



Data-driven machine learning and finite element-informed surrogate modeling for design optimization and failure prediction of reinforced thermoplastic pipes

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ABSTRACT

Reinforced Thermoplastic Pipes (RTPs) offer a significant advantage as corrosion-resistant alternative to metallic pipelines, yet their mechanical performance under combined loading is not fully understood. This study proposes a comprehensive outline integrating finite element (FE) modeling with machine learning (ML) to predict RTP failure under multi-factorial conditions, including pressure, temperature, and bending. An LS-DYNA model of an experiment of flexural testing with 4.34% mean error validated the FE model and simulation of the RTP behavior with high accuracy. Through 135 parametric simulations, the diameter-to-thickness (D/t) ratio was identified as the most influential factor for bending moment capacity, while fiber orientation angle predominantly affected rotation angle at failure. A Random Forest regression model trained on this data achieved high predictive accuracy ($R^2 = 0.93$ for bending moment, $R^2 = 0.97$ for rotation angle). This ML-enhanced framework enabled the identification of optimal RTP designs, demonstrating significant potential for reducing computational costs and guiding future design optimization strategies for composite pipes.

1. Introduction

Reinforced Thermoplastic Pipes (RTPs) represent a progressive approach to pipeline construction, offering a convincing alternative to traditional materials in various industrial applications. These spoolable composite structures, characterized by a multi-layered design typically comprising a liner, reinforcement layers, and an outer cover, offer a unique combination of flexibility, high strength, and corrosion resistance. RTPs find several crucial applications in the oil & gas and petroleum industries, where their non-metallic nature provides a significant advantage in mitigating corrosion issues prevalent in these harsh operating environments. In this sector, RTPs are used for the transportation of crude oil and natural gas [1,2], injection lines for enhanced oil recovery (EOR) methods such as water and CO₂ injection [3], downhole tubulars for corrosive well environments, and offshore pipelines [4] where corrosion resistance is principal. The three-layer design of RTPs is directly related to the performance requirements of these applications. The liner provides chemical resistance to the

transported fluids, the reinforcement layers offer high tensile strength to withstand internal pressure, and the cover protects against external damage and environmental factors [5].

The non-metallic nature of RTPs is particularly critical in the oil and gas industry because it prevents the degradation of pipes by corrosive agents like hydrogen sulfide and saline water [6], which can severely damage traditional metallic pipes, leading to leaks, environmental damage, and substantial economic losses.

Even though RTPs offer numerous benefits, ranging from lower installation and maintenance costs to a longer service life when compared with conventional materials such as steel and concrete, they also present certain limitations and drawbacks that warrant thorough investigation. A significant concern relates to their thermal properties. Thermoplastic matrices exhibit considerably lower heat deflection temperatures than their metallic counterparts, which can limit the operational temperature range of RTPs. Furthermore, RTPs have the potential to experience gradual deformation when subjected to prolonged loading or elevated temperatures [7]. This phenomenon, often

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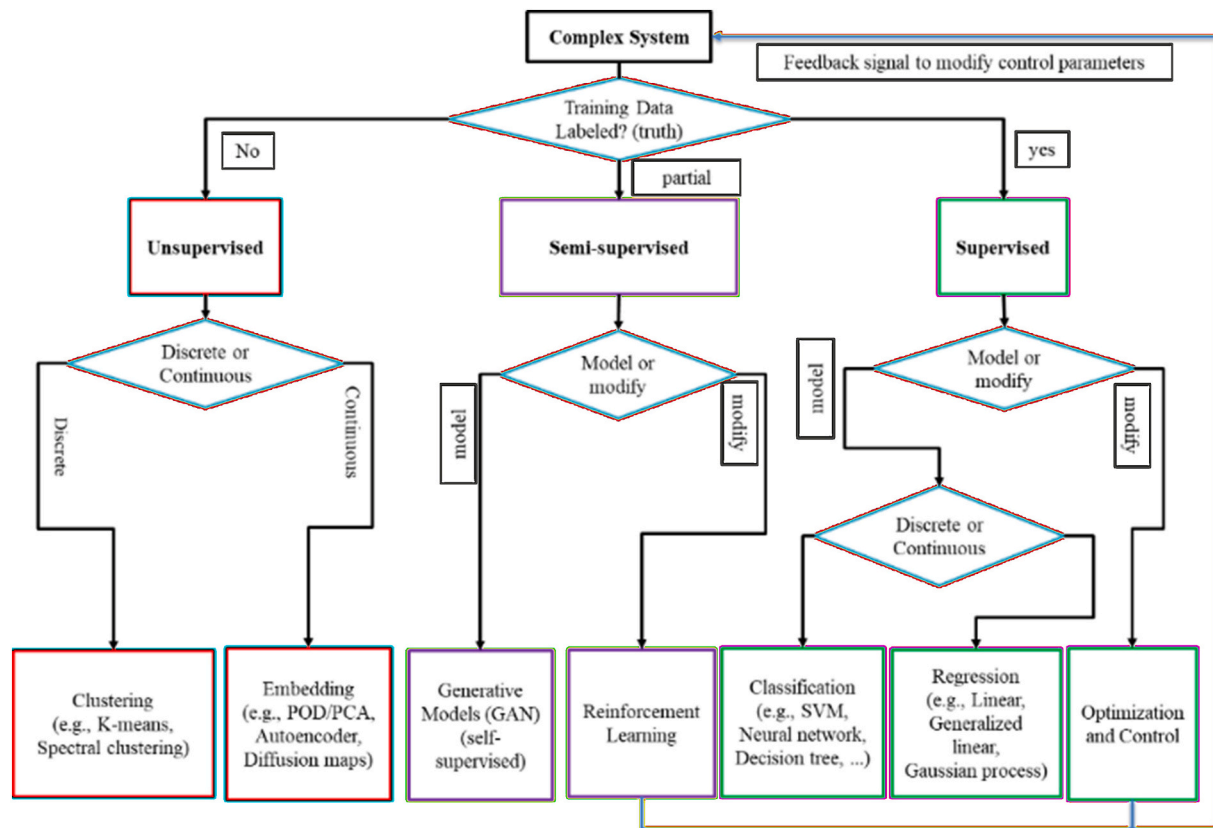


Fig. 1. Schematic representation of diverse machine learning approaches [24].

referred to as creep, involves mechanisms such as chain slippage and viscoelastic deformation within the thermoplastic matrix [8,9]. Factors such as high temperature, sustained pressure, and aggressive chemical environments can accelerate creep [10–12]. Additionally, RTPs may also demonstrate stress rupture, a time-dependent failure mechanism characterized by the gradual degradation of their structural integrity under sustained stress.

Before the development of RTPs, Glass Fiber Reinforced Plastic (GRP) pipes were among the first composite alternatives to conventional metallic pipelines. Research revealed that filament-wound glass fiber-reinforced epoxy pipes with a $\pm 55^\circ$ winding angle demonstrated compressive strength three times higher than tensile strength because of ply orientation [13], but also experienced matrix cracking under hoop tension and inner ply delamination in hoop compression [14].

Comparatively, there is a noticeable lack of extensive data and established design guidelines specifically tailored for RTPs in comparison to conventional piping materials that have a longer history of use and a more mature body of research supporting their application [15, 16]. The limited availability of comprehensive data on the long-term behavior of RTPs under various environmental and loading scenarios poses a challenge to their extensive approval and necessitates further scientific investigation.

Several studies have been performed to predict the failure of RTP under different loading conditions experimentally and numerically. Research findings showed that fatigue damage rapidly escalated before stabilizing and then spiked sharply, leading to a total fracture, while matrix fatigue damage in the reinforcement layer primarily causes fast stiffness degradation [10]. Studies on RTPs through uniaxial tension tests showed that the predominant failure mode was tensile fiber failure for winding angles below 30° , while tensile matrix failure took over for angles above 40° [13,16]. Investigation of $\pm 55^\circ$ wound RTPs with 4 to 12 reinforcement layers demonstrated that burst pressure behaves non-linearly according to the number of layers, which reveals intricate

failure mechanisms [17,18].

Research showed that the optimal winding angle went beyond the constant 54.7° as ply count increases and reaches 58° at 20 plies or less, 60° between 30 and 40 plies, and 62° between 50 and 60 plies [19]. Studies demonstrated that increasing the number of plies led to higher burst pressure and resulted in a 62.7% improvement when the ply count went from 10 to 20. RTPs show that their ability to bend determines their performance, especially when operating in harsh conditions. The nonlinear properties of polyethylene lead to buckling as the primary failure mode instead of brittle failure, with the highest stability obtained with reinforcement angles set at $[\pm 65^\circ/\pm 75^\circ]$ [20,21].

However, the existing body of research primarily concentrates on isolated design configurations, often neglecting the impact of diverse design parameters and the combined effects of multiple loading conditions, such as temperature, internal pressure, and bending. This oversight results in a significant knowledge gap, particularly in accurately predicting the failure criteria of RTPs under realistic, multi-factorial conditions. The multi-island genetic algorithm (MIGA) allowed researchers to improve burst pressure performance with optimized multi-angle winding schemes [22], with RTPs reinforced with 10 and 12 layers showing superior burst pressure performance compared to $\pm 55^\circ$ wound RTPs by 14.01% and 10.16%, respectively.

