

Physics-informed machine learning for near real-time stress prediction on a structural component: Application for landing gears

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ABSTRACT

Lightweight design constitutes a pivotal research and development objective for next-generation landing gear systems. Nevertheless, achieving reduced weight while maintaining structural safety and reliability presents considerable challenges. The establishment of a digital twin (DT) for structural health monitoring (SHM) offers a promising approach to address these concerns across the design, testing, and operational lifecycle of landing gears. In this study, we develop a physics-informed neural network (PINN) model for near real-time stress prediction on the drag strut of a nose landing gear (NLG), specifically for an A320-type aircraft, serving as a foundational component of a DT system. The proposed PINN framework directly outputs displacement fields while deriving stresses as secondary quantities, effectively incorporating the fundamental equations of linear elasticity into the loss function. Displacement boundary conditions, informed by finite element method (FEM) simulations, are integrated as penalty terms to enhance trainability and physical consistency. The training dataset is constructed using load cases statistically representative of actual landing gear operations, with high-fidelity FEM providing corresponding displacement and stress references. The model demonstrates strong predictive accuracy, with relative errors between 5% and 7% compared to FEM results, and significantly outperforms both pure stress-output PINNs and conventional deep neural networks (DNNs). Moreover, the trained PINN achieves inference times within seconds under time-varying loads, highlighting its capability for near real-time stress monitoring. This work underscores the potential of physics-informed machine learning for enhancing DT-enabled SHM systems in safety-critical aerospace structures.

1. Introduction

1.1. Background

The aerospace industry is continually seeking innovative solutions to enhance aircraft structures, optimize component longevity, and streamline maintenance practices. Reducing aircraft fuel consumption, improving environmental sustainability, and lowering operating costs are critical metrics in this pursuit (Zhu et al., 2019a). To achieve these goals, reducing aircraft weight has emerged as a particularly effective and promising strategy (Tsai et al., 2014). In the field of aircraft lightweighting research, the adoption of new designs and materials, such as composites and ultra-high specific strength alloys, has gained significant attention (Parveez et al., 2022; Li et al., 2023). While these advanced technologies offer promising benefits, ensuring the mechanical integrity of aircraft structures throughout their service life remains a critical challenge. This is especially true for the landing gear system, which is one of the most critical components

of an aircraft (Delprete et al., 2023). The landing gear is responsible for supporting the entire weight of the aircraft on the ground and must withstand severe impact and dynamic loads during take-off and landing (Divakaran et al., 2015). The complexity of the landing gear's structure, along with its numerous components, complicates inspection and maintenance processes, underscoring the importance of effective structural health monitoring (SHM) systems.

SHM systems have been successfully implemented in some engineering domains (Sofi et al., 2022; Ferguson et al., 2024), and the potential for application to aircraft structures has also been investigated (Rocha et al., 2021; Giurgiutiu, 2020). The current SHM is mainly based on direct data from sensors, followed by specific data processing and health diagnosis methods unique to different scenarios (Jena and Gupta, 2019; Iadicicco et al., 2019; Jin et al., 2017; Zhou et al., 2018; Hsu et al., 2022). Such SHM systems are generally reference-driven and based on testing of a model of the healthy structure under predefined working conditions (Bao and Li, 2021). However, for structures with complex

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and dynamic loads like aircraft landing gears, the actual load conditions are not easy to reproduce and predict (Ciminello et al., 2023). Therefore, accurately reflecting the actual loads through predefined working conditions is distorted, making this type of SHM have limitations when applied to aircraft landing gears, including: a limited number of sensors cannot provide the field stresses of the entire structure; and predefined working scenarios are not updated in a timely manner, which makes it difficult to provide valuable references for the comparison of sensor data.

A promising approach to address this challenge is the integration of a model of a specific structure into the SHM system through digital twin (DT) (Chia et al., 2024; Holmes et al., 2016; Seshadri and Krishnamurthy, 2017). Established numerical simulation models can be integrated into the DT system to reflect, in real time, the response of the structure at any location under actual loading conditions (Ye et al., 2020). This provides a more accurate and realistic reference than under predefined operating scenarios.

1.2. Related works

Some existing numerical simulations, such as the finite element method (FEM), have proved to be effective in many engineering fields. Caputo et al. (2018) developed a one-dimensional simplified model and a three-dimensional full-finite element (FE) model to investigate the reaction forces and structural stresses of a main landing gear during drop tests. They demonstrated that by introducing force boundary conditions obtained from the simplified model, local analyses of the component of interest could achieve the same accuracy as the full-FE model. Infante et al. (2017) supported this approach by modeling the separation of landing gear forks to analyze local stresses in critical areas. Dong et al. (2023) extended this approach to fatigue life analysis, proposing a stress-strength interference model for a front landing gear subjected to impact loading. In this model, local stresses from the FE analysis were used to create a stress spectrum, which was then converted into an equivalent damage spectrum. FEM has proven effective for investigating the stress behavior of landing gears under loads (Khan et al., 2021; Hameed et al., 2020; Wong et al., 2018). However, FEM is computationally expensive and time-consuming (Hoffer et al., 2021; Hoole et al., 2020; Kudela and Matousek, 2022), limiting its effectiveness for near real-time applications in DT systems. Near real-time data is very helpful in SHM and DT applications for load-bearing structures such as landing gear, as it can assist in the early detection of damage or fatigue before they become critical (Yuan, 2016). It also ensures that any problems in the landing gear, such as misalignment, excessive wear or structural deformation, are immediately flagged and resolved during the critical phases of takeoff and landing, thus increasing safety, improving maintenance processes and facilitating real-time decision-making (El Mir et al., 2024; Jason and Aryan, 2013).

To overcome these limitations, neural networks (Schmidhuber, 2015; Abiodun et al., 2019) are considered a potential alternative, capable of generating near real-time responses with reduced computational requirements. Currently deep neural networks (DNN) have been well established, deriving models such as recurrent neural networks (RNN), convolutional neural networks (CNN), and long short-term memory (LSTM) networks (Subasi, 2020; Cong and Zhou, 2023; Salehinejad et al., 2017; Yu et al., 2019). For the specific problem of stress prediction, some studies have proposed the use of conditional generative adversarial networks (cGAN) for stress field prediction. Ghanbari et al. investigated the prediction of residual stresses in surface indentations using the Kriging model and the K-Nearest Neighbor algorithm (Ghanbari and Mahmoudi, 2022). Hoq et al. investigated the use of CNNs and conditional generative adversarial networks for the prediction of stress distributions in flat plates with holes in non-homogeneous materials and found that cGAN performed better (Hoq et al., 2023). Similarly, Zhao et al. investigated the use of cGAN for the prediction of end-to-end stress field in composite bolted joints (Zhao

et al., 2024). Sun et al. investigated the prediction of the stress field on the inner bottom plate of a ship oil tanker using stress values at a finite number of point locations in a cGAN (Sun et al., 2024). These studies have made considerable improvements and extensions to the traditional deep learning models on the stress prediction problem, and achieved certain effects, especially the proposal of the related cGAN to utilize the image data. However, there are some limitations of this method, which is highly dependent on super-resolution image information, and needs to ensure the accuracy of the initial stress contour maps, and the applicability of stress contour maps for complex 3D structures is a challenge; and it does not take the a priori physical knowledge as a control condition, which may cause problems such as overfitting, and the generalizability is a challenge.

Regularization is essential to prevent overfitting during the training process of neural networks (Vidaurre et al., 2013; Cortes et al., 2012). For regression tasks that require accurate prediction, traditional regularization methods such as L1, L2 may not perform as effectively as desired when encountering training set with noise or small amount of data (Chen et al., 2020). Subsequently, physics-informed neural network (PINN) was proposed as new regularization techniques. PINN integrated real-world physical laws and principles into neural network learning, enhancing the accuracy and realism of predictions with minimal training data. PINN embed physical laws (Wang et al., 2024; Le-Duc et al., 2024; He et al., 2025), described by partial differential equations (PDEs), directly into the learning process by incorporating them into the loss function, which acts on outputs rather than neurons. This integration of a priori knowledge serves as a regularization term, allowing PINN to achieve accurate solutions with limited training data while mitigating overfitting (Raissi et al., 2019). Raissi et al. (2017) implemented a multilayer perceptron training algorithm using automatic differentiation (AD) in TensorFlow, combining it with data-driven methods to introduce the concept of physics-informed learning. Since then, PINN has been applied to solving Navier–Stokes equations in fluid dynamics and addressing complex dynamical system problems (Raissi et al., 2018b,a). Additionally, PINN algorithms have been refined to more effectively impose boundary conditions, solving dynamic weighting strategies in loss function, optimize network parameters, and solve inverse problems (Berg and Nyström, 2018; Al-Atroush, 2025; Kharazmi et al., 2019; Zhu et al., 2019b).

The strength requirements are high for landing gear, which undergoes elastic behavior when loaded. Recently, PINN has also been applied to elastic dynamics problems. de Almeida et al. (2023) developed PINN for a triangular plate under load with explicit boundary conditions, combining elasticity laws and boundary conditions into a neural network architecture to predict stress distribution in the plate. This training used generated analytic expressions instead of labeled data. Similarly, Rao et al. (2021) designed PINN with stress and displacement as mixed-variable outputs to simulate elastic dynamics without labeled data. They trained the boundary conditions, distance function, and generalized solution with separate DNN, then combined these independent DNN to reinforce the boundary conditions' constraints on the output. Integrating physical laws as a priori knowledge into the regularization term of the neural network output not only addresses overfitting but also enhances the interpretability of the network. For problems with well-defined boundary conditions, the automatic differentiation of PINN can be used to generate analytical expressions and train the network without labeled data. This capability has spurred increasing interest in the application of PINN to SHM over the past two years. For instance, Cross et al. (2022) proposed a grey box model for physical information machine learning and investigated two applications of PINN in SHM: predicting the longitudinal deflection of bridges under fluctuating temperatures and traffic loads, and predicting wave loads on bridges. Additionally, Al-Adly and Kripakaran (2024) examined the ability of PINN to predict deflection and bending moments of Kirchhoff plates, evaluating their performance under three

scenarios: constant load conditions as constraint equations, load as an input variable, and semi-rigid connections with noisy data.

Previous studies on PINN have demonstrated their effectiveness as PDE solvers and their ability to address simple physical system problems with well-defined boundary conditions. While these studies highlight the potential for applying PINN in SHM, there remains a significant gap in their application to complex, real-world engineering problems and practical usage scenarios. Specifically, in the context of near real-time prediction of stress in load-bearing structures, such as those in aircraft landing gear, further investigation is required on existing foundations. The core challenge lies in predicting the stress distribution within a load-bearing structure based on real-time load conditions. The loading environment in such scenarios is inherently complex and dynamic, often lacking explicit load boundary conditions that can be described by closed-form solutions (De Borst et al., 2012; Hughes, 2003; Kubenko and Yanchevskiy, 2017). As a result, training PINN in this context cannot rely solely on generated analytic expressions; instead, it necessitates obtaining plausible computed values through robust numerical methods.

