PREDICTING THE SIMULATION RESULT OF LOCOMOTIVE COMPONENTS USING ANN

M.Tech. Thesis

By

SACHIN KUSHWAHA

DEPARTMENT OF MECHANICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY INDORE

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A THESIS

Submitted in partial fulfilment of the requirements for the award of the degree

of

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by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **PREDICTING THE ANALYSIS OF LOCOMOTIVE COMPONENT** in the partial fulfilment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** and submitted in the **DEPARTMENT OF MECHANICAL ENGINEERING, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from July 2023 to June 2025 under the supervision of Dr. Aman Khurana , Assistant Professor .

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

28-05-2025

Signature of the student with date
SACHIN KUSHWAHA

This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge.

29-05-2025

Signature of the Supervisor of
M.Tech. thesis (with date)
(Dr. AMAN KHURANA)

SACHIN KUSHWAHA has successfully given his/her M.Tech. Oral Examination held on **23rd MAY 2025.**

Signature of Supervisor of M.Tech. thesis
Date: 29-05-2025

Convener, DPGC
Date:29-5-2025

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Abstract

This thesis investigates the application of a physics-informed artificial intelligence (ai) model for the structural analysis of locomotive components, with a specific focus on the blower cab, a critical subsystem responsible for ventilation in railway locomotives. The research investigates the ability of the AI model to forecast the structural behaviour of the blower cab under different pillar thicknesses, utilizing a dataset of simulation files to train, evaluate, and predict results.

The methodology encompasses the generation of blower cab models with thicknesses ranging from 3 mm to 6.5 mm, finite element analysis (FEA) to produce result files, and the training of a physics-informed neural network to predict displacements. Testing on six configurations (3.5 mm and 5.5 mm thicknesses) yields accuracies exceeding 97%, with mean absolute errors (MAE) of 0.705 mm and 0.239 mm, respectively, and prediction times of less than 1 minute compared to 20 minutes for FEA. Predictive results for thicknesses of 4.5 mm and 6.5 mm (22.36 mm and 22.25 mm maximum displacements) align with structural mechanics principles, demonstrating a consistent decrease in displacement with increasing thickness. The model's high accuracy can be attributed to minimal design variations, although slight reductions in accuracy for specific configurations indicate sensitivity to the range of training data.

The study also elucidates key concepts in neural network modelling, including epochs, width, depth, confidence values, early stopping, and learning rate, tailored to physics-informed ai applications. The results highlight the model's effectiveness in quickly assessing designs with minor variations, achieving an accuracy rate of over 97% across all test scenarios, while emphasizing the importance of traditional analysis tools for significant modifications. Future research endeavours intend to expand the model to encompass larger locomotive components, such as the engine and platform, and incorporate additional structural metrics, including stress and fatigue, to provide a more comprehensive analysis. This study develops a flexible framework that

combines physics-based artificial intelligence with locomotive design, enabling efficient and automated structural optimization in railway engineering.

TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

ACRONYMS

ANN – Artificial neural network

FNN – feed forward neural network

FEA – finite element analysis

AI – artificial Intelligence

RNN – recurrent neural network

CNN – Convolutional neural network

LSTM – Long short-term memory

MAE – Mean absolute error

AAR – Association of American railroad

CFD – Computational fluid dynamics

HMI – Human machine interface

PTC – Positive train control

APU – Auxiliary Power Unit

PINN – Physics Informed Neural Network

FEM – Finite Element Method

HVAC – Heating Ventilation Air Conditioner

CAD – Computer Aided Design

Chapter 1 Introduction

The fast-paced development of artificial intelligence (AI) has transformed numerous industries, and the rail sector stands out as a significant beneficiary. Rail transportation

heavily relies on locomotives, which are intricate systems that require exceptional reliability, efficiency, and safety. The utilization of artificial intelligence, particularly through neural networks, presents substantial opportunities to improve locomotive performance by enabling predictive maintenance, optimizing traction, and facilitating autonomous operations. The focus of this thesis is the incorporation of neural networks into locomotive systems, taking inspiration from the groundbreaking work done by Wabtec corporation, a renowned pioneer in the field of rail technology. This introduction offers a thorough overview by explaining the basics of neural networks, the functioning of locomotives, and the impact of AI on revolutionizing locomotive systems.

1.1 Neural networks: basics and concepts.

Neural networks are computational models that draw inspiration from the structure and functionality of the human brain, enabling them to handle intricate data and recognize patterns (goodfellow et al., 2016). A neural network is composed of interconnected nodes, known as neurons, arranged in layers: an input layer, one or more hidden layers, and an output layer. Each node holds a value and processes inputs through weighted connections, utilizing an activation function to generate an output. The network refines these weights during the training process, commonly employing backpropagation and optimization methods like gradient descent.

1.1.1 Organization of artificial neural systems.

A typical neural network comprises:

The input layer of the system processes raw data, such as sensor readings or operational parameters, in locomotive applications. Beneath the surface carry out calculations, extract meaningful information, and uncover hidden patterns through interconnected nodes. Output layer generates the final prediction or classification, such as identifying faults or determining maintenance schedules.

Weights are assigned to the connections between nodes, indicating the level of influence one node has on another. Activation functions, including sigmoid, RELU (rectified linear unit), or Tanh, introduce non-linearity, allowing the network to capture intricate relationships.

1.1.2 **Classification of neural networks.**

There are various types of neural networks that are applicable to locomotive applications:

Feedforward neural networks (FNN): data flows in one direction, making them ideal for static data processing tasks, such as predicting the wear of locomotive components. Recurrent neural networks (RNN): specifically designed for sequential data, with loops that enable the retention of previous inputs, making them well-suited for analysing locomotive sensor data over time.

Convolutional neural networks (CNN): highly effective for image-based tasks, such as analysing track images to detect defects.

Long short-term memory (LSTM) networks: a specific type of recurrent neural network (RNN) that is particularly effective in capturing long-term dependencies, making it ideal for analysing track maintenance logs.

Development of Our Skills

Neural networks acquire knowledge through a training process, where they modify weights to minimize a loss function, often utilizing labelled data. The training comprises:

Input data flows through the network, leading to the generation of predictions. The loss calculation involves finding the difference between the predicted and actual outputs, which is done using a loss function like mean squared error.

Backpropagation: The gradients of the loss function are computed, and weights are adjusted using optimization algorithms such as adam or stochastic gradient descent. The ability to learn and adapt makes neural networks valuable tools for predicting outcomes and making decisions in intricate systems like locomotives.

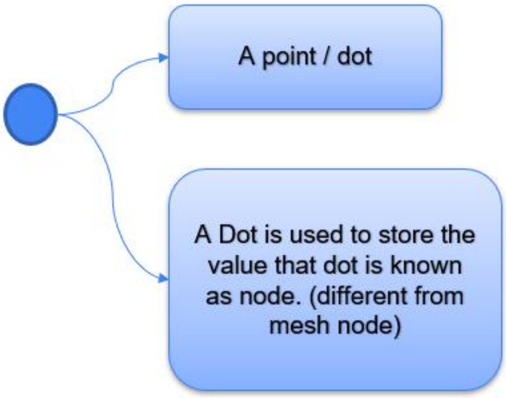

Figure 1 : Showing the node.

In the context of network-based computational models, a node, often represented as a discrete point or vertex within a graph-theoretic framework, serves as a fundamental unit for storing data or values pertinent to the system's operation. These nodes are linked by edges, forming a network structure that encompasses the connections and interactions between individual data points. This network architecture enables the representation and processing of intricate information, like the synaptic connections found within the human brain. Specifically, the network's functionality mirrors cognitive processes by facilitating dynamic information exchange, pattern recognition, and adaptive learning, like neural networks in biological systems. Such a structure underpins various computational paradigms, including artificial neural networks (ANN), where nodes (or neurons) process input data through weighted connections, iteratively adjusting based on learning algorithms to optimize performance, thereby emulating the adaptive and parallel processing capabilities of the human mind.

In the field of computational intelligence and machine learning, a group of nodes, typically represented as vertices in a graph-based structure, are combined to form a layer within a neural network architecture. Each node, acting as a separate processing unit, stores and manipulates data values, often representing features or activations within the context of the model. These layers, consisting of numerous interconnected nodes, are systematically arranged to create a neural network, a highly sophisticated computational structure that is capable of modelling intricate relationships within data. In this architectural structure, every node in a specific layer is connected to nodes in neighbouring layers through weighted edges, creating a network of connections that enables the smooth flow and transformation of information. This intricate network, often called a neural network, mimics the synaptic connections found in biological

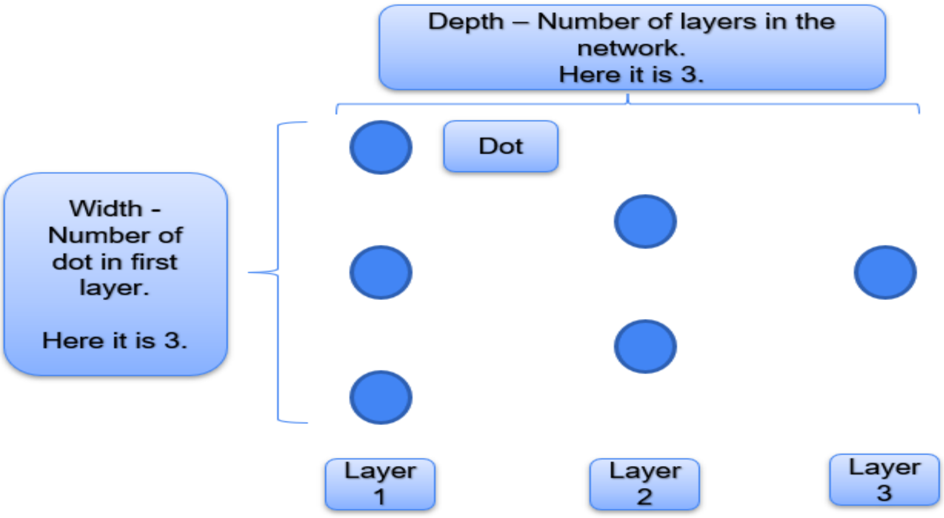

Figure 2 : Artificial Neural Network showing width and depth.

neural systems, allowing for capabilities like pattern recognition, data categorization, and predictive modelling through iterative learning processes guided by algorithms like backpropagation. The neural network's hierarchical processing capability, supported by its layered arrangement and inter-node connectivity, enables it to extract and refine features at different levels, resulting in reliable computational performance.

1.2 Locomotives: Locomotives are mechanical systems created to pull trains, powered by diesel, electric, or hybrid engines. The components of the electric vehicle consist of several critical parts, such as the engine, traction motors, braking systems, and control units, which must function reliably in different conditions. Wabtec, a renowned global company specializing in rail technology, has been at the forefront of innovation in locomotive design and operation, leveraging artificial intelligence (AI) to optimize performance .

1.2.1 **Components of locomotives.**

Engine: supplies power, usually through diesel combustion or electric motors.

Traction motors: Transform energy into mechanical force to propel the wheels, where adhesion control is crucial for optimal performance.

Control systems: Oversee operations, including speed, braking, and diagnostics, with the help of artificial intelligence for real-time decision-making.

Sensors: gather information on variables such as temperature, vibration, and fuel consumption, supplying inputs for artificial intelligence models.

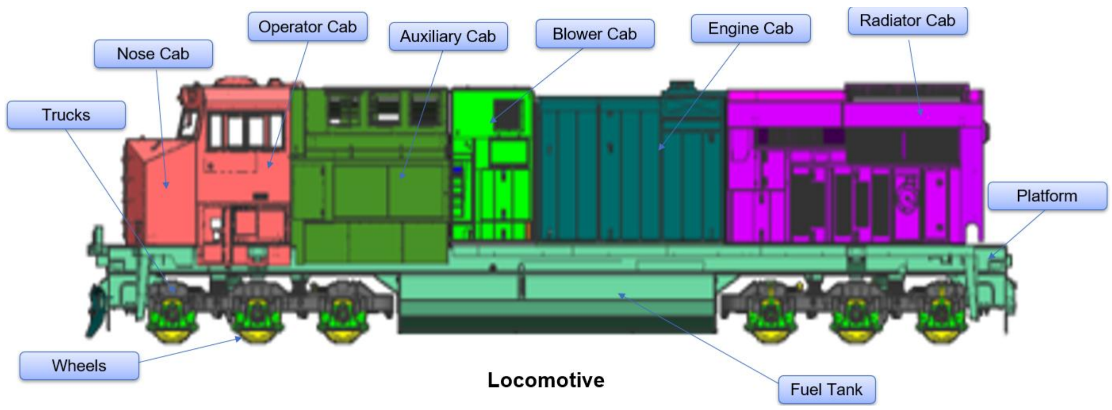

Figure 3 : Locomotive and its parts.

