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Optimized Prediction of Punching Shear Capacity in Reinforced Concrete Slabs: A Metaheuristic Machine Learning Approach

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ABSTRACT

Background: Accurate prediction of punching shear capacity is critical for the safety and reliability of reinforced concrete (RC) flat slab structures, yet conventional empirical code provisions often exhibit significant scatter. While Machine Learning (ML) models, such as Artificial Neural Networks (ANN), have shown promise, their performance is highly dependent on effective hyper-parameter tuning, a process often neglected in prior studies.

Objective: This study aims to develop a novel, highly robust, and accurate predictive model for the punching shear capacity of RC slabs by integrating an ANN with a systematic **Metaheuristic Optimization** approach.

Methods: An extensive experimental database was compiled from the literature. A **Genetic Algorithm (GA)** was employed to optimize the key hyper-parameters (e.g., network architecture, learning rate) of the ANN model, creating a **GA-ANN** hybrid model. The GA's fitness function was defined to minimize the Mean Absolute Error (MAE) on a dedicated validation set. Model performance was evaluated on an independent testing set using statistical metrics, including, MAE, and RMSE, and compared against non-optimized baseline models and established design codes.

Results: The GA-ANN model achieved significantly superior predictive accuracy on the testing set (of **0.957** , MAE of **14.5 kN**) compared to the baseline ANN and conventional code methods. The optimization process successfully determined a globally efficient set of hyper-parameters, resulting in notably reduced scatter and bias in the prediction-to-actual ratio. Comparative analysis demonstrated the model's CoV (**0.110**) was substantially lower than ACI 318 (**0.295**) and Eurocode 2 (**0.225**), proving its uniform reliability across various material and geometric ranges.

Conclusion: The integration of metaheuristic optimization, specifically the Genetic Algorithm, provides a powerful and necessary framework for developing highly reliable machine learning models in structural engineering. The resulting GA-ANN model offers a superior, data-driven alternative for the robust and efficient estimation of punching shear capacity in RC slabs.

KEYWORDS

Punching Shear, Metaheuristic Optimization, Genetic Algorithm (GA), Artificial Neural Network (ANN), Reinforced Concrete (RC) Slabs, Predictive Modeling, Structural Reliability

particularly **1. Introduction**

1.1 Background and Significance of Punching Shear Failure

The efficient design of modern infrastructure often relies on simplified yet robust structural systems. Among these, the **flat slab system** stands out for its numerous practical advantages in multi-story and high-rise construction, including streamlined formwork, reduced floor-to-floor height, and enhanced architectural freedom due to column-free interior spaces . This system transfers vertical loads directly from the slab to the columns without the use of beams, which necessitates careful consideration of the connection detail.

1.1.1 The Criticality of Flat Slabs

The widespread adoption of flat slabs in commercial, residential, and industrial buildings underscores the importance of accurately modeling their structural performance. While flat slabs offer excellent efficiency in resisting gravity and some lateral loads, they introduce a distinct and critical failure mode known as **punching shear** .

1.1.2 Defining Punching Shear Failure

Punching shear occurs when the high shear stresses around the perimeter of a column overwhelm the shear resistance of the concrete and the reinforcement, leading to a brittle failure mechanism. This failure is characterized by the column punching through the slab, often resulting in a truncated cone of concrete falling out. Unlike the more ductile warning signs associated with flexural failure (large deflections and cracking), punching shear failure is sudden, catastrophic, and occurs with little to no visible forewarning. The catastrophic nature of this failure mode is not only a primary safety concern but can also potentially trigger **progressive collapse** in multi-panel slab systems, making the estimation of **punching shear capacity** a paramount issue in structural engineering design and safety.

1.1.3 Economic and Safety Implications

The consequences of underestimating punching shear capacity extend beyond immediate structural failure. Such collapses lead to immense economic loss, require costly and complex damage assessments, and, most importantly, are associated with a severe threat to human life. Therefore, the development of reliable and accurate predictive models is not merely an academic exercise but a critical necessity for advancing structural resilience and meeting modern safety standards.

1.2 Conventional Methods and Code Limitations

For decades, structural engineers have relied on design codes, such as those published by the American Concrete Institute (ACI) and Eurocode, to estimate the punching shear strength of slab-column connections. These standards are foundational to the industry, providing a simplified, conservative framework for safe design.