1.3. Aim, objectives and main contributions

To solve these problems, this study proposes a PINN model trained by datasets generated from FEM simulations for near real-time stress prediction of a load-bearing structural component in landing gear system. We plan to limit the single running time of the PINN model to a few seconds to meet near-real-time prediction requirements. Therefore, embedding the PINN into the DT system enables near real-time computation and response under real-world load conditions. Leveraging the precise numerical capabilities of FEM alongside the adaptability of PINN could facilitate accurate predictions of stress distributions in landing gear structures under real-time load conditions. This integration has the potential to significantly advance SHM techniques, contributing to more effective and reliable engineering solutions in aerospace applications. The main contributions of this work are highlighted as follows.

- (1) Defined the dynamic load ranges of the studied nose landing gear from historical flight data of the A320 aircraft. Using the pseudo-random number method, multiple random load-time series were generated from the load spectrum to enable the predictive capability of the subsequent PINN to cover the real working scenarios.
- (2) Established a local finite element model of the studied landing gear drag strut and verified the model reliability. Structural stresses under the defined load conditions were simulated to generate data sets for training subsequent PINN.
- (3) Developed a PINN model that introduces the linear elasticity theory for near real-time prediction of field stresses in load-bearing structures, which can obtain real-time structural response at more points than the sensor-based approach and greatly reduce computational cost compared to the numerical approach of FEM.
- (4) Proposed several error metrics and compared differences between the PINN prediction results and the FEM benchmark values by visualization to investigate the prediction precision of this PINN model with different network complexity.

1.4. Paper organization

The remainder of this paper is structured as follows. In Section 2, the pseudo-random number method using historical overload data to create load conditions of landing gear is presented; modeling, boundary conditions, and solver selection in FEM are discussed; and the methodology adopted for building PINN model incorporating elasticity theory into the loss function is introduced. In Section 3, the created load conditions are described in detail; the results of convergence checks

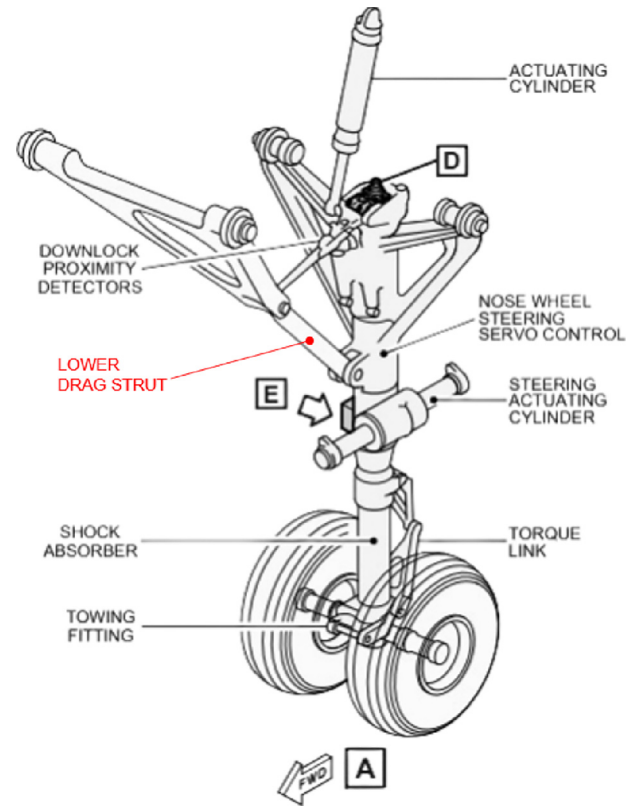


Fig. 1. The position of the referenced lower drag strut in the Airbus A320 NLG marked in red.

Source: Adjusted from Airbus (2022).

and mesh-independence analyses are discussed to ensure the accuracy of the FE model; the results of FEM under these load conditions are then discussed, followed by the evaluation of the PINN's prediction performance with various hyperparameters. In Section 4, the findings and accomplishments of this study are summarized, and outlook for future research is proposed.

2. Methodology

In this study, the load-bearing structure examined corresponds to the Airbus A320 nose landing gear (NLG) lower drag strut (Airbus, 2022), as depicted in Fig. 1. For the NLG, the main impact absorbing and dissipating appliances are the vertical shock absorbers and the tyres, while the drag strut is used to reinforce the longitudinal strength (Wu, 2019). Depending on its loading state, the main load on the drag strut is axial and can be simplified equivalently with axially concentrated force. This serves well as an input to the FEM and PINN. The loads during the landing braking roll (BR) phase were selected as the investigated working conditions.

We simplified the application of force and constraints on the drag strut to facilitate subsequent finite element analysis and PINN training. The simplified model is shown in Fig. 2, with one hole on each side. We assume that the left hole is completely constrained, while a clearance pin is inserted into the right hole. The time-varying load $F(t)$ will be transmitted to the drag strut through the pin.

The purpose of the PINN model proposed in this paper is to predict the stress distribution of the drag strut under a time-varying load. Therefore, its space-time coordinates and corresponding axial load: $(x, y, z, t, F(t))$, are used as inputs. where x, y, z are Cartesian coordinates; t is time; $F(t)$ is the load on the drag strut (F_{strut}) at time t .

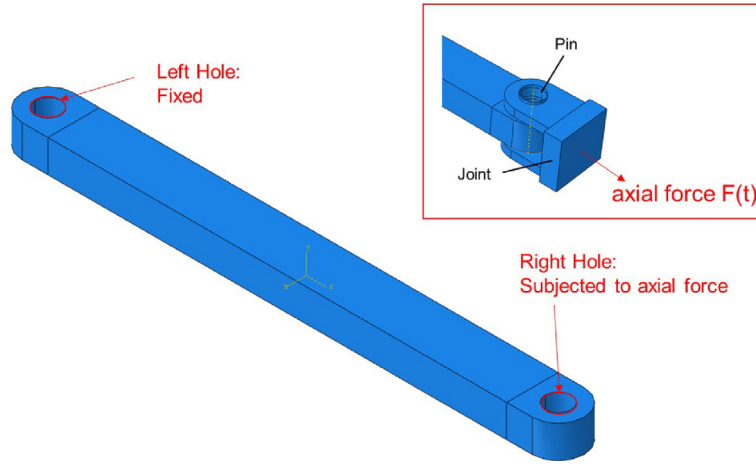


Fig. 2. Simplified drag strut model, with the left hole completely fixed and the right hole subjected to axial time-varying loads through a gap pin.

The research methodology is outlined in Fig. 3. First, the historical flight data of an A320 aircraft flight (Rustenburg et al., 2002) and public reports of landing segment data (van derGeest et al., 2010) were used to create a load spectrum to define multiple sets of the time-varying load conditions of the landing gear. Second, the drag strut was geometrically modeled, and its response under these load conditions during the BR phase was simulated using the FEM, generating field stresses outputs to generate comprehensive datasets. Convergence and mesh-independence checks were implemented to preliminarily assume the reliability of this FE model. Next, the corresponding physical governing equations were derived based on the response behavior, and these equations were incorporated into the loss function during the construction of the PINN to ensure that the predictions adhered to physical laws. Finally, the PINN were trained and validated using the simulation dataset.

2.1. PINN introducing the theory of linear elasticity

The PINN proposed in this paper is based on a deep neural network with multiple hidden layers and the basic equations of elastic theory as the physical governing equations. The results of subsequent FEM indicate that the landing gear structure exhibits a predominantly elastic behavior under the defined load conditions, as will be discussed in detail in Section 3.1.3. Therefore, the theory of linear elasticity was introduced as an a priori physical law for building the PINN. The governing equations can be written in the tensor form as follows:

$$\nabla \cdot \sigma + F = \rho \mathbf{u}_{tt} \quad (1)$$

$$\epsilon = \frac{1}{2}[\nabla \mathbf{u} + (\nabla \mathbf{u})^T] \quad (2)$$

$$\sigma = \mathbf{C} : \epsilon \quad (3)$$

where σ is the Cauchy stress tensor, ϵ is the strain tensor, $\mathbf{u}$ is the displacement vector, F is the body force vector, $\mathbf{C}$ is the constitutive tensor, ∇ is the Nabla operator.

In order to better constrain the PINN with the above governing equations and improve the trainability of the model, we ultimately use displacement $\mathbf{u}$ as the output. Therefore, when calculating the residuals of the PDEs, all three basic equations of the elasticity theory can be involved. In the contrast, if stress σ is used directly as the output, only the equilibrium equation (Eq. (1)) will affect the model training. The differences between these two models will be discussed in Section 3.3. The PINN architecture is shown in Fig. 4. The input is the spatiotemporal coordinate $\mathbf{X} = (x, y, z, t, F(t))$, the output is the displacement field $\mathbf{Y} = \mathbf{u}(u, v, w)$, and the sampling points are the mesh

nodes on the upper surface of the simplified model of the drag strut (in accordance with the mesh of the finite element model).

The loss function of this model consists of two parts: data loss L_d and physics loss L_p . Different from general models, for the data loss term, we define it as the mean square error (MSE) between the stress prediction values at each sampling node and the reference values from the FEM results. These stress prediction values are not the direct outputs of the neural network, but are calculated using displacement prediction values and Eqs. (2) and (3). The data loss L_d is as follows:

$$L_d = \|\sigma_{pred}(\mathbf{x}, F(t), t) - \sigma_{ref}(\mathbf{x}, F(t), t)\|_{\Omega \times [0, T]}^2 \quad (4)$$

where $\|\cdot\|^2$ denotes the MSE on the set of sampling points annotated by the corresponding subscript, $\mathbf{x}$ is the spatial coordinates of the sampling points (x, y, z) , Ω donates the entire training domain consisting of mesh nodes on the upper surface of the drag strut, T is the maximum time value of the time-varying load $F(t)$ in the input.

