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REVIEW PAPER

A Review of AI-Assisted Stress Prediction Models in Mechanical Design

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***Abstract*—Stress analysis constitutes an essential part of mechanical design, by which the safety, reliability, and performance of the components engineered to operate under complex loadings and environmental conditions can be ascertained. Conventional methods for stress prediction, such as analytical approaches, finite element analysis (FEA), and experimental testing, have been implemented extensively in applications like piping systems, pressure vessels, and rotating machinery. these methods are frequently associated with significant computational costs, prolonged solution times, and extensive modeling efforts, thereby hindering their effectiveness in rapid design iterations and real, time applications. In a landmark departure from traditional methods, the advent of artificial intelligence (AI) and machine learning (ML) has spawned data, driven alternatives that can efficiently predict stress responses by learning the nonlinear relationships between geometrical features, materials, and loading conditions. AI, driven stress prediction models, which encompass machine learning and deep learning methods, are capable of quick and precise stress estimations, thus facilitating early, stage design decisions and diminishing the need for a multitude of simulation runs a comprehensive review of AI, assisted stress prediction models in mechanical design, their interaction with traditional stress analysis methods, the main advantages, and the limitations intrinsic to them regarding computational efficiency, predictive accuracy, and obstacles stemming from data quality, generalization, and physical interpretability, thereby sketching the next steps towards intelligent stress analysis frameworks in engineering practice.**

Keywords—Stress prediction, Mechanical Design Optimization, Machine Learning in Stress Analysis, Finite Element, Deep Learning Techniques, stress piping analysis.

I. Introduction

Stress analysis is the basis of mechanical design to make engines or engineered components safe, sound, and efficient [1]. Stress prediction helps designers to consider the reaction of the material and geometries when subjected to external forces, boundary, and the environmental influences [2][3][4]. Traditionally, such determination is done based on analytical formulations, numerical methods like finite element analysis (FEA), and experimental testing. the mechanical behavior of the piping under routine loads like internal pressure and thermal loads, and under unusual and intermittent loads, including those of earthquakes, winds, special vibrations and water hammer of mechanical design practice, and their computational cost and time to solution can be prohibitive and costly to exploration of design space and slows development cycles [5].

Stress prediction with the help of AI is one of the promising cases of the extension of conventional stress analysis techniques. The artificial intelligence methods allow the quick estimation of stress distributions by learning nonlinear connection between design factors, material characteristics, and loading factors and stress reactions without having to solve governing equations repeatedly [6][7]. Such AI-assisted models are used in mechanical design processes, and can serve to complement physics-based simulations, where they are used to rapidly screen design options and locate problem areas of design at early design stages[8]. This interdependence of mechanical design goals and data-driven intelligence is a transition to more efficient and responsive design.

The stress analysis AI concept is also enlarged by the involvement of advanced machine learning and deep learning architectures that can process high-dimensional data and complex geometries [9][10][11]. The trained models designed by simulation or experiment data can reproduce the complex pattern of stress, which is hard to estimate under simple analytical conditions. hybrid methods using AI and physics-based constraints improve the quality of predictions and at the same time make it physically consistent [12]. AI-driven stress analysis that enhances performance in computational domains and helps make more decisions in real-time in the field of mechanical design the quality of information, the integration of physical laws in theories of learning, as well as the verification of the predictions made by AI in terms of numerical and experimental factors [13][14]. AI-assisted stress prediction is a convergence point where the principles of mechanical design, the methods of stress analysis and artificial intelligence are all involved in the promotion of intelligent engineering systems.

II. Conventional Stress Analysis in Mechanical Design

pipe stress analysis can help improve system integrity, preventing issues such as leaks, equipment failure, foundation stress cracking or anchor bolt failure. This preventive measure can extend equipment life and reduce costs for system operations and maintenance stress Analysis in pressure vessel nozzles.. Pressure vessels cause applied loads to be tensile on the internal region of the pipe wall and compressive in the external region [15]. These stresses are principal factors that tend to affect plastic deformation. Current practices include using Finite Element Analysis (FEA) to model stress distribution and/ or to test material performance. the PVC is fast becoming popular due to its inexpensive the following to increase pipe life:fluid load limits, pressure, and strain.

