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Fractional calculus in dynamic analysis of truck frame: a special focus on finite element modelling

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Abstract: This paper investigates an innovative method to analyse and improve the dynamic performance of truck frames. Firstly, a 3D model of the frame was constructed by computer-aided design (CAD), and then meshing and material property sets were carried out by finite element analysis software to simulate the behaviour of the frame under variable working conditions. Fractional calculus is introduced to capture the nonlinear dynamic characteristics of the frame more accurately, and the Grunwald-Letnikov method is used to solve the relevant equations. Deep learning techniques extract key features from FEA data to identify stress concentration areas. Through dimensional optimisation experiments, this study also demonstrates how to adjust the frame plate thickness using gradient-based optimisation algorithms to achieve lightweight and performance improvement. Notably, the maximum stress value under bending conditions increases by 29.6 MPa, while under torsional conditions, it decreases by 65.7 MPa. This study highlights the synergistic potential of artificial intelligence, fractional calculus, finite element modelling, and deep learning techniques in advancing the dynamic analysis of truck frames, setting the stage for more resilient and efficient truck designs in the future.

Keywords: truck frame; artificial intelligence; fractional calculus; finite element analysis; deep learning techniques; dynamic analysis.

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Biographical notes: Yangyang Liu is a Lecturer and has a Master's degree. His main research direction is application engineering of transport vehicles.

1 Introduction

With the vigorous development of China's economy and improving people's living standards, the demand for efficient road transport is increasing. With its excellent mobility and flexibility, trucks not only improve people's quality of life but also greatly promote the development of the road transport industry. In the rapid expansion of the automobile industry today, heavy trucks play a central role in medium and long-distance road transportation because of their excellent adaptability, reliability, and economy. The growing demand in the commercial vehicle market has led to increasingly active technological innovation and research and development activities in the industry.

In the fierce market competition, manufacturers must control the manufacturing cost and shorten the development cycle to improve competitiveness. The frame of a heavy truck is the core of the whole vehicle structure, which affects the performance of the whole vehicle. The frame needs to bear complex loads, and higher design standards are proposed. Computer-aided design (CAD) technology plays a key role in optimising frame design, enhancing overall truck performance, and providing manufacturers with a competitive advantage.

Looking forward to the future, with the continuous progress of technology, the application of CAD technology in heavy truck design will be more extensive, and its development potential will be huge. We believe that with the introduction of new materials, new processes and the improvement of intelligence and automation, the design and manufacturing of heavy trucks will become more efficient and environmentally friendly, which will have a profound impact on the road transport industry.

In this paper, artificial intelligence and fractional calculus are applied to the dynamic analysis of the truck frame, and the performance of the truck frame is evaluated by finite element modelling and deep learning. This paper first introduces the research background and significance and then establishes the research basis through a literature review. Then, the three-dimensional model of the frame, the integrated application of the deep learning model, the creation of the finite element model, and the grid division standard are described in detail. In this paper, the calculation method of bending and torsional stiffness of the frame, the theoretical basis of structural optimisation design, and the topological optimisation process are discussed. Further, the dynamic behaviour of the frame is modelled and the response is analysed by fractional calculus, and the performance of the frame under different working conditions is evaluated by finite element analysis. The dimensional optimisation experiment uses a gradient optimisation algorithm to reduce the weight of the frame while ensuring structural strength and safety. Finally, the effectiveness of the optimisation results is verified by comparison experiments, and the importance and potential impact of advanced technology on frame design is emphasised in the conclusion part.

The major contributions of this paper are to develop a cutting-edge method that integrates artificial intelligence technology and fractional calculus to improve the accuracy and efficiency of dynamic analysis of truck frames. Through the combination of deep learning algorithm and finite element method, the automatic evaluation of frame performance and the optimisation of structure design are realised in this study. In addition, the nonlinear dynamic characteristics of the frame are simulated by fractional calculus. Using experiments, it is also confirmed that the proposed optimisation strategy can reduce the weight of the frame, ensure the safety of the structure, and improve performance, thus highlighting the application value of interdisciplinary research in engineering practice.

2 Literature review

Zhao et al.'s (2022) study explores the pollution level and distribution characteristics of total volatile organic compounds (VOCs) by using experimental and numerical methods, taking a fully enclosed train carriage as an example. It has taken the potential technical requirements of the truck frame assembly as a special background, Li et al. (2017) mainly analysed the high shear strength and fatigue performance, studied the formation of the