The physics loss L_p consists of the governing equation loss L_g and the initial/boundary conditions (I/BCs) loss L_{ic} and L_{bc} . The governing equation loss L_g is obtained by calculating the MSE of the residual of equilibrium equation (1), as shown in the following equation:

$$L_g = \|\nabla \cdot \sigma + F - \rho \mathbf{u}_{tt}\|_{\Omega \times [0, T]}^2 \quad (5)$$

Applying initial conditions and boundary conditions is crucial for solving the PDEs involved in this PINN, as this ensures a unique solution. For the case in this paper, the initial conditions are denoted as $\mathbf{u}(\mathbf{x}, t) = 0, \mathbf{x} \in \Omega, t = 0$, and the boundary conditions are denoted as $\mathbf{u}(\mathbf{x}, t) = 0, \mathbf{x} \in \Omega_L, t \in (0, T)$ and $\mathbf{u}(\mathbf{x}, t) = \mathbf{u}_b(\mathbf{x}, t), \mathbf{x} \in \Omega_R, t \in (0, T)$, where the set of all sampling nodes on the left hole is defined as Ω_L , and the set of all sampling nodes on the right hole is defined as Ω_R . Therefore, the initial condition loss L_{ic} and boundary condition loss L_{bc} are as follows:

$$L_{ic} = \|\mathbf{u}\|_{\Omega \times \{t=0\}}^2 \quad (6)$$

$$L_{bc} = \|\mathbf{u}\|_{\Omega_L \times [0, T]}^2 + \|\mathbf{u} - \mathbf{u}_b\|_{\Omega_R \times [0, T]}^2 \quad (7)$$

where $\mathbf{u}_b$ represents the displacement of all nodes in the Ω_R domain, i.e., the right hole, at time t . Since the external load $F(t)$ is applied through a gap pin, this variable is difficult to express using an explicit equation. Therefore, the value of $\mathbf{u}_b$ is sourced from the subsequent FEM results, i.e., $\mathbf{u}_b(\mathbf{x}, t, F(t)) = \mathbf{u}_{ref}(\mathbf{x}, t, F(t)), \mathbf{x} \in \Omega_R$.

The total loss function L_{total} of the PINN then includes both data loss L_d and physics loss L_p :

$$L_{total} = \lambda_d L_d + \lambda_g L_g + \lambda_{ic} L_{ic} + \lambda_{bc} L_{bc} \quad (8)$$

where λ is used to adjust the weights of these loss terms on the total loss. When training this PINN, we employ a dynamic weight scheduling

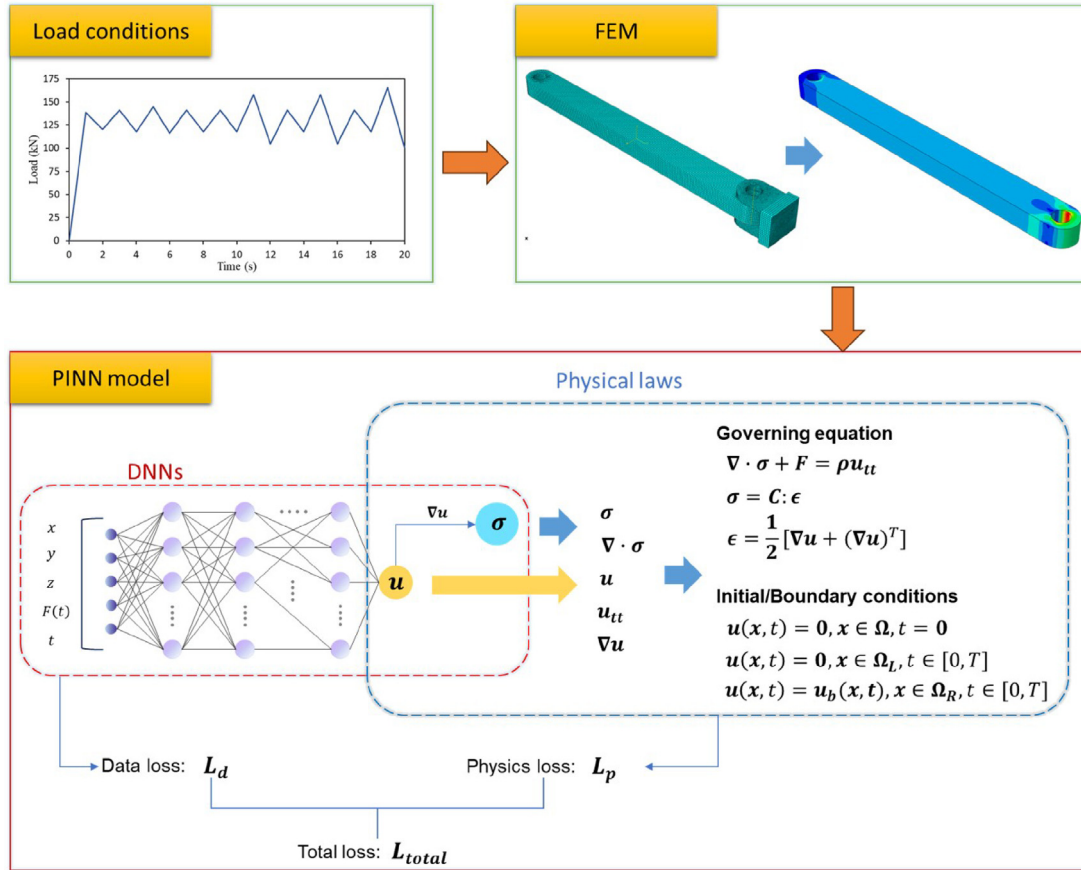


Fig. 3. The overall process of load conditions definition, finite element analysis and PINN development.

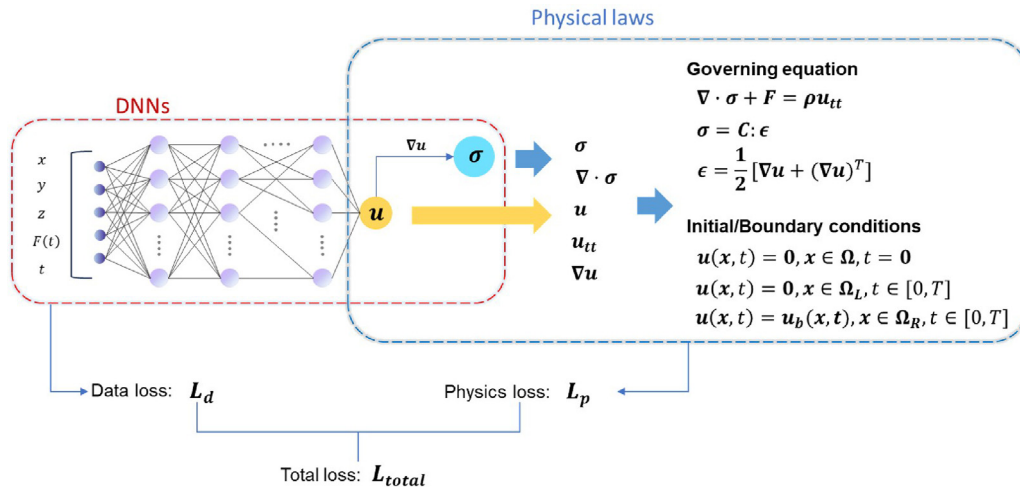


Fig. 4. Architecture of the PINN.

strategy, assigning higher weights to the physical constraint term L_g during the initial phase (when epochs are less than 5000). The objective is to first enable the network to find a solution that roughly satisfies physical principles (even if the displacement and stress are not yet accurate), thereby establishing a good starting point. During the main training phase, the weights of various constraints are dynamically and automatically balanced through the proportions of each loss term, enabling the network to begin fitting the data while adhering to physical laws.

2.2. PINN's automatic differentiation and computation process

For this PINN, in order to construct the loss function for the corresponding PDEs, we need to evaluate the partial derivatives of multiple physical fields with respect to spacetime variables. This computation can be achieved through automatic differentiation. The automatic differentiation adheres to two key rules: (1) Sum rule: the gradient between any two neurons is the sum of the partial differentials of all paths between them; (2) Chain rule: the partial differentiation of a path is the chain multiplication of the partial differentials between

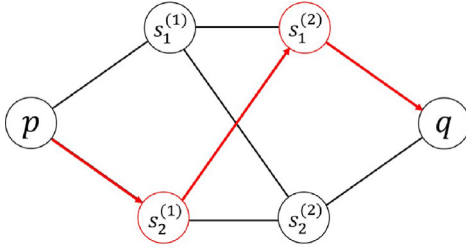


Fig. 5. A shallow neural network with two hidden layers of two neurons each; the partial derivative of q with respect to p has a total of four paths from output to input, each of which is derived following the chain rule and then summed; the red arrow connections represent one of the paths.

Table 1
Final selection of hyperparameters of the PINN architecture.

Hyperparameters	Details
Hidden layers	6
Neurons per layer	64
Activation function	tanh
Learning rate	0.0001
Epochs	40,000
Optimizer	Adam

each neighboring neuron on the path. For example shown in Fig. 5, the variable p is input into the network and transformed to get the output q .

The neuron $s_j^{(i)}$ in the hidden layer represents the output of the j th node in the i th layer. Then the partial derivative of q with respect to p can be calculated like follows:

$$\frac{\partial q}{\partial p} = \frac{\partial q}{\partial s_1^{(2)}} \frac{\partial s_1^{(2)}}{\partial s_1^{(1)}} \frac{\partial s_1^{(1)}}{\partial p} + \frac{\partial q}{\partial s_1^{(2)}} \frac{\partial s_1^{(2)}}{\partial s_2^{(1)}} \frac{\partial s_2^{(1)}}{\partial p} + \frac{\partial q}{\partial s_2^{(2)}} \frac{\partial s_2^{(2)}}{\partial s_2^{(1)}} \frac{\partial s_2^{(1)}}{\partial p} + \frac{\partial q}{\partial s_2^{(2)}} \frac{\partial s_2^{(2)}}{\partial s_1^{(1)}} \frac{\partial s_1^{(1)}}{\partial p} \quad (9)$$

where the red term corresponds to the red path in Fig. 5.

Using this AD technique, the complete computation process of this PINN first computes the displacement u through forward propagation, then automatically computes the displacement gradient ∇u , thereby obtaining the stress tensor σ through geometric equation (Eq. (2)) and constitutive equation (Eq. (3)). Subsequently, the partial differential terms of displacement and stress in the equilibrium equations are computed to obtain the residuals of the equilibrium equation (Eq. (1)), which are ultimately reflected in the corresponding loss function L_g . The process is shown in the Fig. 6.

During training, a conservative [32,4] network is first used to compare the loss function curves under different activation functions and optimizers. Then the network complexity is increased to compare the neural network's performance. After determining the network complexity, the learning rate and the number of epochs are then adjusted according to the training time and the fluctuation of the loss function curve. All sampling points are used for each epoch. Table 1 shows the selection of hyperparameters for this PINN model after experimenting with the model from 3 to 7 hidden layers and three activation functions (tanh, sigmoid and ReLU).

