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THE ARTIFICIAL INTELLIGENCE IN STEEL STRUCTURES: METHODS, APPLICATIONS AND PERSPECTIVES ON JOINT BEHAVIOUR

Summary: Artificial intelligence (AI) is emerging as a powerful tool in structural engineering, enabling data-driven alternatives to traditional analytical and numerical methods. In steel structures, AI has been applied to design optimisation, structural health monitoring, and reliability assessment; however, its application to modelling nonlinear joint behaviour remains limited. This paper reviews AI methods in steel structures, outlining their purpose, capabilities, and current challenges. Focus is given to steel joints, where accurate prediction of moment–rotation (M–θ) response is essential. A framework combining Genetic Algorithms (GA) for component characterisation and Physics-Informed Neural Networks (PINNs) for surrogate modelling and joint behaviour prediction is presented. The approach enables fast and physically consistent prediction of full nonlinear joint behaviour, supporting advanced AI structural design.

Keywords: artificial intelligence, steel structures, steel joints, genetic algorithms, physics-informed neural networks, nonlinear behaviour

VEŠTAČKA INTELIGENCIJA U ČELIČNIM KONSTRUKCIJAMA: METODE, PRIMENE I PERSPEKTIVE U KARAKTERIZACIJI ČELIČNIH VEZA

Rezime: Veštačka inteligencija (VI) postaje moćan alat u građevinskom inženjerstvu, omogućavajući pristupe zasnovane na podacima kao alternativu tradicionalnim analitičkim i numeričkim metodama. U oblasti čeličnih konstrukcija, VI se primenjuje za optimizaciju projektovanja, praćenje stanja konstrukcija i procenu pouzdanosti; međutim, njena primena u karakterizaciji nelinearnog ponašanja čeličnih veza i dalje je ograničena. U ovom radu dat je pregled metoda veštačke inteligencije u oblasti čeličnih konstrukcija, uz prikaz njihove namene, mogućnosti i aktuelnih izazova. Poseban fokus stavljen je na čelične veze kod kojih je tačno predviđanje moment–rotacija (M–θ) odgovora od suštinskog značaja. Predstavljen je okvir koji kombinuje genetske algoritme (GA) za karakterizaciju komponenata i neuronske mreže vođene fizičkim zakonima (Physics-Informed Neural Networks – PINNs) za razvoj zamenskih modela i predviđanje nelinearnog ponašanja veza. Ovakav pristup omogućava brzo i fizički konzistentno predviđanje kompletnog nelinearnog ponašanja veza, čime se pruža podrška naprednom projektovanju čeličnih konstrukcija primenom veštačke inteligencije.

Ključne reči: veštačka inteligencija, čelične konstrukcije, čelične veze, genetski algoritmi, neuronske mreže vođene fizičkim zakonima, nelinearno ponašanje

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1. INTRODUCTION

Structural engineering has traditionally relied on analytical, numerical and experimental methods to ensure the safety and efficiency of load-bearing systems. In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as data-driven complements to these approaches, offering faster, more cost-effective predictions of complex nonlinear structural behaviour, with rapid growth in ML applications reported across structural analysis and design, health monitoring, reliability prediction, and material property estimation [1–3].

Within steel structures, AI/ML is particularly attractive given their strongly nonlinear behaviour and the abundance of experimental and monitoring data, with applications ranging from capacity prediction and failure-mode classification to constitutive modelling and structural optimisation [1].

Analytical methods remain particularly limited in predicting the nonlinear moment–rotation (M–θ) response of steel joints. The component method of EN 1993-1-8 [4] provides a rational, widely used framework for joint stiffness and resistance, but is conservative and restricted to the elastic range, offering little guidance on post-elastic response and reserve deformation capacity [5,6]. Experimental testing and finite element (FE) modelling can capture this behaviour, but both are costly and difficult to generalise across joint configurations, limiting their use in probabilistic and reliability-based design [7,8].