bolt structure and the riveting structure, and discussed the feasibility of replacing the bolt-following structure with the riveting structure. Piwnik et al. (2018) analysed the mechanical properties of welded steel structures of body trucks. It aimed at the problem of insufficient strength and rigidity of the main load-carrying parts of the truck frame, Mi et al. (2019) proposed a commonly used method based on the blind number theory, the short-term target of the interval appears obvious and comprehensive optimisation design and considered the unfavourable factors brought by the necessary manufacturing stage. In terms of deep learning models, many scholars have done a lot of research on them. Ali and Yangyu (2017) studied how to reduce the actual automatic modulation classification system, and also proposed three new classifiers with reduced complexity. Barros et al. (2017) proposed a neural computational model that learns to focus on emotion expression and regulate emotion recognition, and the model consists of a deep architecture that implements a convolutional neural network to learn the location of emotion expressions in cluttered scenes. Rahman et al. (2018) studied the impact of a sophisticated machine learning-based privacy attack (known as a membership inference attack) on state-of-the-art differential privacy deep models. In the aspect of finite element analysis, many scholars have conducted more profound research on it. Elliott and Thomas (2018) defined a new finite-element-assisted method for the mean-drop-to-volume domain as a solution to partial differential equations coupled to surface partial differential equations on the boundaries of the volume domain. Zhan (2017) introduced the finite element analysis and calculation of phase-locked equations and derived the error estimates for semi-discrete and fully discrete equations, including the optimal L^2 and H^1 error estimates. Ma (2017) investigated the large frame and convergence analysis of finite element methods (FEM) with spatial fractional differential equations (FDE) that inhomogeneous boundaries must satisfy. By using the method of interval division and high-strength bolt optimisation, Chen (2018) carried out a lightweight design of the truck frame to reduce the weight of the frame and improve the performance of the truck, while ensuring the strength and stiffness of the truck frame structure. The feasibility of the design was verified through the real vehicle test. Liang et al. (2017) applies fractional calculus theory to the ceiling damping control of semi-active automotive suspension, which is realised by the Oustaloup filter and optimised by a genetic algorithm, which significantly improves the dynamic performance and driving comfort of the suspension system. However, in many studies, the method used to study the truck frame was not high performance and the accuracy was not very high. Based on the research of many scholars, this paper studied the finite element analysis of the truck frame evaluated by the deep learning model and the impact of the truck bed on its performance.

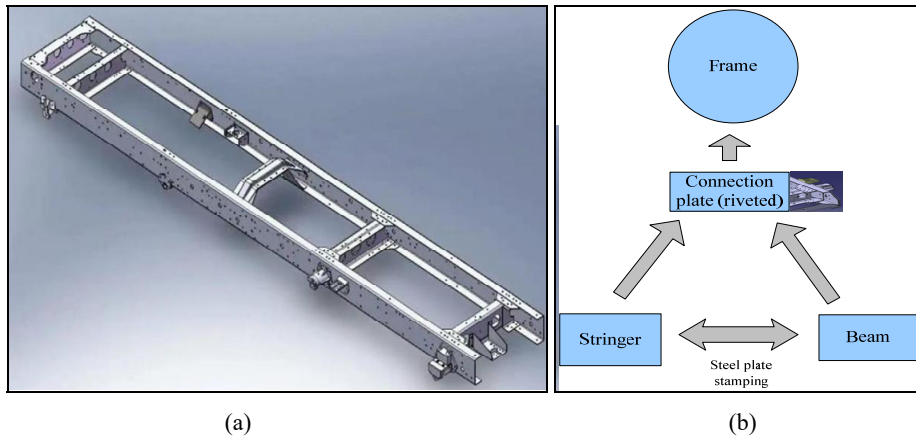
3 Evaluation method of truck frame

3.1 Establishment of the 3D model of the frame

The original frame adopts a side beam frame composed of two single-layer trough-shaped longitudinal beams and several single-layer trough-shaped transverse beams, which have the characteristics of simple structure, convenient manufacture, and good versatility. It is a commonly used structural form on commercial vehicles such as trucks and passenger cars. The frame rails are stamped from steel plates, and a small-section structure is adopted in the front area where the load-bearing mass is small to balance the bending

stiffness and reduce the mass; the frame beam is also stamped from steel plate, and the cross-section is groove-shaped with unequal width, and the width is larger at the connection at both ends to improve the stress distribution of the frame under torsional load (Kim and Park, 2020). The longitudinal beam and the cross beam are connected by punched connecting plates and then fixed by riveting so that the stress distribution is more uniform. At the same time, riveting has natural crack resistance, which can improve the frame's ability to withstand fatigue loads. The length of the frame is 8,445 mm, the front, and rear are the same widths, the width is 860 mm, and the self-weight is 1,306 Kg; according to the CAD drawings provided by the supplier, a three-dimensional model of the original frame is established in the CATIA environment, as shown in Figure 1.

Figure 1 Truck frame model, (a) frame model diagram (b) frame structure diagram (see online version for colours)



The accuracy of the three-dimensional model of the truck frame was verified, and the geometric dimensions of the actual frame were measured, including longitudinal beam, transverse beam, and connecting plate, and compared with the dimensions in the model. The measurement results show that the size deviation between the model and the actual frame is controlled within $\pm 2\%$, which meets the acceptable standard of engineering application. The elastic modulus, yield strength, and tensile strength of B520L steel are 211 GPa, 364 MPa, and 521 MPa respectively. These experimental values are very close to the parameters used in the model, which verifies the accuracy of the material property setting in the model. Finite element analysis software was used to test the grid independence of the model, and the grid was refined step by step and the result was monitored.

3.2 *AI-based deep learning model*

Deep learning, a subset of artificial intelligence, revolutionises machine learning through neural networks capable of automatically extracting intricate features from data. By amalgamating low-level and high-level features, deep learning facilitates comprehensive representations of entities, marking a significant leap in technological advancement. Its prowess extends across diverse domains including detection, tracking, classification, and reinforcement learning (Elallid et al., 2022; Rezaee et al., 2024).