2.3. Generation of datasets for the PINN training

2.3.1. Load conditions definition of NLG drag strut during landing BR phase

This study is focused on the loads on NLG at level landing BR phase. Compared to the impact loads at ground touchdown, the loads in this phase act on the structure for a longer duration and are dynamic, varying over time. This makes the study of these loads particularly

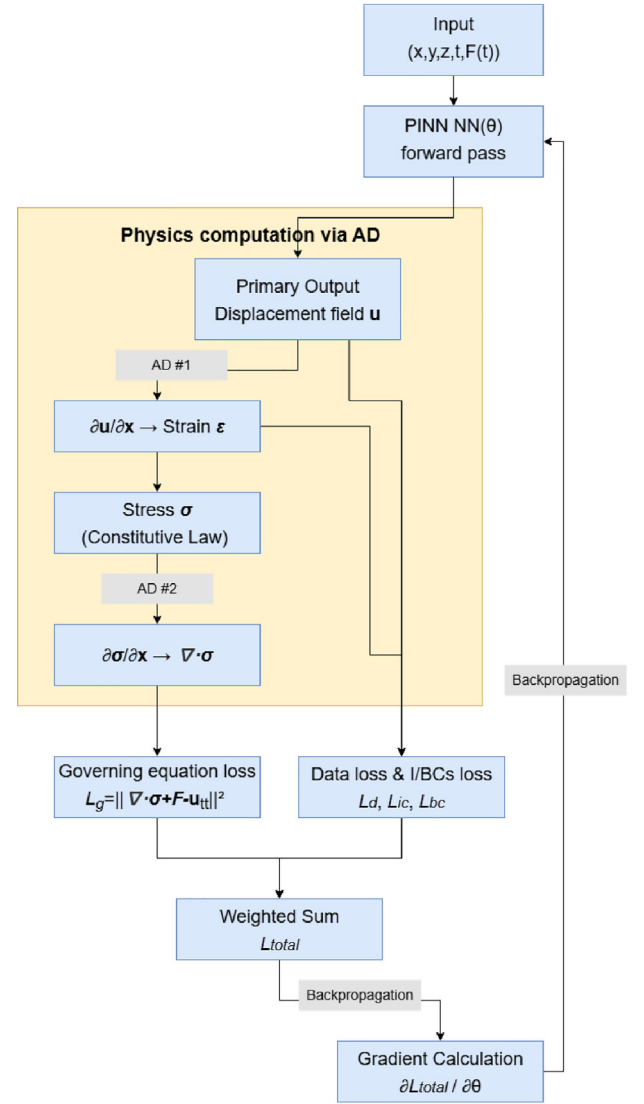


Fig. 6. Complete computation process of this PINN via AD.

Table 2
A320 aircraft typical limitations (Airbus, 2022).

Maximum taxi weight	Maximum takeoff weight	Maximum landing weight	Maximum zero-fuel weight
73 900 kg	73 500 kg	66 000 kg	62 500 kg

significant for SHM. The goal of this section is to define multiple sets of load-time series representing typical load conditions experienced by the NLG in this phase.

Typical parameters for an A320 aircraft are presented in Table 2. During this phase, the primary forces on the NLG considered are the vertical reaction force (vertical load, V_N) and the drag reaction force (longitudinal load, D_N), as depicted in Fig. 7.

The vertical load V_N , which primarily depends on the load factor n , can be calculated according to the following equations:

$$V_N = n \cdot W t_N \quad (10)$$

$$W t_N = p \cdot W t \quad (11)$$

where V_N is the vertical load on the entire NLG at load factor n ; $W t_N$ is the vertical load on the entire NLG at load factor $n = 1$; p is the

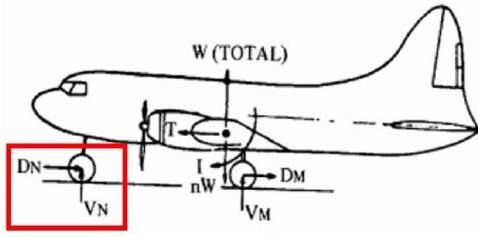


Fig. 7. Schematic of V_N and D_N on the NLG during the landing BR phase.
Source: Adjusted from EASA (2023).

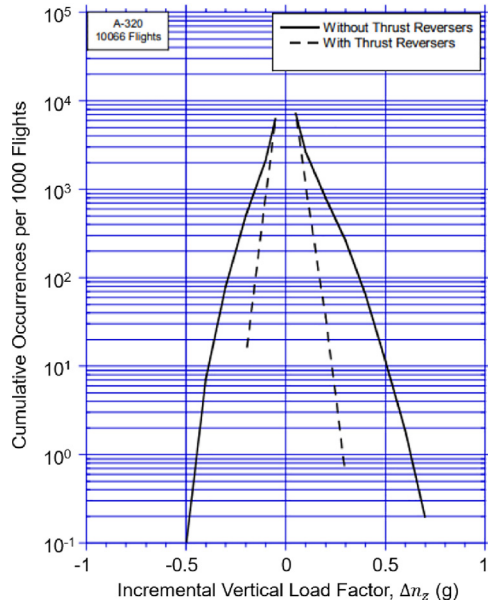


Fig. 8. Cumulative frequency of incremental vertical load factor Δn_z during landing braking roll.

Source: Adjusted from Rustenburg et al. (2002)

proportion of the total aircraft weight carried by the NLG; W_t is the total aircraft weight.

The longitudinal load on the NLG, D_N can be calculated by referring to CS 25.493 (EASA, 2023), where during the BR phase D_N is considered to be equal to the vertical load V_N multiplied by a coefficient of 0.8.

The load factor n was determined by referencing a statistical analysis of an A320 aircraft over 10,066 flights (Rustenburg et al., 2002), which demonstrated the cumulative occurrences of the minimum and maximum incremental vertical load factors (Δn_z) for the BR phase, illustrated in Fig. 8.

Using this cumulative frequency, a random load spectrum specific to the landing BR phase was produced. It should be noted that we take the most extreme cases as the boundaries of overload, specifically the cases where $n_{max} = 1.7$ and $n_{min} = 0.52$. Subsequently, a pseudo-random number method (Leybold, 1971; Heuler and Klaetschke, 2005) was employed to generate the desired load-time series for the load conditions.

The loads acting on the entire landing gear were not necessarily equivalent to those acting on individual components. Therefore, a load analysis of the landing gear was conducted to calculate the loads on the drag struts using a free-body diagram, as shown in Fig. 9.

It can be deduced from $\sum F_x = 0$, $\sum F_y = 0$, $\sum M = 0$ that the load on the drag strut $F_{strut} = 2.44V_N$.

2.3.2. FEM for analyzing stresses of the NLG drag strut

Establishing a well-developed geometrical model is essential for FEM and significantly influences the accuracy and convergence of the solution. Given the complexity of the entire landing gear system, modeling it in its entirety for analysis was difficult, and the computational demands were substantial. This study focused specifically on the stress behavior of the drag strut. To address computational efficiency limitations, the drag strut was isolated from the entire system and analyzed separately by applying equivalent boundary conditions and loads. Due to the lack of detailed part dimensions for the structure in this study, a simplified model of the drag strut was developed based on the schematic provided in the document (Airbus, 2022), as depicted in Fig. 10.

To ensure realistic load transfer, the pin and joint were modeled, taking into account the effect of the hole-pin clearance (0.025 mm) on the contact (Jiang et al., 2023). The overall assembly model is presented in Fig. 10. The primary focus of the analysis in the whole modeling was the drag strut. The stress of the pin and the joint was not of interest. Consequently, their geometries were not modeled as actual shapes but were simplified to ensure the correct application of loads and boundary conditions.

The drag strut was modeled using 7075 aluminum alloy, the joint using 300M steel, and the pin was modeled as a rigid body. Their material properties are presented in Table 3.

By using three different element types for meshing, namely (i) C3D8: 8-node linear hexahedral solid element (8 integration point); (ii) C3D8R: 8-node linear hexahedral solid element with reduced integration (1 integration point); and (iii) C3D20: 20-node quadratic hexahedral solid element (27 integration point), a convergence analysis and mesh-independence verification were performed to achieve an optimal solution with acceptable accuracy and computational efficiency. This will be discussed further in Section 3.1.2. The model after meshing is shown in Fig. 11. Mesh refinement was pre-applied to critical areas of potential stress concentration. The local refinement mesh size was 1 mm, while the overall mesh size was 5 mm. The entire assembly mesh consisted of 57,379 elements and 68,522 nodes.

In the locking state, the main loads on the drag strut were axial forces; therefore, shear and torque were neglected. The overall constraints and loads were applied as shown in Fig. 12. Displacement constraints were applied to allow the pin and joint to move along the X-axis (load direction) and to permit the pin's rotation around the Y-axis within the hole. Fixing the other hole of the drag strut simulated the locking state. The implicit general solver of a commercial software package, Abaqus, was used.

3. Results and discussions

3.1. Results of establishing the dataset

3.1.1. Random load-time series on the NLG drag strut during BR phase

Typically, for the normal center of gravity (CG) position of an A320 aircraft, the NLG supports approximately 10% of the aircraft weight during a level landing (Liu et al., 2023). Considering the maximum landing weight of 66,000 kg according to Table 2, the vertical load of this NLG at load factor $n = 1$ can be calculated from Eqs. (10) and (11), as shown in Table 4.

According to statistical operational flight data for A319/A320/A321 aircraft (van derGeest et al., 2010), the BR phase – defined as the interval from nose gear touchdown to stable taxiing (Exit) during the landing phase – typically lasts approximately 20 s. Consequently, in this study, multiple 20-s load-time series were created as the load conditions in the subsequent analysis.

Given the research objectives, the random load spectrum was formulated based on the overload frequency statistic, as described in Section 2.3.1. The resulting load profile is detailed in Table 5.

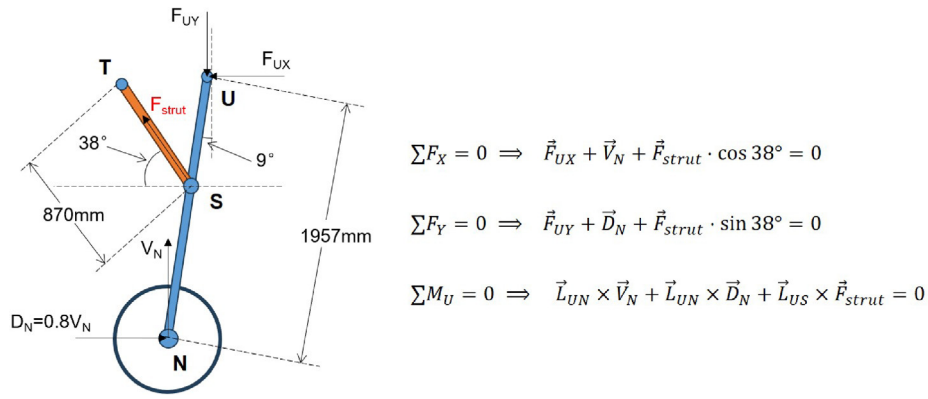


Fig. 9. Schematic of the NLG load analysis to compute the load on the drag strut.