Modern Machine Learning technologies have improved simulation performance when modelling real-world processes and systems in material science and physics. Previously impossible simulations can now be performed within reasonable time limits. Physics-based simulation tools have incorporated machine learning at multiple levels, which leads to faster computations and better resource efficiency. Machine learning approaches are characterized by whether the model training is supervised, semi-supervised, or unsupervised [23]. In recent years, the implementation of a wide range of machine learning algorithms and architectures (Fig. 1) has become more practical to researchers from many fields. Labelled data is required for supervised learning to train a

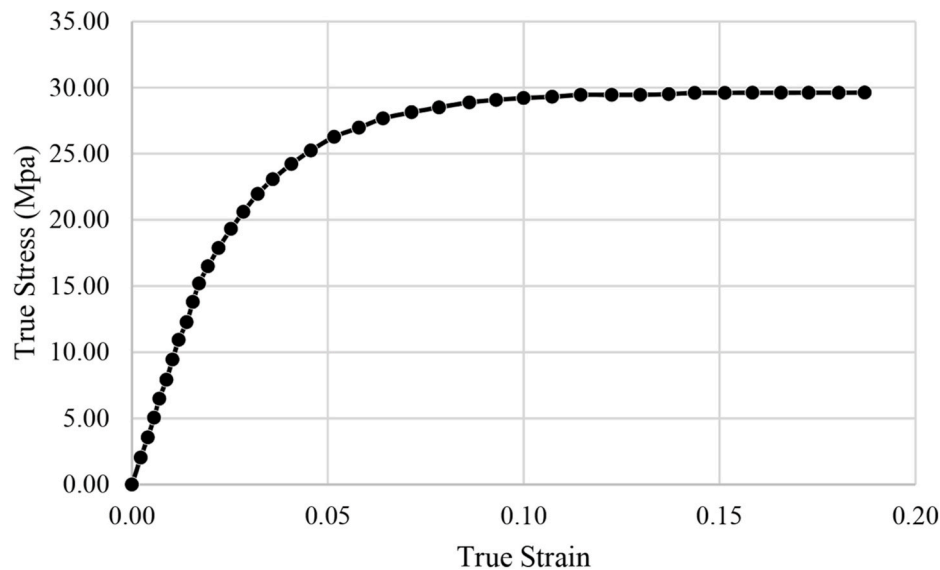


Fig. 2. True stress-strain curve of HDPE for liner and coating materials.

function that maps input to output. Common supervised learning techniques, such as Support Vector Machines (SVMs) and Linear Regression, are mostly employed for classification or regression problems. Unsupervised learning training data differs from supervised learning in that it is unlabelled.

A common job is data clustering, in which the algorithm seeks similarities between data items and attempts to categorize them without being explicitly instructed. Semi-supervised learning uses partially labelled and unlabelled data sets. As a result, it is an intermediary step between supervised and unsupervised learning, to improve one of the two [25]. Reinforcement learning is another type of machine learning method that might be considered semi-supervised. This strategy employs a learning system known as an agent, which investigates its surroundings by performing actions. Actions are rewarded (or penalized), and the agent must discover how to maximize rewards (or reduce penalties) [23–25].

Ang et al. evaluated Random Forest, Support Vector Machines and Artificial Neural Networks for predicting fatigue life in polymeric Functionally Graded Materials. Random Forest achieved the lowest Root Mean Square Error and demonstrated superior generalization [26]. This result establishes the urgency for additional research into different FGM compositions and diverse environmental conditions. Benedetto et al. developed an ANN model to estimate the impact energy absorption of thermoplastic commingled composites [27]. The ANN demonstrated strong predictive capabilities for impact toughness evaluation and failure mode analysis. In another work, pipes with a thermoplastic matrix had much better energy absorption and less damage than those with an epoxy matrix [28].

Another approach [29] assessed an ANN model using an E-Jaya algorithm to predict displacement in composite pipes under low-velocity impact loads. The enhanced ANN model showed better performance, with a correlation coefficient of 0.998 [29]. Research [30] established a system to assess crash behavior in CFRP tubes by integrating machine learning with finite element modeling. Parameters such as friction coefficient, damage criteria, and contact stiffness required meticulous calibration [30]. In the context of composite pipeline monitoring, machine learning has also been successfully integrated with advanced sensing and simulation techniques.

Through intricate pattern analysis machine learning method has shown the ability to successfully predict material degradation. Ang et al. conducted a performance evaluation of Random Forest, Support Vector Machines and Artificial Neural Networks for predicting fatigue life in

polymeric Functionally Graded Materials produced by Material Extrusion. Random Forest achieved the lowest Root Mean Square Error and demonstrated superior generalization compared to other methods. This result establishes the urgency for additional research into different FGM compositions and diverse environmental conditions. In the context of composite pipeline monitoring, machine learning has also been successfully integrated with advanced sensing and simulation techniques. One study [1] employed machine learning to detect damage in thermoplastic composite pipes under random vibrations, using Random Forest (RF) and Long Short-Term Memory (LSTM) models. The application of the Random Decrement Technique (RDT) significantly improved model accuracy, with RDT-RF and RDT-LSTM achieving 99.56% and 100% accuracy, respectively, even under high noise conditions. However, without RDT, the accuracy of RF declined significantly, highlighting the importance of noise mitigation strategies. Further advancing this approach, another study [31,32] focused on long-term creep thermo-mechanical fatigue (LTCTMF) in basalt fiber-reinforced polymer (BFRP) composite pipelines. A multi-physics finite element method (FEM) framework was used alongside electrical capacitance sensors (ECS) to monitor dielectric characteristics for damage identification. A convolutional neural network (CNN)-based deep neural network (DNN) was then developed to predict LTCTMF compliance for stress levels absent from FEM simulations, providing accurate forecasts. This integrated use of ECS, FEM, and DNN presented an efficient and scalable monitoring system, capturing degradation patterns over time [31,32].

The research gap lies in the need for more comprehensive studies that combine experimental, numerical, and analytical approaches to a better understanding of the performance of RTPs. This includes investigating the effects of various environmental factors, such as temperature and chemical exposure (e.g., exposure to specific chemicals present in oil and gas environments, such as H₂S, CO₂, and brine solutions), as well as the influence of different loading conditions, including sustained pressure and combined loading, on the mechanical properties and structural integrity of RTPs. Addressing this gap through structured and demanding technical investigation is essential to establish the limitations of safe and reliable utilization of RTPs in a wider spectrum of applications within the oil and gas sector and potentially beyond.

Therefore, a comprehensive investigation into the mechanical performance and structural integrity of RTPs under a realistic operational condition is of significant interest to the scientific and engineering communities. While RTPs offer numerous advantages, such as corrosion

Table 1
Material Properties of the RTP samples used for experimental test [32].

Properties	Description	Glass/epoxy
ρ	Density (kg/m^3)	1510
E_{11}	Young's modulus in fibre direction (GPa)	42
$E_{22} = E_{33}$	Young's modulus in transverse direction (GPa)	12.2
ν_{23}	Poisson's ratio in plane 2-3	0.27
$\nu_{12} = \nu_{13}$	Poisson's ratio in plane 1-3 and 1-2	0.14
$G_{12} = G_{13}$	shear modulus in plane 1-3 and 1-2 (GPa)	4.7
G_{23}	shear modulus in plane 2-3 (GPa)	3.75
X_T	Tensile strength in fibre direction (MPa)	829
X_C	Compressive strength in fibre direction (MPa)	446
Y_T	Tensile strength in transverse direction (MPa)	25
Y_C	Compressive strength in transverse direction (MPa)	149
S_C	Shear strength (MPa)	68
Properties	Description	HDPE
E	Young's modulus (GPa)	1.12
ν	Poisson's ratio	0.38
σ_y	Yield Strength	15
σ_t	Ultimate Tensile Strength	29

resistance and ease of installation, their mechanical performance and structural integrity are significantly influenced by the complex interplay of various operational conditions, including temperature, sustained pressure, and the effect of content density over the duration of service. Addressing these influences and the development of predictive models to accurately assess their effectiveness over extended periods is essential for facilitating the wider adoption of RTPs as a reliable and suitable alternative to traditional pipeline materials in several applications. Addressing these factors and developing predictive models to assess their long-term performance are essential for enabling the wider adoption of RTPs as a reliable alternative to traditional pipe materials. Therefore, the primary objective of this study is to provide a better understanding of the mechanical behavior of RTP by addressing the identified gaps. This will be accomplished through a multi-faceted, data-driven approach: initially, a damage-based finite element model was developed to demonstrate RTP behavior and failure responses. Subsequently, the results from this validated model were used to train a surrogate supervised learning model. Ultimately, the surrogate model was employed to determine optimal RTP configurations across a spectrum of design parameters.

2. Materials and methods

2.1. Finite element modeling

2.1.1. Material properties

The specimen pipe consisted of an HDPE liner, an HDPE coating layer, and a composite laminate core reinforced with $\pm 55^\circ$ wound glass fiber reinforced polyethylene tapes shown in Fig. 2. The 0.25 mm thick composite laminate plies contained 60% glass fiber by volume. Material properties of glass fiber and HDPE are shown in Table 1.

The non-linear true stress-strain curve of the HDPE liner and coating is shown in Fig. 3. Thermal effects were incorporated through constant temperature application at inner layer nodes, enabling thermal expansion based on material-specific coefficients. The reinforcement layers were treated as orthotropic, with distinct thermal expansion coefficients along axes $\alpha_l = 1.8 \times 10^{-6}$ and $\alpha_h = 2.3 \times 10^{-5}$ for hoop direction, while the HDPE layer was assumed to be isotropic with $\alpha = 1.8 \times 10^{-4}$. Temperature analysis at 10°C revealed accelerated failure progression under combined thermal-mechanical loading compared to pure bending conditions [7,32]. Contributing factors include reinforcement layer contraction at reduced temperatures, differential shrinkage between dissimilar materials at interfaces, and complex mechanical coupling effects.