Deep learning integration enhances the ability of neural networks to deal with domain-specific problems (Fabrizio, 2017; Pan, 2024). It plays a key role in identifying data indicators, where object detection algorithms are the foundation, including traditional and deep learning methods. Traditional methods rely on manual feature extraction (Lee et al., 2017; Bateni et al., 2020). Deep learning, on the other hand, uses large datasets to extract abstract features, providing higher recognition accuracy and generalisation ability (Kang et al., 2017). YOLOv3 algorithm performs well on standard datasets (Shanahan et al., 2017). In this study, customised methods were used to maintain the consistency of evaluation, and deep learning and object detection were combined to improve the accuracy and robustness of evaluation (Sankaranarayanan et al., 2024). Deep learning models use convolutional neural networks to extract key features from finite element data, identify stress concentration areas, and optimise frame design. The model achieves lightweight design by adjusting the component thickness, improves design efficiency and performance, and validates the value of deep learning in complex engineering.

The deep learning model adopts convolutional neural network architecture to extract features through multi-layer convolution, pooling, and fully connected layers followed by activation functions. The training dataset is generated based on finite element analysis contains the frame response data under various working conditions, and is divided to verify the model generalisation ability. Cross-validation and early stop are used to prevent overfitting, and weights are optimised by mean square error. The performance of the model training and testing is analysed in detail to ensure its effectiveness and stability.

3.3 Establishment of the frame finite element model

When integrating artificial intelligence and fractional calculus into truck frame dynamics analysis, especially in combination with finite element modelling and deep learning techniques, deep learning models process noisy data and outliers through a range of techniques. Firstly, in the data pre-processing stage, noise reduction algorithms (such as wavelet transform or Gaussian filter) and data normalisation techniques are used to reduce the noise effects. Second, robust deep learning models are used, such as autoencoders, which learn their low-dimensional representation by reconstructing data to filter noise, and convolutional neural networks, which enhance resistance to noise by extracting local features. In addition, anomaly detection algorithms such as isolated forests and local anomaly factors are used to identify and remove outliers before training the data, ensuring the purity and representativeness of the model training data. Through these methods, deep learning models can deal with noise and outliers more effectively when dealing with complex dynamic analysis tasks, and improve prediction accuracy and reliability. With the rapid development of numerical analysis and computer hardware technology, the time for solving the finite element model has been greatly reduced, while the pre-processing workload of the model has not decreased. In the process of establishing the finite element model of the truck frame, to establish a high-quality grid management analysis and calculation requirements, designers need to comprehensively consider the following aspects.

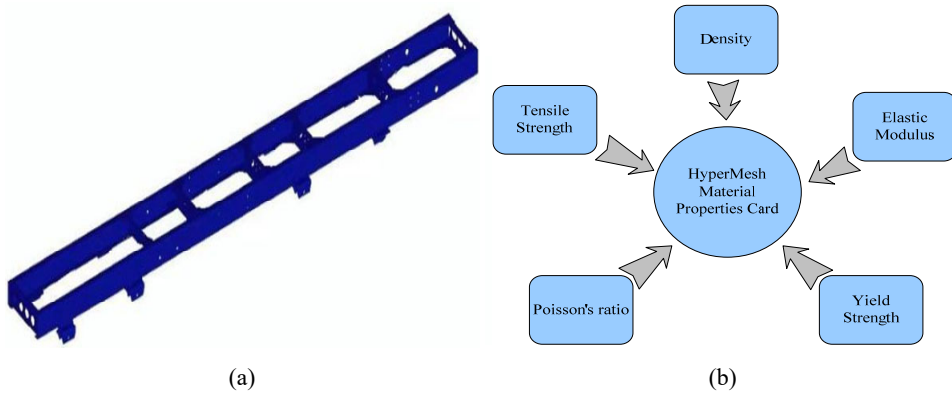
- 1 The objective of the computational analysis.
- 2 The type of calculation analysis, different analysis types have different requirements for grid type, grid density, and grid arrangement direction.
- 3 The time limit and accuracy requirements of the calculation and analysis, and the grid size and density distribution are determined according to the time limit and accuracy requirements.
- 4 The element type selected when the model is established, and the element type is determined according to the geometric characteristics of the analysis target.
- 5 The type of solver used in the analysis and calculation. Different solvers adapt to different analysis types and also have requirements for the element type.
- 6 Control over the number of triangular elements and tetrahedral elements. Triangular elements and tetrahedral elements have a great influence on the local stiffness of the finite element model, and accumulation in some areas may lead to large errors in the calculation.

The main components of the frame are thin-walled parts punched from steel plates, the length and width of the parts are much larger than the thickness and the geometry is relatively regular. For thin-walled parts, it is difficult to simulate with body elements. In this paper, four-node (QUAD4) shell elements mixed with a small number of triangles (TRUA) were chosen to establish a finite element model. By defining the thickness of shell elements to simulate the mechanical properties of plates with different thicknesses, using shell elements to divide the mesh can effectively reduce the amount of calculation, and at the same time avoid the problem of too few layers in the thickness direction of solid elements.

In the integration of artificial intelligence and fractional calculus into truck frame dynamics analysis, although the existing documents have mentioned the performance of the frame under different working conditions, the complexity of the actual driving environment is not considered enough. It is recommended to increase the performance evaluation of the frame under extreme weather conditions (such as high temperature, low temperature, rain, and snow, etc.) and unconventional road conditions (such as rugged, sandy, and muddy roads, etc.). These environmental factors may significantly affect the structural strength, fatigue life, and dynamic response of the frame. Therefore, in the process of finite element modelling, considering these variables can not only improve the accuracy of the model but also provide more practical guidance for practical applications. By introducing simulation tests in a variety of environmental conditions, the safety and reliability of the frame design can be ensured under a variety of adverse conditions, thereby improving the overall performance and service life of the truck. The frame longitudinal beams and beams are made of B520L steel, and the parameters of the B520L steel (density: 7,850 kg/m³; elastic modulus: 206 Gpa; Poisson's ratio: 0.29; yield strength: 355 Mpa; tensile strength: 510 Mpa) are used to create a material property card in HyperMesh.

