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Xue Wang, Biao Wu, Jilan Kong

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Lightweight design of electric box-type trucks based on deep learning models

Xue Wang*

School of Mechanical Engineering,
Yangzhou Polytechnic University,
Yangzhou 225009, China
Email: 101745@yzpc.edu.cn

*Corresponding author

Biao Wu

Technology Department,
Yangzhou CIMC Tonghua Special Vehicle Co., Ltd.,
Yangzhou 225009, China
Email: biao.wu@cimc.com

Jilan Kong

School of Mechanical Engineering,
Yangzhou Polytechnic University,
Yangzhou 225009, China
Email: 101743@yzpc.edu.cn

Abstract: Recently, in order to save energy, there is increasing concern on reducing the weight of electric box-type trucks. Traditional design methods implement finite element analysis (FEA) repeatedly for large truck structures, which is extremely time-consuming. To solve this, we propose a framework that combines a ResNet152-based deep learning model with particle swarm optimisation. The deep learning model predicts key structural metrics, such as weight, maximum stress, maximum displacement, and energy absorption, while particle swarm optimisation searches the design space and tries to find the optimal weight under specific mechanical constraints. We evaluate our proposed method on a generated truck frame dataset, achieving an average R^2 of 0.993. Compared with the baseline models, our method achieves the most reduction in weights and the least computational cost, proving its better reliability and efficiency than other optimisation methods.

Keywords: electric trucks; lightweight design; deep learning; surrogate modelling; particle swarm optimisation.

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Biographical notes: Xue Wang is a Lecturer at the School of Mechanical Engineering, Yangzhou Polytechnic University. She obtained her Master's degree from Nanjing University of Aeronautics and Astronautics in 2007. Her research interests include vehicle structural design optimisation, finite element simulation, and motion control algorithms.

Biao Wu is a Senior Engineer in the Technology Department of CIMC Tonghua Special Vehicle Co., Ltd. He obtained his Bachelor's degree from Taiyuan University of Science and Technology in 2004. His research interests include special vehicle structure improvement, vehicle lightweight design, and finite element simulation.

Jilan Kong is a Lecturer at the School of Mechanical Engineering, Yangzhou Polytechnic University. She obtained her PhD from Chongqing University in 2006. Her research interests include the research on intelligent auxiliary production equipment, the application of sensors, and computer simulation.

1 Introduction

Lightweight design of electric box-type truck frames is important due to the structural weight directly affects vehicle performance and efficiency (Shao et al., 2020). Reducing the weight of the vehicle frame can lower energy consumption, which in turn extends driving range and allows for a higher payload without exceeding weight regulations. A lighter structure also eases the demands placed on the battery and motor, helping to reduce both operational costs and environmental impact. However, it is necessary to weight reduction to meet designing requirements on stiffness and crashworthiness. finite element analysis (FEA) is commonly used to evaluate stiffness and crashworthiness because it can simulate how a structure responds under static and impact loads. It provides estimates of deformation, stress patterns, and energy absorption, which are the main criteria for assessing structural performance. These evaluations help determine whether a design meets safety and durability requirements, so they are essential in lightweight design studies. We cannot compromise safety for weight reduction (Seyfried et al., 2015). Therefore, it is essential to keep a balance between minimising weight and maintaining mechanical performance.

Traditional lightweight design relies on structural optimisation methods, such as topology, shape, and size optimisation (Braga et al., 2014). Specifically, unnecessary material is removed by topology optimisation from the structure. Shape and size optimisation assist to reduce weight by adjusting the geometry and dimensions of structural members (Zuo et al., 2025). However, there still exists requirements for repeated simulation iterations, which involves a large finite element model and is computationally expensive. This even shows more limitation if the structures grow larger.

In recent years, there is an increasing number of researched on deep learning, which provide new solutions to these challenges (Samadian et al., 2025). Deep neural networks have ability to predict structural responses and reduce evaluation time. Furthermore, the exploration of the design space can be accelerated by combining deep models with intelligent algorithms. Combining deep models with intelligent algorithms improves design space exploration because the surrogate model provides fast predictions that allow the optimiser to evaluate many candidate designs in a short time. The optimiser then uses

these predictions to move toward promising regions of the design space and avoid areas that do not satisfy performance requirements. This interaction increases search efficiency, reduces computation, and supports more reliable convergence toward high-quality lightweight designs. This allows faster identification of lightweight designs (Fadlallah et al., 2021; Gong and Ma, 2024; Liu et al., 2019).

Despite the advancements, research on deep learning frameworks for electric trucks is still at an early stage. Existing research mostly focuses on simple models or standard components. There is few studies combining deep learning models with metaheuristic optimisation for large commercial vehicle design (Akay et al., 2022). Therefore, it is significant to develop design frameworks to balance prediction and engineering use in this field.