This paper reviews the current state of AI applications in steel structures, with particular attention to their use, or absence, in modelling nonlinear joint behaviour. Emphasis is placed on the moment–rotation response of steel joints, where a combined Genetic Algorithm (GA) and Physics-Informed Neural Network (PINN) framework, developed by the authors, predicts the full nonlinear M–θ behaviour of welded beam-to-column joints.

2. ARTIFICIAL INTELLIGENCE METHODS

2.1. ARTIFICIAL INTELLIGENCE, MACHINE LEARNING AND DEEP LEARNING

Artificial intelligence (AI) is broadly defined as the branch of computer science concerned with developing systems that exhibit human-like intelligence, including perception, reasoning and decision-making [1,9]. Within AI, three related subfields are particularly relevant to engineering applications: pattern recognition (PR), machine learning (ML) and deep learning (DL).

Pattern recognition classifies input data into predefined categories using feature vectors and statistical decision rules, typically operating in a training mode, in which a classifier is calibrated on labelled data, and a testing mode, in which new inputs are assigned to classes [1]. Machine learning generalises this idea, encompassing algorithms that learn a function from input–output examples (supervised learning) or discover structure in unlabelled data (unsupervised learning), without being explicitly programmed [1,2]. Deep learning is a subset of ML that employs artificial neural networks with many layers to automatically learn hierarchical features directly from raw data, such as images or signals, and underlies many recent advances in structural health monitoring and image-based inspection [10,11].

In supervised ML, two broad problem types are relevant to structural applications: regression (continuous quantities such as resistance, stiffness or displacement) and classification (a discrete label such as a failure mode or damage class) [1]. A typical ML workflow: data preparation, model training and evaluation, is common to essentially all model families [2].

2.2. AI MODEL FAMILIES AND SELECTION CRITERIA

Several AI model families are used in structural engineering, each suited to particular data types and problem structures (see Table 1). Artificial Neural Networks (ANN/MLP) are the most widely used models for general regression problems, such as the prediction of structural resistance, stiffness and constitutive behaviour [12,13]. Tree-based models (Random Forest, XGBoost) are robust and computationally efficient for tabular data, commonly used for capacity prediction and failure classification [14]. Support Vector Machines (SVM) and Gaussian Process Regression (GPR) perform well with comparatively small datasets, with GPR additionally providing uncertainty estimates [15]. Convolutional Neural Networks (CNN) are the standard choice for image-based inspection and crack detection, while Recurrent Neural Networks (RNN/LSTM) are suited to time-series problems such as vibration-based monitoring. Graph Neural Networks (GNN) are increasingly applied to structural layout generation and topology optimisation by naturally representing structural connectivity [16]. Finally, Physics-Informed Neural Networks (PINNs) combine machine learning with governing physical equations or engineering constraints, reducing reliance on large training datasets while improving physical consistency and extrapolation capability [17,18]. Relevant selection criteria include the type and quantity of available data, the required prediction accuracy, computational cost, interpretability, and the availability of physical knowledge suitable for hybrid, physics-informed approaches.

Table 1: Comparison of common AI model families used in structural engineering

Model Family	Typical Applications	Main Advantage(s)	Main Limitation(s)
ANN / MLP	Structural response prediction, constitutive modelling	Flexible; captures nonlinear relationships	Requires relatively large datasets and hyperparameter tuning
RF / XGBoost	Capacity prediction, failure classification	High accuracy, robust, interpretable	Limited extrapolation capability
SVM / GPR	Small datasets, regression and classification	Good with limited data; uncertainty estimation (GPR)	Reduced scalability for very large datasets
CNN	Crack detection, image-based inspection	Excellent spatial feature extraction	Applicable mainly to image data
RNN / LSTM	Structural health monitoring, time-series prediction	Captures temporal dependencies	Longer training time, higher cost
GNN	Structural layout generation, topology optimisation	Naturally represents structural connectivity	High architectural complexity
PINN	Physics-based regression, constitutive modelling	Incorporates engineering knowledge and physical constraints	More complex training and loss-function design

3. APPLICATIONS OF AI IN STEEL STRUCTURES

3.1. DESIGN, OPTIMISATION AND CAPACITY PREDICTION

AI methods have been increasingly applied to structural design and optimisation. Málaga-Chuquitaype [3] reviews ML frameworks for structural design, noting that ML algorithms can explore multi-dimensional design spaces beyond human intuition, though fully automated end-to-end design remains rare. Wang and Zhuang [19] similarly review nearly two hundred studies applying ML to steel–concrete composite structures, reporting that neural networks and ensemble methods have been used across beams, slabs and connectors for design optimisation and capacity prediction; both reviews note that available datasets remain relatively small, requiring careful validation.