1.2.2 Parts of Locomotive

1. Wheels

The wheels of a locomotive are critical mechanical components that facilitate movement along the railway track. Typically constructed from high-strength steel alloys, locomotive wheels are designed to withstand significant dynamic loads, including the weight of the locomotive, payload, and tractive forces. The wheels are arranged in pairs, mounted on axles, and often feature a flanged design to ensure alignment with the track. The wheel-rail interface is engineered to optimize traction, minimize wear, and ensure stability during high-speed operations or under varying track conditions. The wheel geometry, including diameter and profile, is carefully specified to balance load distribution and rolling resistance, adhering to standards such as those set by the International Union of Railways (UIC) or the Association of American Railroads (AAR).

2. Trucks

Trucks, also referred to as bogies in railway terminology, are modular assemblies that support the locomotive's chassis and house the wheelsets, axles, and suspension systems. Each truck typically consists of a frame, multiple wheel-axle sets, and a suspension system (e.g., coil springs or air springs) to absorb shocks and vibrations caused by track irregularities. Trucks distribute the locomotive's weight across multiple axles, enhancing stability and reducing track wear. In modern locomotives, trucks may incorporate advanced features such as traction motors (in electric or diesel-electric locomotives) and braking systems, contributing to the locomotive's dynamic performance and operational safety.

3. Nose Cab

The nose cab refers to the forward section of the locomotive, often aerodynamically shaped to reduce air resistance and improve fuel efficiency, particularly in high-speed locomotives. Structurally, the nose cab may house auxiliary equipment, such as signalling systems, headlights, or collision mitigation devices (e.g., buffers or anti-climbers). In some locomotive designs, the nose cab serves as an aesthetic and functional element, protecting internal components from environmental factors while minimizing drag. The design of the nose cab is informed by aerodynamic principles and computational fluid dynamics (CFD) to optimize performance under diverse operating conditions.

4. Operator Cab

The operator cab, also known as the driver's cab or control cab, is the primary workspace for the locomotive's crew, housing the controls, instrumentation, and interfaces necessary for safe and efficient operation. Ergonomically designed, the operator cab includes throttle controls, brake systems, monitoring displays, and communication systems compliant with railway signalling standards. Advanced locomotives may feature digital dashboards, human-machine interfaces (HMIs), and integration with train control systems such as Positive Train Control (PTC) or European Train Control System (ETCS). The cab is engineered to provide visibility, acoustic insulation, and protection from environmental hazards, ensuring operator comfort and safety during extended operations.

5. Auxiliary Cab

The auxiliary cab is a secondary compartment or designated area within the locomotive that houses auxiliary systems critical to its operation. These may include electrical control panels, battery storage, or auxiliary power units (APUs) that provide energy for non-propulsive functions, such as lighting, heating, or onboard electronics. In some locomotive designs, the auxiliary cab may also contain diagnostic equipment or redundant control systems to enhance operational reliability. The layout and functionality of the auxiliary cab are optimized to ensure accessibility for maintenance and integration with the locomotive's primary power and control systems.

6. Blower Cab

The blower cab refers to a compartment or section of the locomotive dedicated to housing the blower systems, which are essential for cooling and ventilation. In diesel-electric or electric locomotives, blowers (typically centrifugal or axial fans) are used to circulate air through the engine, traction motors, or other heat-generating components to prevent overheating. The blower cab is strategically positioned to ensure efficient airflow and is equipped with ducts, filters, and noise suppression systems to maintain operational efficiency and comply with environmental regulations. The design of the blower cab is critical to thermal management, particularly in high-power locomotives operating under demanding conditions.

7. Engine Cab

The engine cab, often referred to as the engine compartment, is the primary housing for the locomotive's prime mover, which is typically a diesel engine in diesel-electric locomotives or a transformer and power electronics in electric locomotives. This compartment is engineered to protect the engine from environmental factors, facilitate maintenance access, and incorporate vibration-damping and noise-reduction measures. The engine cab is equipped with fuel lines, exhaust systems, and cooling interfaces, ensuring optimal performance of the prime mover. In modern locomotives, the engine cab may also integrate advanced monitoring systems for real-time diagnostics and predictive maintenance.

8. Radiator Cab

The radiator cab is a specialized compartment that houses the locomotive's radiator and associated cooling systems, designed to dissipate heat generated by the engine or electrical components. The radiator cab typically includes a heat exchanger, cooling fans, and coolant circulation systems to maintain optimal operating temperatures. Efficient thermal management within the radiator cab is critical to preventing engine overheating, particularly during high-load or high-temperature conditions. The design of the radiator cab incorporates considerations of airflow dynamics, material selection (e.g., corrosion-resistant alloys), and maintenance accessibility to ensure long-term reliability and performance.

9. Platform

The platform refers to the structural base or chassis of the locomotive, which serves as the foundation for mounting all major components, including the trucks, engine, cabs, and fuel tank. Constructed from high-strength steel or composite materials, the platform is designed to withstand significant mechanical stresses, including torsional forces, vibrational loads, and impacts. The platform also provides structural integrity to the locomotive, ensuring alignment of components and facilitating load transfer to the wheels. In some designs, the platform includes walkways or access points for maintenance personnel, adhering to safety standards for railway operations.

10. Fuel Tank

The fuel tank is a critical component in diesel locomotives, designed to store and supply diesel fuel to the engine. Typically located beneath the platform or integrated into the locomotive's underframe, the fuel tank is constructed from robust materials (e.g., steel or aluminium) to ensure durability and prevent leaks. The tank's design includes features such as baffles to minimize fuel sloshing, fuel gauges for monitoring, and safety systems to prevent spillage or combustion risks. The capacity and placement of the fuel tank are optimized to balance the locomotive's weight distribution and operational range, with considerations for fuel efficiency and compliance with environmental regulations.

1.2.3 Obstacles in our process.

Locomotives encounter numerous obstacles that AI can tackle.

Maintenance: unexpected downtime caused by component failures leads to increased expenses and delays. Predictive maintenance using artificial intelligence can reduce this. Maximizing fuel efficiency and traction while driving on different tracks and in various weather conditions is crucial for saving money.

Safety: identifying track defects or operational anomalies in real-time improves safety

Environmental impact: optimizing operations to minimize emissions in line with global sustainability goals.

AI utilization in trains: Wabtec Corp.'s involvement.

Wabtec corporation has been leading the way in incorporating artificial intelligence (ai) into locomotive systems, utilizing neural networks for a wide range of applications. Notable advancements include:

Predictive maintenance: Wabtec employs artificial intelligence to analyse locomotive data, generating customized maintenance instructions based on the specific needs of each locomotive, resulting in reduced downtime and expenses. Wabtec's cutting-edge adhesion control technology, powered by ai, enhances haulage capability by 15% compared to competitors by dynamically optimizing traction in real-time. Wabtec utilizes edge ai to analyse data in real-time while the locomotive is in operation, allowing for immediate decision-making in locomotive operations (Wabtec, 2024).

Chapter 2 Methodology

Altair hyper mesh physics ai follows a systematic five-step process, with each step playing a vital role in ensuring precise predictions and efficient computational modelling. The procedures followed are as follows:

1. Project initiation: this initial phase involves defining and naming the project while specifying the location of the input files. To maintain uniformity and ease of access, all input files should be kept in a single, organized folder.

2. Dataset Preparation: In this step, the necessary data is collected and organized in a way that is suitable for analysis. This dataset forms the basis for model training, significantly impacting the accuracy and dependability of the predicted results.

3. Model Training: The training phase involves feeding the dataset into the AI model, enabling it to learn patterns, correlations, and crucial relationships within the data. Fine-tuning hyperparameters and employing optimization techniques are implemented to improve performance.

4. Model Testing: After the training phase, the model is subjected to extensive testing using a distinct dataset to ensure its accuracy and reliability. This assessment examines the model's accuracy, generalizability, and effectiveness in predicting outcomes on data that it has not been trained on.

5. Prediction Generation: In the final stage, the trained model is utilized to generate predictions using new input data. The AI system employs learned patterns to offer valuable insights and computational solutions for intricate physics-based simulations. By following a structured approach, this method guarantees a step-by-step progression from project initiation to final predictions, maximizing the potential of Altair hyper mesh physics ai for scientific and engineering purposes.

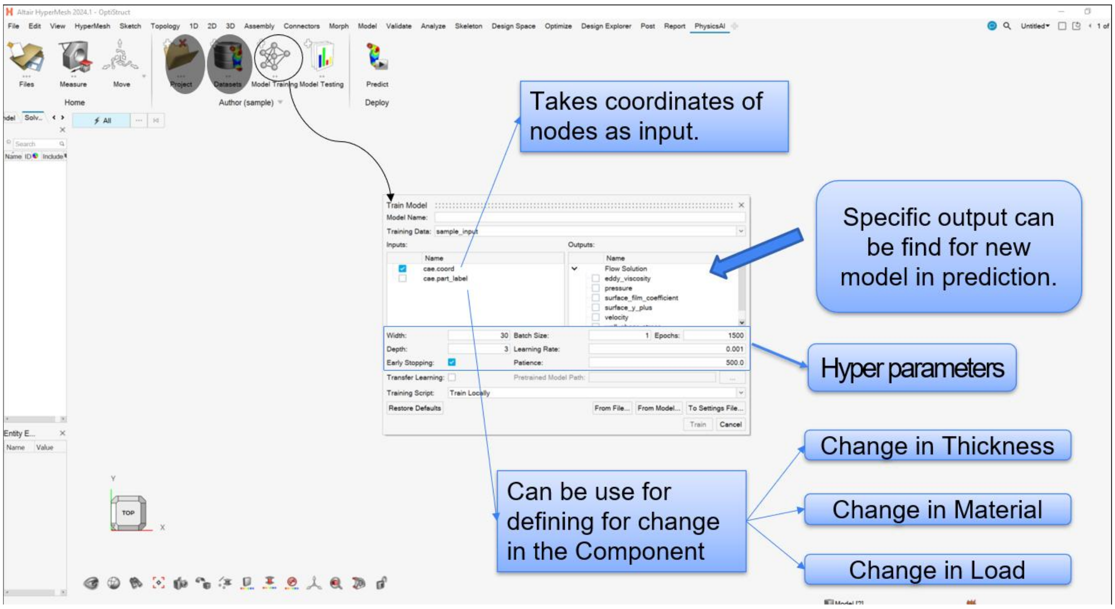

Figure 4 : Altair Hyper mesh user interface

2.1 Model Training and Hyperparameters

The process of training a model involves repeatedly adjusting the neural network's parameters using the training dataset to improve its performance. Key hyperparameters requiring adjustment include**:**

- **Epoch**: Denotes the number of complete iterations over the training dataset. Each epoch involves processing all training samples, computing losses, and updating model weights via backpropagation. The choice of epoch count is critical to achieving convergence while avoiding overfitting.
- **Width:** Refers to the number of nodes in the input layer or a given layer. A wider layer increases the model’s capacity to capture diverse input features, enhancing accuracy by processing more data points from the input space, albeit at the cost of increased computational requirements.
- **Depth:** Represents the total number of layers in the neural network. Greater depth enables the model to learn hierarchical feature representations, improving its ability to model complex relationships among input features. However,

deeper networks may require advanced techniques (e.g., residual connections) to mitigate issues like vanishing gradients.