To address this gap, this paper presents a framework that uses a ResNet152 surrogate model with particle swarm optimisation (PSO) optimisation for electric box-type truck frames. The surrogate model predicts structural weight, maximum stress, maximum displacement, and energy absorption from design parameters. PSO searches the design space to find designs that reduce weight and meet all mechanical limits. Compared with FEA-only optimisation, this method reduces computation time without losing prediction accuracy.

The main contributions of this study are as follows:

- 1 We develop a ResNet152-based deep learning surrogate model to predict structural performance metrics of electric truck frames.
- 2 We combine a surrogate model with PSO to achieve efficient lightweight optimisation under multiple mechanical constraints.
- 3 The framework is tested on a real dataset of truck frame designs.

The remaining part of this paper is given as follows. In Section 2, we review the related works. Section 3 explains the proposed methodology, including data generation, deep learning model, and PSO. Section 4 presents experimental results and relevant analysis. In Section 5, we conclude the paper and discuss our future work.

2 Relevant works

2.1 *Lightweight design of vehicle structures*

Lightweight design is a way to improve vehicle energy use and range for electric trucks. Researchers used to implement overdesign on truck frames to ensure stiffness and safety, which adds structural weight. However, the extra weight leads to the range reducing and energy wasting. As a result, there are more researches focusing on topology optimisation, material design, and size and shape optimisation. These methods help to reduce weight and keep mechanical properties.

Boltyanski (2005) employ mathematical programming and FEA to determine the optimal distribution of material within a design domain. They implement FEA to evaluate the structural performance of different material distributions within the design space. Moving asymptotes (MMA) is used to search for optimal solution. Meanwhile, a topology optimisation framework is introduced by Suresh et al. (2020), which incorporates a continuous-time high-cycle fatigue model to improve the durability of

structural designs. This model utilises the concept of a moving endurance surface, which is a function of the stress and back stress. To incorporate this fatigue model into TO, a global high-cycle fatigue constraint is implemented, using an aggregation function that approximates the maximum damage. The optimisation process employs gradient-based methods, with fatigue sensitivities determined through adjoint sensitivity analysis. Since the damage is related to the load history, the adjoint variables can be obtained by solving the final value problem.

Silva et al. (2025) study topology optimisation of vehicle crash boxes for frontal impact in order to maximise energy absorption and reduce weight. Their optimised structure performed better than traditional designs in impact and energy absorption. Meanwhile, Wu et al. (2025) implements a small electric vehicle frame, which uses FEA to optimise component dimensions under static and dynamic conditions. The optimisation reduces weight by 10.7% while meeting stiffness and stress limits. These two studies show that simulation-based optimisation can reduce weight, but it is time-consuming to apply it to large commercial vehicle structures.

2.2 Deep learning in structural engineering and surrogate modelling

It is popular to use deep learning in structural engineering to build surrogate models that approximate FEA. Surrogate models are useful in structural engineering because they approximate FEA outputs with much lower computational cost. They allow rapid prediction of stress, displacement, and other performance metrics, so the design process can explore many structural configurations in less time. They also support optimisation by enabling fast evaluations inside iterative search algorithms, which would be too slow if each step required a full FEA simulation.

An improved convolutional neural network (CNN) is implemented to predict von Mises stress in steel plates under different loads and boundary conditions (Bolandi et al., 2022). Compared with PDE/FEA results, their CNN model had a mean absolute error of 0.9% and a peak error of 0.46%. What's more, Lee et al. (2025) addressed a problem in structural surrogate models: underrepresentation of high-amplitude responses. Stratified sampling and a shifted label distribution are implemented to balance errors between small and large responses. The model is tested on stress prediction in a two-dimensional beam, transient thermal stress in a fin, and a three-dimensional stress field. According to the results, deep surrogate models with this approach have an improvement on accuracy for high-amplitude responses, which is important for safety.

Mai et al. (2021) present a machine learning-based surrogate model for optimising truss structures that exhibit geometrically nonlinear behaviour. The model combines the trained DNN with a differential evolution (DE) optimisation algorithm to search for lightweight truss designs. This operation helps to meet displacement and stress limits. The proposed DNN-DE framework finally achieves significant computational savings while maintaining design accuracy.

A Transformer framework is introduced by Xing et al. (2025) to predict how reinforced concrete frames behave under stress. The authors first validate the finite element models of the reinforced concrete frames (RCFs) using ETABS and SAP2000, ensuring accurate simulation of structural behaviour under loads. The hyperparameters for transformer are initially optimised based on the database to balance accuracy and complexity. Their method is proved to be useful for its high coefficients of determination (R^2), often exceeding 0.95 for shear-force related outputs.

Moreover, Chen et al. (2025) developed a neural operator-based surrogate model to predict the dynamic responses of vehicle-bridge interaction. Their model takes geometric and material properties as inputs and achieved accurate predictions for vibrations and deflections. The results show that deep learning surrogates can replace repeated finite element simulations in dynamic structural analysis. In comparison, Zhang et al. (2025) propose a multimodal deep learning framework to predict the residual strength of corroded hollow steel section columns. Similar features were used as inputs from the research before. While both studies demonstrate that deep learning can accelerate structural evaluation, Wang et al. focused on dynamic response prediction, whereas Zhang et al. addressed strength and degradation under static and variable loads.

