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Prediction of Strength and Ductility of Thin-Walled Steel Tubular Columns Using Physics-Informed Reinforcement Learning and Agentic Frameworks

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Abstract **-** Thin-walled steel tubular columns (TWSTCs) play a central role in structural systems due to their strength-to-weight efficiency and energy absorption capacity. However, predicting their strength and ductility is complex due to the interplay of material nonlinearities, geometric imperfections, and buckling behaviors. This paper introduces a Physics-Informed Reinforcement Learning (PIRL) framework, combined with Agentic (agent-based) simulations, to predict TWSTC performance. PIRL integrated physics-based constraints as equilibrium equations, buckling criteria, and material constitutive laws into the learning process, ensuring physically realistic and accurate predictions. Agents iteratively interact with virtual environments to optimize column design and prediction strategies, yielding a robust, adaptive tool for advanced structural engineering applications.

Keywords**:** Tubular column, Ductility, Strength, Reinforcement, Agentic, Physics-informed reinforcement learning

1. Introduction

Thin-walled steel tubular columns are increasingly employed in modern structural systems due to their high strength-to-weight ratio, aesthetic flexibility, and efficient use of materials. Despite their widespread application in bridges, towers, and high-rise buildings, accurately predicting their nonlinear behavior under axial and lateral loads remains a formidable challenge. This complexity arises from the interplay between local and global buckling modes, residual stresses, material nonlinearity, and geometric imperfections [1-3]. Traditional analytical methods, while useful for linear and simplified cases, often fall short when applied to real-world conditions where the interaction between strength and ductility dictates failure mechanisms [4,7]. Finite Element Modeling (FEM) has served as a more advanced alternative; however, it is often computationally expensive and sensitive to input parameter assumptions [8]. Recent advances in data-driven methods, particularly machine learning (ML) and deep learning (DL), have shown promise in identifying patterns and predicting structural performance. Nevertheless, most of these approaches lack interpretability and physical consistency, especially when extrapolating beyond trained data regimes.

To bridge this gap, this paper explores the application of Physics-Informed Reinforcement Learning (PIRL) and Agentic exploration frameworks to predict the strength and ductility of thin-walled steel tubular columns. PIRL integrates governing physical laws directly into the learning process, enforcing constraints that improve model generalization and reduce dependency on large datasets. On the other hand, agentic frameworks promote autonomous exploration of the design and loading space, helping to uncover failure modes and performance boundaries that traditional training paradigms may overlook. The novelty of this work lies in the synergy between domain knowledge (physics-based mechanics) and autonomous learning (reinforcement and agentic learning), creating a robust and interpretable model capable of assessing column performance with greater fidelity. Experimental data and parametric simulations form the foundation of the learning process, capturing variations in thickness, yield strength, slenderness ratio, and applied loading conditions.

This study details the development, training, and evaluation of the hybrid PIRL-Agentic model. It also compares the model's performance to conventional approaches, highlighting its superior capability in predicting both peak load (strength) and post-yield displacement behavior (ductility). The findings have practical implications for design optimization, safety assessment, and material-efficient structural engineering.

2. Methodology

40 columns were simulated using a model already validated with the test and these columns were the basis of the preparation of the dataset. The dataset was developed and applying FEM analysis on thin-walled steel tubular columns where geometry and material non-linearities were considered. The study was conducted using a stiffened rectangular column shown in Fig. 1 and with the following cross-section and design parameters varied as per acceptable limits [5,6]. Also, Table 1 shows the geometric and material properties for the column used [6].