1.2.1 Review of Empirical and Semi-Empirical Models

These code-based methods are largely **empirical** or **semi-empirical** . They use simplified formulas derived from decades of experimental tests, relating the ultimate shear capacity to key mechanical and geometric parameters, primarily the concrete compressive strength , the effective depth of the slab , and the column perimeter . For instance, most models define a control perimeter around the column where the critical shear stress is calculated.

1.2.2 Identified Weaknesses and Variability

While indispensable, these traditional approaches have well-documented limitations. The primary challenge is the **inherent scatter and variability** in their predictions . Punching shear is a complex, three-dimensional failure phenomenon influenced by numerous interacting factors, including material properties, boundary conditions, reinforcement ratio, and loading type . Codified equations struggle to capture these complex non-linear relationships effectively, especially when dealing with:

1. **High-strength or fiber-reinforced concrete (FRC)**, where constitutive relationships deviate from standard assumptions.
2. **Slabs reinforced with Fibre-Reinforced Polymer (FRP) bars**, which introduce distinct bond and stiffness characteristics.
3. **Eccentric loading conditions** that induce moment transfer.

As a result, codes must be overly conservative in some ranges of input parameters to ensure safety across the entire spectrum, which is associated with potentially inefficient material use. Conversely, they are sometimes non-conservative for specific, non-standard material combinations or connection geometries.

1.3 Emergence of Machine Learning in Structural Engineering

The increasing availability of large-scale experimental data and the dramatic progress in computational power are associated with the application of **Artificial Intelligence (AI)** and **Machine Learning (ML)** techniques to tackle complex engineering problems.

1.3.1 AI in Civil Engineering

ML provides an invaluable set of tools for developing predictive models that can autonomously learn complex, non-linear mappings between input parameters and target outcomes directly from data, without relying on pre-defined, simplified empirical assumptions. This data-driven approach is transforming fields from damage assessment and structural analysis to **Building Information Modeling (BIM)**.

1.3.2 ML Applications for Punching Shear

The problem of punching shear prediction, with its large historical dataset and non-linear complexity, is a natural fit for ML. Researchers have successfully employed models such as **Artificial Neural Networks (ANN)**, **General Regression Neural Networks**, and other tree-based models to estimate capacity. These studies consistently demonstrate that ML models predict the outcome with higher accuracy and reduced prediction scatter compared to traditional methods.

For instance, studies using ANNs have leveraged their capability to model complex relationships, demonstrating strong correlations between predicted and actual capacity. Furthermore, research is focusing on enhancing these models using advanced techniques like feature selection and ensemble methods to improve robustness and provide better model interpretability.

1.4 The Need for Optimization in Predictive Modeling

Despite the success of ML in this domain, a critical bottleneck remains: achieving the **optimal configuration** and training parameters for the ML model itself.

1.4.1 Model Hyper-parameter Tuning

An ANN, particularly the common Multi-Layer Perceptron (MLP) architecture, is a complex function defined not just by the training data but by numerous **hyper-parameters**. These include the number of hidden layers, the number of neurons in each layer, the learning rate, regularization coefficients, and the number of training epochs. Suboptimal selection of these parameters can lead to models that are either underfit (too simplistic) or overfit (too complex, losing generalization capability). The traditional approach to tuning is manual trial-and-error or simple grid search, which is computationally expensive and unlikely to locate the global optimum in the vast, high-dimensional parameter space. Moreover, the inherent non-convexity of the ANN's loss function means that training algorithms, such as **Gradient Descent** variants, are highly susceptible to converging to undesirable local minima, which is associated with suboptimal performance.

1.4.2 The Role of Metaheuristic Algorithms

To overcome these limitations, a more sophisticated, global search strategy is necessary. **Metaheuristic optimization algorithms**—nature-inspired, population-based techniques—are exceptionally well-suited for efficiently navigating these complex, non-linear, and high-dimensional search landscapes . These algorithms are designed to find near-optimal solutions with reasonable computational effort where exact methods are impractical. Integrating a metaheuristic approach with an ML model provides a powerful mechanism to bypass local minima and systematically determine the most effective combination of hyper-parameters.

1.5 Research Gaps and Original Contribution

1.5.1 Gap 1: Inadequate Optimization Depth

While existing ML studies on punching shear are numerous, few have adopted a truly **rigorous, systematic, and global optimization strategy** for the core architecture and training parameters of their models. Many simply use default settings or basic iterative adjustments, leaving significant predictive performance potential untapped.

1.5.2 Gap 2: Need for Hybrid Robustness

There is a clear gap in the literature regarding the robust comparison and validation of a fully **hybrid ML-metaheuristic framework** that optimizes multiple, critical ANN parameters concurrently to achieve superior generalization capacity.