2.3 Optimisation algorithms

Optimisation methods play a central role in achieving lightweight vehicle structures. Early work focused on classical optimisation algorithms including gradient-based techniques such as sequential quadratic programming, and evolutionary approaches like genetic algorithms (GA) and particle swarm optimisation. These methods require repeated FEA for each candidate design and therefore impose high computational cost when applied to complex designs with many variables. As a result, classical optimisation methods often rely on repeated FEA evaluations, so the computation grows quickly when the problem size increases. These methods also use local search steps, which limits their ability to move through large or complex design spaces. As a result, they may struggle to efficiently explore the design space or handle high-dimensional optimisation problems.

More recent studies combine optimisation with surrogate modelling to reduce computational burden. For example, Pourkamali-Anaraki and Hariri-Ardebili (2021) use CNNs together with imbalance mitigation strategies (stratified sampling and label transformation) to improve accuracy of surrogate models. Although that work does not directly integrate PSO, it shows that more accurate surrogate models enable more reliable optimisation, especially when extreme values of structural responses matter for safety constraints.

Another study develops a hybrid surrogate combining neural network layers and long-short term memory (LSTM) layers to predict transient structural responses under varying load conditions (Franke and Wagner, 2024). The surrogate is paired with optimisation or parameter exploration tasks, and demonstrates that surrogate-assisted optimisation can achieve high accuracy and large reductions in computation time compared to pure FEA-based approaches.

Dan et al. (2023) implement multiple surrogate types (polynomial chaos expansion, support vector regression, kriging, radial basis functions) to predict long-term deflections. Though this work is applied to concrete structures rather than metal truck chassis, it shows how surrogate models can support optimisation by identifying geometric and material parameters with greatest influence, guiding lightweight design choices.

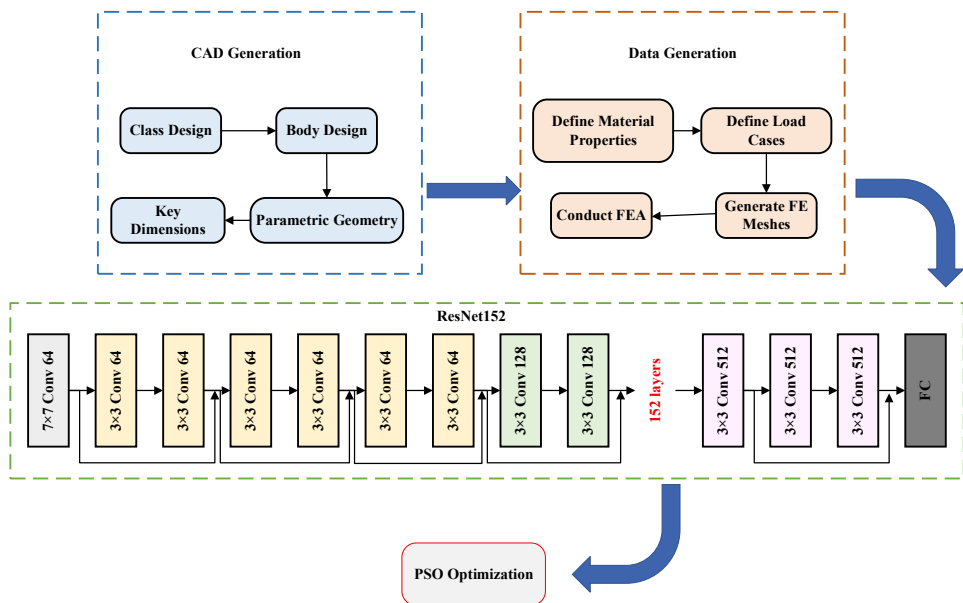
Together, these works illustrate that combining optimisation with surrogate models (especially deep learning surrogates) allows for fast and efficient lightweight design under constraints. They provide the groundwork for using deep networks + PSO in our work, showing that accurate surrogate models are essential for constraint satisfaction, and that optimisation methods must account for data imbalance, transient effects, and sensitivity of load cases.

3 Proposed methodology

3.1 General architecture

The proposed framework for lightweight design of electric box-type trucks integrates data generation, deep learning, and optimisation. Above all, CAD models of the truck chassis and body are created and converted into finite element meshes. Material properties, geometry parameters, and load conditions are defined. FEA is conducted to calculate structural weight, maximum stress, displacement, and energy absorption. This dataset pairs input features (geometry, material, loads) with output performance metrics and serves as the training data for the deep network. Subsequently, a ResNet-based deep neural network is trained on the generated dataset to predict performance metrics for new designs. The inputs are numerical representations of geometry, material properties, and loads. The outputs are predicted weight, stress, displacement, and energy absorption. Once trained, the network acts as a fast evaluator, providing almost instant performance predictions without running FEA. Finally, an optimisation algorithm generates candidate truck designs and searches for the best configuration, as shown in Figure 1.

