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Machine Learning Approaches for Mechanical Rebar Couplers: A Comprehensive Review of Alternatives to Lap Splices

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Abstract*— Mechanical rebar couplers have become a traditional lap splicing in reinforced concrete designs, especially in those areas where reinforcement congestion and high seismic performance are strict. They have a mechanical performance that is dependent on a variety of parameters that are based on material properties, geometry, installation quality, and loading conditions, and their prediction and optimization are challenging under conventional analytical methods. This paper is a critical and detailed review of machine learning methods for the mechanical rebar couplers with an accent on their usage as alternatives to lap splices in modern-day reinforced concrete construction. Types of mechanical couplers, parameters of mechanical and structural performance governance, sources of experimental data and numerical data, and state-of-the-art ML algorithms that allow us to predict the behavior of mechanical couplers are systematically discussed in the review. The current developments, such as hybrid and physics-informed machine learning frameworks, are touched upon in the context of structural reliability, design optimization, and sustainability. The research gaps are recognized, and the main areas include the standardization of datasets, explained models of machine learning, and enhanced correlation between machine learning predictions and structural design codes. This review will also provide a consolidated base of knowledge and a roadmap of future research to researchers and practitioners in intelligent design and evaluation of mechanical rebar couplers.

***Keywords*— Mechanical Rebar Coupler, Machine learning, Lap Slice.**

I. INTRODUCTION

Reinforced concrete (RC) structures are based upon the idea of efficient load transfer through the reinforcing bars for structural performance and maintainability. Traditionally, lap splicing has been the most popular technique of joining reinforcing bars [1, 2]. Lap splices need more bar length, and their performance may be compromised when subjected to cyclic, seismic, or fatigue loading conditions [3, 4]. These restrictions have made the use of mechanical rebar couplers an alternative system of connection.

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Mechanical rebar couplers offer direct load connection between the bars and that of the mechanical interlocking, threading, grouting, and swaging. They have become very prevalent in high-rise buildings, precast construction, seismic-resistant structures, and infrastructure projects where space is very limited and performance needs are important [5, 6]. Although they offer these benefits, the mechanical performance of rebar couplers is affected by various interacting parameters, which include coupler geometry, material properties, quality of installation, loading conditions, and exposure to the environment [7–9].

Parallels Machine learning (ML), a branch of artificial intelligence (AI), has become important in civil and structural engineering to model complex nonlinear relationships that are hard to model with traditional methods of analysis or experiment [10–12]. ML methods have been effectively used to forecast the material properties, structural capacity, durability performance, and failure modes. Combining ML and experimental and numerical data is an effective framework for performance prediction and optimization of mechanical rebar couplers. Purposes of this review is to collect and critically analyze already available literature on ML-based solutions to mechanical rebar couplers. The paper also focuses on their capabilities as alternatives to lap splices of future development of ML-based design and evaluation procedures.