Save the 3D model of the frame in Catia as a compatible stp format, and then import it into HyperMesh to generate a geometric model as shown in Figure 2.

Figure 2 Frame HyperMesh model, (a) frame HyperMesh geometry model (b) HyperMesh material property card (see online version for colours)



Mesh division is a key step in finite element analysis, and its division results directly affect the convergence speed and the accuracy of calculation results. When dividing, the unit size should be comprehensively considered according to the calculation scale of the model, the required calculation accuracy, and the computing power of the hardware. Basic requirements for 2D meshing:

- 1 Triangular elements will increase the local structural stiffness, resulting in difficulty in convergence. The number of triangular elements should be reduced as much as possible.
- 2 The mesh shape after division should be consistent with the actual geometric structure.
- 3 Units should be continuous while preventing overlapping units.

The resulting mesh can be quality-checked and optimised using the QI panel. In the QI panel, the grid quality index was set according to experience or industry standards, and the specific dimensions are shown in Table 1.

Table 1 Mesh quality check criteria

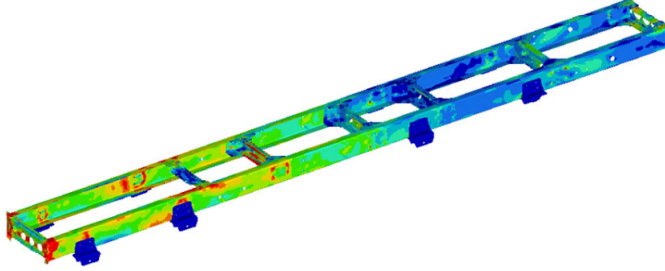
Cell target size (cm)	0.8
Min/max element length (cm)	0.3, 1.2
Aspect ratio	<5
Taper (°)	>0.5
Warpage (°)	<15
Minimum/maximum quadrilateral interior angle (°)	45,135
Minimum/maximum triangle internal angle (°)	30,120
Jacobi	>0.5
Triangular element scale	<10%

After the setting was completed, the extracted midplane model was automatically divided. The symmetrical part of the structure can be pre-divided and then the mirroring function can be used. The connection hole with a radius greater than 1cm was simulated

by an 8-node layout. After the division is completed, use the Find Free Edge function in the edges panel to check the continuity of the elements, and check whether there were duplicate elements in the check element panel.

The final generated FEM model is shown in Figure 3.

Figure 3 Frame finite element model (see online version for colours)



Mesh division results: the number of nodes was 225,508, and the number of elements was 296,598. Among them, the number of triangular shell elements was 3,834, accounting for 1.2% of the total, and the number of quadrilateral shell elements was 189,021.

3.4 Calculation of various properties of the frame

3.4.1 Calculation of frame bending stiffness

The bending stiffness of the frame is an evaluation index for the ability of the frame to bear the bending load when the vehicle is running on a flat road. The bending stiffness is solved as:

When $0 \leq x \leq b$

$$C = EI = \frac{Fax(L^2 - x^2 - a^2)}{6Lf} \quad (1)$$

In formula (1), C is the bending stiffness (N/m):

- F is the concentrated load (N)
- L is the wheelbase
- a is the horizontal distance from the load point to the rear fulcrum (m)
- x is the distance from the fulcrum to the detection point (m)
- f is the deflection of the measuring point (m).

3.4.2 Calculation of frame torsional stiffness

The torsional stiffness of the frame refers to the evaluation index of the capacity of the frame to bear the torsional load when the vehicle is running on an uneven road (Delattre et al., 2024). The loading method is to apply a horizontally opposite force to the rear support point of the frame, measure the displacement, obtain the torsion angle after calculation, and substitute it into the stiffness expression:

The calculation expression of the overall torsional stiffness of the frame is:

$$K = \frac{T}{\theta} \quad (2)$$

In formula (2), K is the overall torsional stiffness of the frame (N/m); T is the loaded torque ($\text{N} \times \text{m}$); θ is the frame torsion angle (Deg).

In the finite element theory, the equilibrium function of the dynamic problem is expressed as:

$$[N]\{x''\} + [B]\{x'\} + [Q]\{x\} = \{F(t)\} \quad (3)$$

In formula (3), $[N]$ is the mass matrix, $[B]$ is the damping matrix, $[Q]$ is the stiffness matrix, $\{x\}$ is the displacement vector, $\{F(t)\}$ is the force vector, $\{x'\}$ is the velocity vector, and $\{x''\}$ is the acceleration vector.

When the system is undamped, the function is:

$$[N]\{x''\} + [Q]\{x\} = \{0\} \quad (4)$$

Because the structure is a simple harmonic vibration when it is in free vibration, it can be concluded that the displacement is a sinusoidal function:

$$x = x \sin(\omega t) \quad (5)$$

Bring in formula (4) to get:

$$([Q]) - \omega^2[N]\{x\} = \{0\} \quad (6)$$

The eigenvalue of formula (6) is ω^2 , its square root ω is the natural circular frequency, and the natural frequency is:

$$f = \frac{\omega}{2\pi} \quad (7)$$

The eigenvector $\{x\}$ corresponding to the eigenvalue ω is the mode shape corresponding to the natural frequency $f = \frac{\omega}{2\pi}$.