Figure 1 General architecture of the model (see online version for colours)



3.2 Data generation

The first step of the framework is to build a dataset that connects truck design parameters with their performance. Since no public dataset exists for electric box-type trucks, the data is generated through CAD modelling and FEA.

3.2.1 CAD stage

The CAD stage defines the structural model of the truck and prepares it for simulation. It provides the input variables that describe the design. The geometry of the truck chassis is described in parametric form so that different design variants can be generated automatically. The key parameters are chassis length (L), width (B), height (H), and thickness of structural members (t). The structural volume is computed from these parameters. For a rectangular hollow beam, the volume is:

$$V = L \cdot (B \cdot H - (B - 2t)(H - 2t)) \quad (1)$$

The total chassis volume is then expressed as the sum of all beams:

$$V_{\text{total}} = \sum_{i=1}^n V_i \quad (2)$$

where n is the number of beams in the chassis. The structural weight is then calculated as:

$$W = \rho \cdot V_{\text{total}} \quad (3)$$

where ρ is the material density.

Each beam is assigned a specific material. The material properties include density (ρ), Young's modulus (E), and yield strength (σ_y). These properties are recorded as part of the input vector. The material properties influence the structural performance predicted later by FEA and the deep learning model.

To represent real operating conditions, three load scenarios are applied to each CAD design: cargo load (F_c), braking force (F_b), and crash impact load (F_{cr}). These loads define the boundary conditions for FEA and are included in the input vector. By changing L , B , H , t , and ρ , new truck structures with different volumes and weights can be generated directly in CAD.

$$X = [L, B, H, t, \rho, E, \sigma_y, F_c, F_b, F_{cr}] \quad (4)$$

where E is Young's modulus, σ_y is the yield strength, and F_c , F_b , F_{cr} are cargo, braking, and crash loads respectively. This parametric representation allows automated generation of multiple truck designs for training the deep neural network.

3.2.2 FEA stage

After generating the CAD models, each truck design is evaluated using FEA to obtain key performance metrics. The CAD input (including geometry, material properties, and loading conditions) is converted into a finite element mesh and solved under the specified boundary conditions.

The structural weight of the chassis is computed directly from the FEA model as the sum of each beam's mass, calculated by multiplying its density by its volume:

$$W = \sum_{i=1}^n \rho_i \cdot V_i, \quad (5)$$

where ρ_i and V_i are the density and volume of the i^{th} beam, respectively. The maximum stress in the chassis is determined by the component stress field. For linear elastic analysis, the stress in each element can be expressed as:

$$\sigma = \mathbf{D} \cdot \varepsilon \quad (6)$$

where ε is the strain vector obtained from nodal displacements and $\mathbf{D}$ is the material elasticity matrix. The maximum displacement of the structure is calculated from the nodal displacement vector $\mathbf{u}$ as:

$$\delta_{\max} = \max \left(\sqrt{u_x^2 + u_y^2 + u_z^2} \right) \quad (7)$$

Over all nodes, where u_x, u_y, u_z are the displacements in the x, y , and z directions.

The energy absorption during crash is obtained by integrating the internal force over displacement:

$$E_{\text{abs}} = \int F d\delta \quad (8)$$

where F is the reaction force along the crash direction and δ is the corresponding displacement. The FEA outputs – structural weight (W), maximum stress ($\sigma_{\max}$), maximum displacement ($\delta_{\max}$), and energy absorption (E_{abs}) – form the output vector Y for each design. These outputs, together with the CAD input vector X , create the dataset used to train the deep neural network:

$$X = [L, B, H, t, \rho, E, \sigma_y, F_c, F_b, F_{cr}] \rightarrow Y = [W, \sigma_{\max}, \delta_{\max}, E_{\text{abs}}] \quad (9)$$

3.3 Deep learning model

In this research, a ResNet152 deep neural network is implemented to predict structural performance of electric box-type truck designs. ResNet152 is selected for its deep architecture, which helps capture complex relationships between design parameters and structural performance. The residual connections also allow stable training even at large depth, so the model can learn detailed patterns that simpler networks may miss. This capacity makes the architecture effective for predicting multiple coupled structural metrics from high-dimensional design inputs. It serves as a fast surrogate for time-consuming FEA simulations. The network takes a parametric design vector as input, including chassis beam dimensions, material properties, and load conditions. This input vector is normalised to improve training stability.