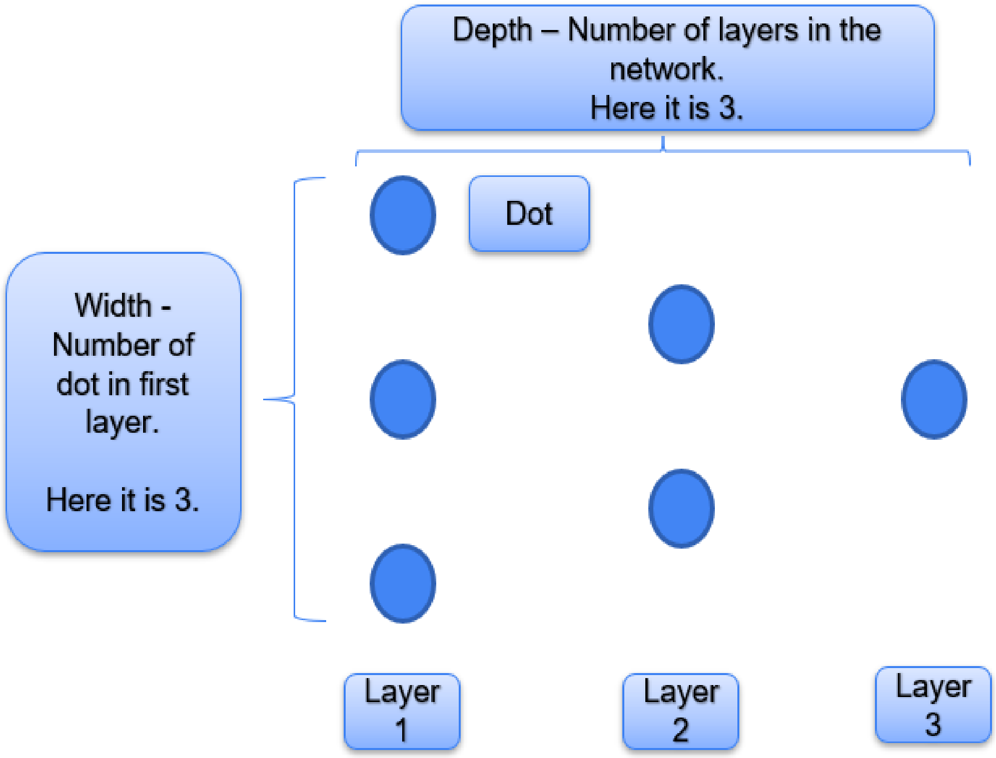

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Figure 5 : Width and Depth in neural network

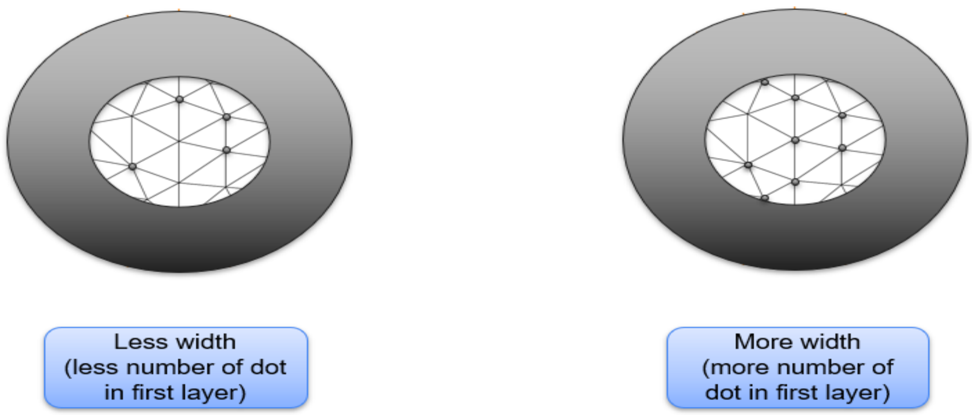


Figure 6 : Physical significance of width

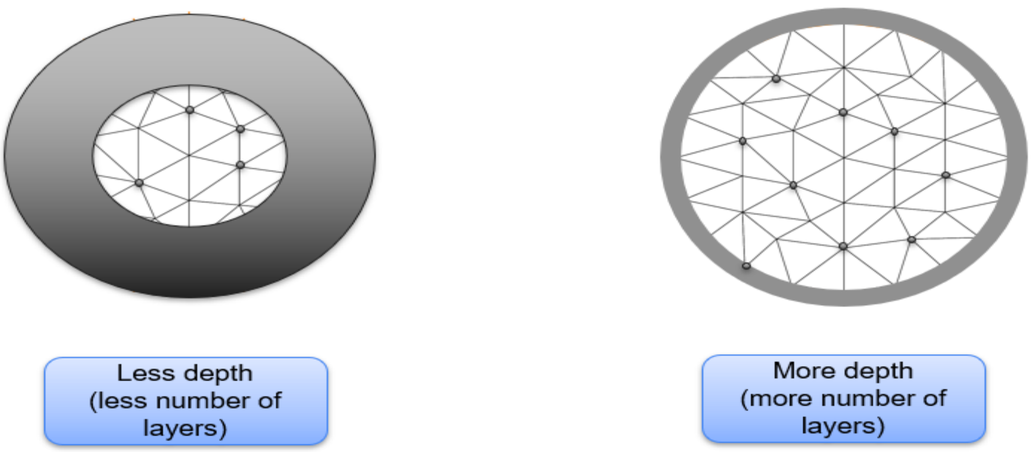


Figure 7 : Physical significance of depth

2.2 Early stopping

Early stopping is a common technique employed during the training of physics-informed neural networks to avoid overfitting and efficiently utilize computational resources. By tracking the validation loss at the conclusion of each training cycle, the training process is terminated if the loss does not show any improvement after a predetermined number of cycles (patience parameter). This guarantees that the model maintains its ability to generalize, especially in physics-based applications where following the governing equations is crucial, while minimizing training on noisy or sparse data.

2.3 Learning rate

The learning rate determines the size of parameter adjustments made during the optimization process in neural network training. In physics-informed ai, where loss functions combine data-driven and physics-based terms, an appropriately tuned learning rate (typically 10^{-3} to 10^{-5}) guarantees stable and efficient convergence. Adaptive learning rate schedules or optimizers, commonly utilized to navigate the intricate loss landscapes of physics informed neural network (pinn), thereby improving the model's capacity to accurately model physical systems.

Table 1 : Supported solvers

Supported Solvers	File Format
Abaqus	.odb
AcuSolve	.ensight .h3d
ANSYS	.rst .rth
CCM+	.ensight
Custom/user-generated	.ensight .unv .h3d
Fluent	.ensight
LS-DYN	.d3plot .d3eigv

Table 2 : Supported solvers

Supported Solvers	File Format
Marc	.t16
Nastran	.op2 .h5 .xdb
PAM-CRASH	.dsy
OptiStruct	.h3d .op2
Radioss	.h3d .anim
ultraFluidX	.ensight

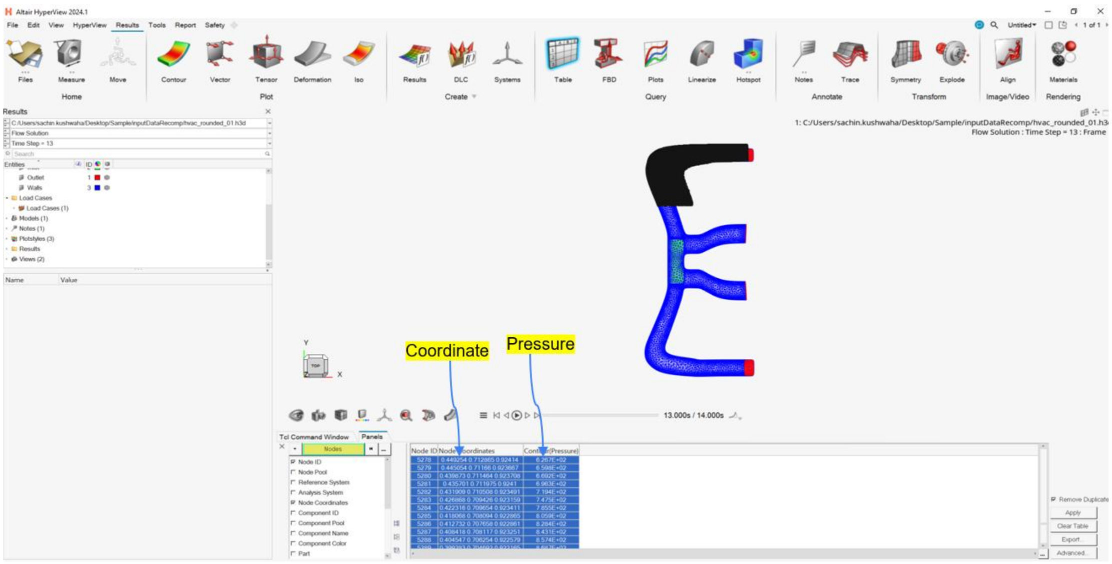


Figure 8 : Showing coordinate of nodes and pressure.

In the context of computational modelling, particularly within finite element methods (FEM) or mesh-based numerical simulations, the values of relevant variables—such as displacements, stresses, or other physical quantities—are stored at the nodes of a discretized mesh. The mesh, which can be structured or unstructured, divides the computational domain into a finite number of elements connected at nodes, which act as discrete points for data representation. Each node within the mesh is uniquely defined by its spatial coordinates, typically expressed in a cartesian coordinate system (e.g., (x,y) in two dimension and (x,y,z) in three dimensions), as illustrated in the referenced figure. These coordinates serve as reference points within the geometric domain, facilitating the accurate mapping of physical phenomena across the mesh. The nodal values, along with their respective coordinates, enable the interpolation of field variables across elements, forming the foundation for numerical solutions to partial differential equations that govern the system's behaviour. The establishment of nodal-based storage and coordinate associations is crucial for guaranteeing the precision and consistency of the computational model, as they establish the spatial connections and data distribution within the discretized domain.

Table 2 : Options for input

Input Feature	Description
cae.coord	Spatial coordinates used as a predictor of behaviour. It is recommended to always keep it on.
cae.part_label	Part name is used as a predictor of behaviour. This is valuable when working with large assemblies. In most cases, it is recommended to keep it on. However, it may make sense to turn it off in cases with inconsistent part names.
cae.shell_thickness	The thickness of 2D shell elements is used as a predictor of behaviour. This is required when the dataset has varying thicknesses between simulation models. This feature is only detected for Opti Struct and Radios. Solver input files must be in the same directory as the associated output file and have the same base name.
cae.material_label	Material name is used as a predictor of behaviour. This is required when the dataset has varied material assignments between simulation models. This feature is only detected for Opti Struct and Radios. Solver

	input files must be in the same directory as the associated output file and have the same base name.

2.4 Overall flow

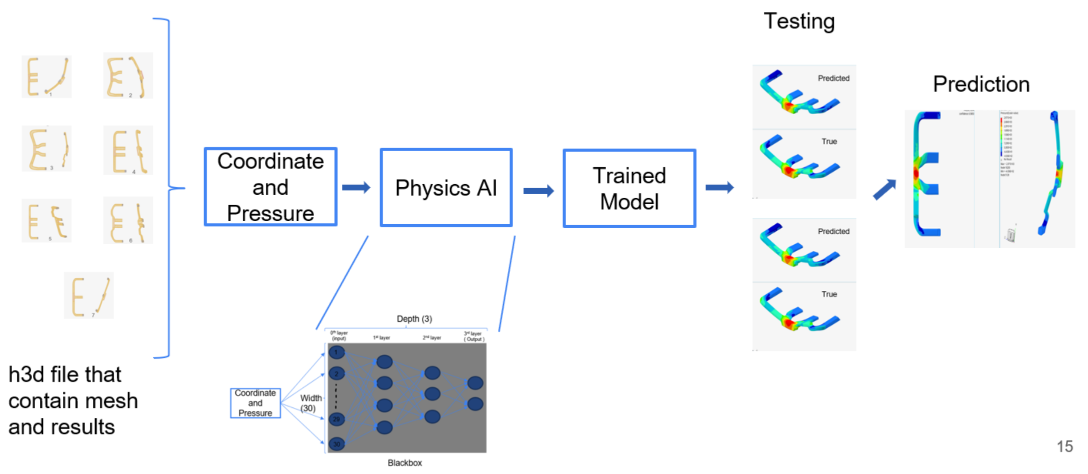


Figure 9 : Overall flow of prediction

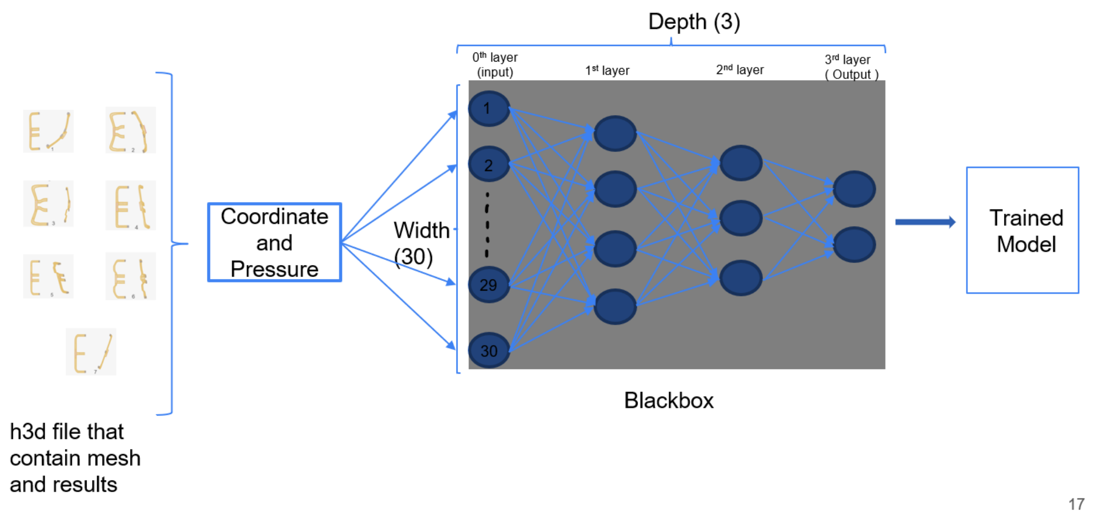


Figure 10 : Overall flow (ANN shown)