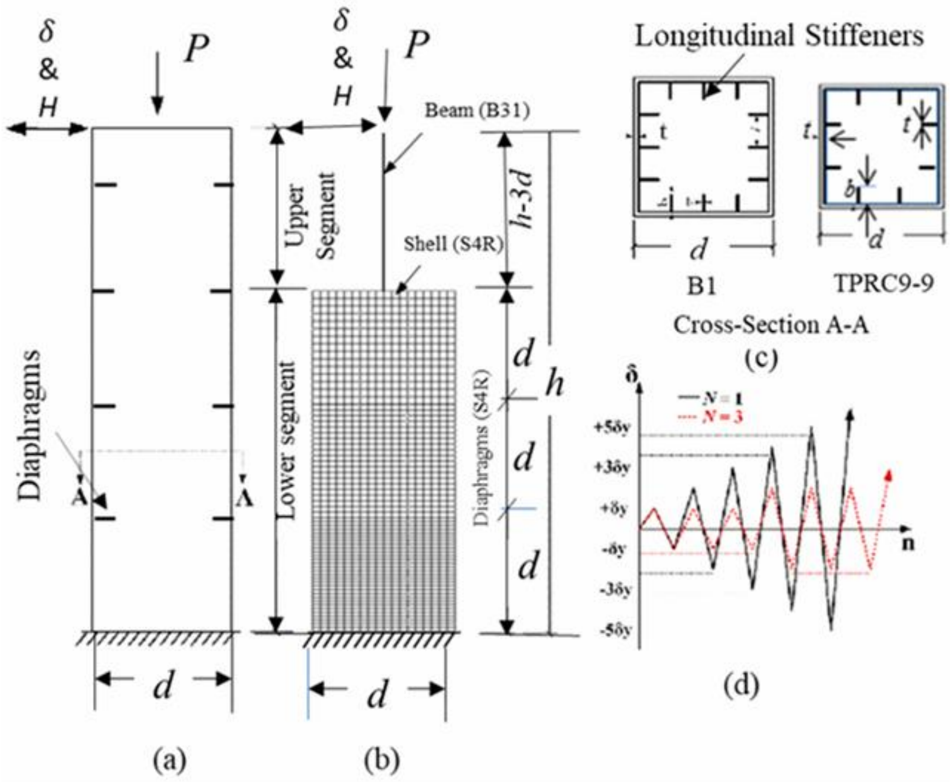

Fig. 1: Finite Element Modelling (a) Column (b) FEM Meshing (c) Cross-section (d) Loading path protocol

Table 1: Geometric and material properties

Column	h (mm)	d (mm)	E (GPa)	σ_y (MPa)	R_f	λ	P/P_y
TPRC9-9	2141	450	204	266	0.3	0.29	0.122

2.1. Experimental Data and Parameters

The developed dataset contained eight key hyper-parameters which were tuned until a proper prediction was achieved. These hyper-parameters were thickness, axial load parameter, slenderness ratio parameter, thickness-width ratio parameter, experimental normalized strengths and ductility and predicted normalized strengths and ductility. Machine learning techniques have also been explored in concrete-filled steel tubes and predictions have been analysed [9-10].

2.2. Physics-Informed Reinforcement Learning (PIRL)

PIRL integrates physical knowledge directly into the learning process. The learning process was broken into three major inputs and as described below.

The state space in the study was defined by (P/P_y, $t_f R_f$, λ) and the action space was defined using the predicted (H_m/H_y, δ_m/δ_y) and the reward function R was defined as

$$R = -\left(\alpha_1 \left|\frac{H_m}{H_y} - \frac{H_m}{H_{y\ exp}}\right| + \alpha_2 \left|\frac{\delta_m}{\delta_y} - \frac{\delta_m}{\delta_{y\ exp}}\right|\right) \quad (1)$$

Where; α_1 *and* α_2 are balance strength and ductility errors.

Physics embedding constraints such as equilibrium, constitutive behavior, and slenderness effects are integrated to guide learning.

2.3. Agentic Frameworks

The Agentic approach adaptively tunes hyperparameters (learning rate, exploration rate) and infuses expert knowledge into the model (e.g., empirical relationships like Johnson-Ostenfeld buckling curves) into the model:

$$\frac{H_m}{H_y} = f\left(\frac{P}{P_y}, R_f, \lambda\right) \quad (2)$$

$$\frac{\delta_m}{\delta_y} = g\left(\frac{P}{P_y}, R_f, \lambda\right) \quad (3)$$

Where f and g are accuracy improvement factors.

3. Results and Discussion

The prediction of both strength and ductility was performed using a 40-column dataset. The model incorporated reward assignment during hyperparameter tuning as part of the prediction process.

3.1. Learning Rate Evolution

The learning rate vs epochs plot is as shown in Fig. 2, and the prediction was more accurate as the plot decayed to 0.001