The network has 152 layers arranged in residual blocks. Each block contains several convolutional layers and skip connections, as shown in Figure 1. These residual connections not only help the network learn complicated nonlinear relationships within features, but also reduces the gradient vanishing problem, which is common in deep networks. Meanwhile, each convolutional layer is followed by one batch normalisation and one ReLU activation to improve convergence and add nonlinearity. The output of a residual block is:

$$Y = X + \text{Conv} \left(\text{ReLU} \left(\text{BN} \left(\text{Conv} \left(\text{ReLU} \left(\text{BN}(X) \right) \right) \right) \right) \right) \quad (10)$$

where *Conv* is convolutional operation, *BN* is batch normalisation and *ReLU* is the activation function. *X*, *Y* are the input and output, respectively. '*X* +' represents the skip connection, which allows the network to learn residual information.

After the residual blocks, the model use fully connected layers to map the features to the output vector. The fully connected layers can be expressed as:

$$Z = FC(ReLU(FC(X))) \quad (11)$$

where *FC* is a fully connected layer. The first fully connected layer with *ReLU* extracts high-level features from the residual block output. The final fully connected layer maps these features to the predicted structural performance metrics, including structural weight, maximum stress, maximum displacement, and energy absorption..

3.4 Optimisation model

We employ a PSO algorithm to achieve lightweight design for electric trucks. This optimisation algorithm aims to minimise the total structural weight while satisfying constraints.

During the optimisation process, design variables are iteratively adjusted. At the same time, the design must meet all safety and performance requirements. These constraints are evaluated using the trained surrogate model, which predicts performance metrics for each candidate design during the optimisation loop. The predicted values are then checked against the allowable limits for stress, displacement, and energy absorption to determine whether a design is feasible. This process allows the algorithm to filter out unsafe or invalid solutions without running full FEA simulations. This ensures that the final structure is both lightweight and mechanically reliable. First, the maximum stress in the structure must not exceed the permissible stress limit to ensure it does not fail under load. Maximum displacement must remain within safe limits to prevent the structure from excessive bending or deformation. Furthermore, energy absorption must be above the required level to ensure the truck can safely withstand impacts. All design variables must be kept within their minimum and maximum values to correspond to physical and manufacturing limitations.

In the PSO algorithm, each design candidate is treated as a particle moving through the design space. The position and velocity of the i^{th} particle at iteration t are updated as:

$$v_i(t+1) = \omega \cdot v_i(t) + c_1 \cdot r_1 \cdot (pbest_i - x_i(t)) + c_2 \cdot r_2 \cdot (gbest - x_i(t)) \quad (12)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (13)$$

where v_i is the velocity vector, x_i is the position vector (design variables), $pbest_i$ is the personal best position of particle i , and $gbest$ represents the global best position found by the entire swarm. The parameters ω , c_1 , and c_2 denote the inertia weight, cognitive coefficient, and social coefficient, respectively. r_1 and r_2 are two random numbers between 0 and 1. The inertia weight ω is linearly decreased from 0.9 to 0.4 to balance global exploration and local exploitation during the search.

Constraint violations are handled using a penalty function added to the objective function:

$$\begin{aligned}
 F(X) = & W_{\text{pred}}(X) + \alpha_1 \max(0, \sigma_{\text{max_pred}}(X) - \sigma_{\text{allow}})^2 \\
 & + \alpha_2 \max(0, \delta_{\text{max_pred}}(X) - \delta_{\text{allow}})^2 \\
 & + \alpha_3 \max(0, E_{\text{req}} - E_{\text{abs_pred}}(X))^2
 \end{aligned} \tag{14}$$

where α_1 , α_2 , and α_3 are penalty coefficients used to discourage infeasible designs. The use of penalties ensures that particles gradually converge toward the feasible region while minimising the objective function.

The PSO parameters are selected with a swarm size of 60 particles, a maximum of 300 iterations, cognitive and social coefficients $c1 = c2 = 1.5$, and velocity clamping at 20% of the design variable range. To ensure stable convergence, all design variables are normalised within their upper and lower bounds before optimisation. FEA is implemented for each optimisation loop to maintain high prediction accuracy. New high-fidelity data is added to the training dataset. If the prediction error exceeds a set threshold, the ResNet152 model is fine-tuned. The PSO algorithm continues running until a stopping criterion is met. This occurs either when the maximum number of iterations is reached or when the improvement in the objective function becomes minimal.

4 Experimental results and analyses

4.1 Dataset

The dataset used in this study is summarised in Table 1. It includes geometric, material, and loading features as inputs, and structural weight, maximum stress, maximum displacement, and energy absorption as outputs.

Table 1 Variables description

<i>Feature type</i>	<i>Variables</i>	<i>Description</i>
Geometry	Beam length, width, height, thickness	Dimensions of structural members in the truck frame
Material	Density, Young's modulus, yield strength	Mechanical properties of structural materials
Load	Distributed load, point load	Typical operational and impact loads
Output metrics	Structural weight (kg), Maximum stress (MPa), Maximum displacement (mm), Energy absorption (J)	Performance measures obtained from FEA

We split the dataset with 70 % for training, 15% for validation, and 15% for test sets. The 70:15:15 train-validation-test split is chosen to keep a large portion of the data for parameter learning while still providing a dedicated set for tuning and early stopping. This balance helps prevent overfitting and supports stable model generalisation. The test set is kept separate so that the final evaluation reflects how the model performs on unseen designs, which strengthens the reliability of the reported accuracy. All continuous variables in the dataset are normalised to the range [0, 1] to improve the convergence of the deep learning model. Categorical variables are one-hot encoded.

