm·s/rad	2.1e5~3.9e5
firing angle	°	0~35
firing direction	°	0~90
friction coefficient	/	0.28~0.52
charge number	/	1~7

Table 2

Responses of firing stability

Response	Unit
maximum pitch angle	°
pitch period	s
maximum recoil length	mm
maximum high jump at the front measured point	mm
maximum high jump at the rear measured point	mm

Table 3

Performance of the surrogate model

Response	R^2	R_{MSE}	E_{MAE}	RR_{MSE}
maximum pitch angle	0.9272	0.3144°	0.2348°	0.1013
pitch period	0.9998	5.1448e-05 s	3.7742e-05 s	2.8636e-05
maximum recoil length	0.9998	2.5343 mm	1.6795 mm	0.0029
maximum high jump at the front measured point	0.9247	20.6719 mm	16.5918 mm	0.1029
maximum high jump at the rear measured point	0.9584	10.8490 mm	8.1083 mm	0.1065

According to the method mentioned in Section 4.3., the performance of the surrogate model in test samples is listed in Table 3. It can be seen from that the fitting results of the neural network-based surrogate model on the entire testing sampling set are optimal for the accuracy requirement.

The comparison between the actual test results on the operation condition and the predictive results of the surrogate model is shown in Table 4. It can be seen that the predicted response values are in excellent agreement with the experimental test response values, with the relative errors all being within 5%.

Additionally, the performance curves of the surrogate model on the testing sample set are depicted in Fig. 11. The consistent trend is clearly visible in the diagrams.

Table 4

The comparison between the actual test results and the predictive results of the surrogate model

Response	Unit	Test results	predictive results	relative error
maximum pitch angle	°	5.8331	5.9453	0.0192
pitch period	s	1.772	1.8019	0.0169
maximum recoil length	mm	1020	1032.0569	0.0118
maximum high jump at the front measured point	mm	386.5709	382.0078	0.0118
maximum high jump at the rear measured point	mm	222.9438	223.6492	0.0032

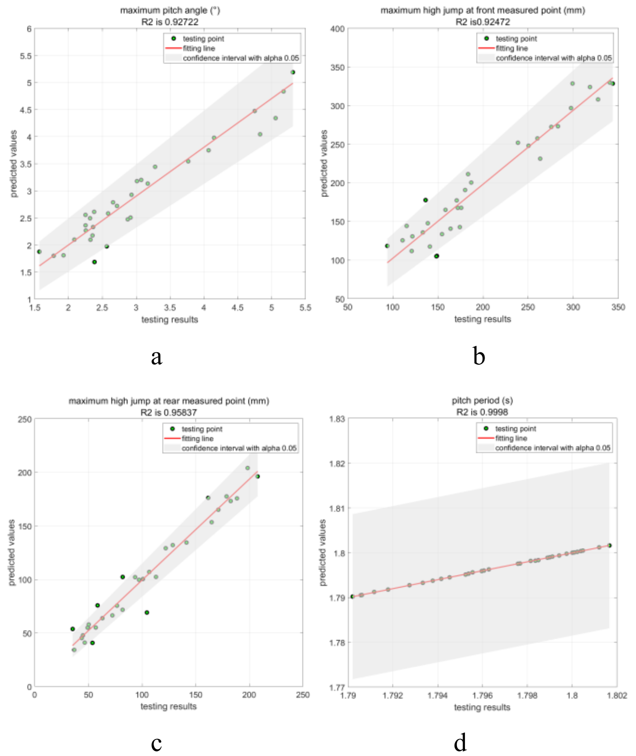


Fig. 11 The performance curves of the surrogate model on the testing sample set: a – maximum pitch angle, b – maximum high jump at the front measured point, c – maximum high jump at rear measured point, d – pitch period