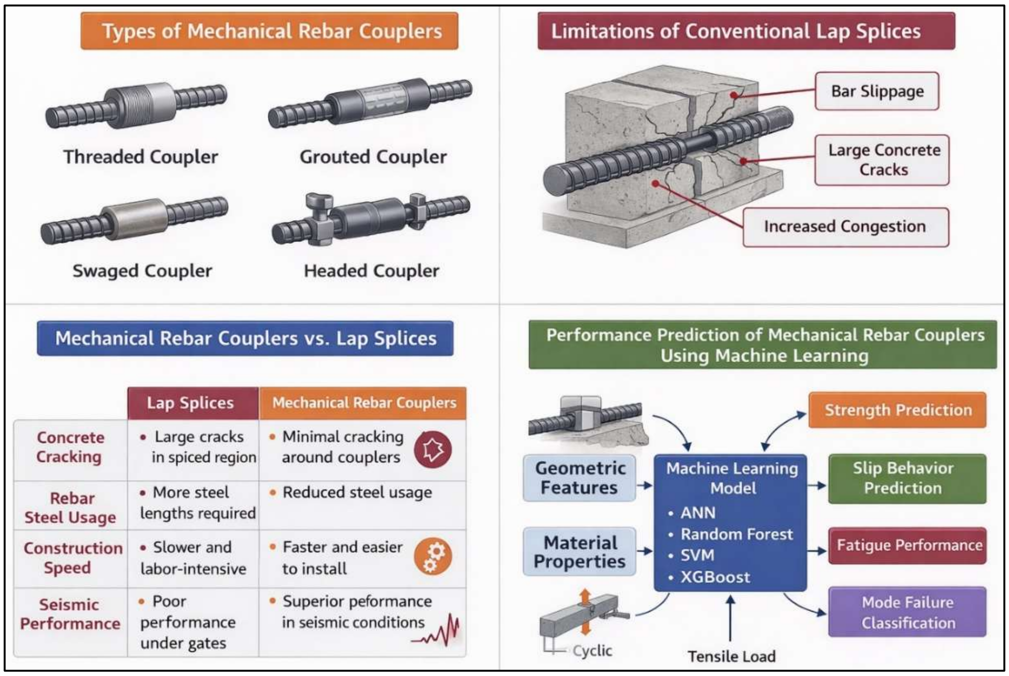

Figure 1: Overview of Mechanical Rebar Couplers, Limitations of Lap Splices, and Machine Learning-Based Performance Prediction

A. Methodology and Perspective of this Review

Though various works have been conducted on the mechanical performance of rebar couplers and other researchers explored the use of machine learning in structural engineering, there is still no critical review specifically on the use of ML-based to measure the mechanical performance of rebar couplers as an alternative to lap splices [13,14].This review is unique which offers an integrated perspective that bridges numerical modelling, and experimental mechanics. The significant contributions made by this review can be summarized as follows:

The type of mechanical rebar coupler and its controlling mechanical performance parameters, which are relevant to structural design, are tabularly organized. It highlights the advantages and disadvantages of the method and provides a critical analysis of the most recent cutting-edge machine learning applications for coupler performance prediction, classification, and optimization. In the context of structural reliability and code-compliant design, it discuss emerging trends such as hybrid and physics-informed machine learning structures. It is hoped that by taking these factors into account, this review will serve as a comprehensive reference and research guide for both practicing engineers and academic researchers regarding intelligent and performance-based reinforcement connection systems [15].

II. Weaknesses of Traditional Lap Splices

In lap splicing, tensile or compressive forces are transfer between reinforcing bars in the development length by bond-building stresses. Even though it was approved by design codes, lap splices have a number of limitations:
Reinforcement congestion: Bar overlapping has increased, which results in congestion, especially in beam-column intersections, shear walls, and highly reinforced members.
Construction issues: It is difficult to place and compact concrete properly in busy areas, which exposes the construction to the risk of voids and honeycombing.
Seismic zones: Lap splices in plastic hinge areas could have early bond failure in cyclic loading.
Material inefficiency: Increased amount of steel length will add material consumption and total cost of construction.
Performance uncertainty: Bond-dependent behaviour is affected to concrete quality, cover and confinement as well as workmanship.
These limitations have led engineers and contractors to consider mechanical rebar couplers as more secure and space-saving [16].

A. Comparative Summary Tables

TABLE I. Difference between Conventional Lap Splices and Mechanical Rebar Couplers

Aspect	Conventional Lap Splices	Mechanical Rebar Couplers
Load transfer mechanism	Bond-dependent between steel and concrete	Direct mechanical load transfer
Required reinforcement length	Highly additional in lap length	Least in butt connection
Reinforcement congestion	Significant in joints	Substantially reduced
Constructability	Difficult in heavily reinforced zones	Improved soft skill development
Seismic and cyclic performance	Vulnerable to bond degradation	Superior and more stable
Material efficiency	Higher steel consumption	Reduced steel usage
Quality control	Difficult to verify after casting	Easier inspection and verification
Suitability for precast construction	Limited	Highly suitable

TABLE II. Summary of Machine Learning Applications for Mechanical Rebar Coupler Performance Assessment

ML technique	Typical input parameters	Predicted outputs	Key advantages	Limitations
Artificial Neural Networks (ANN)	Bar diameter, coupler length, material strength, thread geometry	Tensile capacity, slip, stiffness	Captures strong nonlinear relationships	Requires large datasets, limited interpretability
Support Vector Machines (SVM)	Geometric and material properties, loading parameters	Strength classification, failure mode	Effective with small datasets	Sensitive to kernel selection
Random Forest (RF)	Multi-parameter experimental and numerical data	Strength, deformation, feature importance	Robust, interpretable feature ranking	May require tuning for accuracy
Gradient Boosting / XGBoost	High-dimensional parametric data	Capacity prediction, optimization	High accuracy, handles complex interactions	Computationally intensive