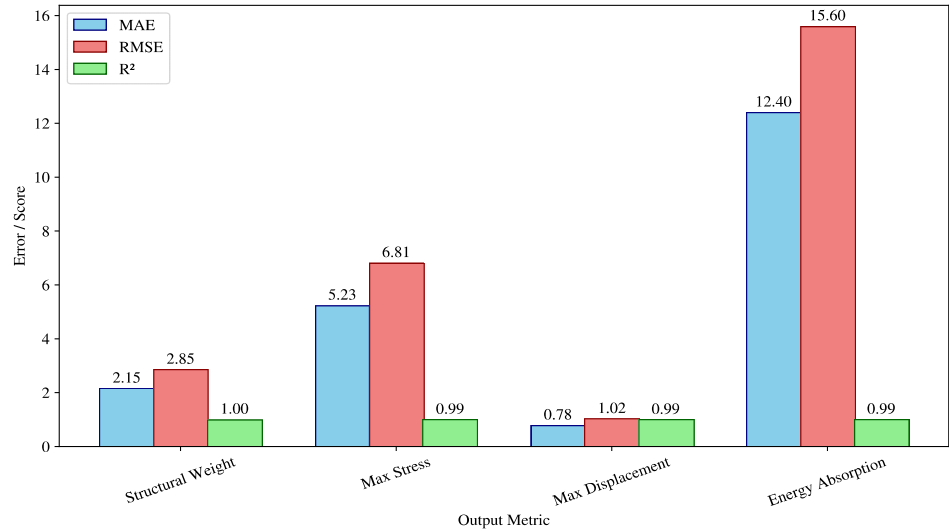
4.2 Model performance evaluation

The prediction performance of the ResNet152 model on the test set is summarised in Table 2. We use MAE, RMSE and R^2 to evaluate the performance of our proposed method.

Table 2 Prediction performance of ResNet152 on test set

Output metric	MAE	RMSE	R^2
Structural weight (kg)	2.15	2.85	0.997
Maximum stress (MPa)	5.23	6.81	0.992
Maximum displacement (mm)	0.78	1.02	0.989
Energy absorption (J)	12.4	15.6	0.995

Figure 2 Performance visualisation of ResNet152 (see online version for colours)



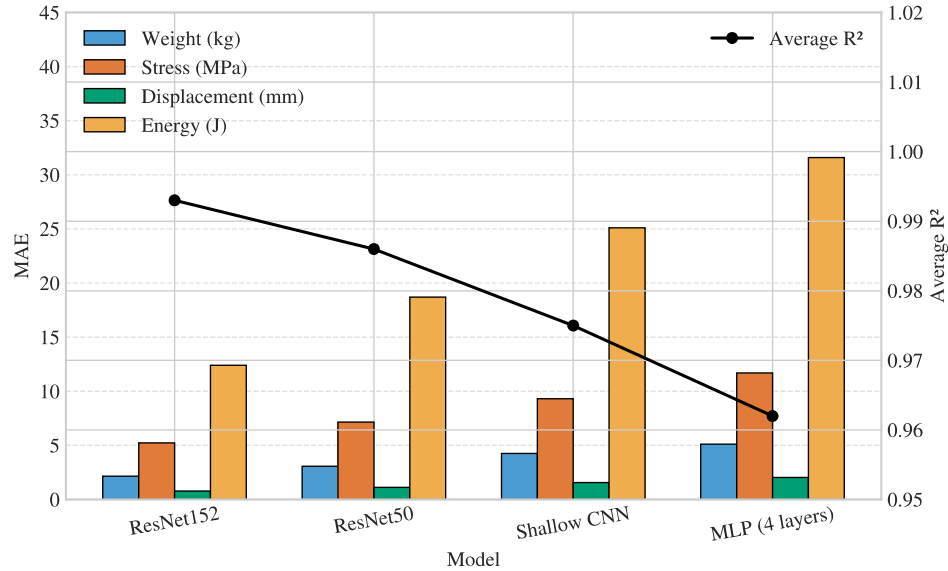
The table shows that our model has low mean absolute error and root mean square error, together with high R^2 values, Figure 2 visualises the results of this experiment. These results indicate that the ResNet152 surrogate can accurately predict structural performance metrics, enabling fast evaluation of new truck frame designs without repeated finite element analyses.