A. *Inputs for Piping Stress Analysis*

Stress Isometric from piping designer, P&ID & Line Designation Table (LDT from process department, Equipment GAD and other vendor data from the mechanical group.PFD the process department, Specification of piping (PMS) from the piping material group, All control valves and other valve data from Instrumentation. Project-specific nozzle allowable standard, overall plot plan, and area plot plan for finding HPP elevation and equipment orientation from piping layout group:

Governing codes and standards for pipe stress analysis

- ASME B31.3: Process piping Code
- Centrifugal Pumps: API 610
- Centrifugal Compressors: API 617

B. *Stress Analysis of Pump Piping System*

The analysis of pump piping consists of suction and discharge piping. The static analysis and modal analysis of suction and discharge lines of Pump One of the piping unit's refinery systems consists of 2 pumps with two suction and discharge nozzles [16]. The pump piping loads exerted on the pump discharge nozzles have exceeded the pump manufacturer's limit. It is required to bring the nozzle loads within the limit by stress analysis (static) of the pump piping system. The static analysis of the complete system is performed in finite element analysis software (CAESAR-II), see in Figure 1. It includes finalizing the piping system routing and supports.

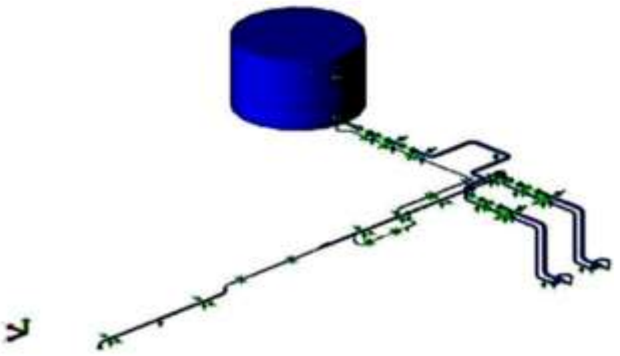

Fig. 1. CAESAR-II Model

CAESAR-II is a basic tool to the piping stress analysis exercise which offers various functions to the user. Through accurate forecasting of stresses and deformations

C. *Optimization of piping*

The design and cost comparison among the cases optimization. However, these are not being used in consultancies due to many drawbacks like time, cost, etc. For this project, the optimization is achieved mainly by material optimization and engineered support, resulting in cost optimization cases are being analyzed in terms of the cost of material used in the piping.

D. *Stress Evaluation*

The standard-purpose FEA codes will not consider the supports' geometric properties, valve data, and engineered support. Constructing the analytical models for each load case scenario is of utmost critical. Moreover, the evaluation of allowable stresses for each load case is very strenuous. So, CAESAR-II program was used in this research, which is used in all the process industry. From the below Figure 2, software modelling is done as per stress isometric.

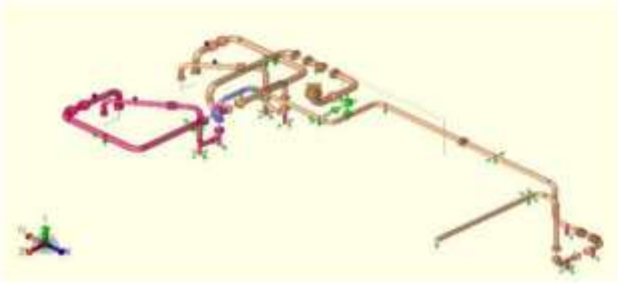

Fig. 2. Temperature Profile for A Two-Pump System Isometric Views.

Procedure of the piping modelling piping system part Node and coordinates of the piping system Piping parameters" (like length, diameter, and schedule), complete the equipment modelling and then start modelling the piping based on piping isometric drawing. Always make a closed system to get the correct results. Typically, pump lines are connected to heat exchanger, horizontal or vertical vessel and tank.

1) *Finite Elements Methods*

The process of creating a model, which is a representation of how a system of interest is constructed and operates, is called modelling [17]. A model is a simplified version of the system it depicts. A model's ability to help analysts forecast the impact of system modifications is one of its goals. A model should, on the one hand, closely resemble the real system and include the majority of its unseen characteristics it is hard to comprehend and use. Realism and simplicity are wisely traded off in a good model. The geometrical model of the Pressure vessel is shown in Figure 3.