To implement the mechanical effect of constant temperature on the pipe, a thermal expansion card was added to the material model for HDPE and PE fiberglass. The temperature difference was defined in the model's load section, with thermal constants applied later based on the input dataset suggested by Response Surface Methodology (RSM), within the normal operational range between 10 and 30°C for RTPs. Alternatively, a constant pressure load, ranging from 3 to 10 bars, was applied to the nodes of the HDPE inner layer to represent the operational pressure. The mechanical effects of thermal expansion and internal pressure on the inner HDPE section, as well as their transfer to the reinforcement and outer layers, were subsequently monitored through the contact reaction forces.

2.1.2. Damage model and failure criteria

The Hashin damage model parameters for predicting the failure of reinforced composite layers consist of four criteria was employed for this analysis. This damage model regulates the fiber and matrix damage during tension or compression throughout all simulation increments

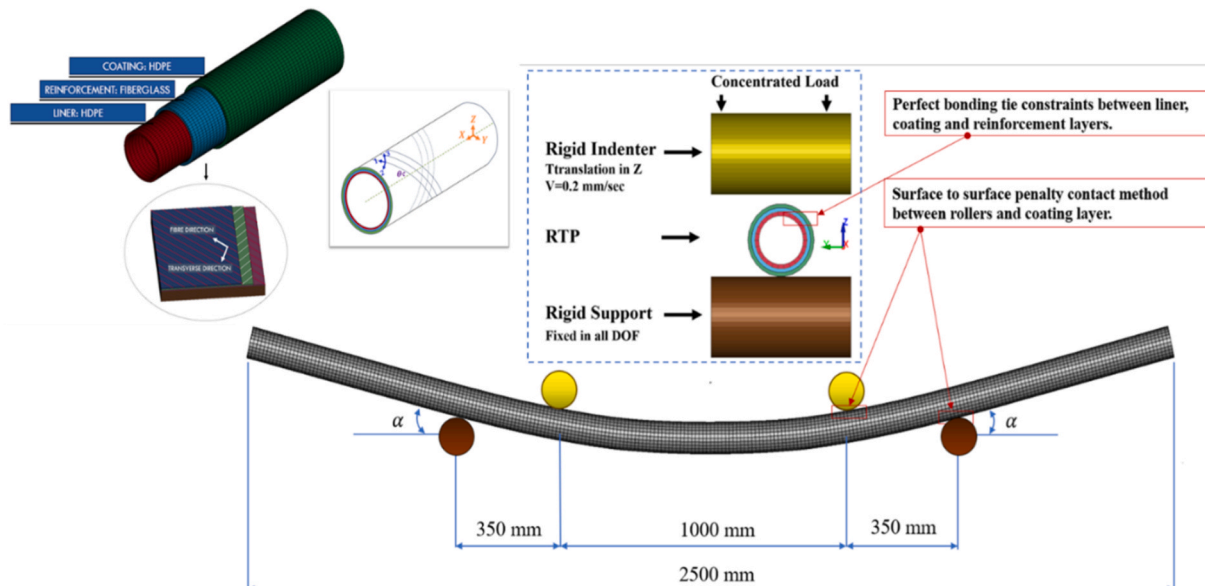


Fig. 3. The schematic view and general dimensions of a 4-point bending setup.

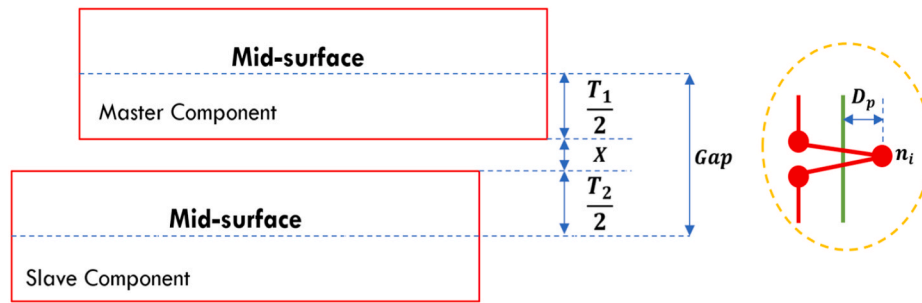


Fig. 4. Contact detection algorithm for shell element in LS-Dyna.

[33]. If any of these criteria are met, damage initiation is recognized. When the damage factor in one of these criteria attains a value of 1, it indicates that complete rupture has happened. Equations (1)–(4) delineate Hashin's damage criterion.

$$F_f^t = \left(\frac{\sigma_{11}}{X_T} \right)^2 + \alpha \left(\frac{\tau_{12}}{S_L} \right)^2, \bar{\sigma}_{11} \geq 0, \text{fiber tension} (\bar{\sigma}_{11} > 0) \quad (1)$$

$$F_f^c = \left(\frac{\sigma_{11}}{X_C} \right)^2, \text{fiber compression} (\bar{\sigma}_{11} < 0) \quad (2)$$

$$F_m^t = \left(\frac{\sigma_{22}}{Y_T} \right)^2 + \left(\frac{\tau_{12}}{S_L} \right)^2, \text{matrix tension} (\bar{\sigma}_{22} \geq 0) \quad (3)$$

$$F_m^c = \left[\left(\frac{\sigma_{22}}{2S_r} \right)^2 + \left[\left(\frac{Y_c}{2S_r} \right)^2 - 1 \right] \left(\frac{\sigma_{22}}{Y_c} \right)^2 + \left(\frac{\tau_{12}}{S_L} \right)^2 \right], \text{matrix compression} (\bar{\sigma}_{22} < 0) \quad (4)$$

In this study, HDPE was represented by the material model Piecewise Linear Plasticity which perfectly includes the material's nonlinear stress-strain behaviour by using a piecewise linear true stress-strain curve. Failure of HDPE was defined based on the plastic strain $\varepsilon_f = 0.175$. Additionally, the Enhanced Hashin Composite Damage model, was used to simulate reinforcement layer. This card was chosen as it included factors like damage initiation and gradual deterioration to account for composite material failure. It captured the orthotropic character of fibreglass and ensured accurate modelling of its behaviour under loading by including qualities such as tensile and compressive strength in both matrix and fibre directions. The Hashin failure criterion was applied using the failure parameter CRIT 54 with a beta value of 1. Upon reaching a failure criterion, the failure stress value, failure location, and failure mode were documented.

2.1.3. Geometrical design and test conditions

The analysis involved two main phases: finite element (FE) model development and failure prediction model through machine learning method. To validate the FE model against experimental data the four-point bending test on reinforced thermoplastic pipes was selected from the literature [30]. According to the experimental setup described in Ref. [30], a 1000 mm pure bending section was employed exceeding six times the pipe's outer diameter to comply with the DNVGL-ST-F119 standard. The distance between the loading and support points was maintained at 350 mm, as illustrated in Fig. 3. The specimen was subjected to loading at a constant displacement rate of 0.2 mm/s. Based on the referenced experiment, the model was developed with an inner diameter of 25.4 mm and a thickness of 4.5 mm for the inner layer, a reinforcement layer with a thickness of 4 mm, and an outer layer with a thickness of 4 mm.

A shell model was used as it provided good accuracy in agreement with the experimental results, incorporating 19500 deformable elements. Two rigid moving rollers and two rigid supports were

symmetrically modeled according to the referenced experiment, containing 8320 rigid elements for rollers and supports. In order to get results reliability and to reach mesh size's independency the mesh convergence study was performed and the converged and stable element size for all three layers were achieved by the size of 2.4 mm for shell elements. The same size also was considered for the rigid roller to avoid roller penetration in the deformable bodies. The lower rollers are fixed in all DOF, and the upper rollers are free to move vertically. The HDPE layers for the inner and outer were modeled using Belytschko-Tsay shell element section type.

The reinforced composite layer was modeled with a fully integrated shell element using 16 integration points across the thickness, simulating 16 lamina layers. Fiber orientation angle was alternately set as $\pm 55^\circ$ to best represent the structure of the experimental composite in the analysis. To generate contact between the deformable body (RTP) and rollers, a penalty surface-to-surface contact model with a 0.3 friction coefficient was applied to the contact model, assuming Coulomb friction behavior under dry contact conditions. The friction coefficient is taken from the scientific work of the same author; however, to ensure the validity and transferability of the measurement, this parameter was further calibrated while tuning the model within a physically reasonable range, such that the best bending moment matching the experimental curve is achievable.

The contact algorithm in LS-DYNA considers the contact active when the current gap between the slave node and master surface becomes less than $\left[\frac{T_1}{2} + \frac{T_2}{2} + x \right]$, as shown in Fig. 4. This condition accounts for shell-thickness offsets, enabling thickness-based contact.

When using the penalty method, each slave node is evaluated to determine whether it penetrates the master surface. If no penetration occurs, no action is taken. However, if penetration is detected, an interface force is applied at the contact point between the slave node and the master surface [34]. This force is directly proportional to the depth of penetration, effectively simulating a spring-like interface between the two surfaces. Penetration of a slave node n_s into the corresponding master segment (which contains its contact point) is indicated when:

$$D_p = n_i \times [t - r(\xi_c, \eta_c)] < 0 \quad (5)$$

where, $n_i = n_i(\xi_c, \eta_c)$ is normal vector to the master segment at the contact point, $r(\xi_c, \eta_c)$ is position vector of the contact point on the master segment, defined by the local curvilinear coordinates and D_p is the depth of penetration.

Thus, if slave node n_s penetrates by master segment s_i , an interface force vector will be added:

$$f_s = -D_p k_i n_i < 0 \quad \text{if } D_p < 0 \quad (6)$$

To the degrees of freedom corresponding to n_s and

$$f_m^i = \phi_i(\xi_c, \eta_c) f_s \quad \text{if } D_p < 0 \quad (7)$$

to the four nodes ($i = 1, 2, 3, 4$) that comprise master segment s_i . The

Table 2
Defined variables range for simulation.