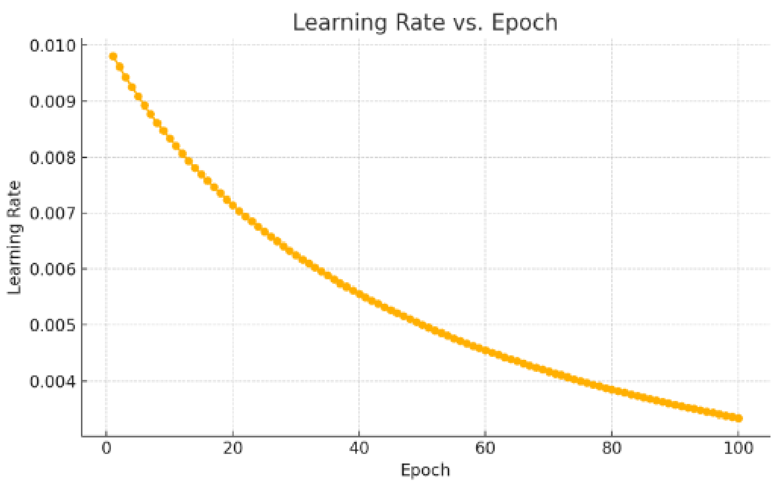

Fig. 2: Learning rate vs. Epoch during the prediction

3.2. Sensitivity analysis

The relationship between input features and output targets (strength and ductility indicators) is illustrated in Fig. 3, which reveals key insights into the sensitivity of strength and ductility to various parameters. The parameter $(1+P/Py)R_f\lambda$, a compound index reflecting axial compression interaction with geometry, was found to be the most influential factor on strength. Higher values of this index were associated with earlier onset of buckling and lower strength, consistent with classical mechanics expectations.

In contrast, ductility metrics were more strongly influenced by the wall thickness and the radius-to-thickness ratio, with thinner walls and higher slenderness ratios contributing to reduced post-yield deformation. These findings support established knowledge in structural engineering while also highlighting the model's ability to reproduce such relationships autonomously.

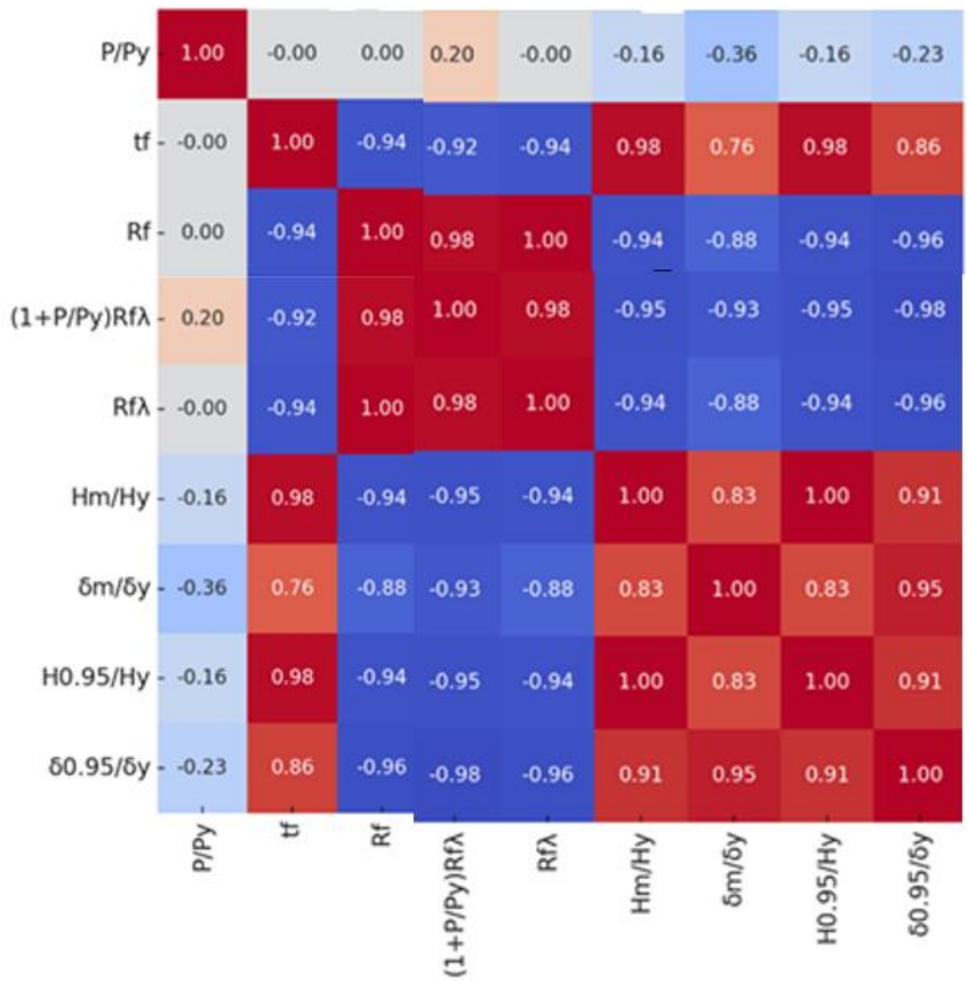

Fig. 3: Sensitivity heatmap

3.3. Model Performance on Strength and Ductility Prediction

The predictions shown in Figure 4, obtained using reinforcement learning through agentic learning, accurately estimated the strength and ductility, demonstrating satisfactory and reliable results for engineering design.