At the component level, Alagundi and Palanisamy [20] developed an ANN model that predicts the shear strength of exterior reinforced-concrete beam–column joints more accurately than code-based empirical formulas. Horton and Hajirasouliha [21] applied deep neural networks to reduced-beam-section steel moment connections, predicting the parameters of a hysteretic model directly from connection geometry and material properties, enabling accurate reproduction of the full cyclic moment–rotation response. In fatigue and welding applications, Bai and Xie [22] combined fine-scale finite element stress analysis with machine learning to update fatigue-damage accumulation in welded spherical joints in real time, while Mezher and Pereira [23] compared several ML regressors for the tensile-shear strength of dissimilar resistance spot-welded joints, finding that a multilayer perceptron achieved the highest accuracy ($R^2 \approx 0.95$). Capacity prediction has also been demonstrated for cold-formed steel built-up columns [14] and for corroded steel plates strengthened with adhesives and bolts [24]. These studies consistently show that AI models can outperform code-based formulas for component-level resistance and response parameters, provided that sufficiently representative training data are available.

3.2. STRUCTURAL HEALTH MONITORING AND DAMAGE DETECTION

Structural health monitoring (SHM) is one of the most mature AI applications in steel structures, given the abundance of image and sensor data. Kompanets [25] evaluated an encoder–decoder network for automatic crack segmentation on steel bridges, finding detection capability comparable to manual inspection, though with a non-negligible false-positive rate. Jia et al. [26] fine-tuned a DeepLabv3+ network for fatigue-crack detection in steel box-girder bridges, improving the mean Intersection-over-Union from 0.618 to 0.724, while Tseng and Kalaycioglu [27] integrated a MobileNetV2 network into an inspection robot, achieving about 85% precision across six defect categories.

In a review of 337 studies, Jia and Li [28] report that vibration signals and images account for roughly 80% of SHM data sources, with CNNs the dominant algorithm (about 60% of works) and crack detection the most common problem. Vision-based techniques have also diagnosed bolt-loosening without deep networks [29]. Collectively, these studies confirm AI-based inspection can match or exceed manual performance, although field reliability and false positives remain open challenges.

3.3. RELIABILITY ASSESSMENT AND MATERIAL MODELLING

AI has also supported reliability assessment and material characterisation. Guo et al. [30] trained neural networks and ensemble regressors to estimate collapse resistance and progressive-collapse probability of steel frame–composite floor systems, using interpretable models to identify governing parameters and providing a fast surrogate for expensive FE analyses. Guo and Yang [31] review supervised methods (MLPs, CNNs, RNNs) for predicting elasticity, strength and fracture behaviour from microstructural data, and generative approaches for exploring novel material designs, highlighting graph neural networks and reinforcement learning as emerging tools. Gaussian Process Regression has similarly been applied to constitutive modelling of stainless steel under varying strain rate and temperature [15]. A recent fatigue-life survey [32] finds random-forest and hybrid ensemble models most frequently used, with steel the most common material studied.

Taken together, these applications show AI is a mature, validated tool for steel design, monitoring and reliability assessment. However, most studies address global structural response, damage classification, or isolated scalar quantities. Direct prediction of the full nonlinear moment–rotation response of steel joints, arguably the most important source of nonlinearity governing frame behaviour, remains comparatively underexplored, as discussed next.