Parameter	Unit	Min. value	Max. value
Internal Pressure (P)	bars	3	10
Temperature (T)	°C	10	30
Fiber Orientation Angle (FOA)	degree	30	60
Diameter to Thickness Ratio (D/t)	—	8	26
Number of Layers (NOA)	—	12	24

stiffness factor k_i for master segment s_i is given in terms of the bulk modulus K_i , the volume V_i , and the face area A_i of the element that contains s_i as:

$$k_i = \frac{f_{si} K_i A_i^2}{V_i} \tag{8}$$

for shell elements where f_{si} is a scale factor for the interface stiffness and normally defaulted to 10. Larger values may cause instability unless the timestep size is scaled back in the timestep calculation.

Table 3
Data collection from FE Model.

D/t	Pressure (bar)	Temperature (C)	Fibre Angle (degree)	Number of layers	Ang of Rotation (degree)	Bending Moment (N.m ²)
12.7	7.5	22.5	42.5	16	6.95	588.68
12.7	5	30	50	12	11.52	1016.42
8.47	10.5	15	30	16	4.9	428.32
12.7	7.5	22.5	42.5	12	6.88	563.45
8.47	7.5	22.5	42.5	12	7.36	808.38
8.47	12	22.5	42.5	16	7.18	498.35
25.4	7.5	9.89	42.5	24	6.84	354.32
25.4	7.5	22.5	65	12	8.06	322.47
12.7	3	22.5	42.5	16	7.78	728.4
25.4	12	22.5	42.5	24	6.45	280.79
12.7	12	22.5	42.5	12	6.2	378.16
8.47	7.5	22.5	42.5	24	7.67	817.3
12.7	7.5	35.11	42.5	12	7.08	442.41
8.47	10.5	15	50	24	12.07	921.35
8.47	7.5	22.5	65	12	8.3	886.29
8.47	3	22.5	42.5	12	8.18	741.49
12.7	10.5	30	50	24	10.1	617.14
8.47	7.5	22.5	25	12	3.87	229.24
8.47	5	15	30	24	5.24	468.87
8.47	3	22.5	42.5	16	8.29	747.94
25.4	7.5	22.5	42.5	24	7.02	456.87
8.47	5	15	30	12	5	434.25

2.2. Data generation and collection method

The validated model was used for an efficient exploration of the relationship between input variables and their impact on responses, even when dealing with non-linear behaviours.

According to the Latin Hypercube Sampling (LHS) method, a total of 135 simulations were generated, providing a dataset for training and validating the surrogate model to predict failure responses in RTPs under various design configurations and operational conditions. The input variables are provided in Table 2.

After filling data in the design table and extracting the model responses from FE analysis, the dataset will be ready for data screening and data analysis. Table 3 shows some of the extracted data from FE simulation.

The response variables recorded were the bending moment exerted from rollers to RTP at failure and the associated angle of rotation α shown previously in Fig. 3. The Random Forest model was used to train the surrogate model. This study employed a multi-output Random Forest regressor to predict the two response variables. As the nature of data is non-linear and changes, going far beyond the simulation input range, the main objective was to predict results within the range of the normal

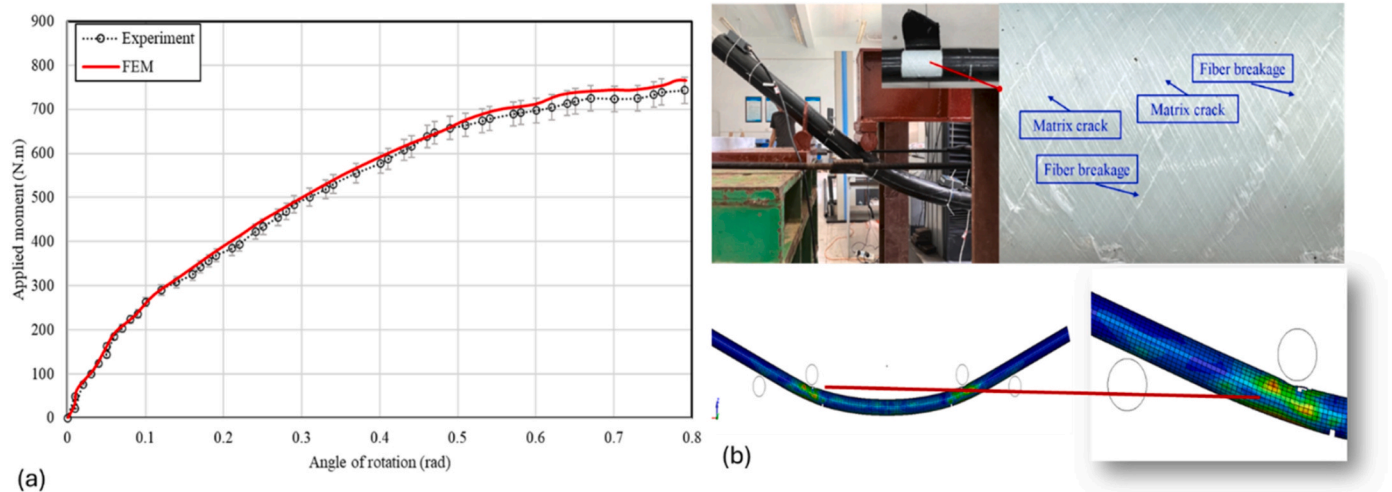


Fig. 5. (a) FEM model validation through pure flexural experimental test (b) visual observation of failure location [32].

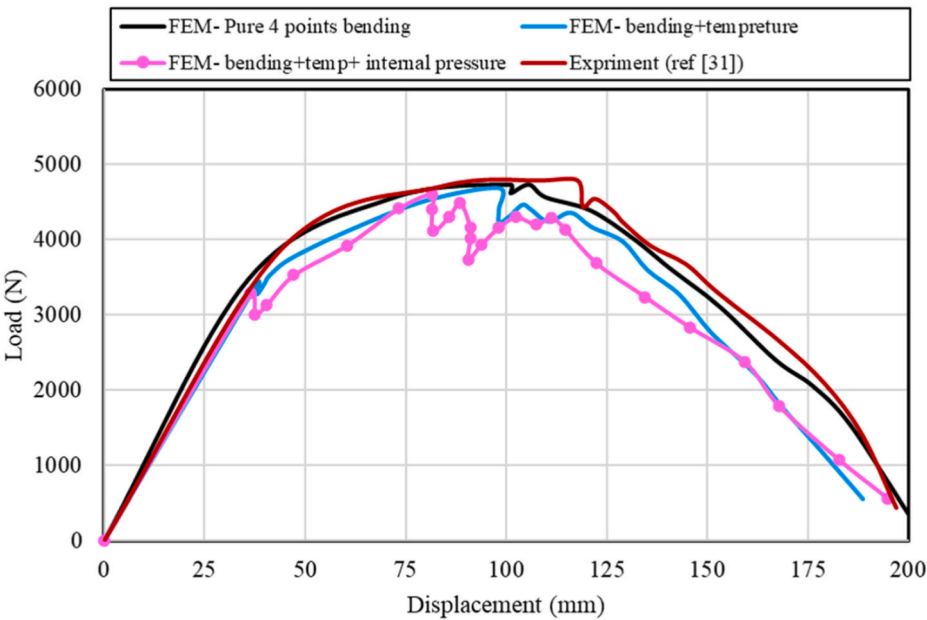


Fig. 6. The load-displacement curve of various RTPs under different loading conditions.

operational condition. This study emphasizes estimation of responses using interpolation over extrapolation. The Random Forest RF algorithm is appropriate for this objective, as its ensemble methodology reduces overfitting and guarantees consistent performance within the limits of the training data. In contrast to individual decision trees, which are susceptible to bias and overfitting, the RF technique combines numerous decision trees to yield a more reliable prediction. Its capacity to capture nonlinear and multivariate interactions rendered it a good choice for simulating the complexity of the mechanical behaviour of RTPs. Each decision tree in the Random Forest was trained with the Classification and Regression Tree (CART) algorithm, which determined the best splits to enhance predictive accuracy. To ensure the training set is providing

sufficient data for RF, several combinations of different shares of training sets and test sets were tested. Considering bias, overfitting criteria, and accuracy, finally, 80% of the records in the dataset were used for RF model training. The dataset was divided into predicted and actual results, and the loss function was calculated. The training process continued until the accuracy of the actual and predicted results reached a satisfactory threshold. The remaining 20% of the dataset was used to evaluate the accuracy of the machine learning model. When the error of the predictive model was reduced to less than 5% of the FE results, the model was considered accurate. This model was then used to generate a larger dataset to observe the failure responses for numerous different RTP configurations and operational conditions.