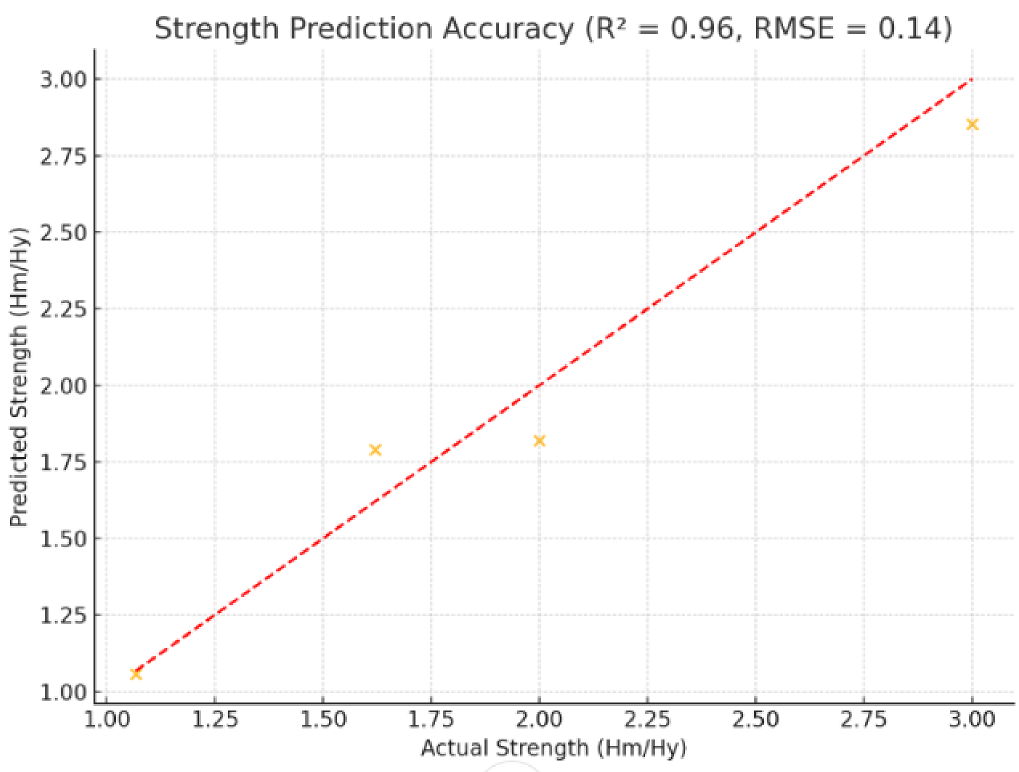

Fig. 4: Actual strength vs Predicted strength

4. Conclusion

This study presents a novel framework for predicting the strength and ductility of thin-walled steel tubular columns by combining Physics-Informed Reinforcement Learning (PIRL) with agentic exploration strategies. The proposed approach successfully integrates physical governing principles with autonomous learning mechanisms, achieving higher prediction accuracy and interpretability compared to traditional data-driven and empirical methods.

Key findings of this study include:

- PIRL effectively enforces equilibrium and constitutive relationships within the learning process, ensuring predictions remain physically meaningful, even in untrained loading conditions.
- The agentic framework facilitates comprehensive exploration of parameter spaces, including cases of high slenderness ratios and low thickness-to-diameter ratios, those are typically underrepresented in standard training datasets.
- The model demonstrated strong generalization capabilities, accurately predicting both strength (ultimate load capacity) and ductility (displacement capacity) across a range of configurations.
- Results from the hybrid model aligned closely with experimental trends, especially in capturing post-peak behavior and deformation softening which is critical for safety and failure assessment.

Beyond predictive accuracy, this framework introduces an efficient and scalable methodology for structural design optimization. By reducing reliance on exhaustive physical testing and high-fidelity simulations, the approach offers significant time and cost savings for engineering applications.

Future work may extend this method to account for dynamic loading conditions such as seismic actions or wind-induced vibrations, and to explore its integration with digital twin technologies for real-time monitoring and control. Additionally, the incorporation of multi-material or composite behavior into the learning process would further enhance the model's applicability in hybrid structural systems. Ultimately, this study underscores the transformative potential of physics-informed and agent-based learning techniques in structural engineering, paving the way for more resilient, sustainable, and intelligent infrastructure systems.

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