6. Application of the Multi-Level Optimization Method

For a relatively complex dynamic model, using RecurDyn for a single calculation takes 20 minutes or even longer. If the model is optimized, it is difficult to debug the model due to the difficulty in predicting the convergence speed of the problem, especially when there are many design parameters. Directly using parameter optimization methods is difficult to solve such problems. For such problems, the commonly used solution is to use experimental design methods to calculate the sensitivity of each parameter, select the design parameters with higher sensitivity to establish an approximate model, and then optimize and solve the approximate model. For more complex situations, such as problems that require the use of various interdisciplinary optimization methods, more complex computational processes need to be constructed, and data needs to be transferred between more components for computation. Taking multi-level optimization methods as an example, there are often multiple disciplines intertwined and coupled in engineering problems, and traditional methods or multi-objective optimization methods alone cannot solve them. In such cases, multidisciplinary optimization methods have been widely applied. The multidisciplinary optimization method mainly decomposes the original problem into multi-level optimization problems, such as system-level optimization and multiple subsystem-level optimization, and solves the problem of multidisciplinary and multi-system collaborative design in engineering. The general multi-level optimization algorithm divides the original problem into two levels: system level optimization and subsystem level optimization, which are solved separately. Different constraints can be allocated to different subsystems as needed to achieve decoupling. Each design parameter is calculated separately in different subsystem-level optimizations and then transmitted to the system-level optimization for overall planning. The solution process of a multi-level optimization method built in Isight is shown in Fig. 12.

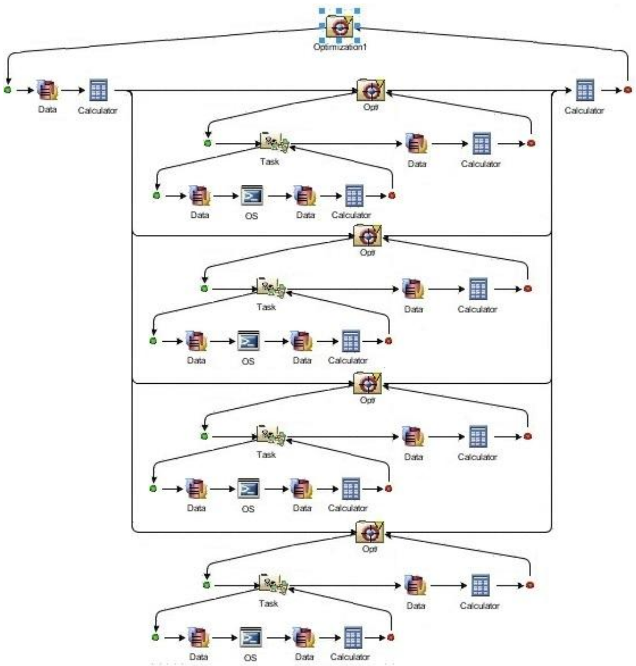


Fig. 12 The solution process of the multi-level optimization method

By using the above methods, various complex combinatorial optimization methods can be created according to one's actual needs. Combined with the various solving functions provided by Isight itself, it is possible to avoid spending a lot of time writing and debugging code, making it convenient to study various optimization problems. After verifying the feasibility of the algorithm in Isight, other languages are used to write and encapsulate it, forming specialized software modules.

The IAOD system integrates the aforementioned features into a user-friendly software interface. The interface is shown in Fig. 13. It includes:

1. Top Function Selection Area: Users can choose between simulation and optimization functionalities. The interface adjusts according to the selected function.

2. Left Object and File List: Displays the list of simulation and optimization objects and options for opening and importing files.

3. Right Model Illustration: Shows a visual representation of the currently selected model, providing users with a clear view of the model structure.

4. Central Parameter Setting Area: Used to input and modify parameters needed for simulation, design, and optimization.

5. Bottom Function Buttons: Allow users to quickly complete simulation and optimization tasks, avoiding the complex process of model creation in traditional simulations, thus significantly improving work efficiency.

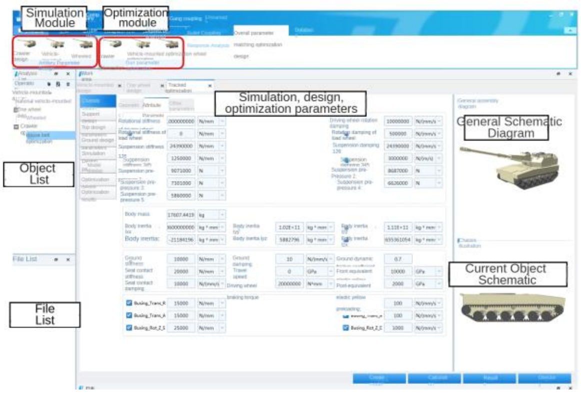


Fig. 13 Basic functions of software operation interface

The IAOD system was used for a practical application involving a vehicle-mounted artillery system. The specific steps and results are as follows:

1. Actual Testing:

Prototype Testing: Fig. 14, a shows the prototype test of the vehicle-mounted artillery. During the test, markers were placed on the front and rear sides of the vehicle. High-speed video captured the horizontal (X-direction) and vertical (Y-direction) displacements of these markers.