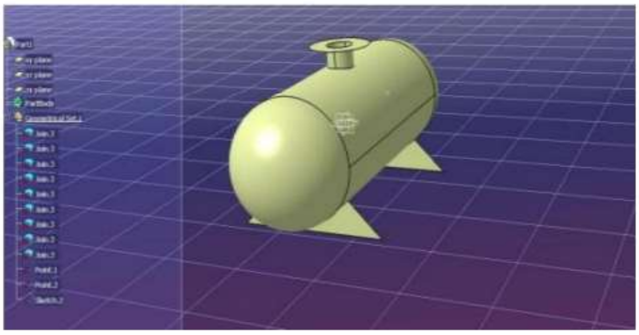

Fig. 3. Geometrical Model of Pressure Vessel

Hyper mesh 9.0 is utilized for finite element modelling. Hyper Mesh is a powerful pre- and post-processor for finite element solvers that aids in the design process in a visually immersive and interactive setting. An essential part of finite element analysis.

Popular FEM Software for Pressure Vessel Analysis

- **ANSYS:** ANSYS is a popular software used for finite element analysis (FEA), which is great for studying how pressure vessels handle stress. It's known for being flexible and powerful, making it a top choice for engineers. ANSYS is especially good at dealing with materials that don't behave in simple ways, such as those that stretch or deform over time.
- **ABAQUS:** ABAQUS is another widely used FEA software designed for the nonlinear and dynamic analysis and has traditionally been most effective for analyzing pressure vessels. Where stress concentration is highest.

2) Stress is Classified into Three Categories

This section categorizes stress analysis into three distinct types: primary, secondary, and tertiary stresses [18]. providing a detailed explanation of each.Primary Stress: This type is created with the purpose of support stability against the external and internal loads and the moments Secondary Stress: This category of stress is caused due to displacement constraints for every structure member, for example the thermal expansion Tertiary Stress: This is known as the high stress which causes susceptibility to fatigue fracture which exists in heavily stressed areas The system is expected to be able to compute stresses like hoop, axial, and even bending stresses, among others.

3) Pipe Support Impact to Pipe Stress Analysis

stresses on a piping system is to ensure that the piping is well supported and does not fall or deflect under its own weight and also to ensure that the deflection is under the limit when thermal loading takes place. Stress analysis determines the forces exerted in the pipe, anchor points, restrains in piping system, stress induced in pipe stress and the effect of using pipe supports on the stress in the piping system [19]. The findings revealed that the type of support chosen, such as the gap and distance of pipe support, has a significant impact on the stress value in the piping system. The results of the analysis are carried out several times to get the stress value so that it does not exceed the allowable stress. The selection and location of these supports is based on the results obtained from displacement, stress, reaction and equipment nozzle analysis of the piping system. The design is in accordance with ASME B31.3, which is the standard code for process piping. The proposed method can be adapted for piping configuration of any industrial plant.

4) Pipe Layout Impact to Pipe Stress Analysis

piping system is mainly dependent on the Equipment Layout. While finalizing the location of equipment, the connecting piping flexibility is also to be considered along with the process flow, accessibility to valves, instruments, equipment maintenance, cleaning, operational safety, headroom clearance and aesthetics. The piping layout designer has to undergo number of iterations to reach to a final layout. Pipe Routing is always decided based on the Equipment layout. The design will have an impact on the design, material cost and safety of the plant. In the project, dimensions of pipe rack loops for a process plant are optimized based on temperature, pipe size, pressure etc.

5) Standards for stress and displacement of pipelines

CAESAR II is capable of choosing different stress validation standard according to different conditions. ASME B31.8 Gas Transportation and Distribution Piping Systems (ASME 2012c) is normally used for gas pipeline while ASME B31.4 Pipeline Transportation Systems for Liquids and Slurries (ASME 2012b) is used for oil pipeline[20]. For the validation of displacement (GB 50251; GB 50316), GB 50251 Code for design of gas transmission pipeline engineering is used for transverse displacement validation and GB 50316-2008 Design code for industrial metallic piping is used for axial displacement and angular displacement.