4. AI FOR STEEL JOINT BEHAVIOUR

4.1. RESEARCH GAP

A small number of studies have applied AI specifically to the moment–rotation behaviour of steel joints, but each addresses only a narrow aspect of the problem. Kueh [33] trained an ANN on connection test data and regressed its output via multivariate linear regression to obtain closed-form expressions for the initial rotational stiffness of flush end-plate connections. Tran [34] combined finite element analysis with ANNs to predict the ultimate moment capacity and bilinear shape parameters of flush end-plate joints at elevated temperature. Sarothi et al. [35] used Random Forest regression to predict the bearing strength of double-shear bolted connections ($R^2 = 0.88$), outperforming code-based formulas, while Jiang et al. [36] trained eight ML algorithms to predict the failure load and failure mode of high-strength steel bolted connections, achieving over 97% classification accuracy compared with 68–85% for design-code predictions. Rabbani et al. [37] compared an ANN and a multi-gene genetic programming (MGGP) model for the M–θ response of semi-rigid connections, finding that the symbolic MGGP model generalised better than the ANN.

These studies demonstrate that AI can capture specific aspects of joint performance (stiffness, strength, or failure mode) with high accuracy, but each targets a narrow joint typology or a single scalar output. No framework has yet been proposed that predicts the complete nonlinear M–θ curve, together with its underlying component-level behaviour, for a general class of joint configurations. Addressing this gap requires (i) a physically consistent, computationally efficient method to characterise the nonlinear force–deformation (F–d) behaviour of the governing joint components, and (ii) a surrogate model capable of reconstructing the full-range M–θ response from these component-level relationships while remaining consistent with mechanical principles. The following subsections present such a framework, developed by the authors for one-sided welded beam-to-column joints, combining GA-based component characterisation with PINN surrogate modelling [38,39].

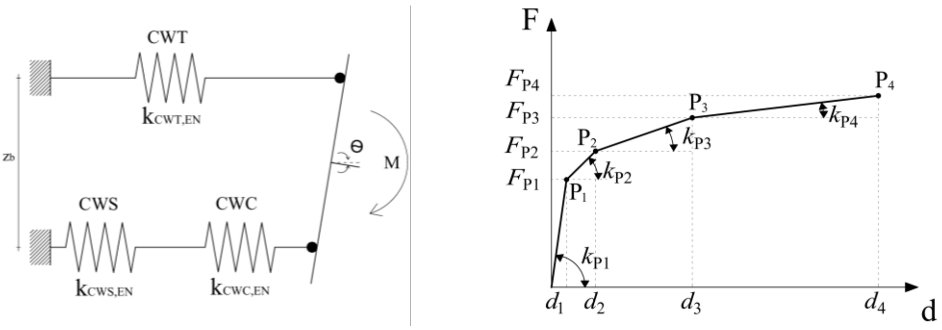
4.2. GA-BASED COMPONENT CHARACTERISATION

In one-sided welded beam-to-column joints, the global M–θ response is governed by the interaction of three components: the column web in shear (CWS), in compression (CWC) and in tension (CWT) (Fig. 1a). Each component is represented by a nonlinear force–deformation (F–d) relationship, idealised through proposed four characteristic points, $P1$–$P4$ [38], covering the initial elastic stiffness through to the ultimate deformation capacity (Fig. 1b) [4,6,40]. While EN 1993-1-8 [4] provides analytical expressions for the first two points, the elastic stiffness k_{ini} and the resistance $F_{\mathrm{R,EN}}$, the nonlinear branch beyond yielding ($P3$, $P4$) is not codified and must be calibrated against experimental or numerical data. Here, k_{P1} and F_{P2} correspond to these two values, while the remaining values (F_{P1}, k_{P2}, F_{P3}, k_{P3}, F_{P4}, k_{P4}) are obtained from them as detailed in Table 1 of [38].

The Genetic Algorithm (GA) is a stochastic, population-based optimisation method inspired by natural selection [41,42], well suited to problems such as multi-point curve calibration, where the fitness landscape is non-convex and difficult to differentiate analytically.