Data Processing: The processed displacement curves are shown in Fig. 14, c.

2. Simulation Model and Results:

Dynamic Simulation Model: Fig. 14, b depicts the constructed dynamic simulation model. After performing parameter identification for the recoil system, jacks, and tires, the resulting simulation curves are shown in Fig. 14,d.

Result Comparison: The simulation results were compared with the actual test results, indicating that the simulation effectively reflects the actual testing results.

3. New Wheeled Artillery Design:

Application of the Turret System: The turret system of the vehicle-mounted artillery, which features high levels of automation, is to be mounted on a new 8×8 wheeled chassis to create a new type of wheeled artillery.

Model Construction and Optimization: Using the IAOD system, the corresponding turret and wheeled chassis models were called, and parameters were adjusted to build a new dynamic simulation model in under 2 minutes, as shown in Fig. 15. This model can be directly used for simulation and optimization, greatly improving work efficiency compared to the traditional method of rebuilding simulation models, thus significantly reducing development time.

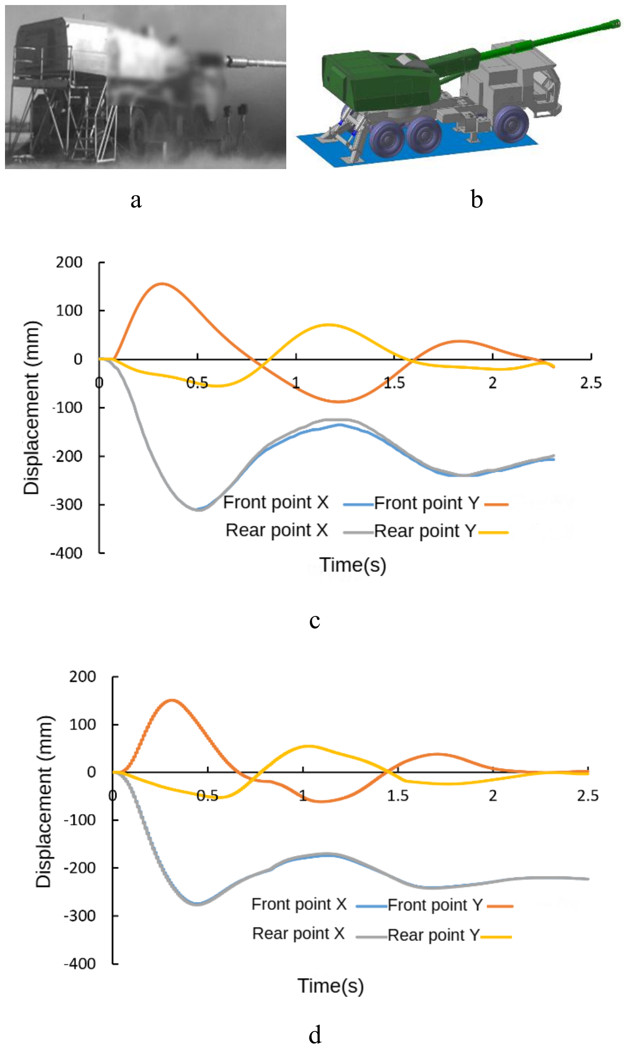


Fig. 14 Comparison of simulation and experimental results of a vehicle-mounted artillery: a – test and experimentation of a vehicle-mounted cannon proto-type, b – dynamic simulation model of a vehicle-mounted cannon, c – high-speed camera measurement results, d – simulation results after parameter identification of boundaries

Fig. 15 Dynamic simulation model of the new wheeled artillery based on the vehicle-mounted artillery

7. Conclusions

In current artillery equipment development, the integration between design and simulation is often weak. The iterative process of design, simulation, improvement, and re-simulation leads to inefficiencies, which are increasingly problematic given the shorter development cycles for modern projects. During simulations of artillery firing stability and other kinematic analyses, multi-body dynamics models are typically independent of geometric appearance, and similar large caliber artillery systems exhibit common structural characteristics. This allows for the use of the same parameterized model across different models.