a) Checking Stress

the stress of pipeline in normal condition can be categorized as: primary stress, secondary stress, and peak stress. The primary stress represents the effect of internal pressure and gravity on the stress, secondary stress represents the effect of difference in temperature on the stress and peak stress is the combination of primary stress and secondary stress.The general Equation of stress validation is(1)

$$\sigma \leq F\sigma_s \quad (1)$$

which σ represents stress; F is the design coefficient of which the values are listed in Table I; σs is the minimum yield strength of the pipeline material Primary stress is calculated as follows Equation (2)

$$\sigma_L = \frac{F_{ax}}{A} + \frac{PD}{4S} + \frac{M}{W} \quad (2)$$

where σ_L is primary stress, MPa Fax is additional axial force which is caused by pressure, N A is pipe cross-sectional area, mm2 P is pressure, MPa D is pipeline diameter, mm S is pipeline thickness, mm; M is synthetic bending moment, W is bending section modulus, mm3.Secondary stress is calculated as follows Equation (3)

$$\sigma_E = \frac{M_E}{W} \quad (3)$$

where σ_E is secondary stress, MPa; ME is bending moment of thermal expansion, Nmm W is bending section modulus, mm3.

TABLE I. VALUES OF THE DESIGN COEFFICIENT (F)

Stress type	Gas pipeline	Oil pipeline
Peak stress	0.90	0.90
Primary stress	0.75	0.72
Secondary stress	0.72	0.90

b) Checking Displacement

Displacement validation focuses on transverse and axial displacement. GB 50251 Code for design of gas transmission pipeline engineering requires that transverse displacement does not exceed 0.03 times of the diameter of the pipeline. GB 50316- 2008 Design code for industrial metallic piping requires that axial displacement does not exceed 0.4 time of the length of pipeline support. The angular displacement of a horizontal pipeline is generally required to be no greater than 4°.

III. AI-Assisted Stress Prediction Models

There are two approach machine learning and deep learning technique discussed below:

A. Machine Learning Approach

Machine learning (ML) and artificial intelligence (AI) are increasingly transforming mechanical engineering and machine systems[21]. These technologies enhance efficiency, reduce costs, and minimize errors in engineering processes, as shown in Figure 4 are given below:

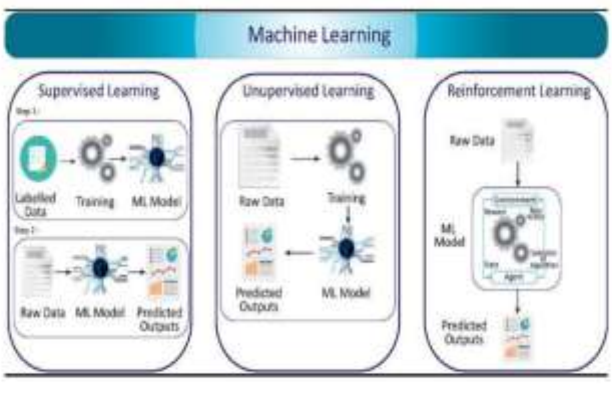

Fig. 4. Demonstration of the Types Of Machine Learning

- Supervised learning forms the backbone of predictive modelling in mechanical engineering applications. This approach utilizes labelled training datasets to learn mapping functions between input features and target outputs. Common supervised learning algorithms extensively used.
- Unsupervised learning techniques focus on discovering hidden patterns and structures within unlabelled datasets, making them invaluable for exploratory data analysis and feature extraction in civil engineering.
- Reinforcement learning is an emerging AI technique in mechanical design that enables systems to learn optimal decisions through interaction with their environment based on reward-driven feedback. In stress prediction and structural optimization.

1) KNN

The KNN model is a statistical tool for estimating the value of an unknown point based on its nearest neighbours. Two simple techniques are used in this study: the Euclidean distance function d(x, y), provided in Equation (12), and the Manhattan distance function d(x, y), provided in Equation where x = (x1, where (x1. . . , xn), y = (y1, . . . , yn), and n is the vector size. The K neighbour point that has the shortest distance to the unknown point is used to estimate its value using Equation (4)

$$\widehat{y_i} = \sum_{i=1}^{n} w_i y_i \tag{4}$$

Where w_i is the weight of every single neighbor point y_i to the query point $\widehat{y_i}$.