3.5 Structural optimisation design of the frame

The basic elements of optimal design are variable design, objective function, and constraint conditions (Khan et al., 2024). The design of the variables is a set of actual parameters that adjust their values in different ways to improve performance; the objective function is other functions about the design variables; the constraints are the satisfaction of the constraints of the cultural concept of optimal design and the inclusion of the design performance requirements.

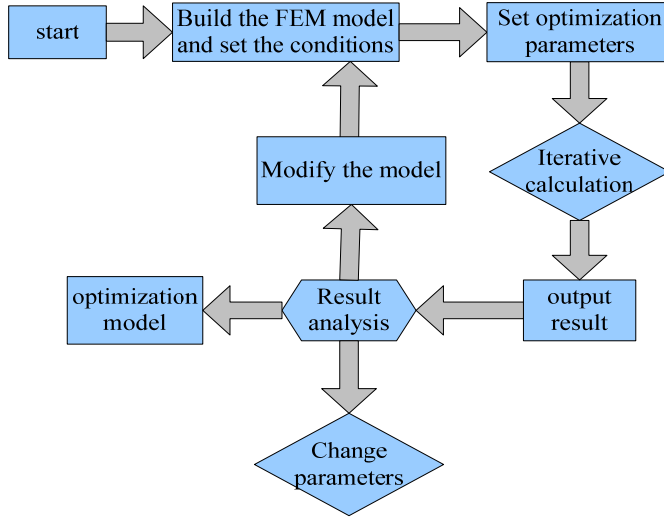
The optimised mathematical model can be expressed as:

$$\begin{aligned}
Min : f(x) &= f(x_1, x_2, \dots, x_n) \\
Sub : g(x) &\leq 0 \\
h_\beta(x) &\leq 0 \\
X_\mu^L &\leq X_\mu \leq X_\mu^U
\end{aligned} \tag{8}$$

Among them, $X = (x_1, x_2, \dots, x_n)$ are the design variable, that is, size, density, etc. $f(x)$ is the objective function, that is, volume mass, etc. and $g(x)/f(x)$ and are constraints, such as restrictions on product stress and deformation during optimisation.

The topology optimisation process is shown in Figure 4.

Figure 4 Topology optimisation process (see online version for colours)



The mathematical model of topology optimisation is established based on the variable density method, which can be deduced when the element density is used as the design variable:

$$\rho = \delta_i \rho_0 \tag{9}$$

In formula (9), δ_i is the relative density of a single unit, and ρ_0 is the inherent density of the unit in the design area.

In the finite element theory, the shell element stiffness calculation expression is:

$$[k_i] = \iiint [A_i]^T [C_i] [A_i] [J_i] d\zeta d\mu d\zeta \tag{10}$$

Let the relationship between material properties and density be:

$$\begin{aligned}
E &= \mu^a E_0 \\
\nu &= \nu_0
\end{aligned} \tag{11}$$

Among them, E are the elastic modulus, and ν the Poisson's ratio, in summary, it can get:

$$[k_i] = E_i \iiint [A_i]^T [C_i] [A_i] |J_i| d\xi d\mu d\zeta = \mu_i^\alpha E_0 [G_i] \quad (12)$$

In formula (12), C_i is a constant, and the expression of G_i is:

$$[G_i] = \iiint [A_i]^T [C_i] [A_i] |J_i| d\xi d\mu d\zeta \quad (13)$$

The strain energy in a single element is expressed as:

$$\overline{M}_i = \frac{1}{2} \{\delta_i\}^T \{k_i\} \{\delta_i\} \quad (14)$$

The overall structural strain energy is:

$$M = \sum_{i=1}^n \overline{M}_i = \frac{1}{2} \{M\}^T [K] \{M\} \quad (15)$$

In formula (15), $[K]$ is the overall stiffness matrix, and $\{U\}$ is the overall displacement matrix.

From the composition set of the element stiffness matrix, it can be known that:

$$\{M\}^T [K] \{M\} = \sum_{i=1}^n \{m_i\}^T [k_i] \{m_i\} \quad (16)$$

In this paper, the element density was used as the design variable, the unconstrained area of the frame was selected as the design space in the topology panel, and all 2D elements with design properties were included in the design space.

3.6 Application of fractional calculus

The application of fractional calculus to the dynamic analysis of truck frames involves two aspects: model building and dynamic response analysis. In this way, the dynamic behaviour of the frame can be described more accurately, and its nonlinear and non-integer order characteristics can be effectively captured. Specific processes are as follows:

Firstly, the dynamic behaviour of the truck frame is modelled using the FDE, the equation is as follows:

$$F(t) = D^\alpha y(t) + \sum_{i=1}^n a_i D^\beta y(t) + y(t) \quad (17)$$

D^α is the fractional derivative of α , a_i is a constant, and β is a fractional derivative.

In this paper, the Grunwald-Letnikov method is used for dynamic response analysis using numerical methods. Grunwald-Letnikov method uses a finite difference formula to express fractional derivative as a linear combination of time step and historical data, to realise numerical solution. When Grunwald-Letnikov is used, $D^\alpha y(t)$ is approximately:

$$D^\alpha y(t) = \frac{1}{h^\alpha} \sum_{k=0}^N (-1)^k \binom{\alpha}{k} y(t - kh) \quad (18)$$

h is the time step and $\binom{\alpha}{k}$ is the generalised binomial coefficient.