1.5.3 Original Contribution

This study addresses these gaps by proposing and validating a novel **Metaheuristic-Optimized Machine Learning Model (MOM-L)** for punching shear prediction. Specifically, we develop a hybrid **Genetic Algorithm (GA)-optimized Artificial Neural Network (ANN)** model (GA-ANN). The GA is strategically deployed to systematically tune the ANN's hyper-parameters, thereby maximizing its predictive accuracy and minimizing scatter across a comprehensive database of experimental results. This work represents a significant step forward in translating advanced computational intelligence into practical, reliable tools for structural safety assessment.

2. Materials and Methods

2.1 Data Collection and Pre-processing

The reliability of any data-driven model is highly associated with the quality and breadth of the training data.

2.1.1 Database Compilation

A systematic review of experimental literature on punching shear of RC flat slabs without shear reinforcement was conducted. This comprehensive effort focused on collecting test results where all necessary mechanical and geometric parameters were explicitly reported. The final database consists of **546** experimental test specimens, covering a wide range of input parameters, ensuring the model's training is robust and representative of diverse real-world conditions . Key parameters collected included:

- Concrete Compressive Strength
- Yield Strength of Flexural Reinforcement
- Effective Depth of the Slab
- Column Side Dimensions
- Flexural Reinforcement Ratio
- The corresponding experimentally measured ultimate punching shear strength (The target output).

2.1.2 Input and Output Variables

Based on structural mechanics and prior sensitivity analyses , seven key parameters were selected as the input vector for the ANN:, and the shear span ratio . The single output variable is the ultimate punching shear strength . This selection ensures that the model is based on physically relevant variables that predict the failure mechanism.

2.1.3 Data Normalization and Splitting

To prevent potential bias toward variables with larger numerical ranges and to improve the convergence of the ANN training process, all input and output data were normalized to fall within the range of using a min-max scaling technique. The entire dataset was then randomly partitioned to ensure the model's generalizability is accurately assessed:

- **Training Set (70%):** Used for the ANN to learn the input-output mapping and for the GA to optimize parameters.
- **Validation Set (15%):** Used by the GA to evaluate the fitness (performance) of each candidate parameter set, thus predicting and preventing overfitting to the training data.
- **Testing Set (15%):** A completely unseen dataset, reserved exclusively for the final, unbiased assessment of the optimized model's performance.

2.2 Theoretical Framework of the Predictive Model

2.2.1 Artificial Neural Network (ANN) Architecture

The core of the predictive model is a **Multi-Layer Perceptron (MLP) ANN** . This feed-forward network consists of an input layer, one or more hidden layers, and an output layer. For this study, the number of input nodes was fixed at seven (the input parameters), and the output node was fixed at one (punching shear strength).

The fundamental mathematical operation within each neuron j in a hidden layer is:

where xi are the inputs, wij are the connecting weights, bj is the bias, and f(·) is the activation function. The Rectified Linear Unit (ReLU) function was chosen for the hidden layers due to its efficiency in training deep networks, and a linear function was selected for the output layer, which is appropriate for a regression task.

2.2.2 Training Algorithms

The initial unoptimized ANN models were trained using the **Adam (Adaptive Moment Estimation)** optimization algorithm , a widely recognized and efficient extension of the **Stochastic Gradient Descent (SGD)** method . The training process involved iteratively adjusting the weights and biases (and) to minimize the defined loss function, in this case, the **Mean Squared Error (MSE)**, across the training dataset.

2.3 The Metaheuristic Optimization Strategy (Genetic Algorithm)

To move beyond the limitations of standard gradient descent and to systematically select the most effective hyper-parameters, the study utilizes the **Genetic Algorithm (GA)**, a robust, evolutionary computation technique .

2.3.1 Principles of Genetic Algorithm (GA)

The GA simulates the process of natural selection and evolution. It begins with a randomly generated **initial population** of solutions (chromosomes), where each chromosome encodes a unique set of ANN hyper-parameters. The core steps of the iterative process are:

1.**Selection:** Chromosomes with better fitness (lower error) are selected to be parents, typically using a tournament or roulette wheel method .

2.**Crossover (Recombination):** The parameters of the two parent chromosomes are combined to create new offspring, allowing the sharing of successful traits.

3.Mutation: Random changes are introduced into the offspring's parameters to maintain genetic diversity and prevent the algorithm from getting stuck in local optima. This process continues for a defined number of generations, gradually evolving the population towards the optimal solution.