III. Mechanical Rebar Couplers: Types and Mechanisms

Mechanical rebar couplers have been used to hold reinforcing bars together by mechanical forces, avoiding the use of bond stress. The main types include Threading couplers Threaded couplers are made by using parallel or tapered threads on the reinforced bars. The transfer of the load is by means of thread engagement, which gives high tensile strength and stiffness. The reason why these couplers are used extensively is because of their ease of inspection and reliability. Grouted couplers are made of a steel sleeve stuffed with high strength grout. The bars are plugged into the sleeve, and the transfer of the loads is by bond and confinement. In precasting, grouted couplers are most common.
Swaged couplers are based on the plastic deformation of the coupler sleeve to hold reinforcing bars. This is an effective process that maintains a high mechanical bond with a need of special equipment. Mechanical anchorage or bolts are used to transfer forces between headed couplers or bolted couplers. The systems can be used in those applications where fast installation and demount ability are needed. Each type of coupler is determined by its performance that is dependent on the material properties, geometry, installation accuracy, and loading conditions and, therefore, each of them can be considered as a suitable candidate to the ML-based modeling.

IV. Mechanical and Structural Performance Parameters

Mechanical rebar couplers have a number of performance indicators like Stiffness and tensile strength, Slip and deformation properties, Failure mode (bar fracture, thread stripping, grout failure), Fatigue and performance cycling, Seismic wave and power loss, Resistance of exposure to the environment. They are usually retrieved by means of experimental testing and numerical simulations, which provides the foundation of the development of ML models.

V. Rebar Coupler Applications of Machine Learning Techniques.

Machine learning methods make it possible to achieve the prediction and optimization of coupler performance through learning of experimental and numerical data. ANNs are popular in the modeling of nonlinear relationships between input parameters (e.g. bar diameter, coupler length, material strength) and output responses (e.g. tensile capacity, slip). They are effective at the coupler performance prediction because of their capacity to capture complex interactions. SVMs can be used in regression and classification problems, including predicting failure modes or differentiating acceptable and unacceptable coupler behavior. The tree-based models are resistant to overfitting and the importance of features. The influential parameters that influence the strength of couplers and their deformation have been ranked using RF models. The algorithms of boosting boost prediction accuracy through the combination of weak learners. These are especially practical with small to medium-sized datasets that are common in the case of structural engineering research.

VI. Sources of Data and Model Development

The quality and diversity of the input data is critical to the performance of the ML models. Common data sources include like Tensile and cyclic tests using experiments, Simulation results of the finite elements, Data on performance supplied by manufacturers, preprocessing of data, selection of features, normalization, and validation of models are key elements in the development of sound MLs. The cross-validation and sensitivity analysis is widely used to increase the generalizability.

A. Conceptual Framework and Figure Descriptions

Figure 1. Framework of mechanical rebar coupler performance assessment with machine learning assistance.
This number demonstrates an imaginary process behind the experimental testing, numerical simulation, and machine learning combination to evaluate the performance of mechanical rebar couplers. The framework will start with the tensile, cyclic, and fatigue tests with the finite element simulations, including the stress transfer and failure mechanism. Data preprocessing and feature engineering stages handle input parameters like bar diameter, coupler geometry, material properties, installation quality, and loading conditions. Machine learning models are then trained for key performance indicators, such as tensile capacity, slip behavior, stiffness and failure mode. Future study paradigm of ML-based design and code generation of mechanical rebar couplers. It consists of standardized experimental databases, hybrid physics-informed ML models, quantification of uncertainty and explainable artificial intelligence tools. The eventual goal is to close the gap between experimental predictions and actual design applications such that mechanical rebar couplers can be used as substitutes of lap splices in code-compliant, reliable and sustainable ways.

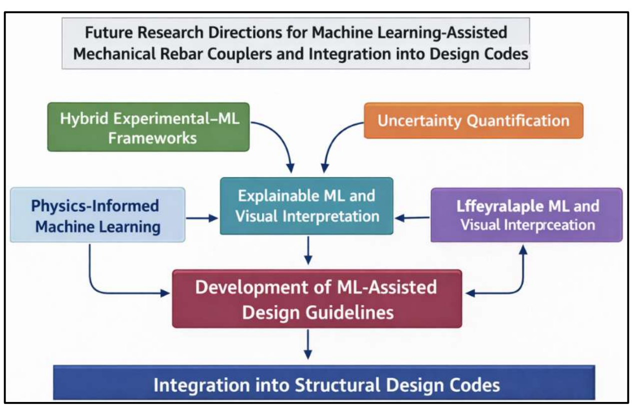

Figure 2: Machine Learning-Assisted Framework for Performance Assessment and Optimization of Mechanical Rebar Couplers