In [38], a GA was developed and applied to 20 one-sided welded beam-to-column joints selected from the SERICON II database [43], tested by Klein and Braun and previously identified as the most complete test records using an established evaluation framework [44]. Each GA individual encodes 24 genes, eight resistance/stiffness parameters per component, initialised within physically meaningful bounds around the EN 1993-1-8 [4] reference values. Candidate solutions are evaluated using a Python-based nonlinear component model (NLCM), which reconstructs the full M–θ response from the F–d curves of the three components; the fitness function is the coefficient of determination (R^2) between the predicted and experimental M–θ

curves of the three components. Tournament selection, blend crossover (BLX-α) and bounded Gaussian mutation with an annealed step size are used to evolve the population, with multiple early-stopping criteria to limit computational cost [38].



a) *b)*

Figure 1: Component method for a one-sided welded beam-to-column joint: a) mechanical spring model; b) F–d component characterisation with four characteristic points (adopted from [38])

Benchmarked against the 20 experimental joint configurations with failure component CWS according to EN 1993-1-8 [4], the GA-calibrated *M–θ* curves achieved R^2 values above 0.98 at the joint level, with the component-level shear and connection responses also closely matching the experimental trends [38]. Across all configurations, the GA consistently identified statistical admissible ranges, rather than single values, of stiffness and resistance for each *F–d* point. The ranges subsequently adopted as physics-based constraints for the surrogate model of Section 4.3 are summarised in Table 2 [38]. These ranges are physically meaningful: the first two points remain close to the EN 1993-1-8 [4] reference values, while larger deviations are observed for the post-limit points *P*3 and *P*4, reflecting the greater uncertainty in the nonlinear range. Because they define a continuous, experimentally validated domain rather than a discrete set of samples, these ranges provide a natural basis for physics-based constraints in a machine-learning surrogate model, as described next.

Table 2: Statistical descriptors of calibrated normalised component parameters (% values relative to EN 1993-1-8 [4] k_{ini} and $F_{\text{R,EN}}$) [38]

Point	**CWS**		**CWT**		**CWC**	
	***F* [%]**	***k* [%]**	***F* [%]**	***k* [%]**	***F* [%]**	***k* [%]**
$P_{1,GA}$	60 – 90	60 – 140	55 – 75	30 – 140	80 – 98	50 – 150
$P_{2,GA}$	90 – 120	13 – 50	80 – 110	6 – 30	85 – 115	6 – 65
$P_{3,GA}$	120 – 165	2 – 6	115 – 150	0.4 – 4	120 – 145	1.5 – 6.5
$P_{4,GA}$	165 – 240	0.6 – 1.2	185 – 220	0.4 – 1	185 – 220	0.6 – 2

4.3. PINN SURROGATE MODELLING

Building on the GA-derived component characterisation, a Physics-Informed Neural Network (PINN) was developed [39] to act as a fast surrogate for the full nonlinear *M–θ* response, extending the earlier PINN formulation of Ljubinković et al. [45], in which only the analytically derived initial-stiffness expressions of EN 1993-1-8 [4] were embedded. Rather than predicting only global scalar quantities (initial stiffness or resistance) the present formulation reconstructs the complete *F–d* behaviour of the CWS, CWC and CWT components, from which the joint-level *M–θ* response is subsequently derived, ensuring a physically consistent, component-based representation of the global behaviour [39].

The PINN maps a 19-parameter input vector describing joint geometry, material properties, weld size and the EN 1993-1-8 [4] reference values of component stiffness and resistance, to 24 output quantities, corresponding to the four force values and four stiffness values defining the *F–d* curve of each of the three components. The network follows a fully connected feed-forward architecture with four hidden layers of 128 neurons, Sigmoid Linear Unit (SiLU) activation, and a linear output layer, trained using the Adam optimiser with an initial learning rate of 1×10^{-3}, a batch size of 16, and 1200 training epochs [39].