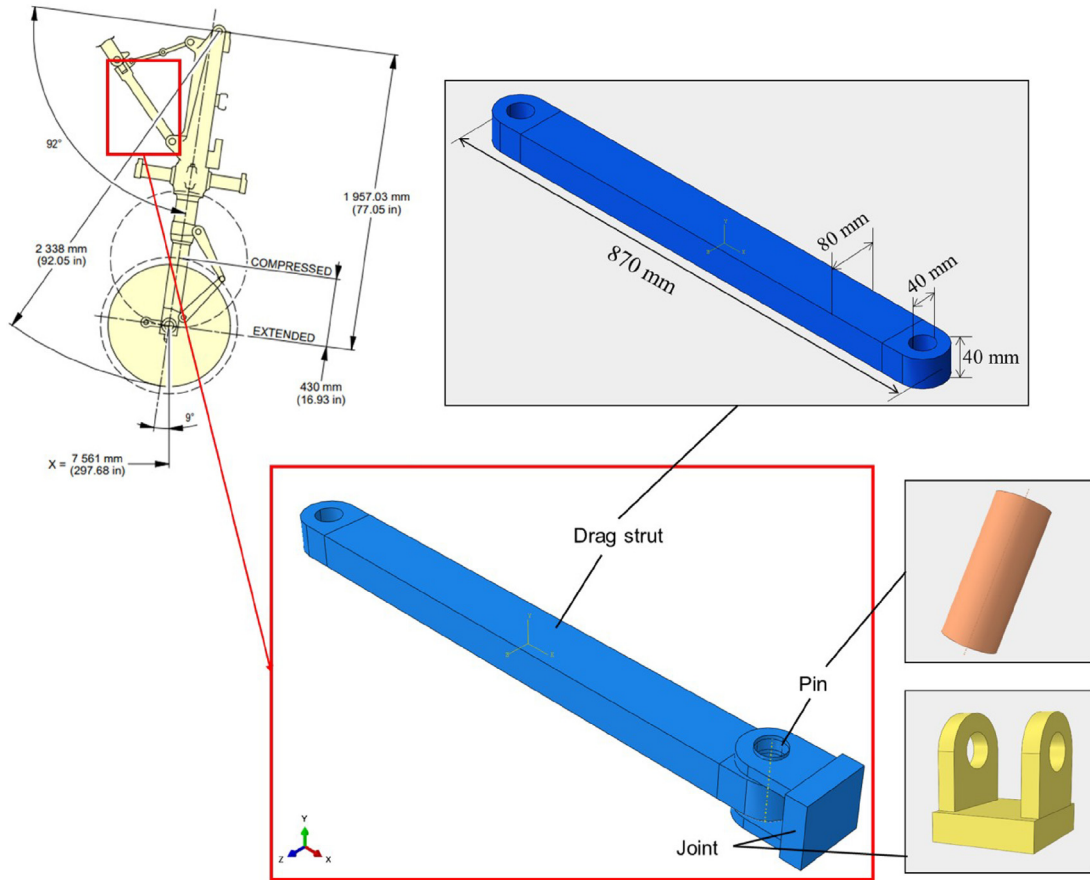


Fig. 10. Simplified local assembly model.

Table 3

Material properties of aluminum 7075 and 300M ultrahigh strength steel.

	Density	Young's modulus	Poisson's ratio	Tensile yield strength	Shear modulus
Aluminum 7075-T6	2810 kg/m ³	71.7 GPa	0.33	503 MPa	26.9 GPa
300M steel	7870 kg/m ³	205 GPa	0.28	1672 MPa	80 GPa

Table 4

Load on NLG at maximum landing weight with load factor $n = 1$.

Maximum landing weight	Weight-bearing ratio	NLG vertical load (W_{t_N})
66,000 kg	10%	6600 kg

The n_{max} and n_{min} were the maximum and minimum load factor, i.e., $1 + \Delta n_z$ from Fig. 8, which appeared in pairs in the load spectrum to indicate a cyclic load. Multiplying the frequencies per 1000 flights by 10,066 flights yielded the number of cycles in 10,066 flights for each load case. A total of 12 pairs of load cases were subdivided and each pair was assigned a number. Each pair was labeled according to the number of cycles in 10,066 flights.

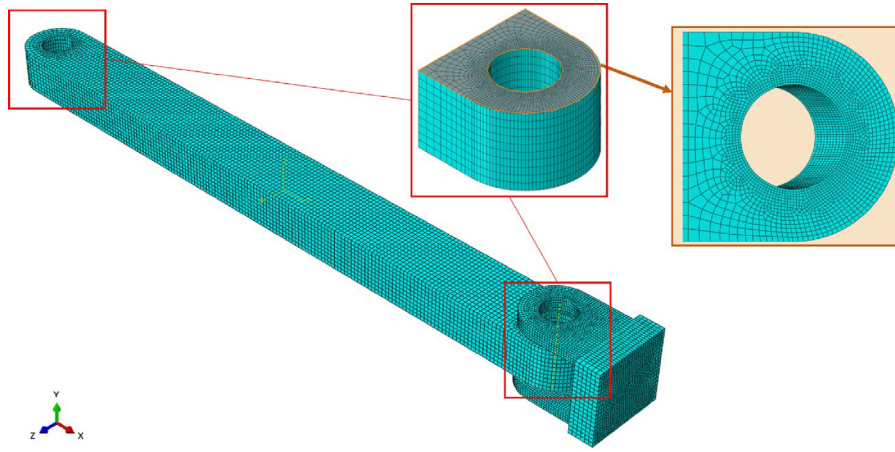


Fig. 11. Meshed view of the NLG drag strut local assembly and critical area mesh refinement.

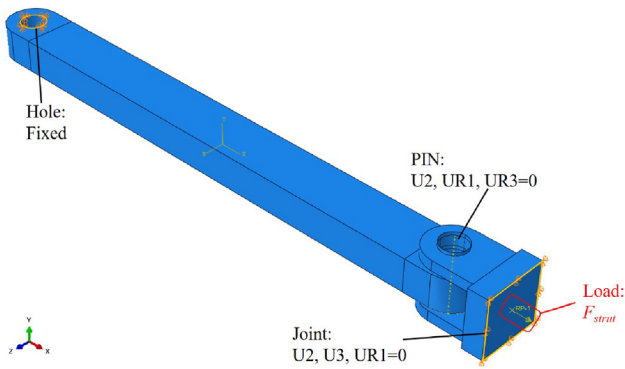


Fig. 12. Boundary conditions (U: translational displacement; UR: rotational displacement; 1, 2, 3: x, y, z).

Table 5

Random load spectrum based on cumulative frequency plots of incremental load factors in braking roll for 10066 flights data.

No.	n_{max}	n_{min}	Frequencies per 1000 flights	Cycles in 10066 flights	Label
1	1.70	0.52	0.2	2	1~2
2	1.62	0.54	1	10	3~12
3	1.55	0.60	3	30	13~42
4	1.51	0.68	10	100	43~142
5	1.40	0.69	60	603	143~745
6	1.36	0.72	100	1006	746~1751
7	1.28	0.78	300	3019	1752~4770
8	1.26	0.79	400	4026	4771~8796
9	1.22	0.81	600	6039	8797~14,835
10	1.12	0.90	2000	20,132	14,836~34,967
11	1.09	0.91	3000	30,198	34,968~65,165
12	1.07	0.93	4000	40,264	65,166~105,429

The sampling rate of load sensors to record the frequencies of incremental vertical load factor Δn_z from the history flight data (Rustenburg et al., 2002) was 1 Hz. Therefore, by defining each maximum-to-minimum load factor as one cycle over 2 s, the number of load cycles in the BR phase during a landing was $20/2 = 10$. Consequently, random load-time series were generated from this load spectrum using the pseudo-random number method, with a time length of 20 s and a total of 10 load cycles.

To generate this time-series load, a range of pseudo-random numbers between 1 ~ 105,429 was established, from which 10 numbers were sequentially extracted. The load cycles corresponding to these numbers (see “Label” in Table 5) were then arranged sequentially: the load at

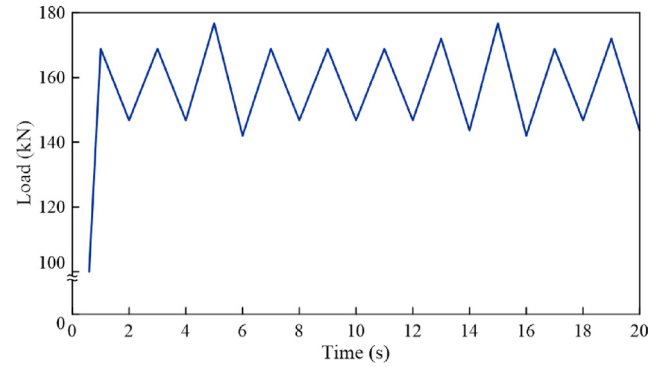


Fig. 13. Schematic of the load-time series on the drag strut during the landing BR phase referring to Table 7.

the first time stamp (at 1 s) is set to as n_{max} , the load at the next time stamp (at 2 s) is set to as n_{min} , and so forth, forming a load-time series with a length of 20 s.

For example, Table 6 shows a set of pseudo-random numbers with corresponding load factors. According to Eqs. (10) and (11), the force F_{strut} on the drag strut under this load condition could be calculated using n_{max} and n_{min} in Table 6: $F_{strut} = 2.44 \cdot n_{max/min} \cdot W_{tN} \cdot g$. Then the load-time series can be obtained, presented as in Fig. 13 and Table 7.

To ensure sufficient datasets for training the PINN while minimizing the amount of data, 25 sets of such load-time series were created as load inputs used for FEM and input variables in the PINN. 20 sets of these simulation results were used to train the developed PINN, while the remaining 5 sets were reserved for validation. One load-time series containing a set of maximum and minimum load pairs ($n_{max} = 1.7$, $n_{min} = 0.52$ in all created load-time series) were grouped into the training set, ensuring that the load range of the validation set is within the load range of the training set, since normalized feature scaling was applied to the inputs in PINN. The remaining ones were then randomly grouped.

3.1.2. Verification of convergence and mesh-independence of FE model

Iterative optimization of the FE model through convergence analysis and mesh-independence verification is essential to guarantee both the quality of the mesh and the accuracy of the output. Fig. 14 illustrates the stress results at $F_{strut} = 263.89$ kN.