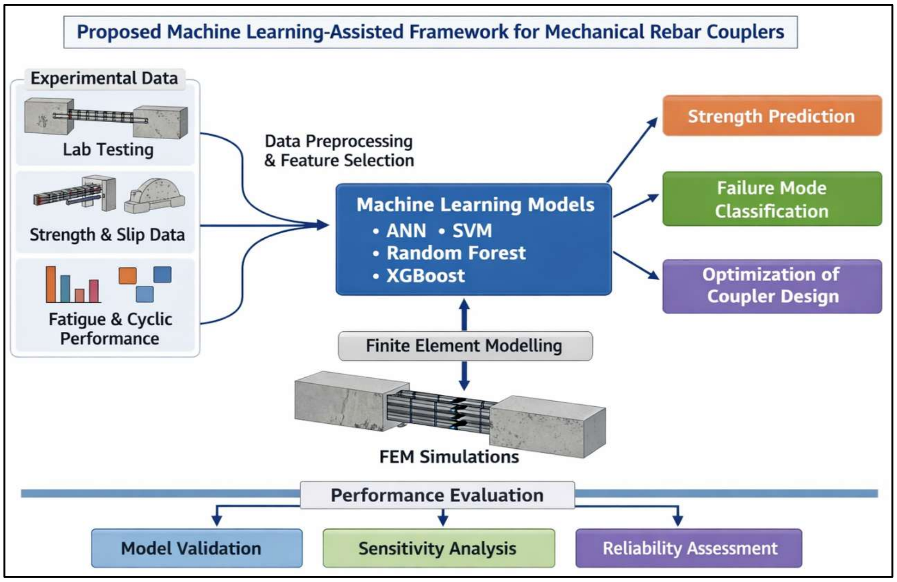

Figure 3: Future research framework for machine learning-driven design and integration of mechanical rebar couplers into structural design codes.

VII. New Examined Trends: Physics-Informed and Hybrid Models

In recent works, it has been pointed out that the use of exclusively data-driven ML models has limitations, especially when it comes to making predictions outside the training set. PIML is a approach to machine learning that combines the principles of governing mechanics with machine learning algorithms to enhance interpretability and robustness. Hybrid experimental-numerical-ML models are coming out as a potent means of coupler design optimization and performance evaluation.

VIII. Sustainability and Lifecycle

Mechanical rebar couplers are designed to enhance sustainable construction through the consumption of less steel, better constructability, and modular and precast construction. Life cycle performance prediction using ML can also be used to create a better coupler design that is more sustainable in terms of durability, maintenance, and EOL.

IX. Research Gaps and Future Directions

Even in the light of the developments made, there are still multiple gaps in research: Data (ML) Low publicly available datasets, Absence of standardized parameters of inputs and performance measures, Lack of adequate research on long term durability and environmental impacts, Low assimilation between ML and design codes and standards, Requirement of explainable and physics-informed ML models, Future studies must aim at creating open-access databases, hybrid frameworks, and ML-aided design tools in accordance with structural design codes.

X. Conclusions

The application of machine learning methods in assessing and designing mechanical rebar couplers as alternatives of the traditional lap splices in reinforced concrete structures has been fully explored in this review paper. The mechanical couplers have overcome a number of shortcomings that lap splicing has, such as reinforcement congestion, constructability issues, and cyclic and seismic loading weaknesses. They are thus becoming more popular in high-rise buildings, precast structures and performance-based structural designs.
Artificial neural networks, support vector machines, random forest models, and gradient boosting algorithms are a few machine learning methods that have shown great success in modelling the complex and nonlinear relationships that exist between coupler performance.

Models allow numerical and experimental data to accurate predict tensile capacity, slip behaviour, stiffness and failure modes. New developments like hybrid and physics informed machine learning models contribute to improved robustness and extrapolation ability of models, which are the main limitations of data driven models. In addition, little study has addressed long term durability, environmental exposure impact ML prediction into structural design codes and guidelines.

These challenges will overcome in order to achieve wider usage of ML assist coupler design in engineering practice as it further develops, ML paradigm changes in intelligent design and lifecycle assessment of mechanical rebars couplers in the next generation of RCC.

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