Physical knowledge is embedded through a composite loss function [17,39]:

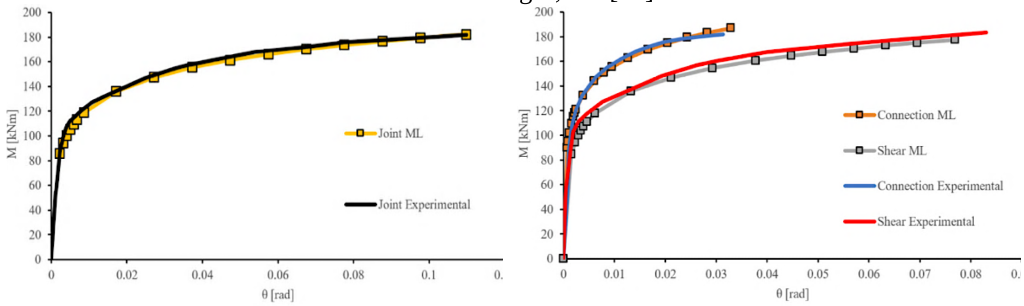
$$L = L_{\text{data}} + \lambda_{\text{phys}} \cdot L_{\text{phys}} \tag{1}$$

combining a standard mean-squared-error data term L_{data}, with a physics-based penalty L_{phys}, that penalises predictions falling outside the admissible GA-derived ranges of Table 2, weighted by a coefficient $\lambda_{\text{phys}} = 0.5$ [39].

4.4. RESULTS

The PINN was trained on a dataset of 20 one-sided welded beam-to-column joints, 19 used for training, one held out for testing and evaluated using a leave-one-out strategy, so that every joint configuration was assessed independently as an unseen test case [39]. Across all configurations, the coefficient of determination R^2 consistently exceeded 0.97 for the M–θ response at the global joint level, with slightly lower but still robust correlation at the component level, reflecting the greater sensitivity of individual component responses in the nonlinear, post-limit range [39].

Representative comparisons for three joint configurations (105_14 (HEB180 column, IPE360 beam), 105_18 (HEB240 column, IPE450 beam) and 105_11 (HEB140 column, IPE300 beam)) show close agreement between the PINN-predicted and experimental M–θ curves throughout the loading history, capturing the initial stiffness, the progressive stiffness degradation, and the post-limit evolution up to large rotations, with only minor deviations at higher rotation levels that do not affect the overall stiffness or ultimate moment capacity (see Figures 5–8 in [39]). As an example, Fig. 2 compares the predicted and experimental M–θ response for joint 105_14 showing a close match in both the linear and nonlinear ranges; see [39] for further details.



a) b)

Figure 2: Comparison of experimental and PINN-predicted M–θ curves for joint 105_14: a) global (joint) level; b) component (connection and shear) level (adopted from [39])

5. CONCLUDING REMARKS

This paper reviewed the current state of AI applications in steel structures, from general model families and selection criteria to specific applications in design optimisation, structural health monitoring, and reliability and material modelling. AI methods, particularly ANN/MLP, tree-based models, CNNs and, increasingly, physics-informed approaches, have demonstrated the ability to match or exceed traditional empirical and code-based methods, given sufficiently representative data.

However, AI applications targeting the nonlinear moment–rotation behaviour of steel joints remain limited to narrow joint typologies and isolated scalar outputs; no general framework was previously available to reconstruct the complete nonlinear $M–\theta$ response together with its component-level behaviour.

The GA–PINN framework presented in Section 4 addresses this gap for one-sided welded beam-to-column joints. GA-based calibration of multi-point $F–d$ curves provides physically validated admissible ranges for the governing components (CWS, CWC, CWT), embedded as physics-based constraints in a PINN surrogate model. Across 20 welded joint configurations evaluated in a leave-one-out validation, the framework achieved R^2 values consistently above 0.97 at the joint level, reproducing both initial stiffness and post-limit evolution with good component-level accuracy [38].

Some limitations remain: the training dataset is relatively limited (20 joint configurations), which may restrict generalisation to other joint types, and surrogate accuracy is bound by the quality of the GA-derived parameter ranges [39]. Future work will expand the dataset using experimentally calibrated FE simulations within the same GA–PINN framework, and extend the methodology to additional joint typologies (two-sided, interior/exterior, bolted and mixed), consistent with EN 1993-1-14 [7,39].

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