2.5 Right value of epoch, width and depth

Epoch: An epoch signifies the completion of a complete pass through the training dataset, involving the forward propagation of inputs, the calculation of loss, and the adjustment of weights using backpropagation. The suggested range for epochs is between 500 and 3000, with a preference for starting at the higher end to guarantee an adequate number of training iterations. To avoid overfitting, an early stopping mechanism is put in place, which terminates training if the validation loss does not show any improvement after a predetermined number of epochs, enhancing computational efficiency and model performance.

Width and depth. The width of a neural network, which refers to the number of nodes in each layer, and the depth, which refers to the number of layers, are crucial hyperparameters. It is suggested to begin with a configuration of 30 nodes per layer and 3 layers for optimal performance. The evaluation of model performance involves comparing the errors made during training and testing phases. Overtraining: happens when the training error is much smaller than the testing error, suggesting that the model is overfitting. This implies that the model has learned from the training data but struggles to apply that knowledge to new, unseen data. Undertraining happens when the training error surpasses the testing error, suggesting that the learning capacity is not sufficient to capture data patterns. Preference: a slight bias toward overtraining is preferred, as it guarantees strong feature learning, as long as overfitting is prevented using techniques like regularization or early stopping. The iterative adjustment of width and depth, guided by error analysis, is crucial to fine-tune the model's architecture for tailored applications.

2.6 confidence value

Evaluation of Our Model and Its Reliability Confidence value. After a neural network generates a prediction, a confidence value is calculated to measure the degree of agreement between the predicted output and the model's learned parameters. The confidence value, expressed as a normalized score ranging from 0 to 1, represents the model's level of certainty in its prediction. When the value of a value approaches 1, it indicates a strong alignment with the learned representations, resulting in improved predictive accuracy. This metric is a starting point for assessing prediction reliability but needs to be complemented with other validation methods. Model Assessment via Experimentation. In addition to confidence values, model validation is performed by conducting empirical testing on a distinct test dataset. This process assesses the model's ability to generalize by calculating error metrics, such as mean squared error (MSE) or classification accuracy, which offer a precise evaluation of prediction errors in practical situations. The testing process uncovers the practical effectiveness of the model, uncovering potential problems such as overfitting or underfitting, and complements the probabilistic insights provided by confidence values. By combining these methods, we can thoroughly assess the model's ability to make accurate predictions.

Chapter 3 Sample Model 1

3.1 Overview of geometric models and data file.

The research concentrates on examining heating, ventilation, and air conditioning (HVAC) duct systems, employing eleven different geometric models to explore the influence of geometry on performance metrics, particularly pressure distribution. These models act as the basis for training and testing a predictive framework that aims to evaluate the impact of geometric changes on the performance of heating, ventilation, and air conditioning (HVAC) systems. The dataset consists of seven separate files, all in the h3d format, which are utilized for training purposes. These files contain information about the shape and layout of the HVAC duct model, as well as the pressure distribution that was calculated using computer simulations. Furthermore, two separate files, both in h3d format, are designated for testing purposes to assess the model's ability to accurately predict outcomes. Furthermore, two prediction files are included in the dataset: one file contains solely the geometric data, stored with an .x_b extension, while the other is a mesh file, stored with a .fem extension, which provides the discretized computational domain for finite element analysis.

Figure 11 : HVAC duct

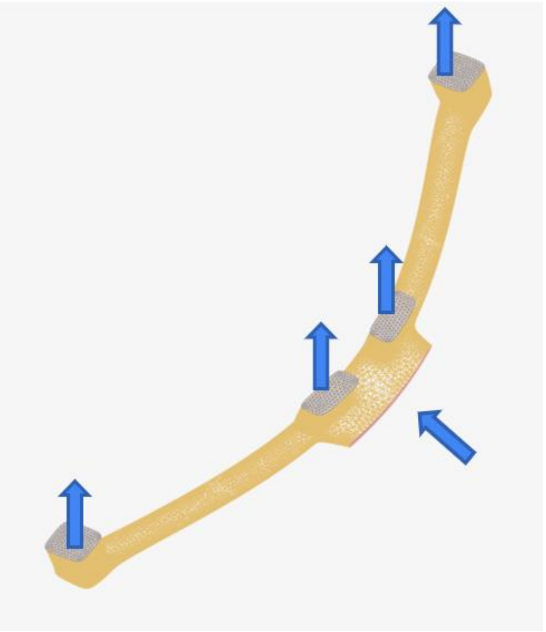


Figure 12 : HVAC duct with entry and exit

3.2 Changes in the shape of HVAC ducts.

The eleven geometric models are created with slight differences in their arrangements to investigate how the performance of the HVAC system can be affected by changes in geometry. Specifically, the training process focuses on identifying and quantifying how these geometric changes affect the pressure distribution within the duct system. Each result file combines the geometric model and the pressure results, allowing for a thorough examination of how design parameters impact system performance.

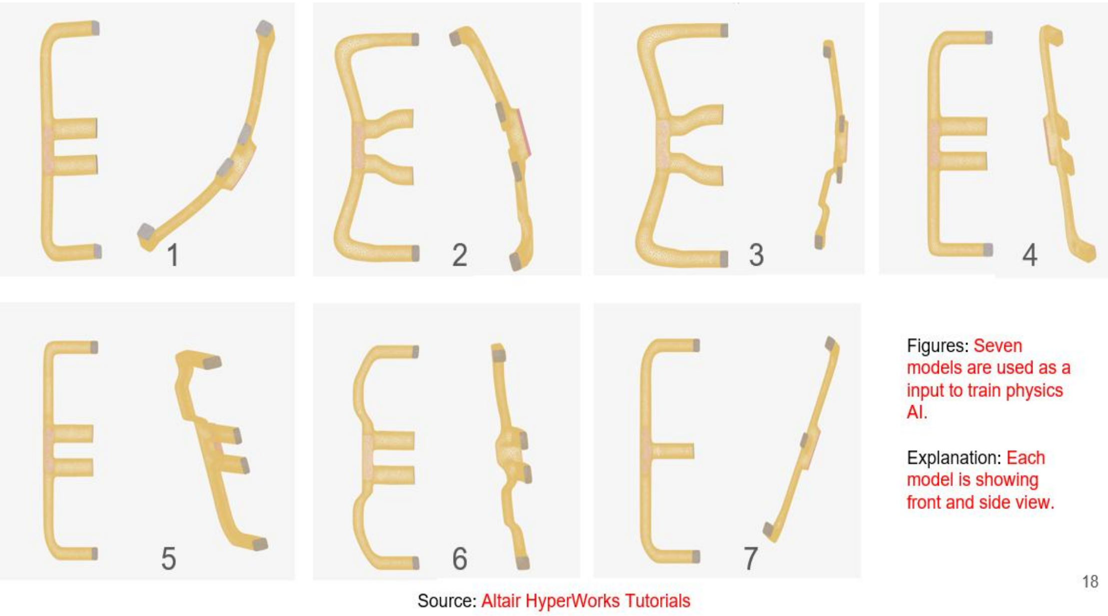


Figure 13 : All seven input models are shown.

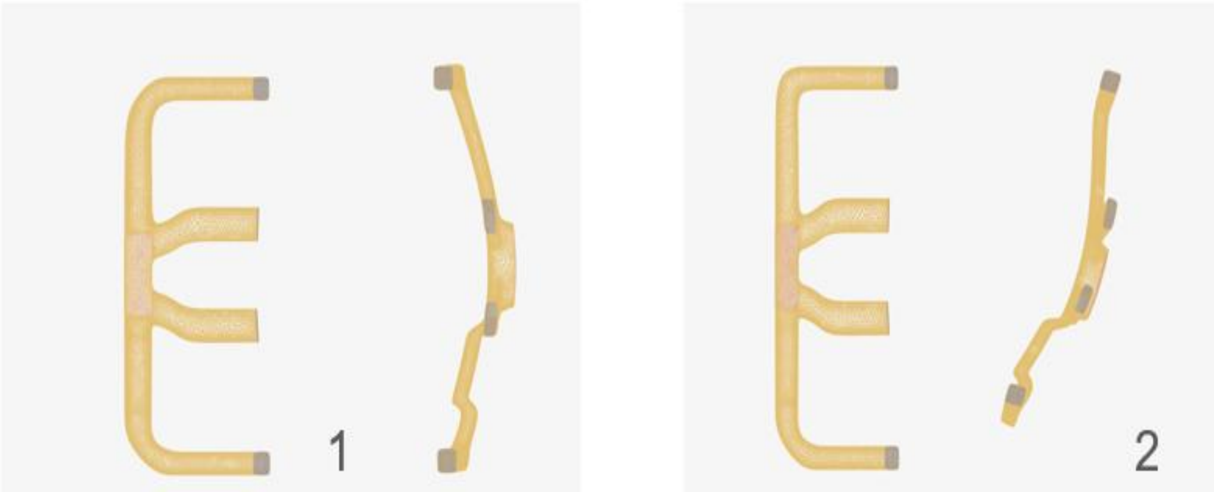


Figure 14 : Two testing models of HVAC.

Assessment of Machine Learning Algorithm Utilizing Physics-Based Constraints. Experimenting with shapes. The validation of the physics-informed AI model requires two distinct testing geometries, each representing a different computational domain to evaluate the model's predictive accuracy. The second geometry, as shown in the figure, is thoroughly examined to assess the model's effectiveness. The mean absolute error (MAE) for these geometries is calculated as 200 Mpa, indicating the average difference between the predicted stress values and the reference data, thereby serving as a measure of the model's accuracy. Prediction of the results using cad and mesh files. The subsequent visualizations, depicted in the figure below, illustrate the model's predictions obtained from computer-aided design (cad) models and their corresponding mesh files. The CAD model specifies the system's shape and structure, while the mesh file divides it into smaller units called nodes and elements for numerical calculations. These visualizations allow for a side-by-side comparison of predicted and actual results, emphasizing the model's compatibility with engineering processes and its practicality in real-life scenarios.