2) SVM

Particularly effective for classification problems such as soil type identification and structural damage classification. SVMs excel in handling high-dimensional data and nonlinear relationships through kernel functions.

B. Deep Learning Technique

There are some deep learning approach are using ai stress prediction model of ANN, RNN and LSTM are discussed below:

1) ANN

The ANN model is based on the concept of the brain's self-learning ability, mimicking the human nervous system to process information the numbers of neurons and hidden layers are increased, the ability to handle nonlinearity improves. However, these conditions may result in high computational complexity, overfitting. ANN model, a_i^l is the ith activation element of the lth layer in the hidden layer. b_i^l is bias, a_i^l is equal to input value times weight w_{ji}^l and add the bias in Equation (5)

$$z_i^l = \sum_{i=1}^{n} w_{ji}^l a_i^l + b_i^l \tag{5}$$

the input layer data combined with bias and weight to obtain some value.

2) RNN

RNN is a type of neural network that can model "time-like"-series data, and it commonly adopts a nonlinear structure in deep learning.

The ring-shaped neural network is expanded along the "time" axis, as shown in the right half of Figure 5, where the "time" step t and the hidden state st can be expressed as a function of the output from the previous (st−1) "time" steps and previous layers (xt).

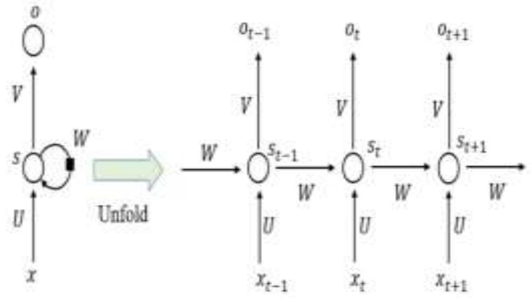

Fig. 5. Schematic Structure of Recurrent Neural Network

3) LSTM

advanced regularization and optimization techniques to improve the model's performance. After normalizing the data using an LSTM model consisting of two LSTM layers, with 128 hidden units and a 50% dropout to prevent overfitting. Batch normalization was applied to enhance stability and convergence. A fully connected layer makes the final prediction, followed by a Softmax activation to obtain probabilities.

IV. Advantages and Limitations of AI-Based Stress Prediction

The stress prediction AI methods provide huge advances in terms of computational efficiency, quick design assessment, and the capability to address non-linear stress patterns complicated by complex nonlinear stress behaviors than the traditional methods. Nonetheless, in spite of these strengths, issues connected with data dependency, model generalization, interpretability and reliability are still burning issues, as outlined below.

A. Advantages of AI Stress Prediction In Mechanical Design

1) High Predictive Accuracy

AI models have the ability to reproduce complex and nonlinear relationships between two or more variables (e.g. geometry, material properties, loading conditions) that can often be more accurate than traditional analytical or empirical models.

2) Quick Analysis and Time-Saving

AI-based models are capable of predicting the stress in near-instances after training, and they can save a lot of time in comparison to the finite element analysis (FEA) when used in large-scale or real-time.

3) Cost Reduction

By minimizing the need for repeated simulations, physical prototyping, and extensive experimental testing, AI-based stress prediction can lower overall design and validation costs.

4) Capability to Handle Large and Complex Datasets

AI methods are capable of processing high-dimensional data simulation, sensor or historical data, and thus they can be applied to complex structures and operating conditions.

5) Support for Real-Time Monitoring and Decision-Making

AI models can be used to support real-time estimation of stress, early fault detection, and predictive maintenance when combined with sensor data and digital twins..

B. Limitation of AI Stress Prediction In Mechanical Design

1) Data Quality and Coverage

Stress prediction models based on AI have a strong dependence on large, accurate, and representative datasets. When the training data is not comprehensive to encompass all the relevant geometries, boundary conditions, loading cases and material behaviours, the model may make unreliable predictions. Noise, measurement errors or inconsistencies

2) Limited Generalization and Extrapolation Ability

The AIs tend to perform good in the region of the same conditions that the training data encompasses without extrapolating them. Extreme loading conditions or novel materials In the case of new designs, extreme loading conditions or new materials the prediction accuracy can greatly decrease and they should not be used in an early-stage or innovative engineering design.