In this study, modal analysis and fractional calculus methods are used to reveal the natural frequency and resonance of the frame and predict its performance and durability. Grunwald-Letnikov method was used for numerical solutions to optimise design parameters, improve frame durability and lightweight, ensure strength and stiffness, and improve fuel efficiency and load capacity.

4 Finite element analysis of truck frame dynamic performance test

4.1 Performance evaluation results of the frame

In the dynamic analysis of automobile frames integrated with artificial intelligence and fractional calculus, the performance verification of dimensional optimisation should consider the maximum stress, deformation, fatigue life, and durability. Fatigue life is a key index to measure the long-term use of the frame under repeated loads, while durability reflects the ability of the frame to resist various damages in the actual working environment. By introducing fatigue analysis and durability evaluation, the performance of the frame in long-term operation can be more accurately predicted to ensure its safety and reliability under various working conditions, thus improving the practicality and performance of the overall design. The overall stress of the frame is relatively complex, and the corresponding boundary conditions under the four main working conditions are usually considered, namely, the bending working condition, the torsional working condition, the braking working condition, and the turning working condition (Qiao, 2018).

The bending condition is the rated condition for simulating the truck driving with external force under good road conditions. If the four wheels are on the same plane, the lateral and vertical displacements are ignored.

The braking condition is to simulate the test condition of the frame when the semi-trailer is braking on a flat road. At this time, an acceleration of 0.7G along the $-x$ axis needs to be applied to the frame.

The torsion condition is a comprehensive condition in which a single front wheel is suspended in the air when the truck is running under uneven road conditions (D'Souza and Aras, 2017). Due to the position of the centre of gravity when fully loaded, the impact on the frame is greatest when the rear wheel is suspended. Here, the state where the left rear wheel is lifted and the right rear wheel is suspended is simulated.

The turning condition is to simulate the working condition of the frame when the truck is turning. Here, a right turn is selected, and an acceleration of 0.4G along the $-y$ axis needs to be applied to the frame.

The original chassis is a 6 * 4 drive type, the front axle is a leaf spring suspension, and the leaf spring lifting lugs are connected to the frame's longitudinal beam through four supports. The rear axle is a leaf spring balanced suspension, which is connected to the frame's longitudinal beam through a support plate above the balance shaft. The engine is arranged at the front of the frame at four points.

According to the analysis of these four working conditions, the boundary conditions of the frame under each working condition are determined. The codes numbered 1, 2, 3,

4, 5, and 6 represent the translation and rotation of the wheel centre point along the x , y , and z axes, respectively. The frame constraints are shown in Table 2.

Table 2 Frame restraints

<i>Working condition</i>	<i>Restrictions</i>
Bending condition	Constrain the left front wheel 120, the right front wheel 25, the left rear wheel 14, the right rear wheel 3
Torsional condition	Constrain the left front wheel 120, the right front wheel 15, the left rear wheel 4 + displacement -10 mm, and the right rear wheel 4 + displacement 10 mm
Turning condition	Restraint front wheel 120, right front wheel 15, rear wheel 25
Braking condition	Front-wheel 120, rear wheel 15

Under these four constraints, the four working conditions have different values and positions of the maximum stress, and the maximum deformation also occurs at different positions. Through the stress-strain program technique, the following experimental data were obtained, as shown in Tables 3 and 4.

Table 3 Values and locations of maximum stresses

<i>Working condition</i>	<i>Value</i>	<i>Location of maximum stress</i>
Bending condition	145.0 Mpa	The middle position of the two longitudinal beams
Torsional condition	271.3 Mpa	The connection position of the fourth beam and the longitudinal beam
Turning condition	195.4 Mpa	Location of the connection hole in the middle of the left-side rail
Braking condition	147.1 Mpa	The middle position of stringer

Table 4 Values and locations of maximum deformations

<i>Working condition</i>	<i>Value</i>	<i>Location of maximum stress</i>
Bending condition	3.4 mm	The rear end of the stringer
Torsional condition	13.4 mm	The rear end of the stringer
Turning condition	2.8 mm	Middle left side rail
Braking condition	2.7 mm	On beam 3

It can be seen from Tables 3 and 4 that the stress distribution of the frame under bending and braking conditions was reasonable, the value was lower than the yield strength of the material, the deformation was within a reasonable range, and the safety factor was high, which met the design requirements. In the torsional condition, stress concentration occurred at the edge of the beam and the location of the connecting plate. Although the stress value on the connecting plate did not exceed the yield limit of the material, when subjected to alternating loads for a long time, the stress concentration was likely to cause cracking and damage (Pastorek et al., 2017). It is speculated that the uneven stress distribution may be related to the excessive torsional stiffness of the frame longitudinal beams and cross beams. Under the turning condition, the stress of the frame is concentrated on the left side rail and the connecting plate of the cross member, and the specific position is similar to that in the torsion condition: the stress distribution is

uniform, the area with large deformation is concentrated in the middle of the left longitudinal beam, and the deformation amount is within the normal range.