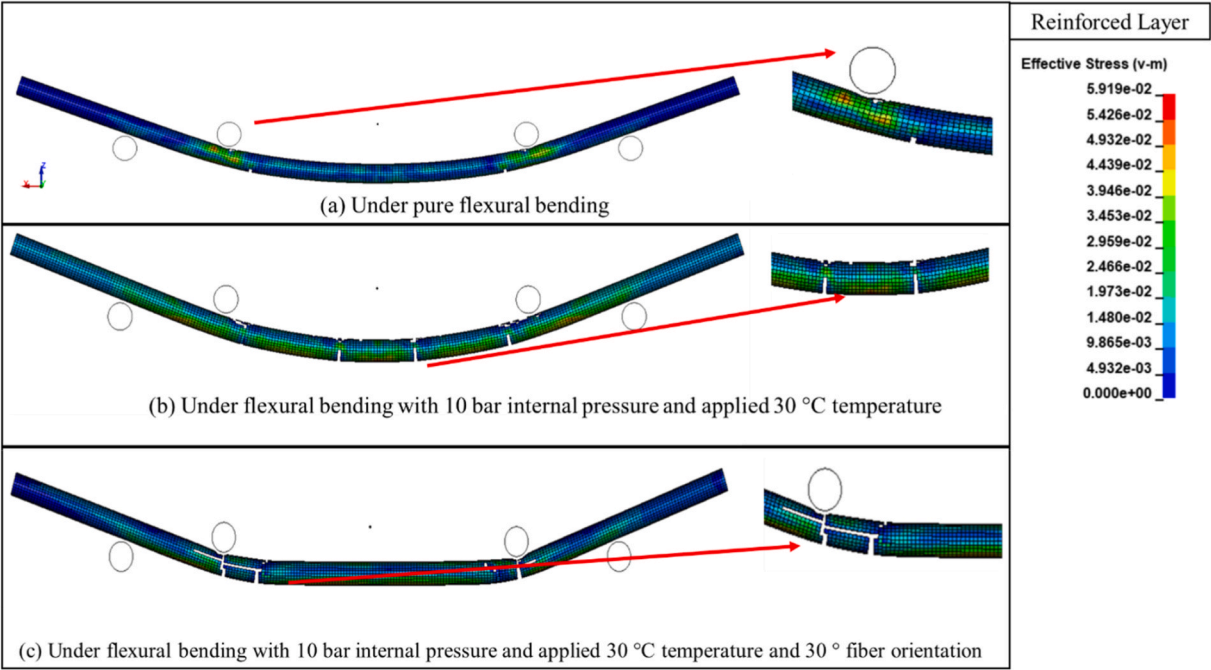


Fig. 7. Stress distribution and fracture mode observation of reinforced layers of various RTPs under different loading conditions: (a) pure bending condition, (b) combined thermal, internal pressure, and flexural loading, (c) combined loading with 30° fibre orientation angle.

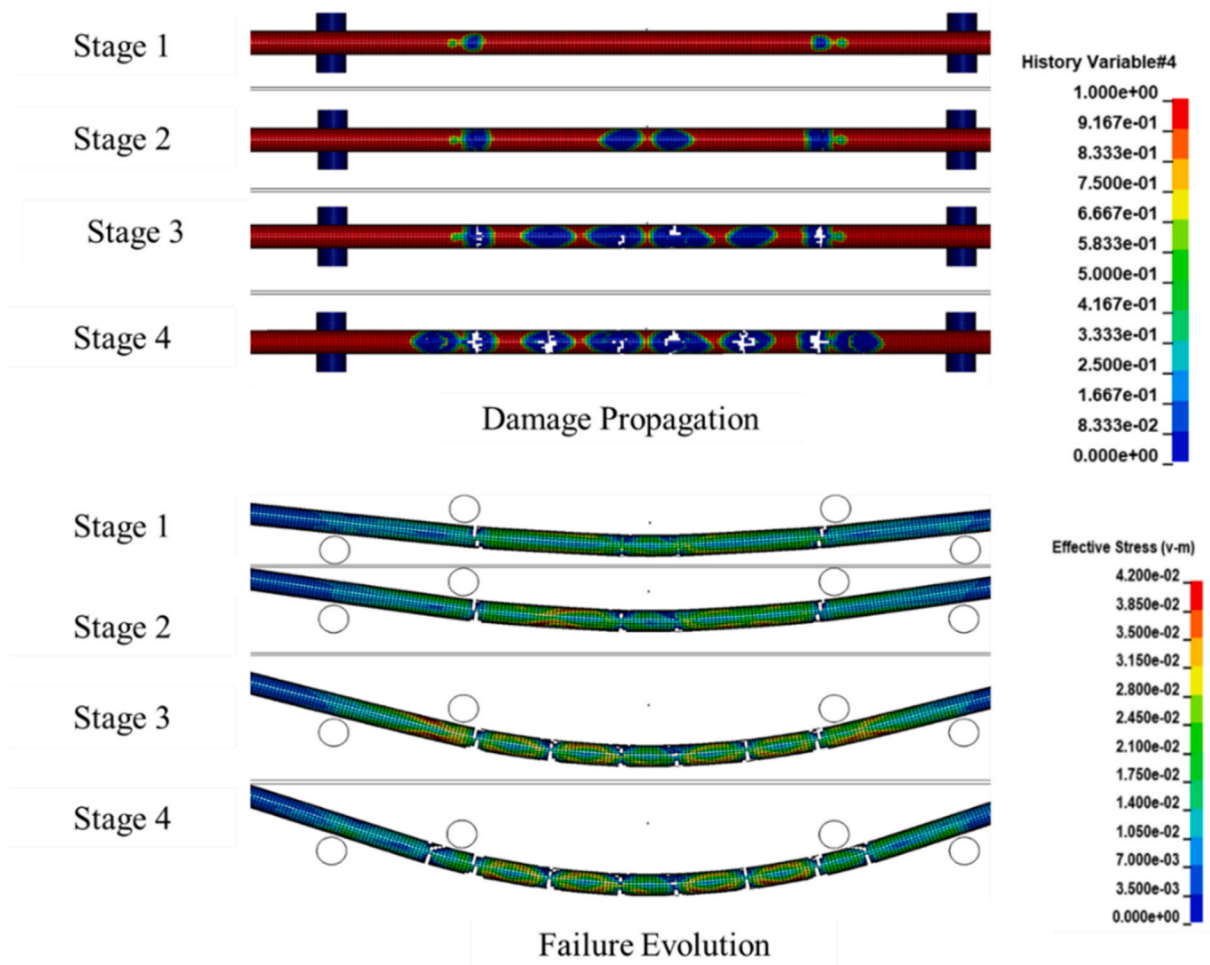


Fig. 8. Damage propagation (top side) and failure evolution (bottom side) of the reinforced layer of RTPs under combined loading over time.

3. Results and discussion

3.1. Validation of finite element model

Finite element modeling overcomes the physical constraints inherent in experimental testing by providing a comprehensive visualization of failure locations. Individual layer analysis yields critical information regarding failure mechanisms, stress concentrations, and failure initiation points, fulfilling a primary objective of this investigation. Experimental approaches are limited by inter-layer adhesion, requiring pipe rupture before intermediate layer damage or failure identification becomes feasible.

Fig. 5a presents a comparison between three sets of experimental data (with an error margin of $\pm 2\%$) and the corresponding numerical simulation results. The applied moment-angle of rotation curve was plotted and shows that in the first stage of loading (elastic region), the deviation between experiment and numerical results was less than 0.5%; however, by degradation of materials and especially failure observation in the middle layer (composite layer), the difference between FE results and experimental data rose to 3%. In order to reduce the error between model and experimental data, model calibration was performed to match the force displacement curve for both the elastic and plastic regions. While the elastic region was purely dependent on elastic parameters (E, G), the plastic region was dependent on Hashin failure criteria, hourglass energy, and a factor to determine the minimum stress limit (SLIMT = 0.3). Moreover, visual inspection confirmed that both approaches exhibited the same dominant failure mode, i.e., matrix cracking and fiber breakage, which occurred in the pure bending region

(over the roller span), as illustrated in Fig. 5b.

The load–displacement response of various RTPs under different loading conditions, obtained from both experiments and FE models, is presented in Fig. 6. The experimental data show a smooth elastic response with no noticeable scattering or stiffness variation, reflecting the natural behavior of such pipe, which has two thick HDPE layers surrounding the inner and outer surfaces of the main composite tube. Unlike pure composite tubes with a more brittle behavioral nature, which typically show rapid changes in load response due to nonlinear behavior, the present RTPs exhibit a smoother mechanical response. As reflected by FE model data, in all case studies, the elastic behavior has the same trend, and the yield force started at 3.4 kN. However, by applying different loading conditions such as pure bending, internal pressure, and thermal effect on the inner content, the material degradation was observed. The results show that, in the real condition, obtained by superimposing the induced temperature, internal pressure, and flexural bending, the load–displacement curve drops significantly by 14% in the worst case. These findings highlight the critical importance of considering combined loading effects when evaluating the mechanical response of RTPs.

The initial failure in the pure four-point flexural simulation occurred within the reinforcement layer, specifically in the constant moment region between support spans, as demonstrated in Fig. 7a. This layer experienced a maximum stress of 63.09 MPa at failure initiation. Matrix failure represented the predominant failure mode, revealing under both tensile and compressive loading conditions near the roller contact areas. Stress distribution analysis showed that inner and outer HDPE layers sustained significantly lower stresses, measuring 22.36 MPa and 24.78