3) Lack of Physical Transparency and Interpretability

A lot of AI models are black-box systems that do not provide much understanding of the physical concepts underlying stress distribution. This interpretability deficiency makes engineers more likely not to know whether the result is correct, how the failure occurred or what decisions were taken in making the design, especially in safety-related applications.

4) High Computational Cost During Training Phase

Though AI models offer rapid predictions after training, their training can be computationally costly, and particularly when it comes to deep learning structures. This is further expensive since simulation or experiments based on high fidelity generate training data.

5) Sensitivity to Changing Operating Conditions

Model drift due to variations in temperature, material degradation, corrosion, fatigue or varying conditions at the boundary with time, result in decreased model accuracy. To ensure stable performance, constant monitoring and recurrent retraining are necessary.

V. Literature Of Review

The reviewed literature highlights recent advancements in AI assisted stress prediction model in mechanical design. This Table II, The summary table systematically organizes research studies key findings, challenges are discussed below:

Manguri, Saeed and Jankowski (2025) It offered adjustment and regulation of shape, stress, or both in structures and emphasizes such control's importance. The control of systems is classified into three primary classes nodal movement control, axial force control, and controlling the two classes. Each class is thoroughly assessed, to reduce the number of devices (actuators) to adjust and optimize actuators' placement to achieve optimal structural control, considering the cost implications of numerous actuators [22].

Fatouma, Abdejallil and Omar (2025) stress tolerance analysis applying empirical values for levels in the lens. The main idea of this research study is to obtain a configuration performance with less stress tolerance for glass thermal effects in opto-mechanical instruments a theory to estimate the magnitude of the compression stress used at the glass-metal interface tensile stress can be statistically established for the lens under different cryogenic temperatures. stress tolerances is best performed by finite element analysis methods more efficient prediction of component failure from stress tolerance analysis and a more accurate prediction [23].

Sotoodeh (2024) Oil and gas plants require piping components and systems to transport fluids and gases. A number of factors affect piping, including pressure, temperature, load, and flow. The purpose of this study is to prevent mechanical failure of piping a result of mechanical loads, which is called a piping stress analysis. piping failures caused by mechanical loads. This is done by applying stress analysis based on piping codes the first part examines piping stress analysis against principal stresses, stress analysis against sustained loads, occasional load analysis on the analysis of piping stresses of stresses related to piping reaction forces [24].

Sankardoss, Iei and Mimeche (2024) the significance of pipe support stiffness in both thermal expansion and seismic conditions. The actual support stiffness is included in the analysis by modelling the structural member using the CAESAR II software. Incorporating actual support stiffness is important because it helps accurately simulate the behavior of piping systems under different loading conditions, leading to more accurate and better decision-making during the design and operational stages actual support allows for a more optimal design, reduces the risk of failure due to excessive stresses and improves overall piping system performance [25].

Tiwari et al. (2024) Machine learning (ML) is a promising approach for forecasting the fatigue life of components an effective approach for reliably estimating the fatigue lifespan of mechanical components beneath uniaxial loads in high-cycle fatigue conditions. circumstances, notch shapes, and fatigue lifetimes. Conventional techniques have depended heavily on any of the mechanical reaction characteristics, like strain, stress, or power variables can be used well to estimate fatigue lifespan, with stress-based estimates being the most accurate. Gradient boosters and Random Forest outperform all other ML techniques tested a considerable enhancement in prediction accuracy obtained by adding novel data acquired using the Basque formula [26]

Hovanec et al. (2023) mechanical-stress prediction using a NN is described. The method essentially replaces finite element methods (FEMs), which require large amounts of time. as the NN predicts the mechanical ATT stress in 0.00046 s, whereas the solution time using FEM is 1716 s for the same load step. whereas the novel method calculated the ATT stress for 36 regimes in 0.0166 the development of a method that can predict. The partial results from the experimental tensile tests are also presented, and they are used for FEM calculations [27].