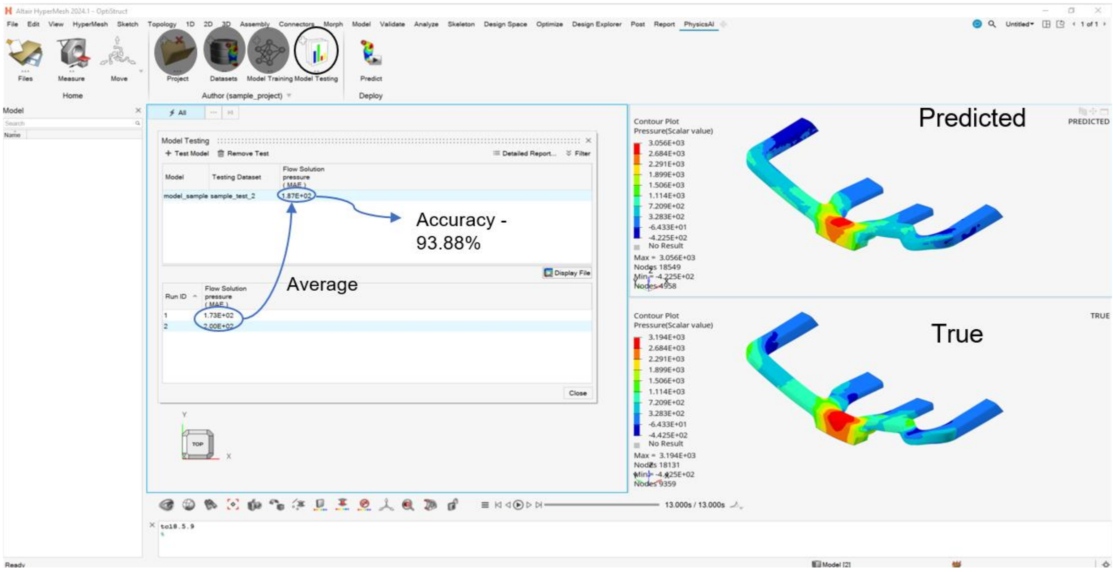


Figure 15 : Testing of HVAC duct

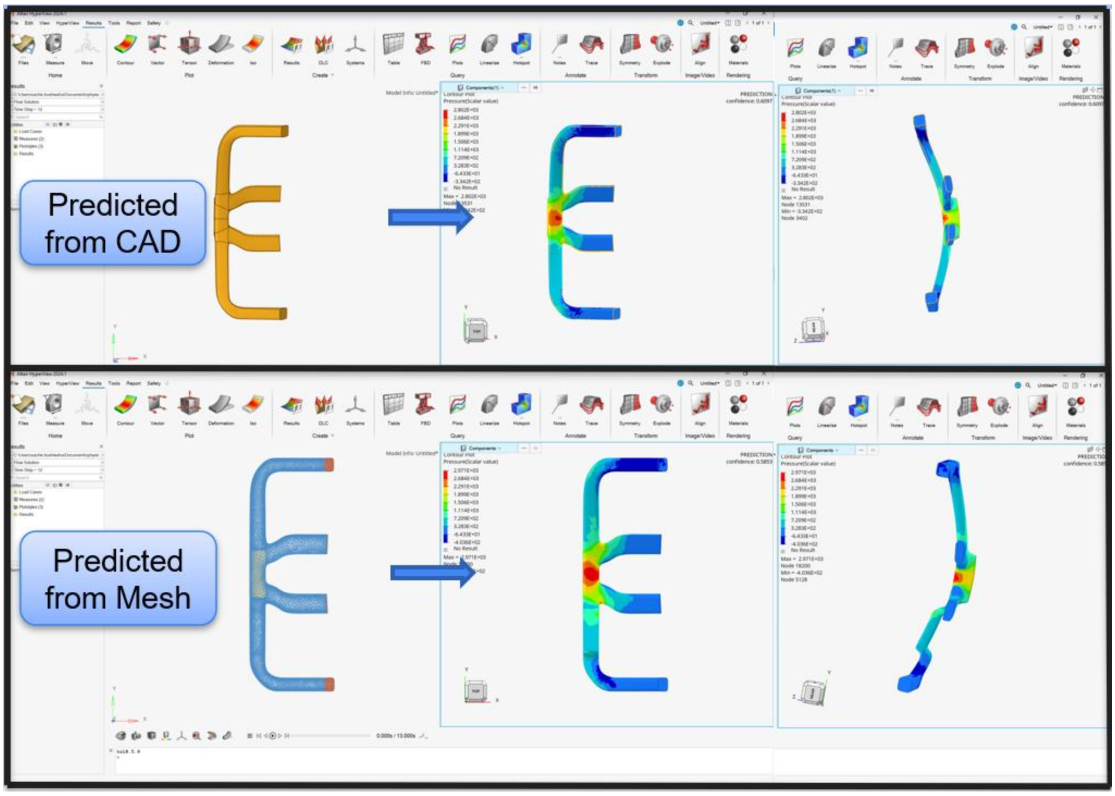


Figure 16 : Prediction of HVAC duct

3.3 Creation and assessment of novel frameworks.

In order to strengthen the predictive power of the trained model, two more HVAC duct models were created. These models include minor adjustments in the geometry, particularly in the design of the exit vent and the length of the duct. These modifications were purposefully implemented to evaluate the model's resilience and its capacity to perform well even when faced with variations that were not part of the training data. The effectiveness of these new models is assessed by comparing their predicted pressure distributions with the simulation results, offering valuable insights into their ability to capture the impact of geometric changes. This approach guarantees a thorough examination of the HVAC duct system's behaviour in different geometric settings, ultimately contributing to the overarching goal of improving HVAC design for increased efficiency and performance.

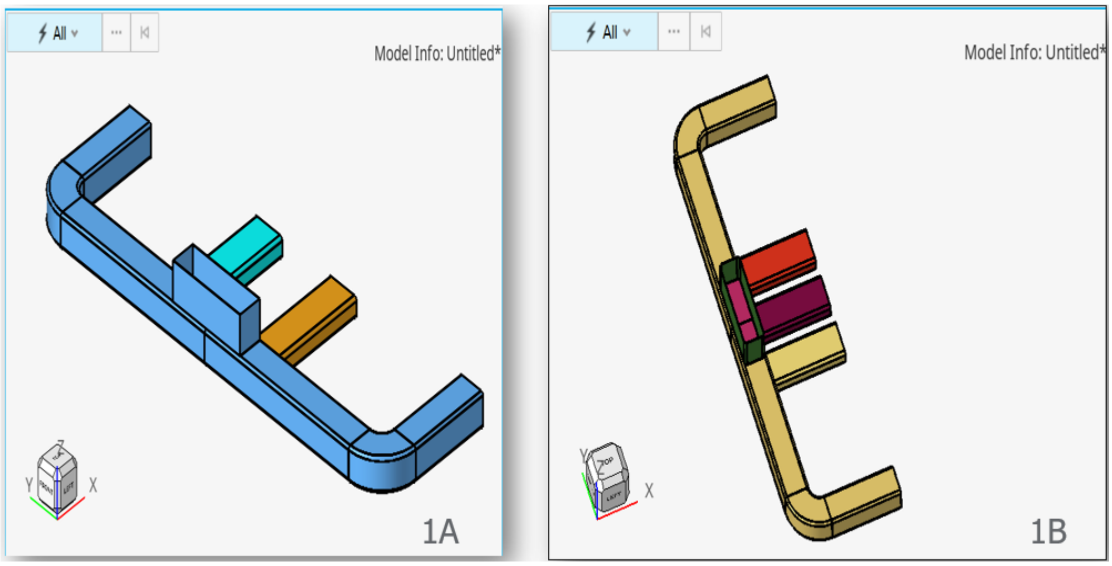


Figure 17 : Newly formed geometry.

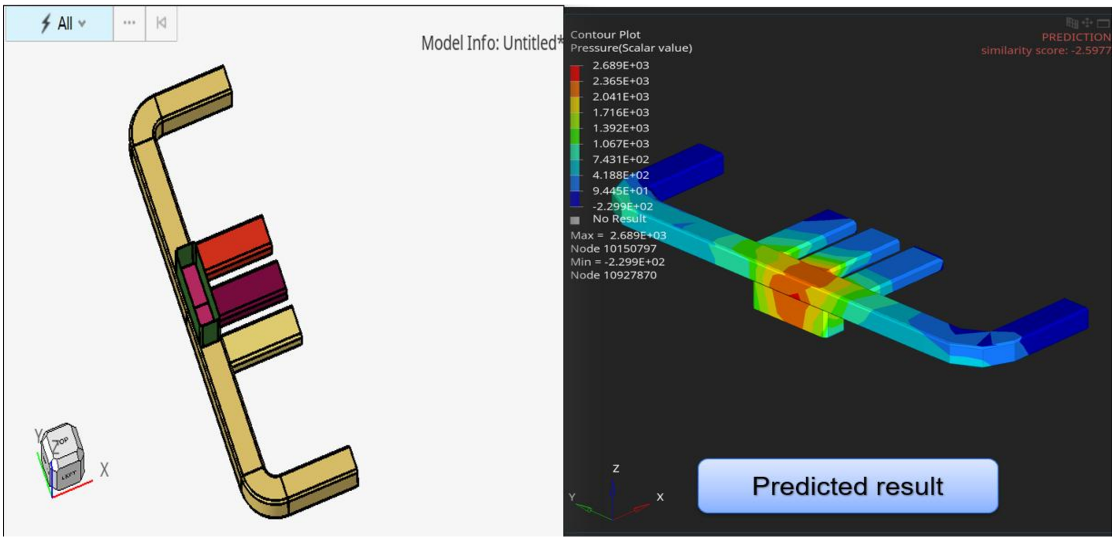


Figure 18 : Prediction of newly formed geometry

Chapter 4 Sample Model 2

When creating and assessing a physics-based artificial intelligence (AI) model for structural analysis, a sample model with a mechanical arm is utilized to simulate a typical engineering situation. The arm is designed with a fixed boundary condition at one end, limiting all its movements, while an external force is applied at the other end, causing mechanical stresses and deformations. This arrangement mirrors a typical loading scenario in structural mechanics, allowing for the evaluation of the model's predictive abilities in a controlled environment. The model's training and testing processes involve a dataset consisting of 30 separate simulation files. Among these, 24 files have been designated for training the neural network, furnishing a comprehensive dataset to fine-tune the model's parameters and accurately capture the physical behaviour of the arm in different scenarios. The remaining 6 files are set aside for testing, acting as a separate dataset to assess the model's ability to generalize its performance.

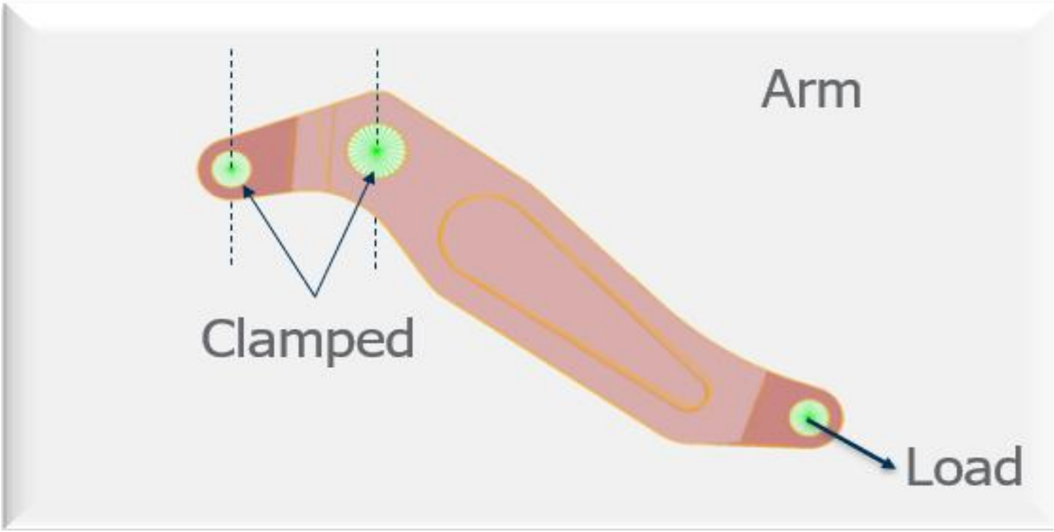


Figure 19 : Structural arm

The differences in design among these files are quite minimal, mainly consisting of minor geometric or parametric adjustments, as depicted in the accompanying image. This image overlays two distinct geometries to visually emphasize the subtle modifications in the arm's structure, enabling a comprehensive comprehension of the incremental design modifications. After the training phase, the model is evaluated on the six designated geometries to determine its ability to accurately predict outcomes. The findings of this assessment are depicted in the figure provided, which illustrates the model's effectiveness in various test scenarios.

