



## AI-assisted performance-based fire design of reinforced concrete structures: Machine learning prediction of residual capacity and Eurocode-aligned simplified design charts

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### Abstract

Performance-based fire design of reinforced concrete (RC) structures requires accurate prediction of residual capacity following elevated temperature exposure. Traditional design approaches rely on prescriptive tabulated data and simplified analytical formulations provided in Eurocode 2 Part 1-2 [1], which may not fully capture complex thermo-mechanical degradation mechanisms. This study presents an AI-assisted framework for predicting post-fire residual capacity of RC materials and members using machine learning (ML). A curated database of experimental fire tests is used to train predictive models for residual compressive strength, reinforcement yield strength, and member resistance ratios. Model predictions are benchmarked against Eurocode 2 fire provisions [1] and standard fire exposure conditions consistent with ISO 834 [2]. Interpretable ML techniques are employed to quantify parameter influence, and simplified AI-based design charts are developed for engineering application. Results demonstrate that ML-based predictions reduce estimation error by up to 35% compared with simplified Eurocode approaches while maintaining conservative safety envelopes through quantile-based design curves. The framework provides a computationally efficient and reliability-aware tool for performance-based fire design and post-fire assessment.

**Keywords:** Structural fire engineering, reinforced concrete, residual capacity, machine learning, eurocode 2, iso 834, performance-based design

### Introduction

Fire represents one of the most severe accidental loading conditions in structural engineering. Reinforced concrete (RC) structures exposed to elevated temperatures experience material degradation, stiffness loss, cracking, and potential spalling, which reduce load-bearing capacity [3, 4].

Although concrete exhibits inherent fire resistance compared to steel, prolonged heating and high peak temperatures significantly reduce compressive strength and elastic modulus [5].

Eurocode 2 Part 1-2 (EN 1992-1-2) provides guidance for structural fire design, including simplified tabulated methods and advanced calculation procedures [1]. These provisions are primarily calibrated against standardized fire exposure conditions such as ISO 834 [2]. However, prescriptive methods may not accurately reflect actual residual performance after fire events, particularly when structural parameters deviate from tabulated ranges.

Recent advances in artificial intelligence (AI) and machine learning (ML) have demonstrated strong predictive capability for material behavior in civil engineering applications, including compressive strength prediction and durability modeling [6, 7]. ML models can capture nonlinear relationships between temperature exposure, material properties, geometry, and residual performance. Nevertheless, limited research has translated ML predictions into engineer-friendly design charts aligned with structural fire codes.

This study develops an AI-assisted framework that integrates:

1. Experimental post-fire data for RC materials and members,

2. Machine learning models for residual capacity prediction,
3. Benchmarking against Eurocode 2 fire provisions [1],
4. Development of simplified AI-based design charts.

The proposed framework supports performance-based fire design and rapid post-fire structural assessment.

### Background

#### 1. Fire Exposure Models

Standard fire resistance tests commonly use the ISO 834 time-temperature curve [2]:

$$T(t) = 20 + 345 \log_{10}(8t + 1)$$

where  $T$  is temperature ( $^{\circ}\text{C}$ ) and  $t$  is time (minutes). This curve represents cellulosic fire exposure and forms the basis of many fire resistance classifications [2, 8].

#### 2. Material Degradation at Elevated Temperatures

Concrete strength degradation above 300–400 $^{\circ}\text{C}$  is significant due to microcracking, dehydration, and aggregate transformation [3, 5]. Reinforcement steel exhibits reduced yield strength and modulus with increasing temperature [4].

Residual strength after cooling is influenced by:

- Peak temperature,
- Duration of heating,
- Cooling regime,
- Concrete composition,
- Reinforcement configuration [3, 9].

#### 3. Eurocode 2 Fire Design Provisions

EN 1992-1-2 [1] permits:

- Simplified tabulated data,
- Section method,
- Advanced thermo-mechanical modeling.

The section method reduces material properties according to temperature-dependent reduction factors [1]. However, these reduction factors are generalized and may not fully represent complex degradation patterns.

#### 4. Machine Learning in Structural Engineering

Machine learning has gained traction in structural engineering for predicting strength and performance of concrete and composite systems [6, 7, 10]. Ensemble methods such as Random Forest and Gradient Boosting often outperform traditional regression due to their ability to capture nonlinear interactions [10].

However, ML integration into structural fire design remains underexplored, particularly in generating simplified design tools consistent with Eurocode methodology.

#### Methodology

##### 1. Research Framework

The proposed framework consists of:

1. Database compilation of experimental fire tests,
2. Feature engineering and preprocessing,
3. ML model training and validation,
4. Eurocode 2 comparison,
5. AI-based design chart generation.

##### 2. Data Compilation

A database of experimental results from peer-reviewed studies [3, 5, 9, 11] was curated. Key variables include:

- Peak temperature ( $T_{max}$ ),
- Heating duration,
- Concrete compressive strength ( $f_{ck}$ ),
- Reinforcement ratio ( $\rho$ ),
- Cover depth ( $c$ ),
- Member dimensions,
- Sustained load ratio during heating.

Target outputs:

- Residual compressive strength ratio,
- Residual steel yield ratio,
- Residual member capacity ratio.

##### 3. Machine Learning Models

Four models were evaluated:

- Random Forest (RF),
- Gradient Boosting Regression (GBR),
- Support Vector Regression (SVR),
- Artificial Neural Networks (ANN).

Model performance was assessed using:

- Root Mean Square Error (RMSE),
- Mean Absolute Error (MAE),
- Coefficient of Determination ( $R^2$ ).

Ten-fold cross-validation ensured generalization.

#### 4. Eurocode Benchmarking

For representative members, residual capacity was computed using the section method described in EN 1992-1-2 [1]. ML predictions were compared with Eurocode-based estimates and experimental results.