4.2 *Experiment with frame size optimisation*

In this study, a gradient-based optimisation algorithm is used in the size optimisation experiment, which has high efficiency and accuracy in structural optimisation problems. In the optimisation process, the maximum stress value is set as the constraint condition, the yield strength of the material is not exceeded as the limit, and the goal of reducing the weight of the frame while meeting the performance requirements is achieved by adjusting the number of iterations and the precision requirements. The parameters of the optimisation algorithm are dynamically adjusted according to the changes in the objective function and constraint conditions and the actual improvement of the performance after each iteration to achieve finer control and improve the optimisation efficiency.

Dimensional optimisation is an earlier and more mature design method used in structural optimisation. In the detailed design stage of the frame, by changing the thickness of the shell element in the FEM model to simulate the adjustment of the thickness of the frame plate, the performance of the frame under the required working conditions can meet the design requirements (Chakraborty et al., 2024). In dimensional optimisation, the structural element properties of the main components of the frame, such as thickness, length, width, etc. can be defined as functions of design quantities. In the dimensional optimisation design, the thickness adjustment of each component of the frame is based on the comprehensive consideration of the mechanical properties of the material and the existing design specifications. The upper and lower thickness limits shown in Table 5 are based on the material properties of B520L steel, including its elastic modulus, yield strength, and tensile strength, taking into account the feasibility and cost-effectiveness of the actual manufacturing process. These values refer to existing design standards, combined with the finite element analysis results, to ensure that the optimised frame meets the structural strength and stiffness requirements, and can achieve weight reduction. The initial value of thickness is set based on actual measurement data from the current frame design, while the upper and lower limits are based on an in-depth understanding of material properties and a rigorous evaluation of optimisation objectives:

Table 5 Size optimisation design variables

	<i>Upper limit value (mm)</i>	<i>Lower limit value (mm)</i>	<i>Initial value (mm)</i>
Longitudinal beam	22	12	15
Crossbeam	9	5	6
Connecting plate	10	4	8
Rear reinforcement plate	10	4	8
Tail beam	10	4	8

It aimed at the lightweight of the frame, the size of the frame was optimised with the constraint of the maximum stress value under torsional conditions. In the response panel, establish the response of volume and maximum stress value; in the objective function panel, select the minimised volume; in the constraint panel, set the maximum stress value not to exceed 210 Mpa and select the torsional condition, and start the solution after the setting was completed. After eight iterations of calculation, the volume value was

reduced from 163,082,000 to 143,369,000, and the convergence trend of the objective function is shown in Figures 5 and 6.

Figure 5 Volume convergence trend

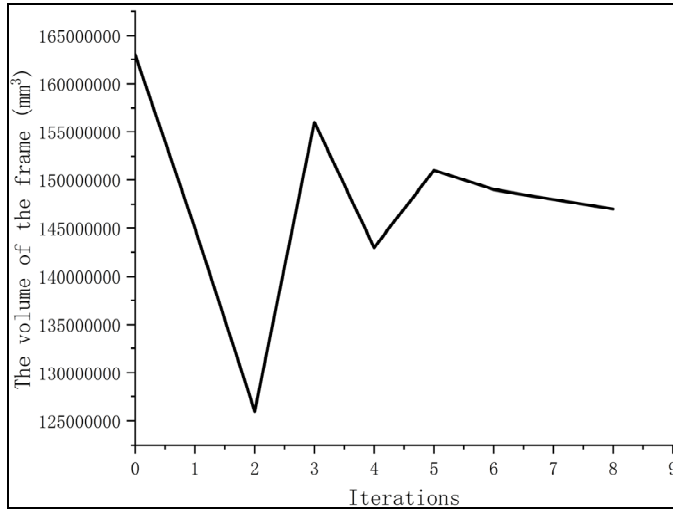
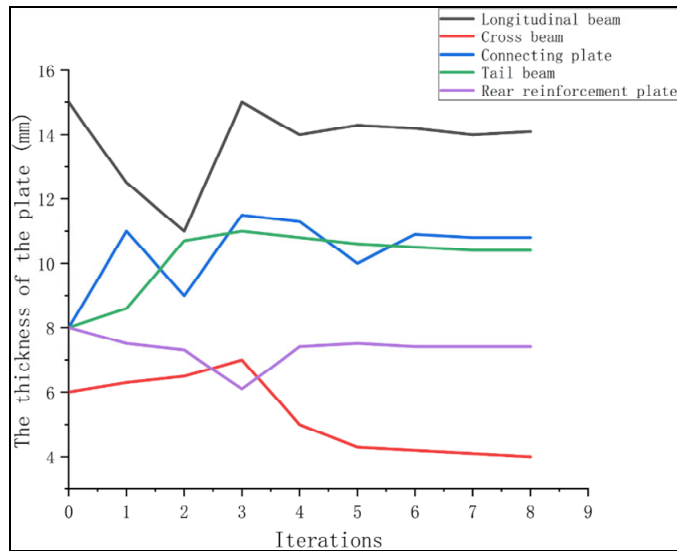
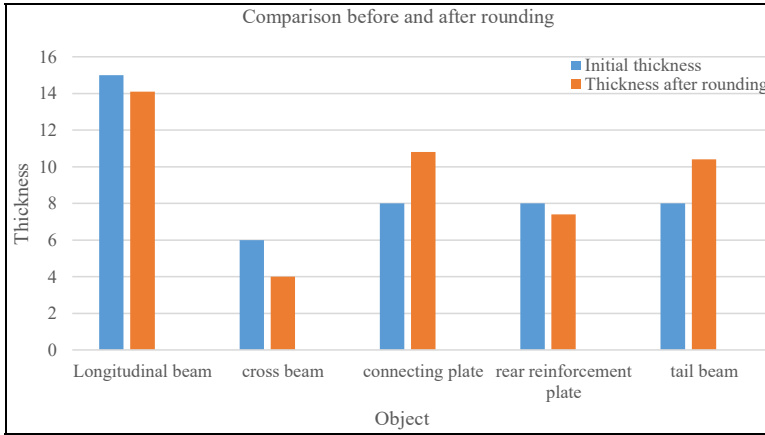


Figure 6 Convergence trend of thickness of each plate (see online version for colours)



According to the actual production needs and the optimisation results, the thickness of the steel plate of the frame is rounded. The comparison of the thickness of each frame of the frame after rounding is shown in Figure 7.