Based on this characteristic, the research described in this paper involves the secondary development of the RecurDyn software to construct the IAOD system, a simulation design tool tailored for artillery overall design.

The IAOD system integrates typical artillery dynamic models and combines approximation modeling and optimization design methods, enabling rapid execution of firing dynamics simulations. It facilitates convenient stability analysis at the overall design stage of the artillery, computing aspects such as elevation, slip, support forces, suspension forces, and recoil processes. Users can quickly obtain design results by simply inputting design parameters, thereby improving efficiency and reducing the complexity of the design process. The IAOD system has the following characteristics:

1. Simple Operation Interface: The interface guides users through settings sequentially with the help of diagrams, making it user-friendly and practical for actual use.

2. Template Model Technology: By implementing template model technology, the system provides a fully parameterized description of typical artillery structures, which aids in quick modeling, simulation, and optimization, thereby enhancing design efficiency.

3. Integration of Parameter Identification, Test Design, and Parameter Optimization: The system incorporates technologies for sensitivity analysis, approximation modeling, and structural optimization. This enables effective completion of tasks such as sensitivity analysis, approximate modeling, and structural optimization.

4. Management of the entire design cycle and automatic transmission of data: Build a data interface based on spreadsheet technology that can manage and transmit data throughout the entire design cycle, and automatically generate report documents.

At present, the initial version of the software has been developed and can be used to calculate the static single-shot stability of large caliber artillery with tracked chassis, vehicle-mounted chassis, and 8 × 8 wheeled chassis using gas hydraulic reciprocating machines and control rod braking machines. Practice has demonstrated that the IAOD system can greatly minimize the burden during the large-caliber suppressed artillery design phase.

However, the current version of the IAOD system has certain significant limitations, which include the following aspects:

1. As the existing IAOD system is a secondary development built on the RecurDyn, which is a general-purpose commercial program, modeling and solution efficiency still require further enhancement. For example, after entering parameters into the system, the software's background modeling process takes two minutes or more, and the solution process usually takes more than 30 minutes. This problem could be easily resolved by creating a specialized solver.

2. The current IAOD system is only capable of conducting firing stability analysis and optimization design for artillery pieces, but is incapable of analyzing aspects such as artillery firing accuracy. This defect can be effectively addressed if the internal ballistic process is simulated and flexible barrel modeling is included. This research requires a considerable amount of work to be invested. Nevertheless, we shall undertake this work in the future.

3. Additionally, the current model library suffers from limited simulation objects and scenarios, necessitating continuous expansion in tandem with equipment development efforts.

In summary, in the subsequent work, the model library and database will be further expanded to enable the completion of shooting simulation during movement, continuous firing simulation of small caliber artillery, and simulation evaluation of shooting accuracy combined with the coupling effect of ammunition and artillery. The artillery simulation design platform will be continuously improved to better support the development of artillery equipment.

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RESEARCH ON EFFICIENT DYNAMICS SIMULATION TECHNOLOGY FOR ARTILLERY EQUIPMENT

S u m m a r y

In response to the efficiency bottleneck in the overall design phase of artillery, this study proposes an agile design tool for artillery – Intelligent Artillery Overall Design (IAOD) – based on the RecurDyn solver. This tool enables rapid evaluation and optimized design of artillery dynamic simulation models via parametric modeling and the integration of firing test data. The IAOD system employs a fully parameterization-driven template model and integrates machine learning, parameter identification, and multi-level optimization algorithms – markedly enhancing the design efficiency of large-caliber self-propelled artillery. Innovatively, the system applies a sparse single-hidden-layer neural network surrogate model and a simulation parameter identification method driven by test data, realizing multi-objective collaborative optimization. The effectiveness and practicality of the IAOD system are verified through the practical application of a vehicle-mounted artillery design case, confirming its application potential in the field of artillery design. This study holds significant military and defense value for enhancing the efficiency and quality of artillery equipment development.

Keywords: efficient dynamics simulation, overall design of artillery, artillery agile design, launch dynamics, surrogate model, optimal design.

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