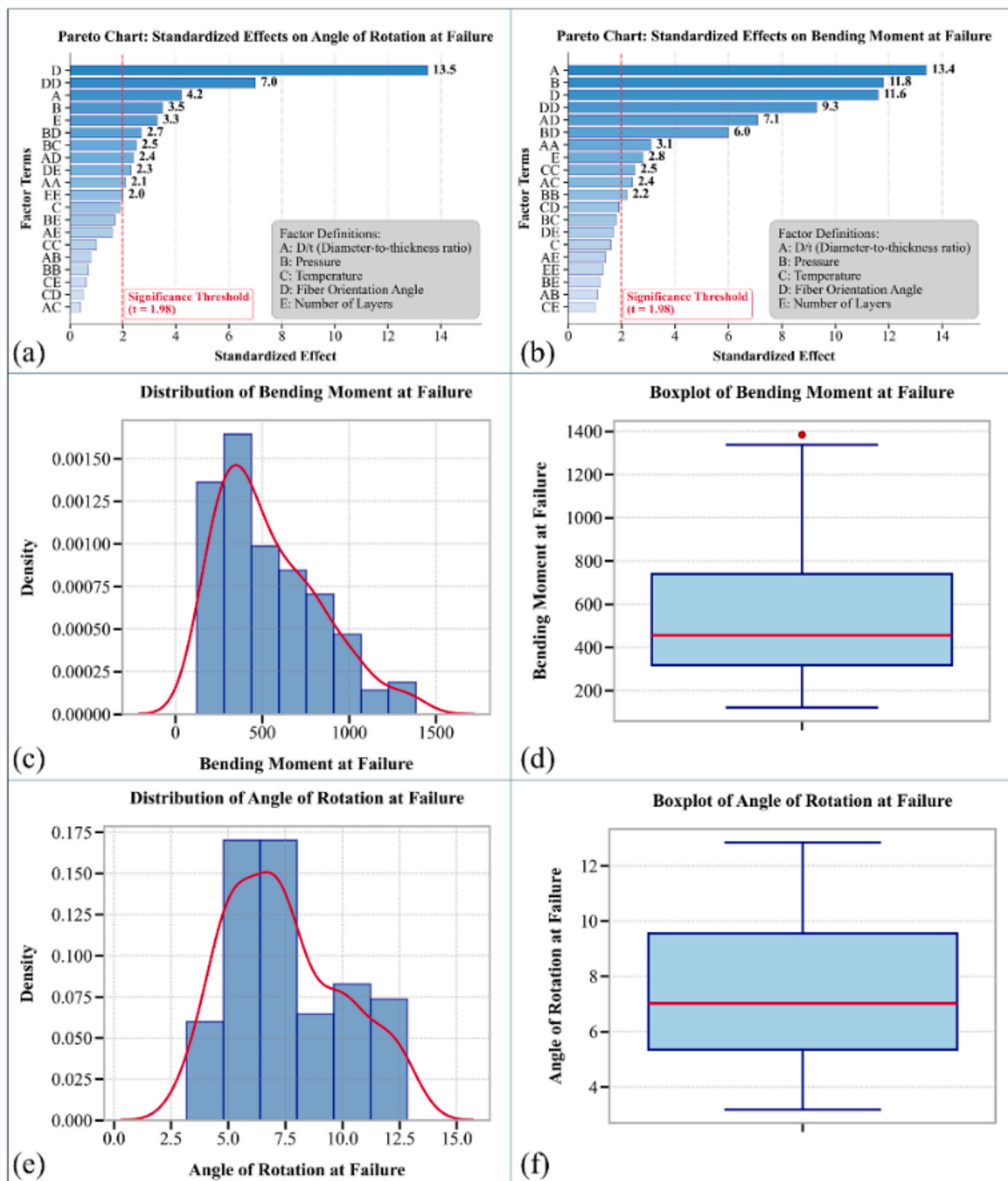


Fig. 9. (a and b) Pareto plot, (c and e) data distribution, and (d and f) Box plot for data processing of multi-objective responses of FE results.

MPa, respectively, representing less than the rupture stress for HDPE material. In pure composite tubes, due to their brittle nature, the fracture response is too fast, and crack propagation is rapid growth to failure. However, the HDPE layer with hyperelastic behavior and perfect bonding at the interface layer make failure mode different. In this case, the failure mode is mostly similar to that of a ductile metallic pipe rather than a FRP composite pipe. It can be mentioned as one of the advantages of RTPs over FRP composite pipes. Internal pressure superposition enabled a more comprehensive analysis of combined loading effects, providing a direct comparison with previous thermal-mechanical simulations as illustrated in Fig. 7b. Results indicated that 3-bar internal pressure combined with bending produced more extensive damage than

thermal-mechanical loading at 10 °C. Post-failure stress measurements recorded 42 MPa under these conditions. Failure distribution occurred uniformly across tension and compression zones within the bending region, confirming bending moment dominance in failure initiation.

Fig. 7b demonstrated extensive failure throughout the inter-roller region under combined tension and compression, emphasizing the continued dominance of bending-induced stresses. Lateral regions experienced reduced stress levels, with matrix failure reaching approximately 40% severity. Fiber orientation effects were also evaluated through simulation analysis. A 30-degree fiber orientation configuration under four-point bending significantly modified both failure characteristics and location, as presented in Fig. 7c. This configuration recorded a

failure stress of 39.19 MPa. The crack propagation pattern transitioned from transverse to longitudinal orientation. Such longitudinal cracking poses substantial operational risks under service conditions. In this study, the prediction of failure and measuring the maximum bending moment and angle or deflection were the targets of FE simulation, however in order to predict more detail of damage evolution and propagation though different layers, multiscale modeling can be useful [35–38].

In this study, the number of reinforcing layers and the diameter-to-thickness ratio (D/t) are identified as two geometric characteristics. The D/t ratio may significantly affect stress distribution, failure location, and failure mode, since it modifies the second moment of inertia and the stress area. The fiber-to-matrix volume ratio directly influences the quantity of reinforcing layers, possibly enhancing the pipe's rigidity. Nevertheless, due to the existence of more interfaces between layers, an increased number of layers may elevate the vulnerability to delamination or debonding failures. Under combined loading, Fig. 8 demonstrates that the damage initiates at the roller area applying the force (stage 1). As expected, in the second phase, damage begins to grow within the pure bending zone at the center in the region of maximum deflection (stage 2).

Element deletion or, in reality, wear production occurs subsequently at (stage 3). From the front perspective, a step-by-step view of the failure evolution is also presented in Fig. 8. Additionally, this simulation's force-displacement diagram shows the pipe experienced elastic behavior (Stage 1), after which damage initiated (Stage 2), gradually developing in the bending section and reducing the pipe's stiffness. In Stages 3 and 4, failure begins to grow, after which the applied force can no longer be withstood by the fiberglass layer. While the liner and coating layers continue to interact with the rollers, this results in a sharp drop in force.

3.2. Machine learning data analysis

The LHS generated dataset, consisting of 135 simulations, was carried out, and two response variables (the angle of rotation and the bending moment at failure) were recorded for surrogate modeling. Based on this dataset, a sensitivity analysis was performed using a Pareto chart to evaluate the contribution of each design factor to variations in the two responses. For the bending moment (Fig. 9a), the analysis revealed that the geometric ratio D/t had the strongest influence, followed by internal pressure and fiber orientation, with only a marginal difference between the latter two. In contrast, the Pareto chart for the angle of rotation (Fig. 9b) showed that fiber orientation angle was by far the dominant factor, with its second-order effect ranking next in importance, while D/t emerged as the third most influential factor.

Once the sensitivity analysis was completed, the dataset was prepared for failure prediction using a Random Forest algorithm. This method was applied to predict the bending moment and angle of rotation within the range of simulated parameters, avoiding extrapolation outside the studied domain. This choice was motivated by the strong nonlinearity of the problem, where parameter effects could change significantly beyond the explored range [38]. Random Forest was therefore selected to establish a reliable database of predictions under operational configurations. With encouraging results (discussed in the following section), the computationally expensive finite element model showed potential to be effectively replaced by the surrogate model. The bending moment distribution at failure (Fig. 9c) indicates that most data points fall between 250 and 750 units, reflecting the randomized design of experiments, which aimed to broadly sample the parameter space. Only a small fraction of optimized configurations achieved higher bending moments before failure. Before training the Random Forest model, the data was standardized using Python's Standard Scaler function. Fig. 9d presents a boxplot of bending moment at failure, highlighting its central tendency and variability through the median and interquartile range (IQR). To prevent a single extreme outlier (~1400 units) from skewing the model, the value was capped during

Table 4

Optimal hyperparameter configuration of the RF regression model obtained through grid search with 5-fold cross-validation.

Tuning parameter	optimal values
max_depth	None
min_samples_leaf	2
min_samples_split	4
n_estimators	2

preprocessing.

The distribution of the angle of rotation at failure (Fig. 9e) shows that the majority of cases lie between 4° and 10° , forming a nearly unimodal distribution with fewer extreme values compared to the bending moment. This suggests the data is well balanced around its core range. The corresponding boxplot (Fig. 9f) confirms this, with the median positioned centrally within the IQR and no outliers observed. Readings consistently ranged from 3° to 12° . Unlike the bending moment variable, no special outlier adjustment was required. Standard scaling methods were nonetheless applied to ensure proper integration of this response variable into the modeling framework.

The Random Forest regression model was used for predicting two response variables: the angle of rotation and the bending moment at failure. The dataset was first preprocessed by separating the input features from the target responses, followed by normalization using a Standard Scaler to ensure a uniform feature range. The data was then partitioned into training (80%) and testing (20%) subsets.

Model hyperparameters were optimized through a grid search with 5-fold cross-validation, tuning parameters such as `n_estimators`, `max_depth`, `min_samples_split`, and `min_samples_leaf`. The optimal configuration was identified as in Table 4.

The optimized model demonstrated strong cross-validation performance with an average $R^2 = 0.9027$, a mean RMSE of 67.60, and a mean absolute error (MAE) of 35.33.

The trained model delivered excellent predictive accuracy for both response variables. For the angle of rotation, performance metrics included $R^2 = 0.97$, $MSE = 0.1607$, $RMSE = 0.4008$, and $MAE = 0.3111$, confirming minimal prediction error. For the bending moment, the model achieved $R^2 = 0.93$, $MSE = 6916.25$, $RMSE = 83.16$, and $MAE = 61.78$, indicating robust predictive capability with moderate variability. Together, the high R^2 values and relatively low error metrics highlight the strength of the Random Forest approach in capturing the complex relationships within the dataset.