Table 3 Comparison of ResNet152 with baseline models on test set

Model	Structural weight MAE (kg)	Maximum stress MAE (MPa)	Maximum displacement MAE (mm)	Energy absorption MAE (J)	Average R^2
ResNet152	2.15	5.23	0.78	12.4	0.993
ResNet50	3.08	7.15	1.12	18.7	0.986
Shallow CNN	4.25	9.32	1.56	25.1	0.975
MLP (4 layers)	5.12	11.7	2.04	31.6	0.962

Table 3 presents a comparison of ResNet152 with 3 baseline models on the test set, including ResNet50, Shallow CNN and MLP. We evaluate the model with mean absolute errors (MAE), maximum of each features, as well as the average R^2 .

Figure 3 Visualisation of comparison all models (see online version for colours)



From Table 3 and Figure 3, ResNet152 provides the most accurate predictions for all metrics. It has smaller errors than ResNet50, shallow CNN, and MLP. The baseline models show higher deviations, particularly in stress and displacement, indicating that shallower or simpler networks may fail to represent complex structural behaviour. ResNet152 performs better because its deeper structure and skip-connection design allow it to learn complex mappings between design parameters and mechanical responses more effectively than shallower networks. These skip connections reduce gradient issues and help the network extract high-level structural features that baseline models cannot represent. As a result, ResNet152 maintains lower prediction errors across all metrics and produces more reliable outputs for surrogate-assisted optimisation.

4.3 Model performance evaluation

Guided by the ResNet152 surrogate model, we apply PSO to reduce structural weight while meeting the limitations. We set the PSO with 60 particles and run it for 300 iterations.

Table 3 compares key metrics of the baseline and optimised designs. Figure 4 shows the performance comparison in four sub-charts. After evaluation, the optimised design reduced weight by 18.4% under FEA verification and met all performance limits.

Table 4 Comparison of baseline and optimised truck designs

<i>Design</i>	<i>Weight (kg)</i>	<i>Max stress (MPa)</i>	<i>Max displacement (mm)</i>	<i>Energy absorption (J)</i>
Baseline design	1,250	210	12.5	5,800
Optimised design	1,020	208	12.3	5,820
Weight reduction	18.4%	–	–	–

Figure 4 Comparison of baseline and optimised truck designs (see online version for colours)

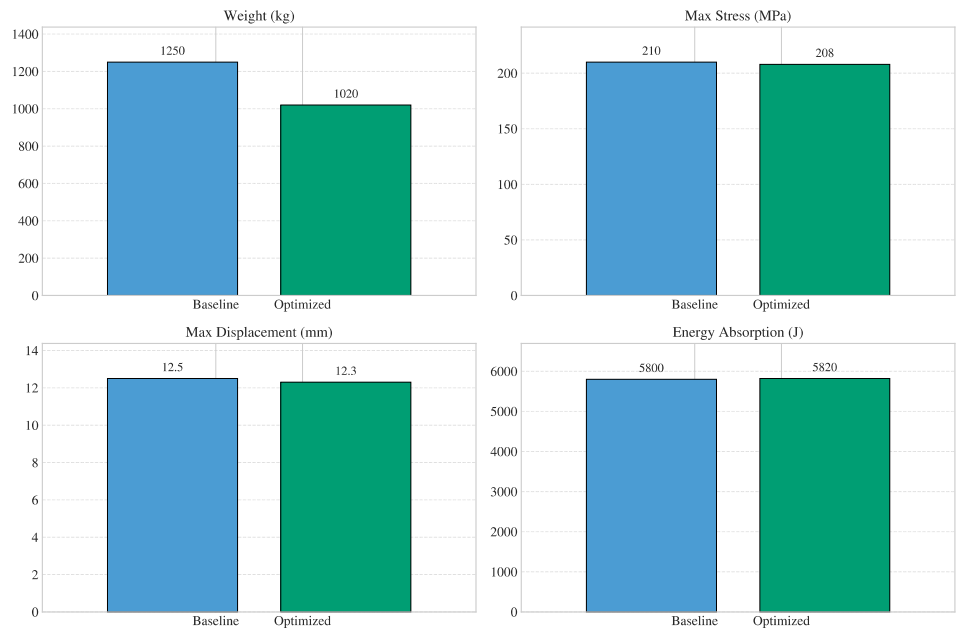


Table 5 Comparison of PSO with other optimisation methods

<i>Optimisation method</i>	<i>Weight (kg)</i>	<i>Max stress (MPa)</i>	<i>Max displacement (mm)</i>	<i>Energy absorption (J)</i>	<i>Notes</i>
PSO	1,020	208	12.3	5,820	Fast convergence, reliable
Genetic algorithm	1,035	210	12.5	5,810	Slightly heavier, slower convergence
Gradient-based (SQP)	1,045	211	12.7	5,800	Stuck in local minima, sensitive to initial guess

We evaluate the performance of the PSO compared with other commonly used optimisation approaches. PSO outperforms other methods in this case because it uses a population of candidate solutions to explore the design space globally, rather than following a single local path. Its particles communicate and adjust positions based on both individual and group best solutions, which improves convergence speed and avoids local minima. This allows PSO to consistently find lighter designs while satisfying all structural constraints, making it more effective than GA and gradient-based approaches

for this optimisation problem. The baselines include a GA, which is widely used for global optimisation but may converge more slowly, and a gradient-based sequential quadratic programming (SQP) method, which relies on local gradients and can be sensitive to the initial design.