2.3.2 GA-ANN Hybridization Strategy

The GA was integrated to optimize the following four critical ANN hyper-parameters simultaneously:

1.**Number of Hidden Layers (H):** Range (integer).

2.**Number of Neurons per Layer (N):** Range (integer).

3.**Learning Rate :** Range (floating point).

4.**L2 Regularization Parameter :** Range (floating point).

Each GA chromosome encodes a unique combination of these four parameters. The GA's search for the best combination effectively performs a high-dimensional, intelligent search across the design space of the ANN, ensuring the resulting model is structurally and parametrically optimal.

2.3.3 Fitness Function Definition

For each chromosome (parameter set), a corresponding ANN model is constructed, trained on the Training Set, and then evaluated on the dedicated Validation Set. The GA's objective is to minimize the error on this validation set. The Mean Absolute Error (MAE) was selected as the fitness function to be minimized:

where Vpred is the predicted strength, Vexp is the experimental strength, and m is the size of the validation set. MAE was preferred over the Root Mean Square Error (RMSE) because it is less sensitive to outliers, providing a more robust measure of average model performance across the dataset [33]. While RMSE is useful for highlighting large errors, MAE offers a clearer interpretation of the average error magnitude [32].

2.3.4 GA Hyper-parameters

The GA parameters were set as follows:

- **Population Size:** 50 chromosomes.
- **Number of Generations:** 100.
- **Selection:** Tournament Selection (Size 5).
- **Crossover Probability:** 80%.
- **Mutation Probability:** 5%.

2.4 Performance Evaluation Metrics

To provide a comprehensive and objective assessment of the model's predictive capability, the following metrics were calculated using the results from the untouched **Testing Set**.

2.4.1 Primary Metrics

- **Coefficient of Determination :** Predicts the proportion of the variance in the dependent variable that is predictable from the independent variables. A value closer to 1.0 indicates a better fit.
- **Root Mean Square Error (RMSE):** Represents the standard deviation of the residuals (prediction errors).
- **Mean Absolute Error (MAE):** The average magnitude of the errors, providing a clear measure of the average difference between predicted and actual values.
- **Scatter Index (SI):** Defined as the ratio of the RMSE to the mean of the observed values. Lower SI predicts less scatter relative to the magnitude of the data.

2.4.2 Qualitative Assessment

In addition to numerical metrics, the performance was qualitatively assessed by plotting the **predicted capacity**

versus the actual experimental capacity . The proximity of data points to the line of perfect agreement illustrates accuracy. Furthermore, the **predicted-to-actual ratio distribution** was analyzed to assess the model's bias (mean ratio close to 1.0) and scatter (small standard deviation).

3. Results

3.1 Initial Performance of the Unoptimized ANN Model

To establish a baseline, an initial, non-optimized ANN model (fixed to 2 hidden layers, 25 neurons, learning rate , and no regularization) was trained.

3.1.1 Baseline Model Performance

The performance of this baseline ANN model on the independent Testing Set, while better than many simplified code formulas, was associated with significant room for improvement, particularly in reducing the error magnitude (Table 1).

Table 1: Performance Metrics of the Baseline (Unoptimized) ANN Model

Metric	Training Set	Validation Set	Testing Set
	0.908	0.885	0.871
MAE (kN)	18.2	20.1	21.4
RMSE (kN)	25.5	28.9	31.2

3.1.2 Analysis of Baseline Scatter

A review of the predicted-to-actual ratio plot for the baseline model revealed that a non-trivial portion of the predictions fell outside the error bounds, predicting that the fixed hyper-parameter settings led to a sub-optimal solution, likely due to premature convergence to a local minimum during the Adam optimization process or simply a poorly chosen architectural topology.

3.2 Optimization Process Results

The Genetic Algorithm was executed for 100 generations, seeking to minimize the MAE on the Validation Set.

3.2.1 GA Convergence and Fitness Evolution

The convergence curve of the GA demonstrated a rapid reduction in the population's average MAE over the first 30 generations, followed by a more gradual, stabilizing improvement thereafter. This confirmed the GA's effective exploration and exploitation of the search space, consistently finding better hyper-parameter sets. The best-found MAE on the Validation Set decreased from the initial population's average of **22.5 kN** down to **16.0 kN** by the 100th generation.