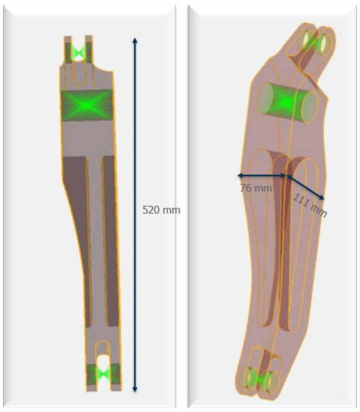


Figure 20 : Structural arm with dimension

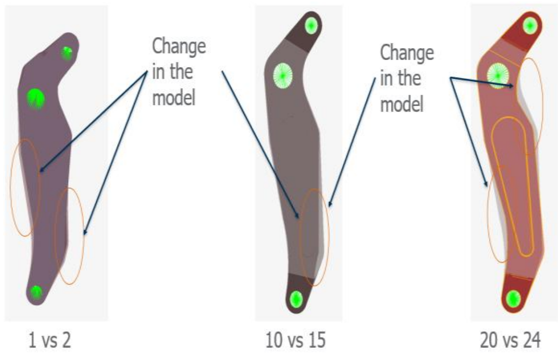


Figure 21 : Changes in structural arm

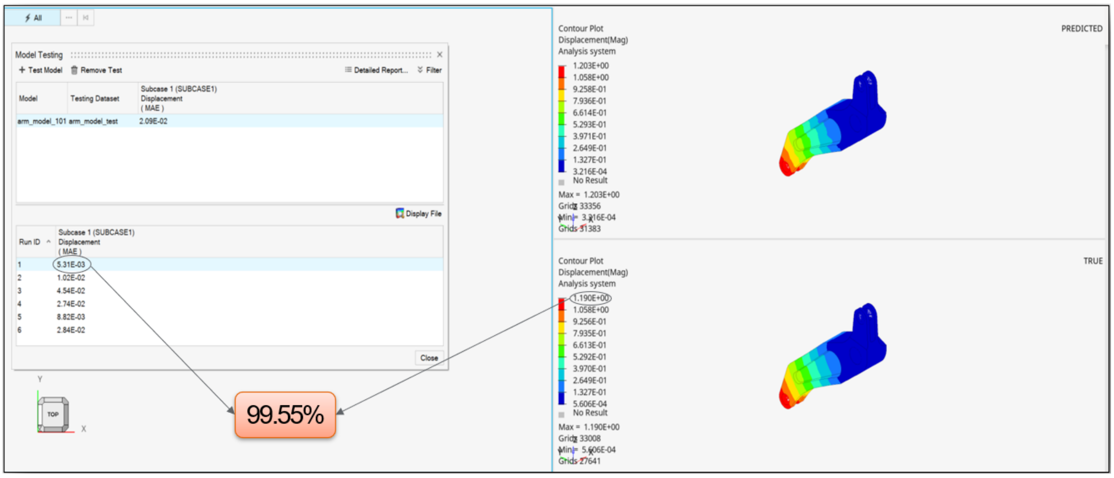


Figure 22 : Testing of first model

Figure 23 : Testing of second model

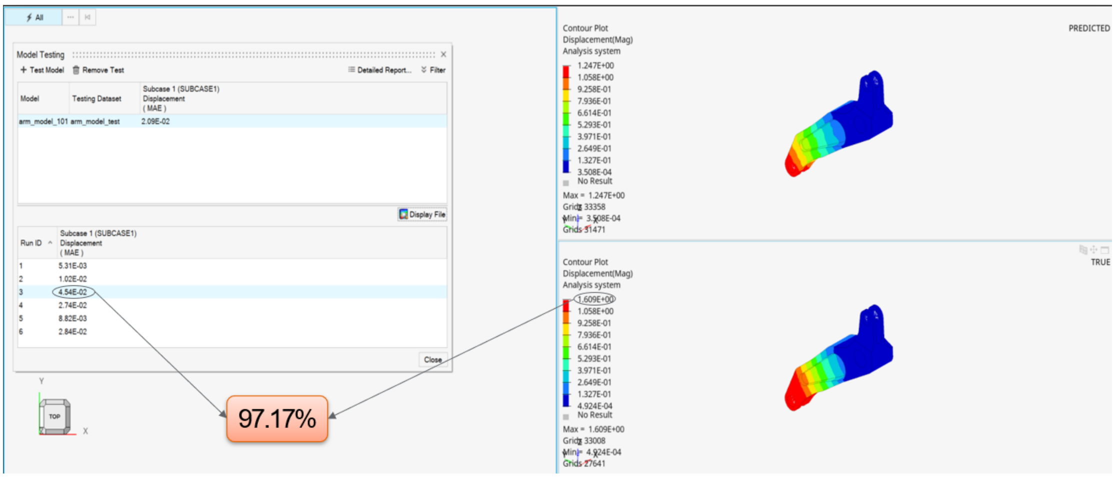


Figure 24 : Testing of third model

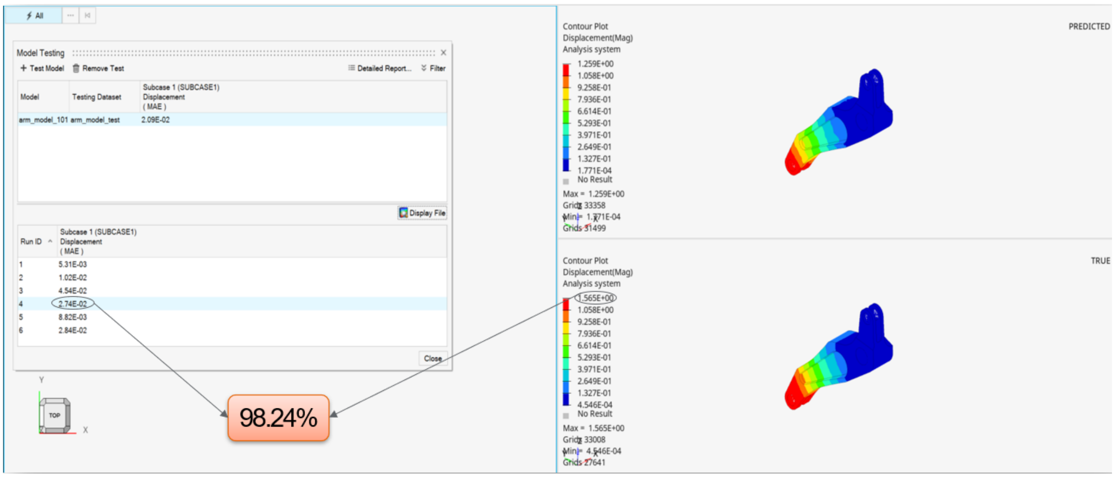


Figure 25 : Testing of fourth model

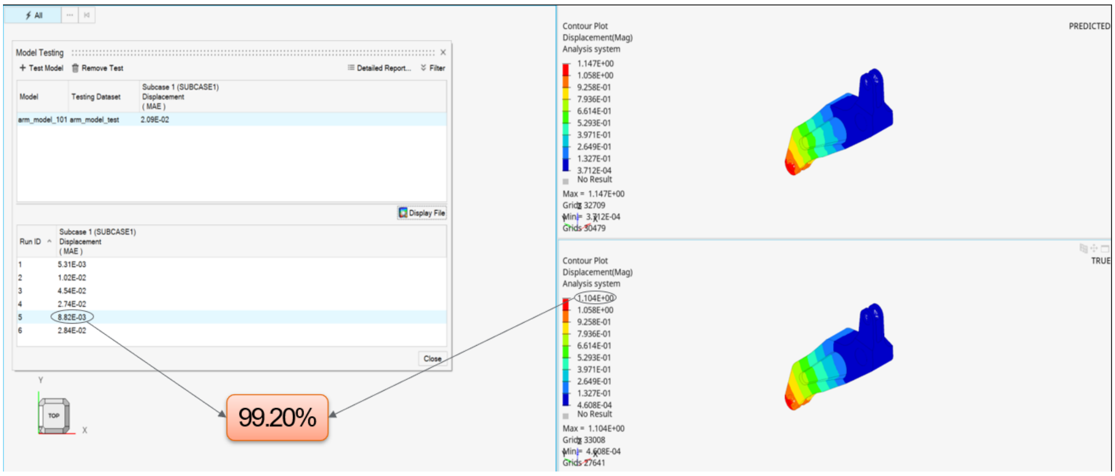


Figure 26 : Testing of fifth model

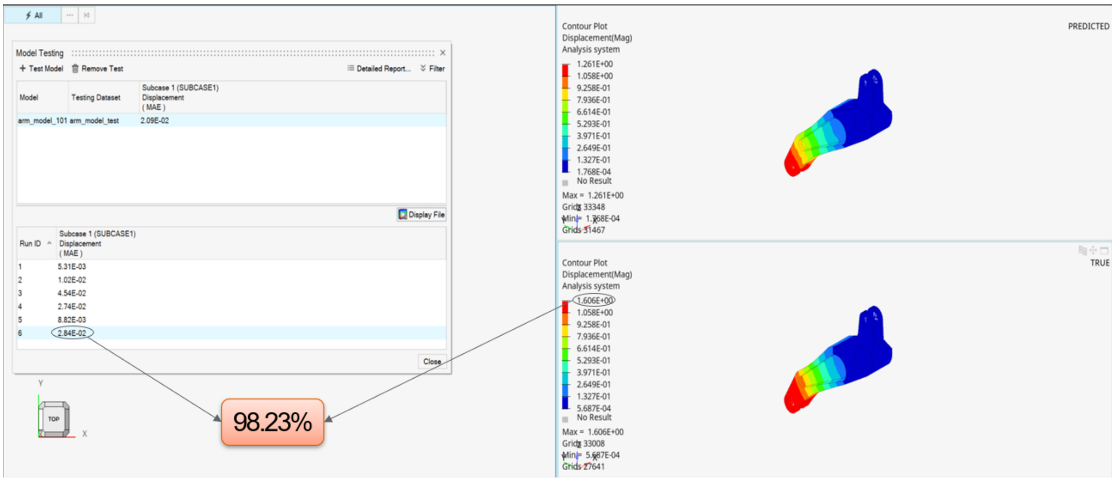


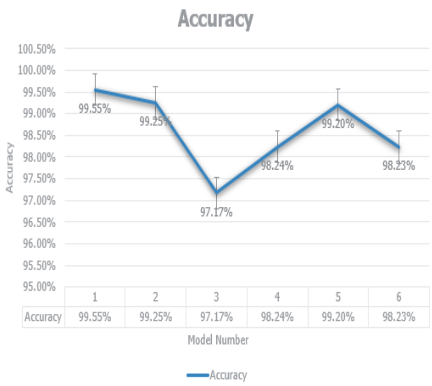
Figure 27 : Testing of sixth model

4.1 Model Testing and Results

The table below presents the summarized quantitative results, indicating that the predictive accuracy of the model consistently exceeds 95% for all tested geometries. The high accuracy of the model can be attributed to its consistent design, which enables the neural network to effectively generalize from the training data to the test cases. The subtle modifications in the model's structure guarantee that the learned representations remain relevant, reducing prediction errors and increasing reliability in situations where configurations are closely related.

Table 3 : Table of accuracy

Model No.	Accuracy
1	99.55%
2	99.25%
3	97.17%
4	98.24%
5	99.20%
6	98.23%



Chapter 5 Locomotive Component

In the context of a structural analysis study utilizing a physics-informed artificial intelligence (AI) model, the real component selected for investigation is the blower cab, a critical subsystem within a locomotive's architecture. Locomotives are equipped with several specialized cabs, including the nose cab, operator cab, auxiliary cab, blower cab, engine cab, and radiator cab, each serving distinct functional roles. For the purposes of this analysis, the blower cab is chosen as the focal component due to its structural significance and relevance to thermal management within the locomotive. The blower cab, designed to house ventilation and cooling systems, comprises six structural pillars or posts, which provide mechanical stability and support. This study focuses on evaluating the blower cab's structural performance by varying the thickness of these pillars and employing a physics-informed AI model to predict the resulting mechanical behaviour.

To facilitate this analysis, a systematic methodology is adopted, encompassing the following steps:

1. **Generation of Blower Cab Models with Varying Thickness**: Multiple configurations of the blower cab are created by systematically altering the thickness of the six pillars. These variations represent distinct design scenarios, enabling the assessment of structural responses under different geometric parameters.

2. **Structural Analysis and Result File Generation**: Finite element analysis (FEA) or equivalent computational methods are applied to each blower cab configuration to simulate mechanical behaviour under specified loading conditions. The resulting data, encapsulating nodal coordinates, stresses, displacements, or other relevant physical quantities, are stored in result files for subsequent use.

3. **Training the Physics-Informed AI Model**: The physics-informed AI model, typically a neural network augmented with physical constraints (e.g., governing equations), is trained using the result files from the analysed configurations.