Residual analysis further validated the model. For the bending moment (Fig. 10a), residuals were well centered around the zero line, with most values between -100 and 100 . Slightly larger deviations occurred at bending moments above 800 units, and a few outliers exceeded ± 200 , suggesting the presence of highly complex configurations. Nevertheless, the residual distribution showed no systematic bias. For the angle of rotation (Fig. 10b), most residuals ranged between -0.6 and 0.6 and were evenly distributed around zero. A modest increase in residual spread was observed at higher rotation angles (10° – 12°), but overall, the residual pattern indicated unbiased and relatively reliable predictions.

The relationship between predicted and actual responses is illustrated in Fig. 9c and d. For the bending moment (Fig. 10c), most data points closely followed the ideal 1:1 reference line, with only minor deviations at values above 800 units. The accuracy of these predictions is consistent with the model's high R^2 of 0.93 and low RMSE of 83.16. Similarly, for the angle of rotation (Fig. 10d), the majority of points clustered tightly along the reference line, particularly within the 4° – 10° range. A slight increase in scatter occurred at angles greater than 10° , reflecting a small decline in accuracy, but this effect was minimal and did not compromise overall reliability. The exceptionally high R^2 of 0.97 and very low RMSE of 0.40 confirm the model's ability to accurately

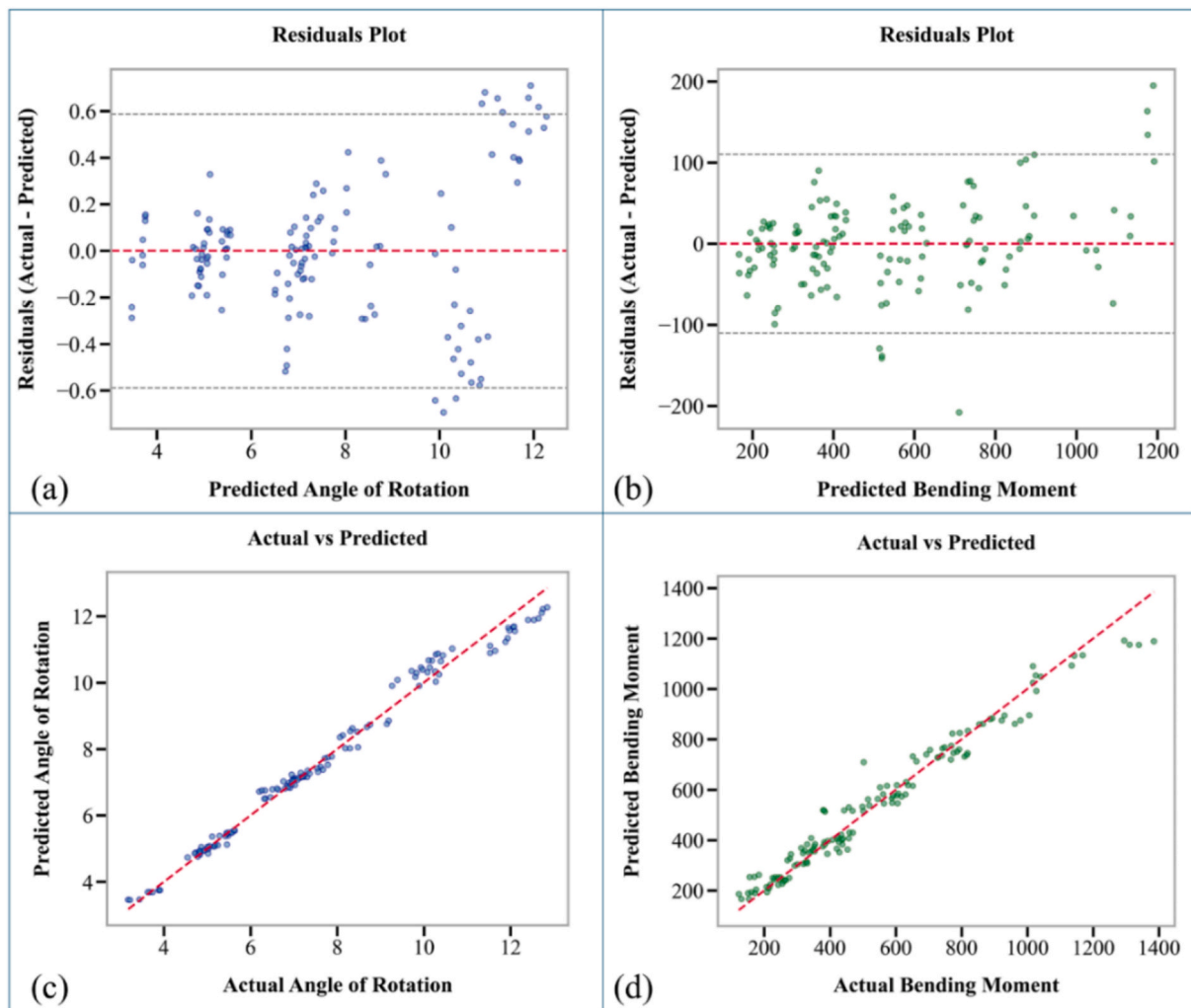


Fig. 10. (a) Residual plot and (b) Actual vs predicted plot for angle of rotation and bending moment.

capture and predict the angle of rotation.

The correlation matrix as shown in Fig. 10 displays the relationships between seven materials testing parameters: diameter-to-thickness ratio (D/t), internal pressure (P), temperature (T), fiber orientation angle (FOA), number of layers (NOA), rotation angle at failure (RAAF), and bending moment at failure (BMAF). The matrix shows both scatter plots for pairwise relationships and histograms along the diagonal for individual parameter distributions. This correlation matrix shows relationships between five testing parameters and two responses in a grid format. The diagonal displays individual parameter distributions through blue density plots, each scatter plot is color-coded by Bending Moment at Failure values, where dark purple indicates low strength, green shows medium strength, and bright yellow highlights maximum strength. The diagonal shows individual parameter distributions. This visualization helps identify optimal parameter combinations that maximize material bending performance by revealing which conditions produce the yellow (high-strength) clusters.

Fig. 11 represents the features relationships; several key patterns emerge that reveal how design parameters influence material performance. The fiber orientation angle (FOA) and number of layers (NOA) have distinct groupings, suggesting these are controlled design variables that create discrete material configurations rather than continuous variations. The diameter-to-thickness ratio (D/t) demonstrates a relatively narrow range of values, suggesting geometric constraints in the testing setup, while its relationship with other parameters indicates structural geometry plays a role in failure behavior. Most notably, the

correlation patterns suggest that mechanical failure properties (rotation and bending moment at failure) are influenced by a combination of material design choices (fiber orientation, layer count) and testing conditions (pressure, temperature), with the color gradients in the correlation matrix revealing that some parameter pairs have stronger predictive relationships than others for determining ultimate material performance.

A design space with the same features was defined to expand the range of the influencing factors to generate a dataset for optimal configuration selection. Approximately 70% of the parameter combinations were retained using a controlled random inclusion probability to ensure diversity in the generated configurations. After removing duplicates, this process yielded 851,999 unique combinations. The dataset thus preprocessed was fed into the trained Random Forest Model to capture complex correlation effects of the parameter settings with the corresponding responses; hence, forming a sound basis for determining the optimum configuration. Table 5 provides descriptive statistics for the dataset, summarizing key parameters (D/t, P, T, FOA, and NOL) across 851,999 unique configurations.

Although the developed Random Forest (RF) surrogate model demonstrates high deterministic accuracy, with coefficients of determination of 0.93 for bending moment and 0.97 for rotation angle, it inherently provides single-point predictions and therefore does not explicitly account for uncertainty arising from model ambiguity or variability in the input parameters. In line with hybrid uncertainty-aware frameworks reported in the literature, a qualitative assessment of uncertainty is