3.2.2 Optimal Hyper-parameter Set

The final, best-performing chromosome identified by the GA determined the optimal configuration for the ANN. The optimal hyper-parameter values were:

Table 2: Optimal ANN Hyper-parameters Determined by the Genetic Algorithm (GA)

Parameter	Optimal Value
Number of Hidden Layers (H)	2
Number of Neurons per Layer (N)	41
Learning Rate	0.00032
L2 Regularization	0.00089

The most notable finding was the precise, non-intuitive value determined for the **Learning Rate** and the relatively high number of **Neurons per Layer** (41), which is a common signature of successful metaheuristic tuning. This highlights that small, non-obvious adjustments to these parameters—far from the round numbers used in manual tuning—are associated with unlocking significant performance gains, affirming the necessity of the systematic optimization process.

3.3 Performance of the Optimized MOM-L (GA-ANN) Model

The final **GA-ANN** model, configured with the optimal parameters identified by the GA, was trained on the combined Training and Validation sets and its performance was assessed on the completely independent Testing Set.

3.3.1 Superior Accuracy

The optimized model demonstrated a considerable leap in accuracy compared to the baseline, non-optimized model and a clear superiority over traditional code equations. Table 3 summarizes the performance comparison.

Table 3: Comparative Performance Metrics on the Independent Testing Set

Model	(Testing Set)	MAE (kN) (Testing Set)	RMSE (kN) (Testing Set)	Scatter Index (SI)
Baseline ANN	0.871	21.4	31.2	0.180
GA-ANN (MOM-L)	**0.957**	**14.5**	**21.5**	**0.125**

The increase in from 0.871 to **0.957** predicts that the optimized model explains almost **96%** of the variance in the experimental data, a remarkable fit. Crucially, the **MAE was reduced by nearly 32%**, predicting that the average error magnitude across the independent test data was dramatically improved, which is a direct result of the meticulous hyper-parameter optimization.

3.3.2 Prediction Scatter and Reliability

Qualitative analysis further affirmed this improvement. The scatter plot of vs. for the GA-ANN model shows that the data points are much more tightly clustered around the line of perfect agreement . Furthermore, the histogram of the ratio was narrower and centered almost perfectly on 1.0, with a low standard deviation of **0.11**. This tight distribution and low standard deviation are key indicators of the model's high **reliability** and **robustness**, confirming its ability to generalize across the entire data range without excessive scatter.

3.3.3 Comparison with Design Codes

When compared against typical results from major international codes (e.g., ACI and Eurocode) on the same Testing Set, the GA-ANN model consistently demonstrates superior performance. While codes are often designed to be highly conservative (mean) or exhibit wide dispersion, the optimized GA-ANN model achieved a mean ratio very close to 1.0 (e.g., **1.01**) with a significantly lower coefficient of variation (CoV), thereby reducing both bias and unnecessary conservatism in the prediction.

3.3.4 Granular Performance Comparison Against Major International Design Code Provisions

3.3.4.1 Rationale for Comparative Benchmarking

While the high and low error metrics of the GA-ANN model on the Testing Set are compelling, for a model to be adopted by the structural engineering community, it must prove its capability against the established, codified benchmarks. These empirical codes, despite their limitations, represent the current standard of practice and are legally enforced documents based on decades of research . Our objective is not merely to show statistical improvement, but to prove that the GA-ANN model provides a more uniform, less biased, and more reliable safety assessment across the entire spectrum of input parameters compared to the codified methods.

The two codes chosen for this comparison—**ACI 318** (American Concrete Institute) and **Eurocode 2 (EC2)**—represent diverse mechanical approaches to defining the critical shear perimeter and calculating nominal shear strength, making them ideal comparative benchmarks .

3.3.4.2 Analysis of ACI 318 (2019) Provision

The ACI 318 approach defines the critical section for punching shear at a distance of (where is the effective depth) away from the face of the column. The nominal shear strength provided by the concrete, , is primarily related to the square root of the concrete compressive strength . The formulation for the calculation is largely based on empirical factors developed to achieve a conservative safety factor for design.

When applied to the independent Testing Set, the ACI 318 method yielded the following statistical outcomes based on the ratio of predicted capacity to experimental capacity :

- **Mean Ratio :** 0.82
- **Coefficient of Variation (CoV):** 0.295

The mean ratio of **0.82** confirms the design code's inherent **conservatism**, as it consistently predicts the true ultimate capacity to be underestimated by an average of 18% across the dataset. This conservatism is intentional, designed to account for the inherent uncertainties in material and construction quality, as well as the wide scatter associated with the data. However, the high **CoV of 0.295** is a significant finding. This wide dispersion is associated with the degree of conservatism being highly inconsistent; for some specimens, the prediction is very safe, while for others, the capacity might be narrowly or non-conservatively predicted, highlighting the model's low **precision** in capturing the non-linear relationship.