Chen et al. (2022) mechanical stress distribution in a representative stator core with models of increasing fidelity, starting from the basic analytical hoop stress model with a simplified back-iron ring to a machine level stress model with stator teeth, windings, slot liners, winding insulations and slot wedges. The impact of windings and stator teeth on the accuracy of the mechanical stress model of the windings and the associated insulations, slot liners and wedges for an accurate prediction of mechanical stress that the core loss in the stator core can be underestimated by ∼10–20% if the mechanical stress caused by shrink fit process is neglected [28]

TABLE II. SUMMARY OF LITERATURE REVIEW OF AI ASSISTED STRESS PREDICTION MODEL IN MECHANICAL DESIGN

Author (Year)	Study On	Challenges Addressed	Key Findings	Limitations	Future Work
Manguri, Saeed & Jankowski (2025)	Structural shape and stress control using actuator-based systems	High cost and complexity due to large number of actuators; optimal actuator placement	Classified control systems into nodal movement control, axial force control, and combined control; demonstrated reduction in actuators while maintaining effective stress and shape control	Limited consideration of real-time adaptability and nonlinear structural behavior	Integration of intelligent optimization and AI-based actuator placement strategies
Fatouma, Abdejallil & Omar (2025)	Stress tolerance analysis of glass lenses under cryogenic conditions	Accurate estimation of tensile and compressive stress at glass–metal interfaces	Established a statistical approach for stress tolerance using FEA; improved prediction of failure due to thermal effects	Heavily dependent on empirical data and FEM accuracy	Incorporation of AI-driven surrogate models for faster stress tolerance prediction
Sotoodeh, (2024)	Piping stress analysis in oil and gas plants	Mechanical failure due to pressure, temperature, sustained and occasional loads	Demonstrated effectiveness of code-based stress analysis in preventing piping failures; evaluated principal and reaction stresses	Conventional analysis is time-consuming and sensitive to modeling assumptions	AI-assisted stress monitoring and predictive maintenance for piping systems
Sankardoss, Iei & Mimeche (2024)	Effect of pipe support stiffness under thermal and seismic loading	Inaccurate modeling of actual support stiffness in piping systems	Showed that incorporating real support stiffness using CAESAR II improves accuracy and system reliability	Software-based approach limited by predefined modeling capabilities	Development of intelligent digital twins integrating real-time stiffness data
Tiwari et al. (2024)	Machine learning–based fatigue life prediction under high-cycle fatigue	Reliable fatigue life estimation across varying notch shapes and stress levels	Gradient Boosting and Random Forest models outperformed traditional methods; stress-based features yielded highest accuracy	Limited generalization outside trained datasets	Expansion to multiaxial loading and physics-informed ML models
Hovanec et al. (2023)	Neural network–based mechanical stress prediction	Extremely high computation time of FEM simulations	NN predicted stress in milliseconds compared to hours using FEM; validated using experimental tensile data	Model accuracy dependent on training data quality and range	Hybrid FEM–NN frameworks and broader experimental validation
Chen et al. (2022)	Mechanical stress modeling in stator cores of electrical machines	Underestimation of stress effects due to simplified analytical models	Demonstrated that neglecting shrink-fit stress leads to 10–20% underestimation of core loss; higher-fidelity models improve accuracy	Increased computational complexity with higher model fidelity	AI-assisted reduced-order models for accurate yet efficient stress prediction

VI. CONCLUSION WITH FUTURE WORK

AI, assisted stress prediction models in mechanical design have been the main topic of discussion, emphasizing their increasing importance in overcoming the limitations of traditional methods of stress analysis. Conventional methods such as analytical formulations, finite element analysis, and experimental testing are still the main tools for ensuring structural safety and compliance with design codes; however, their intensive computational resource and time requirements limit rapid design iterations and real, time applications. AI, based stress prediction models have shown remarkable potential by providing quick, cost, effective, and accurate estimation of stress responses through data, driven learning of complex nonlinear relationships among geometry, material properties, and loading conditions. These models facilitate early, stage design evaluation, allow for the efficient optimization of design, and, when combined with sensor data and digital twins, enable condition monitoring and predictive maintenance. However, the issues of data dependency, limited generalization beyond trained domains, lack of physical interpretability. Future research should be the creation of hybrid physics, informed AI models that incorporate the mechanical principles governing the phenomena into the learning frameworks to increase the models' reliability and explain ability. a large volume of quality data sets through state, of, the, art simulations and experimental validation will improve the models' robustness. Moreover, the coupling of AI, assisted stress prediction with on, line monitoring systems, digital twins, and adaptive retraining protocols is an intriguing prospect.

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