This training process optimizes the model's parameters to capture the relationship between pillar thickness and structural performance.

4. **Model Testing**: The trained model is evaluated on a separate set of blower cab configurations to assess its generalization capability and predictive accuracy, ensuring robustness across unseen data.
5. **Model Prediction**: The validated model is deployed to predict the structural behaviour of new blower cab configurations, providing insights into the impact of pillar thickness variations on performance.

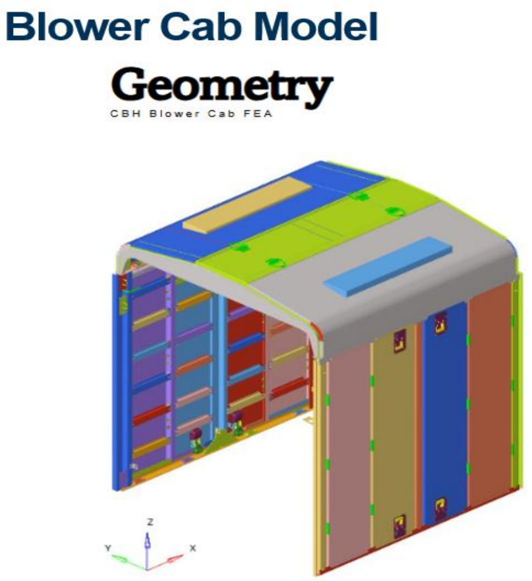


Figure 28 : Geometry of blower cab

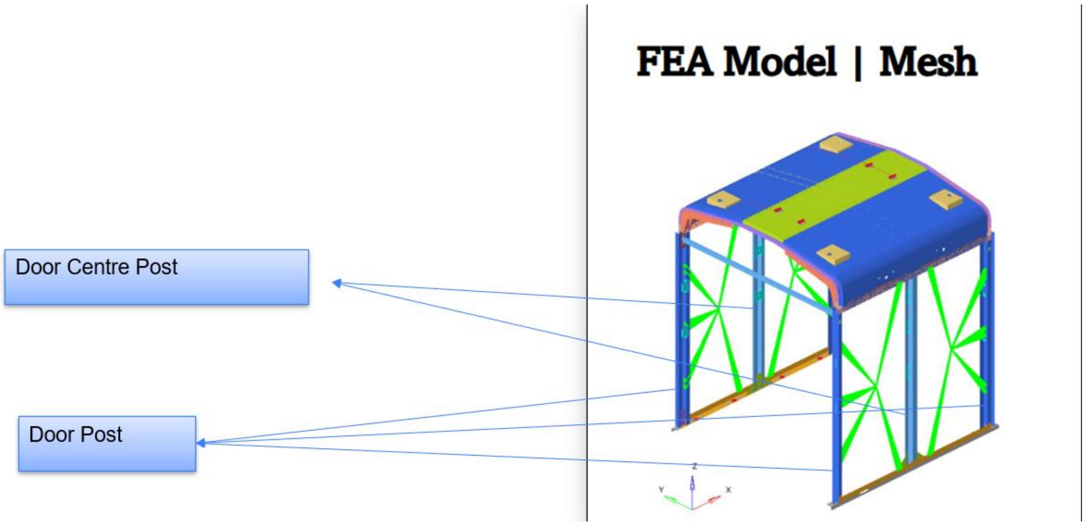


Figure 29 :Door centre Post and Door post in blower cab

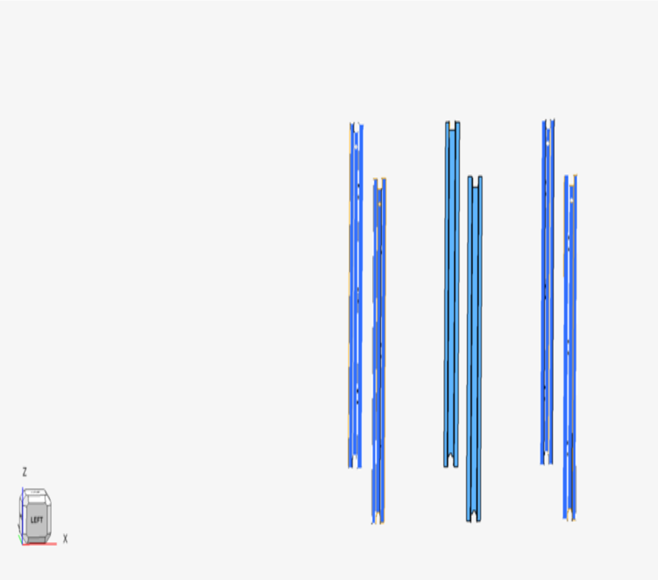


Figure 30 : Post in blower cab model

A total of eight simulation files are generated to support this study, strategically divided as follows: four files are allocated for training, two for testing, and two for prediction. The training files correspond to blower cab configurations with pillar thicknesses of 3 mm, 4 mm, 5 mm, and 6 mm, which provide a comprehensive dataset to capture the structural behaviour across a range of thicknesses. The testing phase utilizes configurations with thicknesses of 3.5 mm and 5.5 mm to evaluate the model's performance on intermediate values. Finally, the prediction phase involves configurations with thicknesses of 4.5 mm and 6.5 mm, enabling the model to forecast outcomes for novel designs. These configurations and their respective purposes are summarized in the table below, ensuring a structured approach to data allocation and model evaluation.

Figure 31 : Table of thickness

Training Thickness	**Testing Thickness**	**Prediction**
3	3.5	
4		4.5
5	5.5	
6		6.5

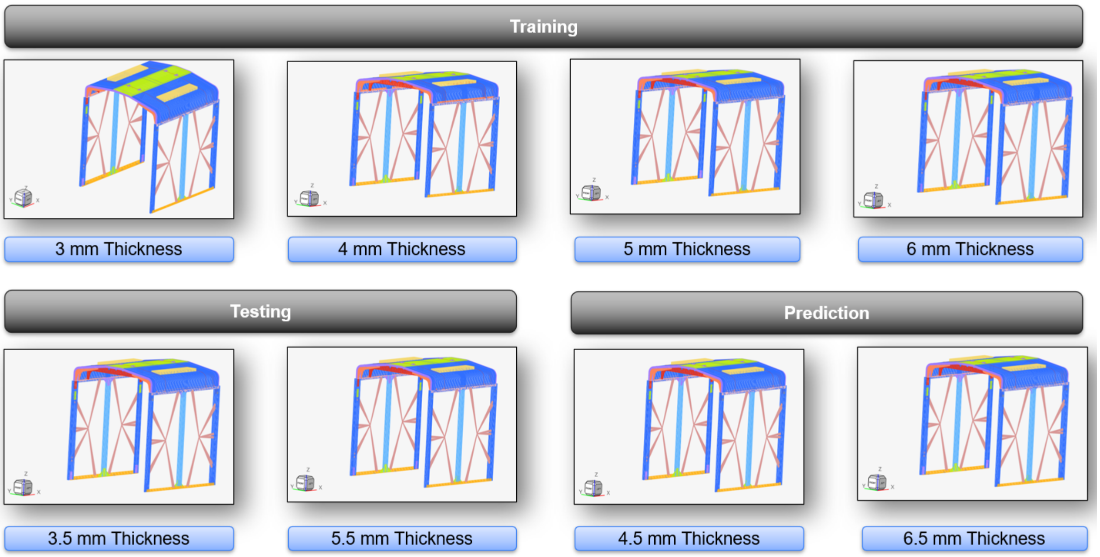


Figure 32 : Different thickness used of training, testing and prediction

Chapter 6 Result & Discussion

The structural integrity of a blower cab, a vital part of a locomotive that houses ventilation systems, is assessed using a physics-based artificial intelligence (ai) model. The blower cab, which was previously described as having six structural pillars, is subjected to simulations with different pillar thicknesses to evaluate its mechanical behaviour, particularly the displacement caused by applied loads. The study examines four different configurations, each characterized by pillar thicknesses of 3.5 mm, 4.5 mm, 5.5 mm, and 6.5 mm, as illustrated in the accompanying figures. These simulations compare the predicted displacements (from the AI model) with the simulated displacements (from finite element analysis, FEA), allowing for an assessment of the model's predictive accuracy. The first set of figures demonstrates the predicted and simulated displacement fields for a blower cab with a pillar thickness of 3.5 mm. The contour plots, labelled as "contour plot (mag)," illustrate the magnitude of displacement in the system, with a colour gradient ranging from blue (minimum displacement) to red (maximum displacement). The projected displacement graph displays a maximum displacement of 2.372e+01 mm (23.72 mm), whereas the simulated graph indicates a maximum displacement of 2.423e+01 mm (24.23 mm). The average absolute difference (MAE) between the predicted and simulated outcomes is 0.705 mm, indicating a high level of accuracy with a 97.2% confidence. The simulation time for the feature extraction is around 20 minutes, while the AI model's prediction time is less than 1 minute, emphasizing the computational efficiency of the AI approach. The note clarifies that the time taken for preprocessing and training the model is not included in these metrics. 5.5 mm thickness configuration: the second set of figures presents the displacement fields for a blower cab with a pillar thickness of 5.5 mm. The displacement fields are shown for the case of a single-stage blower with a fan diameter of 1.5 m and a fan speed of 1,000 rpm. The projected displacement graph displays a maximum displacement of 2.228e+01 mm (22.28 mm), whereas the simulated graph suggests a maximum displacement of 2.317e+01 mm (23.17 mm). The mean error is 0.239 mm, with an accuracy of 98.9%, indicating a more precise alignment between predicted and simulated outcomes compared to the 3.5 mm case. The simulation duration is around 20 minutes, while the prediction time is significantly shorter, taking less than a minute. The third figure illustrates the anticipated movement for a blower cab with a pillar thickness of 4.5 mm. The maximum displacement is 2.236e+01 mm (22.36 mm), with a colour distribution indicating areas of high displacement primarily at the top centre of the structure, consistent with the loading conditions (likely an axial or distributed load applied to the top surface). The fourth figure illustrates the predicted displacement for a thickness of 6.5 mm, with a maximum displacement of 2.225e+01 mm (22.25 mm). The displacement distribution is comparable to the 4.5 mm case, but with a slightly lower maximum displacement, indicating enhanced structural stiffness as a result of the increased thickness.