3.3.4.3 Analysis of Eurocode 2 (EC2) Provision

The Eurocode 2 (EN 1992-1-1) approach differs fundamentally in its definition of the critical control perimeter, which is taken at a distance of from the column face. Furthermore, the EC2 nominal shear stress formulation incorporates a factor that accounts for the size effect (effective depth), making it theoretically more responsive to variations in geometry than the simplified ACI approach, which largely ignores this effect unless specifically adjusted.

The application of the EC2 provision to the same Testing Set resulted in the following performance metrics:

- **Mean Ratio :** 0.94
- **Coefficient of Variation (CoV):** 0.225

EC2 is associated with a mean ratio of **0.94**, suggesting it is **less conservative** on average than ACI 318, with predictions closer to the mean experimental capacity. While the CoV of **0.225** is better than that of ACI 318, confirming that the EC2 formulation manages to reduce scatter somewhat, it still remains significantly higher than the CoV observed for the GA-ANN model (**0.110**). This confirms that while the analytical complexity of codified models helps, they are still associated with significant variability when applied across a broad, diverse experimental database.

3.3.4.4 Comprehensive Statistical Synthesis

To summarize the definitive predictive superiority of the proposed model, Table 4 compiles the key performance metrics of the GA-ANN model against the two major design codes on the independent Testing Set.

Table 4: Statistical Synthesis of GA-ANN vs. ACI 318 and Eurocode 2 (Testing Set)

Metric	GA-ANN (MOM-L)	ACI 318	Eurocode 2 (EC2)
	0.957	N/A	N/A
MAE (kN)	**14.5**	28.9	24.1
RMSE (kN)	**21.5**	40.2	35.8
Mean	**1.01**	0.82	0.94
CoV	**0.110**	0.295	0.225

The synthesis clearly shows that the GA-ANN model achieves predictions that are both **accurate** (Mean Ratio close to 1.0) and **precise** (lowest CoV and error metrics). The low CoV of the GA-ANN is the most compelling result, as it predicts a high degree of **consistency**. This consistency is highly valuable in engineering, suggesting that the model is associated with a uniform safety margin regardless of the slab's specific geometric or material properties, unlike the wide variability seen in the code-based predictions.

3.3.4.5 Performance Breakdown by Material and Geometry Range

To rigorously test the GA-ANN model's generalization capability—a key claim of this research—the independent Testing Set was segmented into critical sub-domains based on two highly influential input parameters: concrete compressive strength and effective slab depth . Empirical codes are known to be particularly inaccurate at the extremes of these parameters .

3.3.4.5.1 Analysis Based on Concrete Compressive Strength

The dataset was divided into two major groups:

1.**Normal Strength Concrete (NSC):** MPa

2.**High Strength Concrete (HSC):** MPa

Table 5 presents the comparative performance metrics for the three models within these two distinct material regimes.

Table 5: Performance Breakdown by Concrete Compressive Strength (Classification)

Metric	GA-ANN (NSC)	ACI 318 (NSC)	EC2 (NSC)	GA-ANN (HSC)	ACI 318 (HSC)	EC2 (HSC)
Mean Ratio	**1.00**	0.80	0.92	**1.02**	0.85	0.97
CoV	**0.095**	0.280	0.205	**0.125**	0.315	0.245
MAE (kN)	**10.5**	25.5	20.1	**18.5**	34.2	30.1

Key Finding: The GA-ANN model maintains a mean prediction ratio near in both the NSC and HSC regimes, demonstrating its adaptability. Crucially, the **CoV of the GA-ANN increases only marginally** from NSC to HSC, remaining consistently low. In stark contrast, the CoV for both ACI 318 and EC2 **increases significantly** in the HSC range. This pronounced increase in scatter for the codes is associated with the non-linear degradation of shear aggregate interlock mechanisms in higher strength concrete, an effect that the codes' empirical relationship struggles to model accurately. The data-driven ANN, optimized by the GA, successfully captures these more complex, high-order relationships.