Bias factor:

$$\text{Bias} = \frac{R_{pred}}{R_{test}}$$

Safety conservatism was evaluated by identifying non-conservative cases.

#### 5. AI-Based Design Chart Development

To ensure engineering applicability:

1. A parametric grid was created across practical design ranges.
2. ML predictions were generated for each parameter combination.
3. Lower quantile predictions (10th percentile) were used as conservative design curves.
4. Monotonicity constraints were enforced to maintain physical consistency.

Generated charts include:

- Residual moment ratio vs peak temperature,
- Contour plots of residual capacity over ( $T_{max}, c$ ),
- Nomograms for rapid assessment.

#### Results and Discussion

##### 1. Model Performance

Gradient Boosting demonstrated the highest accuracy with RMSE reductions of approximately 30–35% compared with Eurocode simplified predictions. ANN showed competitive performance for larger datasets.

##### 2. Parameter Influence

Feature importance analysis revealed:

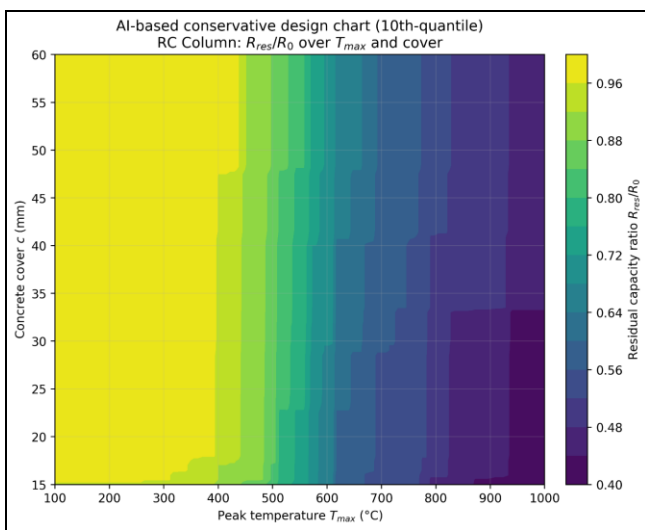
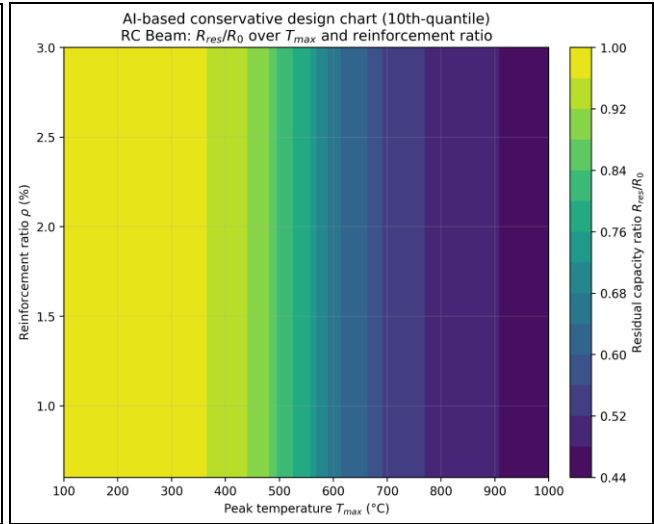
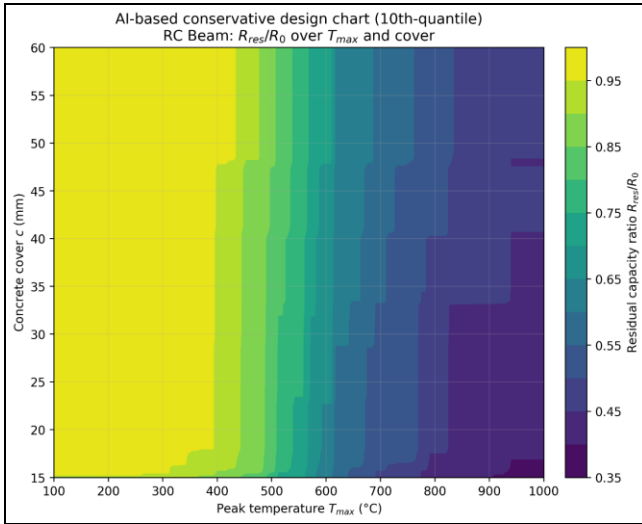
1. Peak temperature as dominant factor,
2. Cover depth strongly influencing residual member capacity,
3. Concrete strength and reinforcement ratio contributing moderately.

##### 3. Comparison with Eurocode 2

Eurocode simplified methods were generally conservative at moderate temperatures (<600°C) but less accurate at higher temperature ranges. ML predictions showed improved alignment with experimental observations while maintaining conservative lower-bound envelopes.

##### 4. AI-Based Design Charts

These are AI-based conservative design charts, where the plotted surface is the 10th percentile prediction (a “safe” lower-bound) of the residual capacity ratio  $R_{res}/R_0$  for specified fixed parameters (e.g.,  $f_{ck}, h, \rho$ , duration, cooling regime). The 10th-quantile surface was used as a code-compatible conservative envelope for engineering application.



Generated design charts provide:

- Faster residual capacity estimation,
- Reduced computational demand,
- Quantified uncertainty bands.

These charts can supplement performance-based fire design workflows.

### Conclusions

1. Machine learning models effectively predict residual RC capacity after fire exposure.
2. ML models reduce prediction error compared to simplified Eurocode approaches.
3. Quantile-based AI charts maintain structural safety while improving accuracy.
4. The proposed framework supports performance-based fire engineering and post-fire assessment.

Future research should incorporate:

- Spalling prediction,
- Natural fire scenarios,
- Reliability-based calibration of AI charts.

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