Figure 5 Bar chart between different optimisation algorithms (see online version for colours)

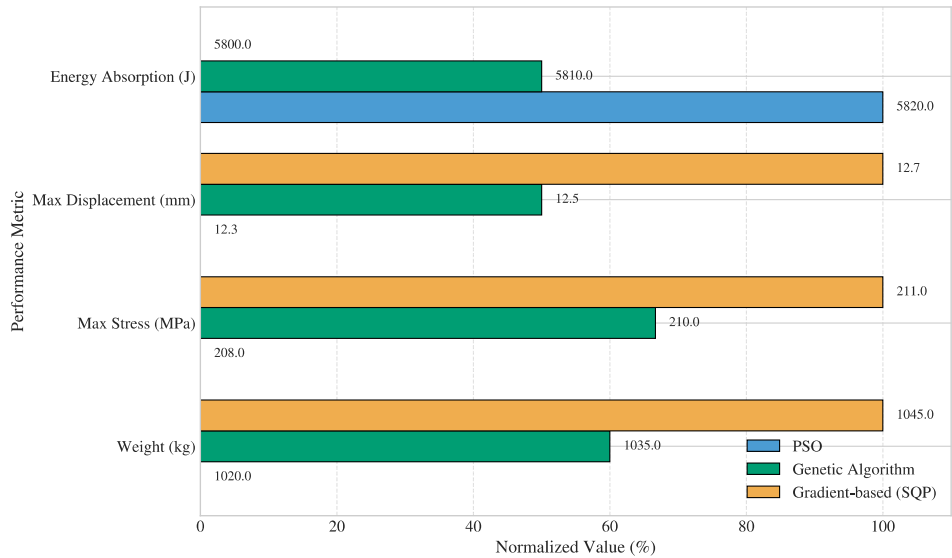


Table 4 and Figure 5 show that PSO achieved the lowest structural weight while meeting all constraints. GA found a feasible solution but was slower and produced slightly worse results. SQP often got stuck in local optima in this nonlinear problem. The results show that PSO has better global search ability and stability in truck structure design.

4.4 Computational cost evaluation

Table 5 gives the running time for each baseline models. It shows that using the ResNet152 surrogate greatly reduces computation time. Full FEA optimisation takes 48 hours. Surrogate-assisted PSO takes only 6 hours. GA and gradient-based methods are slower than PSO. The surrogate allows fast evaluation of many designs. PSO also finds better solutions than other methods. This result shows that combining deep learning with PSO improves efficiency and maintains reliable performance.

Table 6 Computational cost comparison

Method	Total time (hours)	Notes
FEA-only PSO	48	All designs evaluated with FEA
ResNet152 + PSO	6	Surrogate predicts performance, periodic FEA validation
ResNet152 + GA	8	Slower convergence than PSO
ResNet152 + gradient-based	7	Often trapped in local minima

ResNet152 + PSO is faster than the other methods because it does not run FEA for every candidate design. The surrogate predicts performance metrics quickly. PSO evaluates many designs in parallel and moves the swarm toward better solutions efficiently. GA requires more iterations to converge. Gradient-based methods are easily to be stuck in local minima, which slows progress. Using ResNet152 to replace most FEA evaluations saves most of the computation time. Periodic FEA validation ensures accuracy but does not add much extra time.

5 Conclusions

This paper presented a framework for lightweight design of electric box-type truck frames. The framework combines a ResNet152 deep learning surrogate with PSO optimisation. The surrogate predicts structural weight, maximum stress, maximum displacement, and energy absorption. PSO searches for the optimal design while satisfying all constraints. According to the evaluation results, ResNet152 achieved mean absolute errors of 2.15 kg for weight, 5.23 MPa for stress, 0.78 mm for displacement, and 12.4 J for energy absorption, with an average R^2 of 0.993. It indicates that integrating deep learning surrogates with metaheuristic optimisation provides a practical method for designing lightweight electric commercial vehicles.

Although our model achieves a good performance, there are still some future work we need to implement to enhance our work. First, considering the quick development of deep networks, more up-to-date CNN models can be used to enhance the prediction of structural performance. Meanwhile, there are also a lot of PSO variants which integrate other optimisation algorithms. Designing a new PSO architecture also can be under consideration. Another direction is to expand the surrogate model to handle larger and more complex truck structures, including multi-material components and modular designs. The surrogate could also be combined with other optimisation algorithms to balance weight, cost, and safety simultaneously. Finally, integrating real-world experimental data could further validate the surrogate's predictions and enhance the reliability of the optimised designs.

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Declarations

All authors declare that they have no conflicts of interest.

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