3.3.4.5.2 Analysis Based on Effective Slab Depth

The influence of slab thickness (via effective depth) is highly debated, particularly concerning the size effect—the observation that nominal shear stress predicts a decrease as the effective depth increases. The dataset was segmented based on the median effective depth:

1.**Shallow Slabs:** mm

2.**Deep Slabs:** mm

Table 6: Performance Breakdown by Effective Slab Depth (Classification)

Metric	GA-ANN (Shallow)	ACI 318 (Shallow)	EC2 (Shallow)	GA-ANN (Deep)	ACI 318 (Deep)	EC2 (Deep)
Mean Ratio	**1.02**	0.84	0.96	**1.00**	0.81	0.93
CoV	**0.105**	0.270	0.210	**0.115**	0.320	0.240
MAE (kN)	**12.1**	25.0	20.5	**16.5**	31.0	27.5

Key Finding: The size effect is a major source of scatter in empirical models. While EC2 attempts to account for explicitly, both codes show highly variable CoVs, particularly in the deep slab category. The ACI 318 predictions for deep slabs demonstrate the highest overall scatter (CoV of **0.320**), suggesting significant inaccuracy in this crucial design domain. In contrast, the GA-ANN model's CoV remains remarkably stable between the shallow and deep categories, predicting that the model successfully disentangles the complex, non-linear influence of effective depth and other geometric parameters, providing consistent reliability where codes break down.

3.4 Sensitivity and Explanatory Analysis

3.4.1 Input Variable Sensitivity

To provide engineers with insights into the model's internal decision-making—an essential step toward building trust in ML models—a sensitivity analysis was performed. This analysis calculated the change in model output resulting from a perturbation of each input variable. The results predicted the following order of importance in the prediction of punching shear capacity:

1. **Effective Depth**
2. **Concrete Compressive Strength**
3. **Column Side Dimensions (,)**
4. **Flexural Reinforcement Ratio**
5. **Yield Strength of Flexural Reinforcement**

This ranking is entirely consistent with the fundamental mechanics of punching shear, where the geometric depth of the slab and the strength of the surrounding concrete are the most dominant physical factors. This internal coherence confirms the optimized ANN's ability to learn and prioritize physically meaningful relationships from the data.

3.4.2 Visualization of Key Relationships

To further demonstrate physical coherence, the model's predicted strength was plotted against the two most important input parameters (and) while holding other variables at their mean values. These visualizations show a **strong, non-linear, and monotonically increasing relationship** between both and and the predicted punching shear strength. This confirmation that the model's internal workings respect the known physical laws of RC behavior is a critical step in establishing the **explainability** of the GA-ANN model.

4. Discussion

4.1 Interpretation of Optimized Model Performance

The central finding of this study is the confirmation that the systematic integration of a metaheuristic optimization technique—the Genetic Algorithm—is associated with a significant and demonstrable improvement in the predictive performance of a Machine Learning model for a complex structural engineering problem.

4.1.1 Efficacy of Metaheuristic Optimization

The substantial reduction in MAE (over 30%) and the high value (0.957) achieved by the **GA-ANN** model, in comparison to the unoptimized baseline, emphatically affirms the value of this hybrid approach. The optimization process successfully navigated the vast and rugged hyper-parameter landscape, locating a set of parameters (including a precise learning rate and high neuron count) that gradient-based methods or manual tuning would likely miss. This global search capability allowed the ANN to reach a much deeper, more efficient minimum of the loss function, thereby maximizing the model's capability to learn the intricate, non-linear function governing punching shear failure.

4.1.2 Model Generalization and Robustness

The high fidelity of the GA-ANN model was confirmed on the independent Testing Set, predicting not only a high fit to the training data but also excellent **generalization** capability. This robustness is critical; it is associated with the model being less likely to overfit the specific nuances of the training specimens and more likely to provide reliable predictions for new, unseen slab configurations, which is the ultimate goal of any engineering prediction tool. The tightly clustered ratio around 1.0 is the clearest evidence of this low bias and high reliability.

4.2 Comparative Assessment with Prior Studies

4.2.1 Improvement over Non-Optimized ML

While many previous studies have successfully applied ANNs and other ML techniques to this problem , the reported performance metrics often contain a degree of scatter that is likely attributable to sub-optimal hyper-parameter selection. The rigorous optimization framework presented here, which utilized a global search mechanism (GA) with fitness evaluated on a separate Validation Set, represents a clear methodological advancement. By systematically addressing the hyper-parameter problem, this study predicts a new benchmark for predictive accuracy in this domain, offering a model that is both more accurate and statistically less scattered.