Since the structure of interest was the drag strut, therefore the stress and deformation results for the pin and joint were not analyzed. As shown in Fig. 14, the mesh around the hole on the loaded side (critical area) was locally refined by increasing the number of nodes around

Table 6

A load factor series by the pseudo-random number method from Table 5.

Random number	96,248	72,652	29,022	79,517	81,339	75,163	53,127	32,474	88,966	62,959
No.	12	12	10	12	12	12	11	10	12	11
n_{max}	1.07	1.07	1.12	1.07	1.07	1.07	1.09	1.12	1.07	1.09
n_{min}	0.93	0.93	0.90	0.93	0.93	0.93	0.91	0.90	0.93	0.91

Table 7

Values of the load-time series on the drag strut during the landing BR phase referring to Table 6.

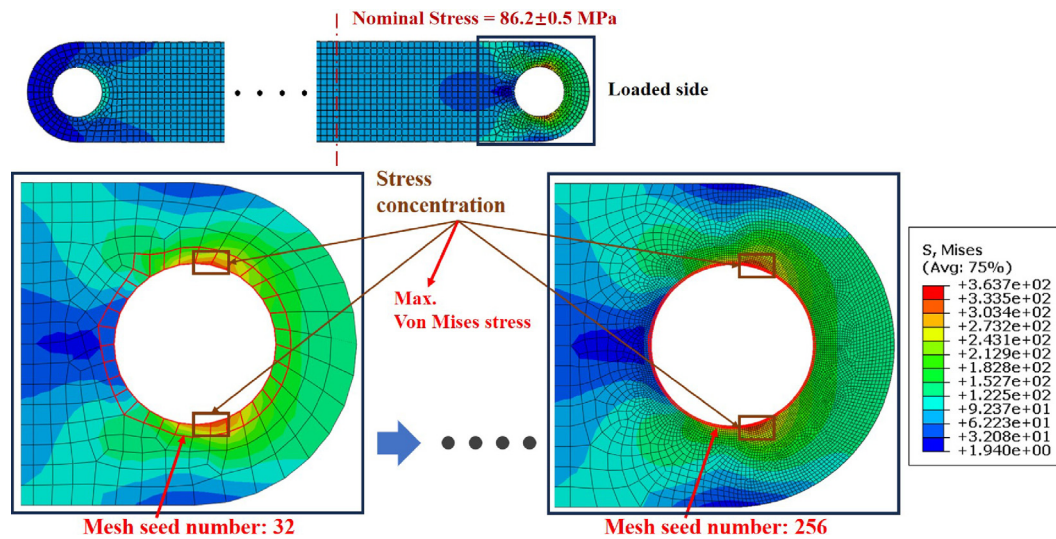
Time (s)	1	2	3	4	5	6	7	8	9	10
F_{strut} (kN)	168.87	146.77	168.87	146.77	176.76	142.04	168.87	146.77	168.87	146.77
Time (s)	11	12	13	14	15	16	17	18	19	20
F_{strut} (kN)	168.87	146.77	172.02	143.62	176.76	142.04	168.87	146.77	172.02	143.62

Table 8

Maximum von Mises stress results for FE models using C3D8R, C3D8 and C3D20 elements with stepwise local mesh refinement.

Element type	Mesh number (around hole)	Max. von Mises stress (MPa)	Elements number	Nodes number	ABS(Error)	Error %
C3D8R	32	293.3	1920	2541	70.8	19.45%
	64	313.9	5560	6831	50.2	13.79%
	128	333.2	18,100	21,186	30.9	8.49%
	256	346.2	59,760	68,090	17.9	4.92%
C3D8	32	332.7	1920	2541	31.4	8.62%
	64	352.2	5560	6831	11.9	3.27%
	128	360.4	18,100	21,186	3.7	1.02%
	256	363.7	59,760	68,090	0.4	0.11%
C3D20	64	361.3	5560	25,988	2.8	0.77%
	128	362.9	18,100	81,542	1.2	0.33%
	256	364.1	59,760	263,816	0	0.00%

The number of elements and nodes are counted within the critical area as shown in Fig. 14.

**Fig. 14.** Schematic diagram of stress distribution under coarse and fine meshes of the hole on the loaded side.

the hole. Simulations were performed using three different element types: C3D8R, C3D8, and C3D20. The minimum number of mesh seeds was 32, with a corresponding mesh size of approximately 4 mm, while the maximum number of mesh seeds was 256, with a mesh size of approximately 0.5 mm.

Fig. 14 illustrates the von Mises stress distribution of the FEM results using C3D8 element, as well as the local mesh refinement process. The stress concentration areas are symmetrically distributed and remain at the same location across different mesh sizes, which is consistent with expectations. A summary of the maximum von Mises stress results for the three element types is presented in Table 8.

The phenomenon of local stress being significantly higher than the average value due to changes in geometry is called stress concentration (Murakami, 2019). The hole in this drag strut can lead to a stress concentration due to the smaller cross-section. Stress concentration factor (SCF) is the ratio of the highest stress in the part to the nominal stress (Craig and Taleff, 2020). Nominal stresses are undisturbed far-field stresses (Fricke, 2011), which in this study are the average stress value of the middle section of the drag strut. The FEM result using the element type of C3D20 with 256 mesh seeds around the hole yields a maximum von Mises stress of 364.1 MPa and a nominal stress of 86.28 MPa, resulting in a SCF of 4.22. The SCFs of certain typical structures have been included in the 'Stress Concentration Handbook' (Pilkey

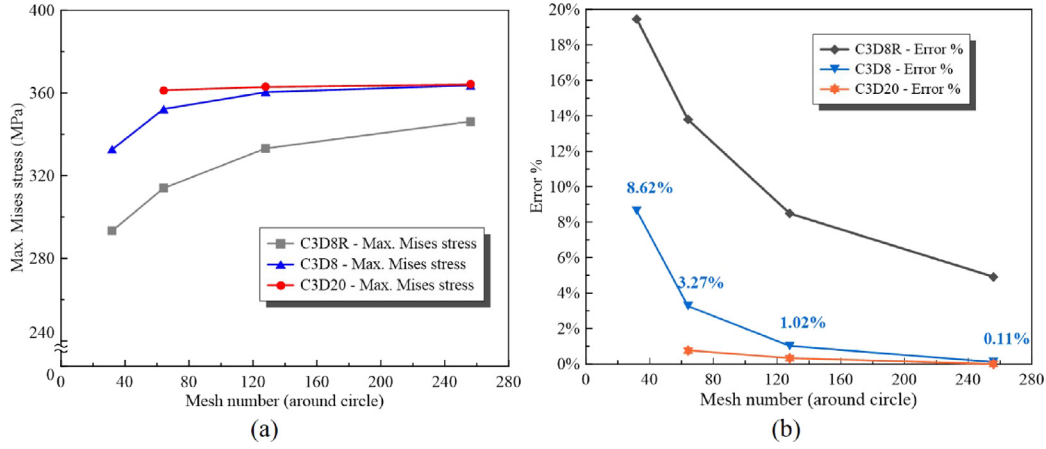


Fig. 15. (a) shows the variation of the maximum von Mises stress with mesh refinement; (b) shows the percentage error between the maximum von Mises stress and the benchmark value.

et al., 2020). The validity of the FE model can therefore be judged by comparing the reference SCFs in the handbook with the SCFs obtained from the FEM results (Kumar et al., 2019). Reviewing the handbook, the SCF of a similar structure to the drag strut with holes at two sides (same critical dimensions: hole diameter and plate width in Fig. 10) is 4.25, which is close to 4.22, indicating that this FE model can be assumed to be valid. For the FE models with different element types and mesh densities in this section, the nominal stresses can be considered identical (nominal stresses computed from different FE models is within 86.2 ± 0.5 MPa) because the total cross-sectional area and load are constant. Therefore, the FE model using C3D20 element with 256 mesh seeds around the hole is used as a benchmark and comparing the maximum von Mises stresses of other cases against it, the error trend can be derived in Fig. 15.

According to Fig. 15 and Table 8, for each element type, the maximum von Mises stress increases with mesh refinement and gradually converges towards the benchmark value of 364.1 MPa. The maximum increase observed is 19.45%, indicating an improvement in solution accuracy with mesh refinement, rather than a stress singularity. This suggests that the FE model exhibits acceptable mesh convergence. Fig. 15(b) shows that accuracy improvement is minimal after refining the mesh around the hole to 128 seeds. To balance both accuracy and computational efficiency, a coarser mesh should be selected within acceptable error limits. Consequently, the C3D8 element with 128 mesh seeds around the hole was selected as the final configuration.

3.1.3. FEM results for the NLG drag strut under load

The simulation results for a certain load condition (as Fig. 13), are discussed here, out of the total 25 random load-time series. The results for all load conditions exhibited a similar pattern, differing only in the specific values.

Fig. 16 illustrates the equivalent stress distribution (von Mises stress) on the drag strut. The maximum stress occurs to the right of the top and bottom vertices of the hole on the loaded side. Considering the clearance between the pin and hole, this location of maximum stress is consistent with expectations. The maximum stress 194.8 MPa is far below the tensile yield stress of 503 MPa for this material. Therefore, in the loss function of the PINN, the differential equations of linear elasticity were introduced.

Fig. 16 also shows the stress distribution in the critical area at the peak load per second. The pattern of stress variations suggests that the structure is in a state of approximate cyclic loading. This is attributed to the low peak random loads acting on the landing gear during the BR phase, which vary at high frequencies. Unlike the significant impact of a landing gear touchdown, these load conditions are prone to cause fatigue accumulation, potentially leading to crack formation. Therefore,

providing near real-time simulation of the loaded structure's state is valuable.

In this study, the structure of the drag strut is symmetric and the stress distribution along the Y-axis is symmetric. Moreover, for SHM applications, the sensing devices are generally mounted near the surface of the structure in practice. Therefore, the data of all the mesh nodes on the upper surface (Y_{max}) in Fig. 17 are used as sampling points in PINN.

3.2. Performance of the PINN with different network complexity

We first investigated the impact of network complexity on the prediction accuracy of the PINN, analyzing the performance of PINN models with the number of neurons and layers (width $\times$ depth) ranging from $[32 \times 3]$ to $[64 \times 7]$. The predictions of the PINN are evaluated using two metrics: normalized root mean square error (NRMSE) and normalized mean bias error (NMBE), as presented in Eqs. (12) and (13). NRMSE evaluates the average percentage magnitude of the error between the predicted values and the baseline values (from the validation dataset generated by FEM) while NMBE evaluates the systematic bias tendency of the model.

$$NRMSE = \frac{1}{\frac{1}{N} \sum_{i=1}^N |b_i|} \sqrt{\frac{1}{N} \sum_{i=1}^N (p_i - b_i)^2} \times 100\% \quad (12)$$

$$NMBE = \frac{\sum_{i=1}^N (p_i - b_i)}{\sum_{i=1}^N b_i} \times 100\% \quad (13)$$

where p_i is the predicted value and b_i is the baseline value.