Figure 7 Comparison of the thickness of each frame of the frame before and after rounding (see online version for colours)



In the size optimisation experiment, this paper uses the gradient-based optimisation algorithm to reduce the frame volume while maintaining the structure strength and safety by setting stress value constraints, dynamically adjusting iterative parameters, and adopting a multi-objective optimisation strategy. The convergence curve of the optimisation process records the response changes of the volume and stress values in detail, showing the efficiency of the algorithm to find the optimal solution and real-time monitoring and adjustment of the optimisation strategy to achieve the design scheme to meet the safety standards while minimising the volume.

4.3 Comparison and verification of optimisation results

Experiments were carried out on the optimised frame, and the optimised data model was used to monitor the performance indicators of the truck frame under bending and torsional conditions through the stress-strain cloud map, and the following experimental results were obtained:

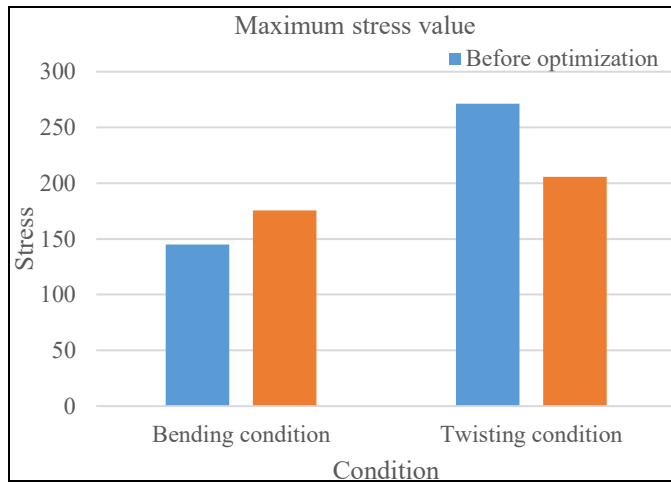
- 1 Bending condition:
 - Maximum stress value: 175.4 Mpa.
 - Appearance: Between two stringers.
 - Maximum deformation: 4.6 mm.
- 2 Torsional condition:
 - Maximum stress value: 205.6 Mpa.
 - Appearance location: Middle rear of frame.
 - Maximum deformation: 12.5 mm.

Figure 7 shows the comparison of various values with the frame bending condition and torsion condition before optimisation:

According to these analysis data, the maximum stress value under bending conditions had increased by 29.6 Mpa; the stress distribution was not significantly different from that before optimisation; the stress value was within the allowable stress range of the

material, and the maximum deformation was slightly increased; the frame's performance against bending loads was slightly degraded within the performance requirements. The maximum stress value of the frame under torsional conditions was reduced by 65.7 Mpa, the stress distribution on the frame was further optimised, and the performance of the frame against torsional loads was further improved (Chen and Qian, 2024; Andrew, 2018). The performance of the frame was slightly reduced in the low-cost mode, which was within the reasonable range of performance requirements, and the optimisation of the frame size improved the performance significantly.

Figure 8 Comparison of the maximum stress values of the frame before and after optimisation (see online version for colours)



In actual road tests, the maximum stress value of the optimised frame is 150 MPa in urban road conditions, 175 MPa in highway conditions, and 205 MPa in off-road sections. These data are very close to the maximum stress values predicted by the simulation (148 MPa, 173 MPa, and 207 MPa, respectively), which verifies the accuracy of the simulation model. In terms of deformation, the maximum deformation of urban road conditions is 3.5 mm, the highway is 4.2 mm, and the off-road sections are 5.8 mm, which is within the range allowed by design. In the simulation environment, the frame shows good durability under the simulated dynamic load. For example, under simulated emergency braking conditions, the stress response of the frame differed by no more than 5% from the data in the actual test, demonstrating the reliability of the optimised design under extreme conditions. In the steering test, the stress distribution of the frame is consistent with the simulation prediction, and the maximum stress appears in the expected connection point area, the value is 198 MPa, and the deviation from the simulation value is less than 3%.

5 Conclusions

With the advent of computer technology and numerical computation, the landscape of truck frame design has been revolutionised by more accessible and dependable

methodologies. The application of computer-aided engineering (CAE) technology and structural optimisation significantly improves the frame design quality and speeds up the development cycle. The deep learning model combines design, modelling, simulation, and optimisation theories to improve the frame structure and enhance mechanical properties through fractional calculus and topological optimisation, especially under torsional conditions. This method combines advanced computing techniques and engineering principles and highlights the potential of fractional calculus in complex structure optimisation. Through comparison with industry standards and competing products, the optimised model was verified to maintain or improve safety performance and durability while reducing weight by 10%.

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