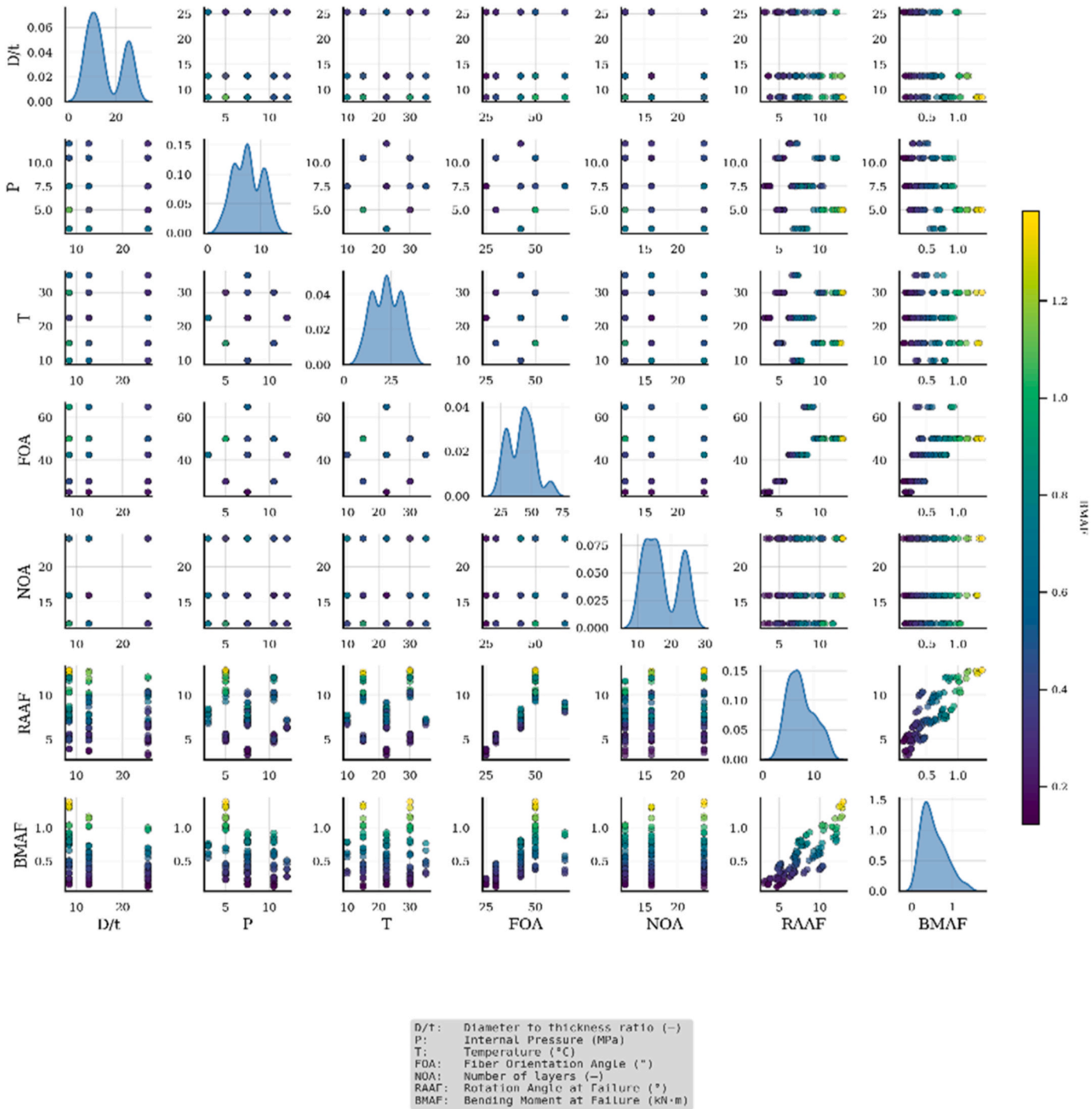


Fig. 11. The correlation matrix to express the relationships between seven testing parameters.

Table 5						
Descriptive statistics of the generated dataset parameters.						
Statistic	D/t	P	T	FOA	NOL	
Count	851999	851999	851999	851999	851999	
Mean	15.5	6.5	19.9	43.6	17.3	
Std	7.1	2.1	6.1	8.2	4.9	
Min	8.5	3	10	30	12	
25%	8.5	4.5	14.29	36.99	12	
50%	12.7	6.5	20	42.82	16	
75%	25.4	8.5	25.71	50.35	24	
Max	25.4	10	30	60	24	

essential to support sound engineering judgment, particularly for safety-critical reinforced thermoplastic pipe (RTP) applications. In this context, uncertainty can be broadly classified into aleatoric and epistemic components. Aleatoric uncertainty reflects irreducible variability associated with the physical system, such as inherent scatter in the material properties of the HDPE liner and glass-fiber reinforcement, as well as operational variations in temperature and internal pressure. Epistemic uncertainty, by contrast, originates from limitations in the surrogate model structure and training data; in this study, it is primarily associated with the finite dataset of 135 finite element simulations, which may limit predictive reliability in sparsely sampled or unexplored regions of the design space, such as extreme diameter-to-thickness ratios or

Table 6

The optimal parameter combination derived from ML model.

Row No	D/t	P	T	FOA	NOL	RAAF	BMAF
72810	8.5	4.5	27.14	51.73	24	12.28	1186.53

unconventional fiber orientation angles. From a reliability perspective, infrastructure-oriented surrogate models must provide not only accurate predictions but also meaningful confidence in those predictions. In a probabilistic modeling framework, such as a Bayesian neural network, predictions would be accompanied by confidence intervals (e.g., 95% prediction bounds), enabling explicit quantification of model confidence. Qualitatively, it can be inferred that RTP configurations exhibiting larger RF residuals would correspond to wider prediction intervals, indicating reduced confidence in those regions of the input space. Looking forward, transitioning from a deterministic RF approach to a probabilistic framework, such as neural networks augmented with Monte Carlo dropout, would enable explicit decomposition of aleatoric and epistemic uncertainties. This evolution would transform the current surrogate model into a robust decision-support pipeline, allowing RTP designs to be optimized not only for nominal performance but also for statistical reliability under extreme and combined loading conditions [39].

3.3. ML model validation

3.3.1. Optimum design

To find the best configuration in the dataset, the predicted values for Rotation Angle and Bending Moment were scaled to fall within the range of 0 to 1. This step made it easier to compare the two metrics on a similar scale. A combined score was then created by averaging these normalized values, ensuring that both metrics were given equal weight in the evaluation. The goal of this method was to maximize both angle and moment variables simultaneously, achieving the best possible trade-off between the two. After calculating the scores, the dataset was sorted in descending order, and the configuration with the highest score was identified as the optimal choice (listed in Table 6). This approach provided a clear and straightforward way to determine the most favourable outcome.

3.3.2. Model confirmation test

The setup was then modeled in LS-Dyna to verify the prediction's correctness. The outcome was almost precise, with the moment and angle of rotation aligning with the forecast at a 4% error margin. The maximum stress was recorded at 73.84 MPa. The finite element result is seen in Fig. 12. This contour shows that, although combined loading was exerted, the optimal parameters resulting in the best configuration minimized the effects of pressure and temperature. These parameters ensured that the Fiber Orientation Angle was arranged such that failure occurred predominantly in pure bending.

To evaluate stiffness, the optimized case was compared with the previous configuration. The results indicate that applying the machine learning approach increases the area under the load-displacement curve, reflecting an enhancement in fracture energy. Moreover, the fluctuations of force drops demonstrate significantly improved behavior in the new design when subjected to bending loads, as well as applied temperature and internal pressure.

4. Conclusion

A computational model incorporating FE and ML was developed to predict the mechanical and failure behaviours of RTPs under complex, multi-factorial loading conditions. The framework integrates finite element modelling with machine learning techniques as a powerful tool for RTP design and performance assessment. The FE model, validated against experimental data with a low mean error of 4.34%, estimates the damage evolution and failure responses in RTPs under combined loading with high accuracy. A comprehensive parametric analysis of 135 configurations revealed that the diameter-to-thickness ratio is the most influential factor on bending moment capacity, while the fibre orientation angle primarily controls the rotation angle at failure. A Random Forest ML model, trained on the FE data, achieved exceptional predictive accuracy with R^2 values of 0.93 for bending moment and 0.97 for rotation angle, allowing for the efficient exploration of vast design spaces. This study identified an optimal configuration ($D/t = 8.5$, pressure = 4.5 bars, temperature = 27.14 °C, fibre orientation of 51.73°, 24 layers) and demonstrated that a proper parameter selection can significantly enhance RTP performance, addressing a critical knowledge gap in performance prediction under realistic operational conditions.

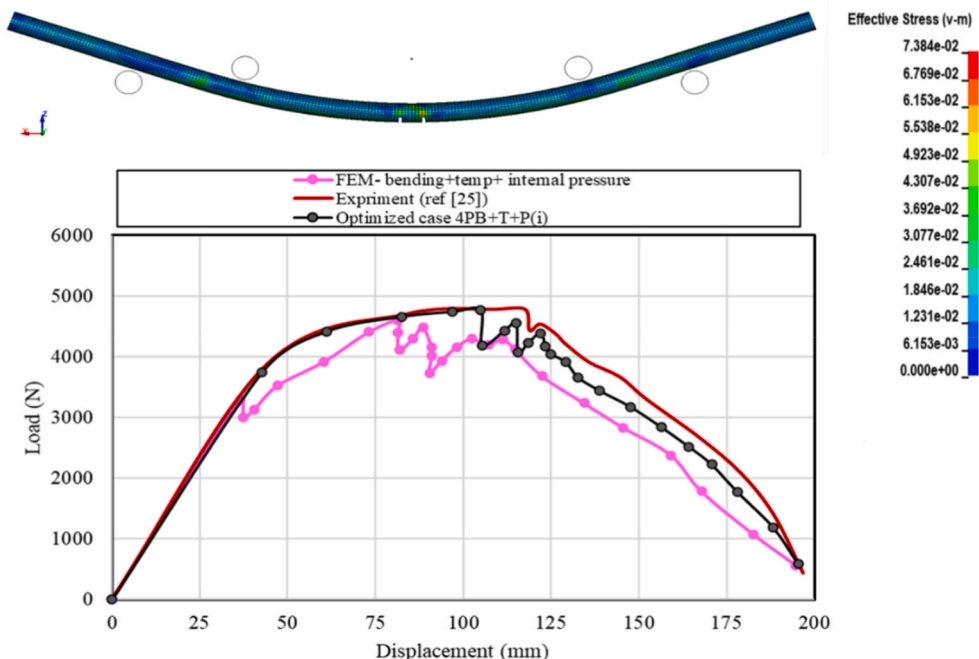


Fig. 12. Contours of effective stress in the reinforcement layer for the best configuration selected from ML.

While the study successfully met its primary objectives, it also highlighted several limitations and areas for future work. The experimental validation was limited to four-point bending.

4.1. Future work

Future research should expand this to include combined loading conditions to ensure broader applicability. The use of a 2D shell model, while computationally efficient, may not fully capture all through-thickness effects. Future work should also extend the parameter ranges investigated and incorporate additional factors such as environmental exposure, long-term creep, and fatigue effects to enhance the framework's comprehensiveness, while multiscale modeling can be useful to investigate detail of damage evolution and propagation through different layers. Additionally, delamination effects could be included in the FE model. On the other hand, integrating more advanced ML algorithms, such as deep learning, could further improve predictive accuracy. The methodology's flexibility, however, allows it to be adapted for other composite pipeline materials, promising a broader industrial impact and establishing a solid foundation for accelerating the adoption of RTP technology in demanding applications.

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.

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Data availability

Data will be made available on request.

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