The error metrics for the prediction accuracy of the PINN with different network complexity are presented in Table 9. It can be seen that as the number of network layers and neurons increases, the error of stress component prediction becomes smaller. Especially when the number of neurons increases from 32 to 64, the error reduction is particularly significant. For each network complexity configuration, the NMBE of the predicted values exhibits a consistent bias (overestimation), which decreases as the network complexity increases. Among these configurations, the $[64 \times 6]$ and $[64 \times 7]$ networks demonstrate significantly higher prediction accuracy, and the NRMSE of the predicted values from the $[64 \times 6]$ network is slightly lower than that of the $[64 \times 7]$ network.

Also, it is important to note that for sampling points with low stress levels, even if the absolute error is only a few MPa, the percentage error can be very large, rendering it meaningless. In addition, low-stress points in the structure are not typically considered failure locations in practice. Therefore, the mean absolute error (MAE) and the percentage error relative to the maximum stress value (REm) are introduced as

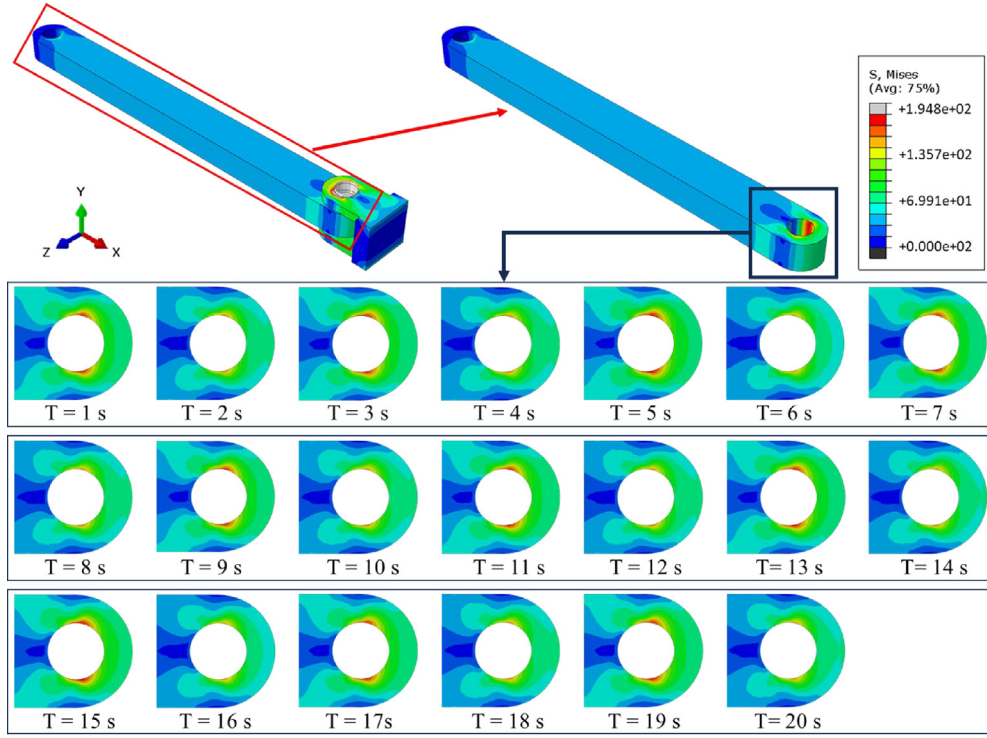


Fig. 16. Equivalent stress distribution on the drag strut over time under a set of load-time series.

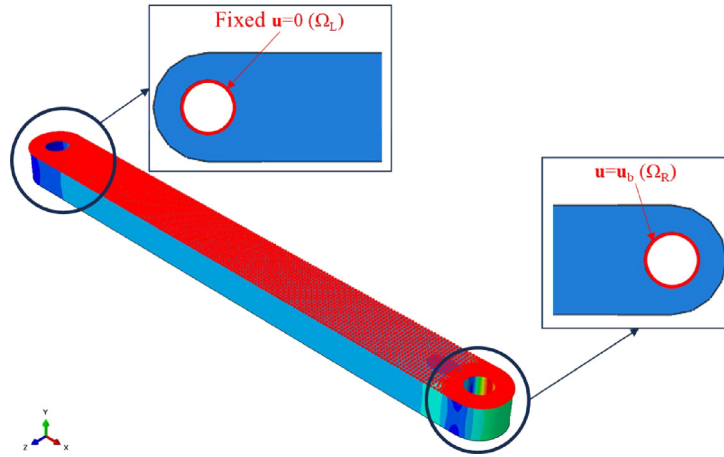


Fig. 17. Data points used in PINN.

Table 9

Error metric summaries with regard to the width and depth of the PINN; The FEM results are used as reference to compute the errors of stress components.

Width × Depth	σ_x		σ_z		τ_{xz}	
	NRMSE	NMBE	NRMSE	NMBE	NRMSE	NMBE
32 × 3	28.72%	16.95%	32.81%	19.89%	29.39%	17.39%
32 × 4	26.51%	14.04%	27.11%	13.99%	27.57%	16.44%
32 × 5	23.28%	12.78%	22.90%	12.55%	23.49%	12.57%
32 × 6	21.08%	10.25%	22.26%	11.35%	22.76%	10.57%
64 × 4	15.33%	8.41%	17.84%	8.39%	17.58%	8.96%
64 × 5	9.66%	5.26%	10.82%	5.82%	10.55%	6.17%
64 × 6	5.98%	3.68%	6.09%	3.64%	6.22%	4.20%
64 × 7	6.02%	3.23%	6.84%	3.98%	6.13%	3.55%

error metrics to evaluate the performance of the PINN, as presented in Eqs. (14) and (15). REM represents the relative error of the absolute error of each data point with respect to the maximum stress point of the

whole structure, providing a more accurate reflection of the prediction accuracy in high-stress areas.

$$MAE = \frac{1}{N} \sum_{i=1}^N |p_i - b_i| \quad (14)$$

$$REM = \frac{|p_i - b_i|}{Max. \sigma} \times 100\% \quad (15)$$

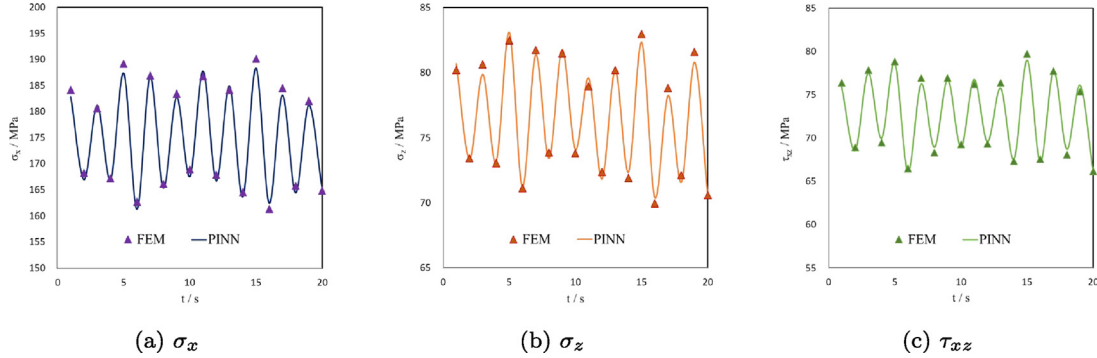
where p_i is the predicted value; b_i is the baseline value; $Max. \sigma$ is a constant ($Max. \sigma_x$, $Max. \sigma_z$ and $Max. \tau_{xz}$)

Table 10 presents the error metrics for further research of the PINN with different network complexity. It can be seen that the values of these two error metrics decrease as the network complexity increases, and the MAE of both the [64 × 6] and [64 × 7] networks is less than 32 MPa. For high-stress regions (greater than 100 MPa), this represents a satisfactory error range. In addition, the [64 × 6] network's predictions are more accurate than those of other configurations, with a maximum REM of around 4%, slightly outperforming the [64 × 6] network.

Table 10

Error metric summaries of MAE and maximum RE_m with regard to the width and depth of the PINN; The FEM results are used as reference to compute the errors of stress components.

Width × Depth	σ_x		σ_z		τ_{xz}	
	MAE (MPa)	Max.RE _m	MAE (MPa)	Max.RE _m	MAE (MPa)	Max.RE _m
32 × 3	6.87	16.95%	7.85	19.89%	7.03	17.39%
32 × 4	6.34	14.04%	6.49	13.99%	6.60	16.44%
32 × 5	5.57	12.78%	5.48	12.55%	5.62	12.57%
32 × 6	5.04	10.25%	5.32	11.35%	5.45	10.57%
64 × 4	3.54	8.41%	4.12	8.39%	4.06	8.96%
64 × 5	2.23	5.26%	2.50	5.82%	2.44	6.17%
64 × 6	1.38	3.68%	1.41	3.64%	1.44	4.20%
64 × 7	1.45	4.15%	1.53	4.68%	1.48	4.19%

**Fig. 18.** Comparison of PINN predictions and FEM reference values for the three maximum stress components.

Based on the analysis above of the number of layers and neurons in PINN, the network configuration [64 × 6] showed better prediction performance. Therefore, this configuration was used for subsequent stress prediction and analysis. Taking the load conditions shown in Fig. 13 as an example for the input of t and $F(t)$, we use the PINN with a configuration of [64 × 6] to predict the stress at the sampling points on the upper surface of the drag strut. We compared the prediction results of several sampling points with relatively high stress with the FEM reference values, as shown in the Fig. 18. It can be seen that under this configuration, the predicted values of PINN for the three stress components are highly consistent with the FEM reference values.

In addition, for the scenario of time-varying load input illustrated in Fig. 13, a comparison between the stress values predicted by the PINN and the FEM results is presented in the Fig. 19. It can be observed that the stress distribution predicted by PINN shows satisfactory consistency with the FEM reference values.