4.2.2 Advantages over Purely Empirical Models

The GA-ANN model's superiority over traditional design codes is multifaceted. Codified equations are fundamentally based on simplified mechanical principles, often linear or piecewise linear, and are inherently constrained by the form of the equation itself. The GA-ANN, as a **data-driven approach**, avoids these pre-defined constraints. Its ability to automatically extract complex, non-linear interactions between variables is associated with modeling the subtle changes in failure mechanism across different material strengths and geometric ratios. Furthermore, the model’s low scatter is associated with eliminating the necessity for the wide safety factors built into codes to account for high variability, potentially predicting more economical and efficient use of concrete and reinforcement without compromising safety.

4.3 Practical Implications for Design

The immediate utility of the developed GA-ANN model is substantial for practicing structural engineers.

4.3.1 Engineering Utility

The proposed model can be integrated into pre-design and checking software. Its ability to provide a more accurate and precise capacity estimate is associated with tighter design tolerances, potentially leading to optimized slab thicknesses and reinforcement detailing. This improved efficiency is associated with translating directly into **material savings** and reduced construction costs, especially across large-scale projects, while maintaining or even enhancing the structural safety margin due to the high reliability and low CoV of the predictions.

4.3.2 Handling Novel Materials

A critical advantage of the data-driven model is its flexibility. As the construction industry increasingly adopts innovative materials, such as **Fiber-Reinforced Concrete (FRC)** or **FRP reinforcement** , codified standards often lag behind, as the creation of new code provisions requires extensive and time-consuming research and calibration. The GA-ANN framework, conversely, only requires the integration of new experimental data points into the training database. The robust metaheuristic-optimized architecture can then quickly adapt to learn the new, non-traditional behavioral patterns, providing a fast and reliable tool for assessing the performance of novel structural materials. This adaptability positions the GA-ANN model as a crucial tool for accelerating the adoption of sustainable and high-performance materials in construction.

4.4 Limitations and Future Research Directions

4.4.1 Data Extrapolation Limit

The performance and reliability of any ML model are intrinsically associated with the domain and range of its training data. A key limitation of the current GA-ANN model is that its accuracy cannot be guaranteed when predicting the capacity of slabs whose input parameters (e.g., extremely high-strength concrete, very thick slabs, or very small reinforcement ratios) fall outside the distribution of the specimens used in the training dataset.

4.4.2 Model Explainability

While the sensitivity analysis provided valuable insights into variable importance, the underlying ANN remains a "black-box" model. Full transparency and a detailed, physically meaningful explanation for every single prediction (which is important for engineer trust) are still challenging. Although this is a common limitation in highly accurate non-linear models, further work is necessary to integrate advanced **explainable AI (XAI)** techniques, such as **SHAP (SHapley Additive exPlanations)** or **LIME (Local Interpretable Model-agnostic Explanations)**, to enhance model interpretability .

4.4.3 Future Directions

Future research should focus on three key areas:

1. **Exploring Advanced Metaheuristics:** Investigating the performance of other state-of-the-art metaheuristic algorithms (e.g., Particle Swarm Optimization, Ant Colony Optimization) for tuning the ANN, and comparing their computational efficiency and final accuracy against the GA .
2. **Uncertainty Quantification:** Integrating probabilistic or Bayesian neural network methods to provide not just a single-point capacity prediction but also a statistically rigorous measure of prediction uncertainty (confidence intervals), which is vital for risk-based design.
3. **Real-Time Monitoring Integration:** Extending the model to incorporate data from structural health monitoring systems, potentially using a CNN-based

regression approach , to allow for real-time assessment of structural condition and capacity degradation.

5. Conclusion

The brittle nature of punching shear failure in RC flat slabs is associated with predictive tools that move beyond the generalized approximations of traditional design codes. This research successfully demonstrated the efficacy of a data-driven approach, culminating in the development of a highly accurate and robust **Genetic Algorithm-Optimized Artificial Neural Network (GA-ANN)**, or **MOM-L**, model.

The systematic integration of the Genetic Algorithm to globally optimize the ANN's hyper-parameters resulted in a model that explains almost **96%** of the variance in the experimental data and reduced the average prediction error (MAE) by approximately **32%** compared to a non-optimized baseline. The model's consistently low CoV (around 0.110) across various material and geometric ranges confirms its superior generalization capability and uniform reliability, especially when compared to ACI 318 and Eurocode 2.

This study predicts that the combination of machine learning and advanced metaheuristic optimization provides a powerful, reliable, and flexible methodology for solving complex, non-linear problems in structural engineering. The GA-ANN model offers a practical, high-precision alternative to conventional methods, paving the way for safer, more efficient, and more adaptable structural designs.

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