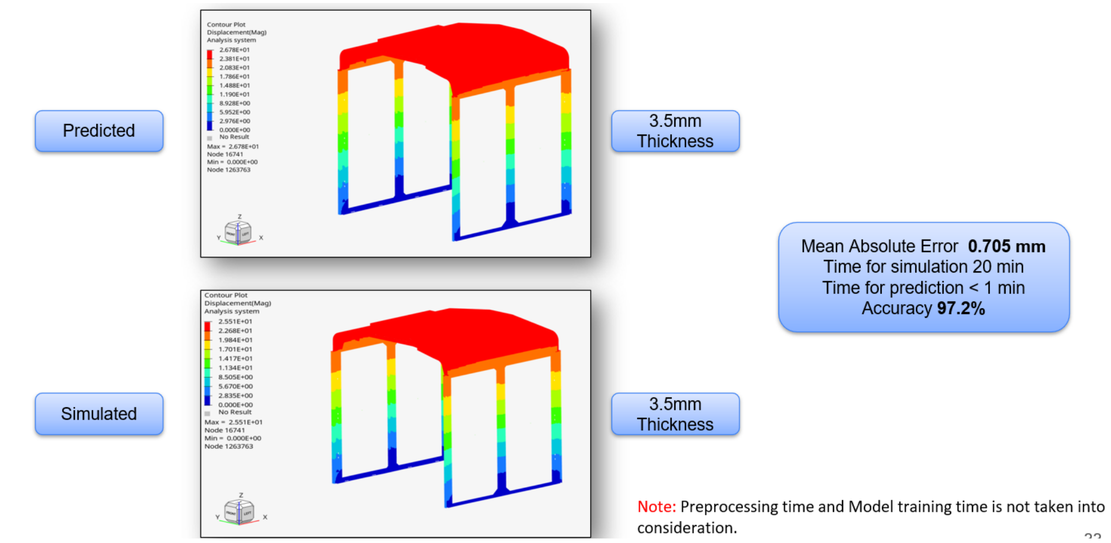


Figure 33 : Testing of 3.5mm blower cab

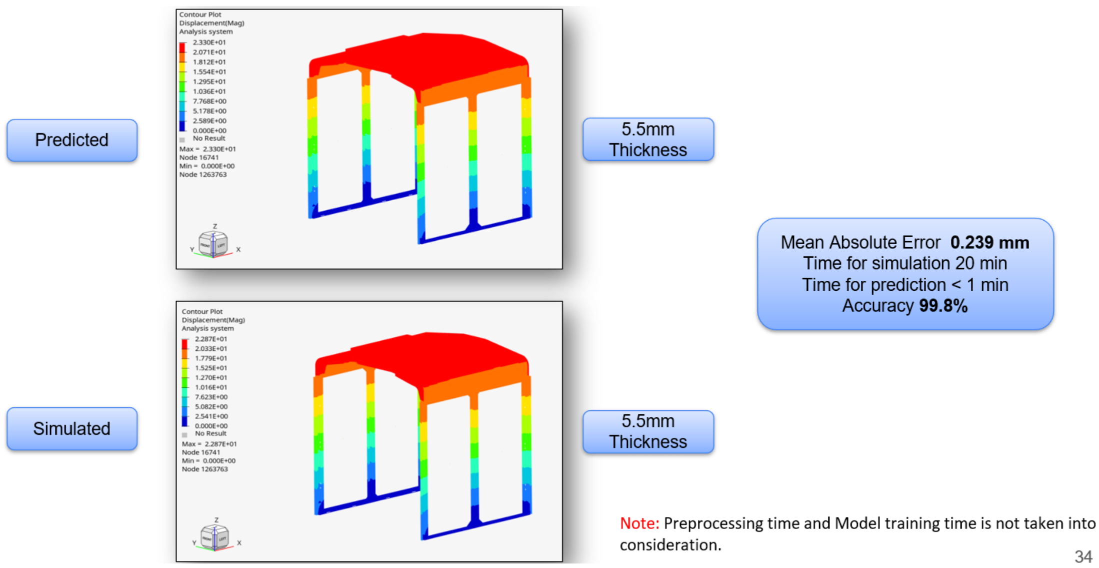


Figure 34 : Testing of 5.5 mm blower cab

6.1 Result:

The outcomes of the simulations and predictions are summarized as follows: Changes in Position: For the 3.5 mm thickness, the maximum predicted displacement is 23.72 mm, which is slightly lower than the simulated value of 24.23 mm, with an MAE of 0.705 mm and an accuracy of 97.2%. For the 5.5 mm thickness, the maximum predicted displacement is 22.28 mm, which is slightly lower than the simulated value of 23.17 mm. The difference is only 0.239 mm, indicating a high level of accuracy with a 98.9% confidence. For the 4.5 mm thickness, the estimated maximum displacement is 22.36 mm. For the 6.5 mm thickness, the estimated maximum displacement is 22.25 mm. Precision and mistake: The accuracy of the AI model increases as the thickness of the model increases, with a higher accuracy rate of 98.9% achieved at a thickness of 5.5 mm. This trend indicates that the model performs better when the configurations are similar to the training data, such as 3 mm, 4 mm, 5 mm, and 6 mm. The mean attenuation coefficient decreases from 0.705 mm at a thickness of 3.5 mm to 0.239 mm at a thickness of 5.5 mm, suggesting better predictive accuracy for thicker configurations. Computational efficiency: The AI model showcases remarkable computational efficiency, as it can predict outcomes in less than a minute, while the simulation time for the feature extraction process is around 20 minutes. This efficiency is a significant advantage of the physics-informed ai approach, although preprocessing and training times are not considered in these metrics.

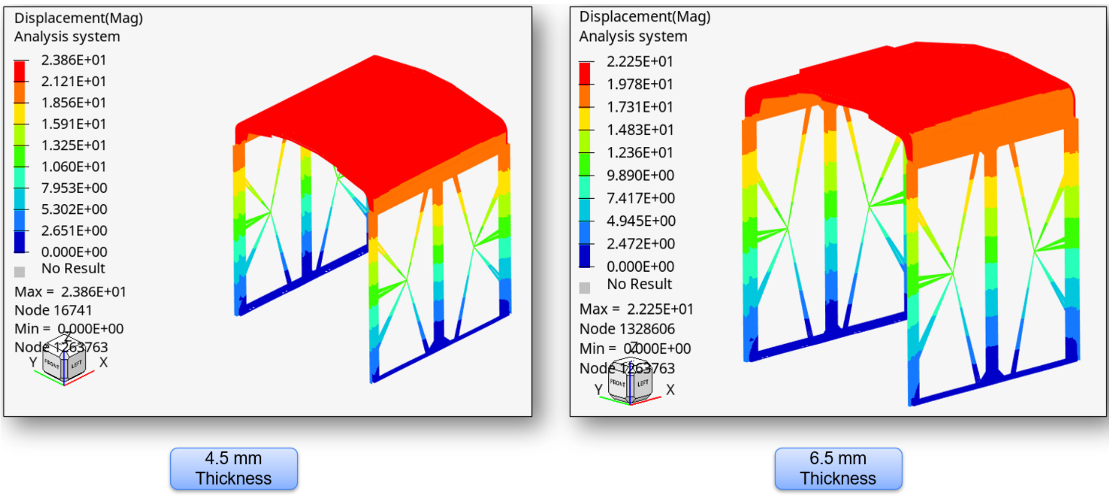


Figure 35 : Prediction of 4.5mm and 6.5 mm blower cab

6.2 Discussion:

The analysis uncovers several significant findings regarding the performance of the physics-based artificial intelligence model and the structural characteristics of the blower cab.

The AI model demonstrates exceptional accuracy, with a range of 97.2% to 98.9%, when evaluated on various thicknesses. The enhanced precision at 5.5 mm in comparison to 3.5 mm indicates that the model performs better when dealing with thicknesses that are closer to the training data (3 mm, 4 mm, 5 mm, 6 mm). The 3.5 mm configuration, being an intermediate value, exhibits a slightly higher MAE, possibly due to its placement at the lower end of the training range, where extrapolation effects may be more noticeable. The high level of accuracy achieved for both tested configurations demonstrate the model's ability to handle minor geometric variations, which aligns with the earlier finding that even small design changes can result in reliable predictions.

The maximum displacement of the structure decreases as the pillar thickness increases, from 23.72 mm at 3.5 mm to 22.25 mm at 6.5 mm (predicted values). This trend is in line with the principles of structural mechanics, where thicker materials exhibit greater stiffness, resulting in reduced deformation when subjected to the same loading conditions. The distribution of displacement, mainly concentrated at the top centre of the blower cab, indicates that the applied load (likely axial or distributed) causes bending or compressive stresses, with the pillars offering resistance. The uniformity in displacement patterns across different thicknesses suggests that the structural behaviour remains consistent, enabling accurate predictions through artificial intelligence.

The computational efficiency of the AI model is impressive, as it can predict the outcome in less than a minute, while the FEA simulation takes around 20 minutes. This demonstrates the model's potential for quick design iterations in engineering projects. Nevertheless, the absence of preprocessing and training times suggests that the overall workflow may necessitate substantial initial computational resources. In practical scenarios, it is crucial to assess this trade-off, as the time spent on initial training may be compensated by the model's capability to offer near-instantaneous predictions during iterative design processes.

Despite its impressive performance, the model encounters limitations when it comes to predicting behaviour for configurations that fall outside the training data. Furthermore, the accuracy metrics are derived from displacement magnitudes, but additional factors, such as stress concentrations or failure criteria, may necessitate further examination to guarantee the overall structural integrity. The note clarifies that preprocessing and training times, although not explicitly mentioned in the reported metrics, are crucial for the practicality of the ai approach.

Chapter 7 Conclusion and scope for future

7.1 Conclusion

The physics-informed ai model demonstrates exceptional performance in predicting the structural behaviour of a blower cab under varying pillar thicknesses, achieving accuracies of 97.2% and 98.9% for thicknesses of 3.5 mm and 5.5 mm, respectively, with corresponding mean absolute errors (MAE) of 0.705 mm and 0.239 mm. The predicted displacements for thicknesses of 4.5 mm and 6.5 mm (22.36 mm and 22.25 mm, respectively) further confirm the model's reliability, showing a consistent trend of decreasing displacement with increasing thickness, in line with expected structural mechanics principles. The ai model's computational efficiency, with prediction times of less than 1 minute compared to 20 minutes for finite element analysis (FEA), underscores its potential as a powerful tool for rapid design optimization in locomotive engineering. This physics-informed ai model proves particularly effective for predicting the behaviour of similar models, serving as a valuable tool to significantly reduce the time required for predictions. By utilizing a trained model, it facilitates quicker analysis of designs that share similar structural characteristics, thereby expediting the design iteration process. In all six testing scenarios, the model consistently attains an accuracy surpassing 97%, with the third model demonstrating the lowest accuracy, albeit still slightly above 97%. The primary reason for this high accuracy is the small changes in the blower cab model, which are even smaller than those observed in previous HVAC models, enabling the ai to generalize effectively within the trained parameter space. Nevertheless, the third model's lower accuracy can be attributed to a more significant variation in thickness compared to the other configurations, emphasizing the model's sensitivity to larger geometric discrepancies. Although it may be tempting to strive for even higher accuracy, it is not recommended, as it can result in overfitting, where the model becomes too specialized to the training data, making it less effective in handling new situations. The effectiveness of the physics-informed AI model relies on the magnitude of dimensional alterations in the design. In cases where the dimensional variations of models are minimal, as observed in this study, the ai model can accurately predict structural behaviour, providing a time-saving alternative to traditional analysis methods. However, when the dimensions vary greatly, the physics-based AI model is less reliable, and traditional analysis tools like

FEA are required to guarantee precise outcomes. Consequently, although the AI model is proficient in expediting the analysis process for repetitive models with minor adjustments, it is crucial to perform a comprehensive validation using recognized analysis tools prior to finalizing any design. This guarantees that the model's predictions match real-world outcomes, reducing the chances of unforeseen risks arising from untested assumptions. The small difference in accuracy observed between the tested thicknesses indicates that the model's performance may be influenced by the range of training data, emphasizing the importance of choosing appropriate training configurations to ensure reliable generalization. Future research should concentrate on increasing the size of the training dataset to encompass a wider variety of thicknesses and incorporate additional structural metrics, such as stress or fatigue analysis, to offer a more thorough assessment of the blower cab's performance. Furthermore, the entire computational process, including preprocessing and training times, should be measured to evaluate the practicality of implementing these ai models in real-world industrial environments. This research establishes a solid basis for utilizing physics-informed artificial intelligence in structural analysis, providing a scalable and efficient method to improve the design and reliability of locomotive components, especially in iterative design processes where similar models undergo minor modifications.

7.2 Future Scope

The present research has effectively showcased the effectiveness of a physics-based artificial intelligence (ai) model in predicting the structural behaviour of a blower cab by adjusting pillar thicknesses, resulting in high accuracy and computational efficiency. Nevertheless, the scope of this research can be greatly broadened to encompass a wider range of applications within the field of locomotive engineering. This study primarily aimed to predict outcomes based on changes in thickness for a smaller component, but future research can expand this approach to larger and more intricate locomotive components, such as the engine and platform. These parts, crucial for the locomotive's stability and efficiency, are more complicated because they are larger, have intricate shapes, and are subjected to various types of forces. By incorporating physics-based AI into the analysis of locomotive components, this approach can automate the process of evaluating design optimization and performance across a broader spectrum of subsystems. For example, automating the prediction of structural responses for the engine, which houses the prime mover and is subjected to substantial thermal and mechanical stresses, could simplify the design process, minimizing the need for time-consuming finite element analysis (FEA). In a similar manner, utilizing the model on the platform, which acts as the base structure supporting various subsystems, could facilitate the evaluation of load distribution and structural integrity under different operational conditions. This automation would not only improve the scalability of the proposed methodology but also contribute to the creation of a comprehensive ai-driven framework for locomotive design, capable of handling various components with minimal human intervention. Additionally, future research could incorporate other design factors beyond thickness, such as material properties, geometric configurations, and dynamic loading conditions, to develop a more comprehensive predictive model. By integrating real-time data from locomotive operations, such as vibration or temperature profiles, the model's effectiveness could be improved, allowing for predictive maintenance and real-time monitoring of structural health. These advancements would make the physics-informed ai model a groundbreaking tool in railway engineering, paving the way for fully automated, data-driven design and analysis workflows for future locomotives.

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