3.3. Comparison between the proposed PINN, a PINN that directly outputs stress, and a purely data-driven DNN

To further investigate the characteristics of the proposed PINN architecture (denoted as PINN(displacement&stress form)), particularly how the output and loss function affect the predictive ability, we trained two other network models and compared them with the proposed PINN model. These two models are: (1) a PINN model based on pure stress output, denoted as PINN(stress form); and (2) a pure data-driven DNN model based on pure stress output, denoted as DNN(pure data). Due to the different output targets selected, the settings of their loss functions differ from those of the proposed PINN. For PINN (stress form), the physics loss reads:

$$L_p = \|\nabla \cdot \sigma\|_{\Omega \times [0, T]}^2, L_{total} = L_d + L_p \quad (16)$$

For DNN(pure data), the loss function only includes data loss, which reads:

$$L_{total} = L_d = \|\sigma_{pred}(\mathbf{x}, F(t), t) - \sigma_{ref}(\mathbf{x}, F(t), t)\|_{\Omega \times [0, T]}^2 \quad (17)$$

Fig. 20 shows the comparison between the stress prediction results of the three models for the drag strut at a certain time and the FEM reference values. From the stress contour plots, it can be seen that the consistency between PINN(displacement&stress form) predictions and FEM reference values is more satisfactory than that of PINN(stress form) and DNN(pure data). In addition, the error contour plots show that PINN(displacement&stress form) has much lower error and a relatively uniform distribution, while PINN(stress form) and DNN(pure data) exhibit regular patterns of error, with significant errors in regions of high stress gradient and high stress values. In comparison, the prediction performance of the PINN proposed in this paper demonstrates a significant advantage.

3.4. Comparison of computational efficiency between the proposed PINN and FEM

For the need to perform near-real-time stress monitoring of landing gear structures, using the drag strut situation shown in Section 2 as a typical example, a simple SHM process is shown in Fig. 21. To achieve this stress monitoring, we hope that the numerical model in this DT has the ability to predict stress in near real time, i.e., after receiving time-varying load input, it can output stress field data within few seconds.

Table 11 shows the running time of the two simulation models under same load conditions. The PINN and FEM in this study are both tested on the same platform, configured as: (1) CPU: Intel i7-10700 @ 2.9 GHz, (2) GPU: NVIDIA RTX A2000 6 GB, (3) RAM: 32 GB. For single stress prediction, the FEM requires approximately 6000 s, while the PINN takes only around 2 s, illustrating the significant speed advantage of PINN over FEM for near real-time simulation. Although the process of training PINN may take longer than establishing an FE model due to the need to build datasets, it is clear that FE models are difficult to solve in a short time for the above stress prediction problem. Compared with PINN, FE models are not suitable for SHM processes that require real-time feedback. It is evident that the proposed PINN model has the potential to be applied in a DT system that requires timely responses, which would contribute to the structural health monitoring of such aircraft load-bearing structures.

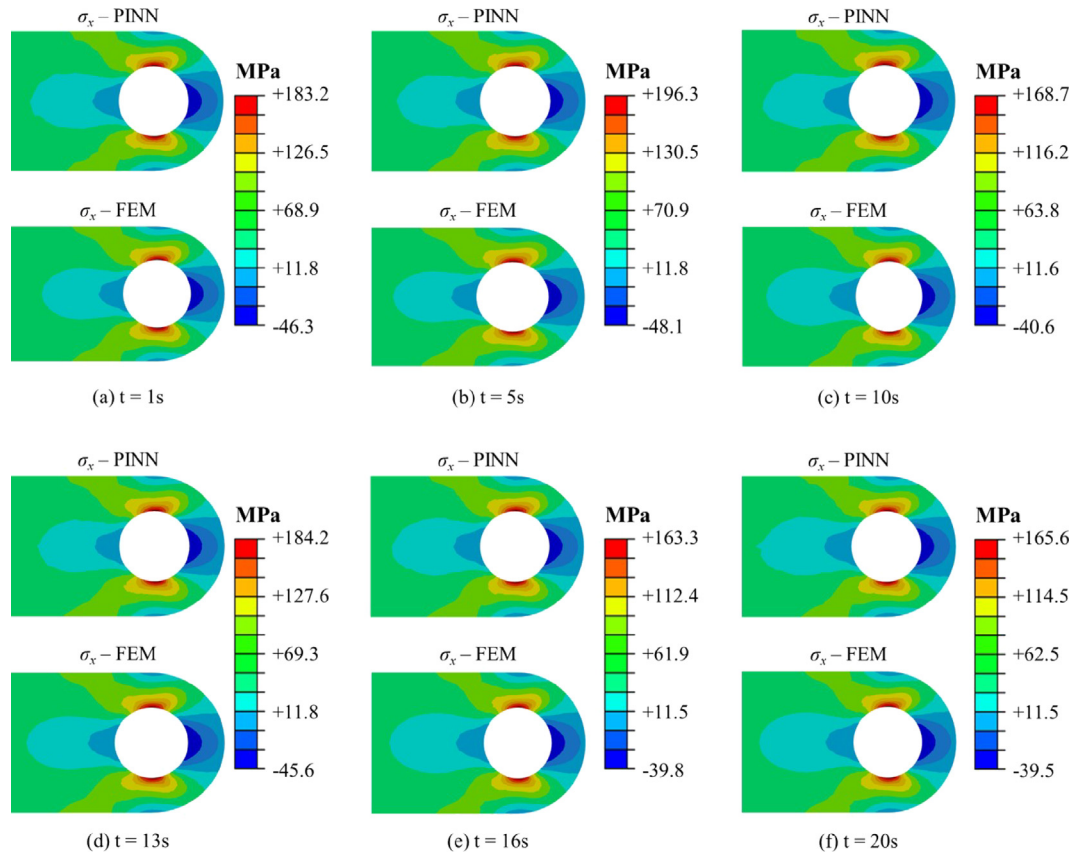


Fig. 19. Comparison of the stress distribution at several time point around critical area of the drag strut under a time-varying load.

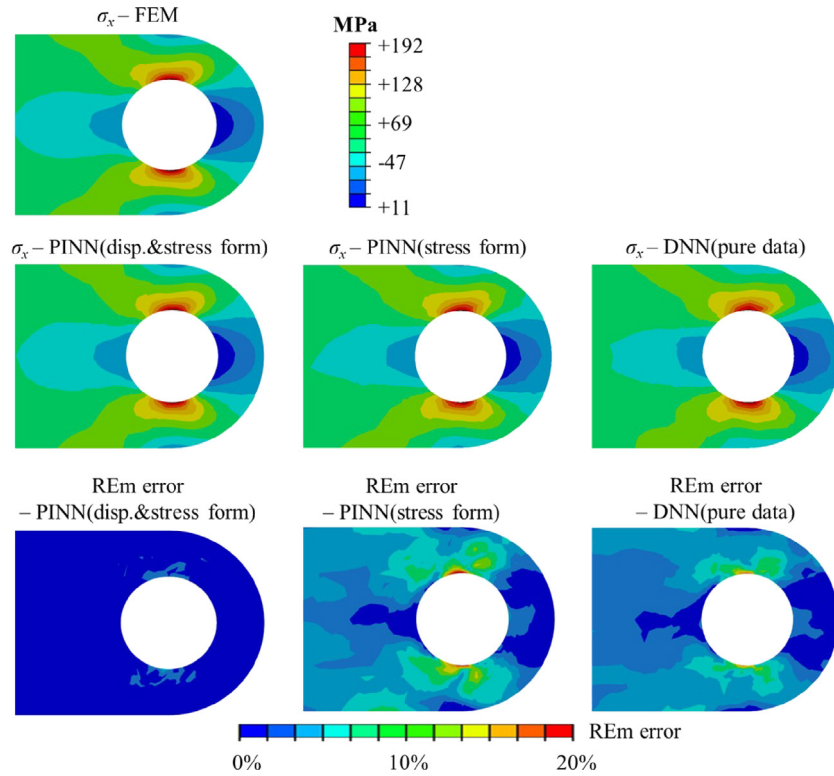


Fig. 20. Comparison of the stress fields produced by the proposed PINN(displacement & stress form), the PINN(stress form), DNN(pure data) and FEM.

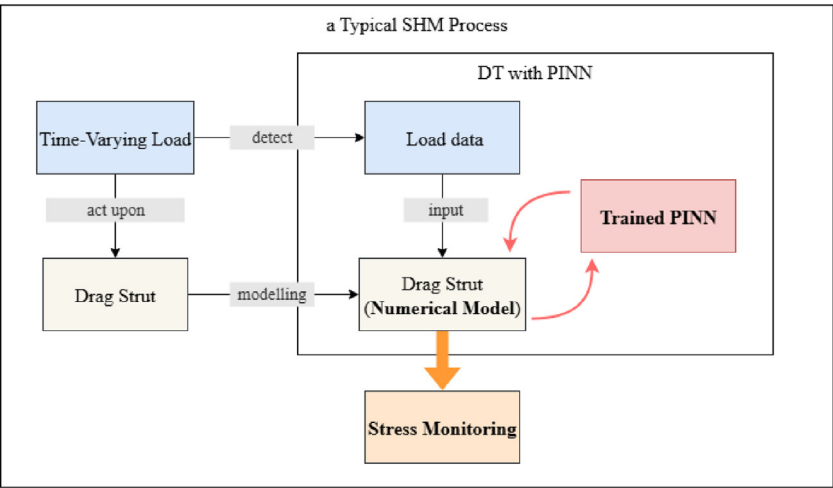


Fig. 21. A typical SHM process using PINN as a numerical model in DT for predicting drag strut stress.

Table 11
Comparison of simulation running time in PINN and FEM.

Method	Simulation time
FEM	~6000 s
PINN	~2 s

4. Conclusion and outlook

In this work, we propose a PINN framework for near-real-time prediction of the stress field of landing gear struts under time-varying loads. The PINN uses displacement as the direct output and stress as the secondary output, incorporating the basic equations of elasticity theory into the physical governing equations of the loss function, and establishing a displacement boundary loss function for the gap hole using FEM data as reference values, thereby improving the trainability of the network. In the stress prediction problem of the A320 NLG drag strut studied in this work, the PINN demonstrates good prediction accuracy, with relative errors ranging from 5% to 7% compared to the reference values. Compared to pure stress-output PINN and DNN, this scheme significantly improves the accuracy and trainability of the network. In addition, when establishing the dataset, this work adopts a load condition definition method based on actual landing gear load statistics and uses FEM to obtain displacement and stress fields under various load conditions, providing more realistic and representative training data for the development of the proposed PINN. Based on this dataset, the PINN demonstrates an excellent near-real-time prediction capability, enabling it to predict the stress field of the drag strut under time-varying loads within seconds, showcasing its potential for application in stress monitoring of landing gear load-bearing structures. In summary, this study contributes to the advancement of DT systems for SHM of aircraft load-bearing components by presenting an in-depth evaluation of the proposed PINN. However, challenges remain in extending the application to more real-world structures. Future research in this topic could focus on: (1) Incorporating physical testing to refine the FE model and mitigate biases in the original dataset; (2) Extending stress predictions from the surface of a structure to include its interior in three dimensions, thereby enabling the monitoring of full-field stresses within complex structural geometries.

CRediT authorship contribution statement

Zixuan Zhu: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Software, Revision. **Yifan Zhao:** Writing – review & editing. **Agusmian Partogi Ompusunggu:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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