



# MACHINE LEARNING FOR PROBABILISTIC ANALYSIS OF CONCRETE STRUCTURES: A TRUSTWORTHY ALTERNATIVE TO CODIFIED DESIGN?

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## Introduction

This research explores machine learning applications for predicting punching shear capacity of reinforced concrete flat slabs. Flat slabs - concrete slabs directly supported by columns without beams - offer numerous advantages including simplified construction, cost-effectiveness, and architectural flexibility. However, they are vulnerable to punching shear failure, a brittle failure mechanism where columns suddenly punch through the slab, potentially triggering progressive collapse of the entire structure (Muttoni et al., 2018). The poster presents a machine learning approach to predict punching shear capacity more accurately than existing code provisions. This research demonstrates that machine learning models can significantly improve the accuracy of punching shear capacity predictions compared to traditional code-based methods. These findings offer a promising alternative to conventional approaches, potentially enhancing structural safety and design efficiency.

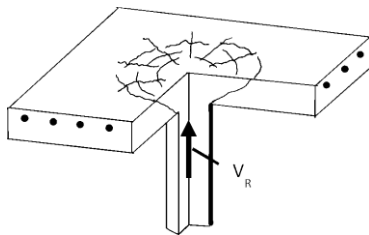


Figure 1: Typical punching shear failure problem

## Research methodology

We collected and analyzed 501 experimental test results from the literature, covering slabs with and without various types of reinforcement (including transverse and fiber reinforcement). The study is also elucidated in Mellios et al. (2023). It employed a Matérn 5/2 kernel Gaussian Process Regression (GPR) function as the primary machine learning algorithm (Rasmussen & Williams, 2006). This approach was compared against the analytical prediction methods in Eurocode 2 (EC2) (CEN, 2004). The dataset was split with 70% used for training and 30% for testing, using randomised cross-validation techniques to ensure model stability.

## Model parameters and evaluation

Ten input parameters were considered in the final model: slab height, column width, concrete compressive strength, flexural reinforcement ratio, presence of shear reinforcement, longitudinal reinforcement strength, shear reinforcement ratio, shear reinforcement strength, fiber presence, and fiber volume. The output parameter was the ultimate punching shear load (see Table 1). Statistical evaluation showed that the GPR model outperformed EC2 in prediction accuracy with an  $R^2$  value of 0.96 (versus 0.95 for EC2), an RMSE of 122.6 kN (versus 170.1 kN for EC2), and an MAE of 71.8 kN (versus 107.9 kN for EC2).

Table 1: Description and range of parameters implemented

Feature	Symbol	Units	Type	Min	Max
Slab ht.	$d$	(mm)	Continuous	39	464
Col. width	$b_w$	(mm)	Continuous	54	520
Conc. strength	$f_{cm}$	(MPa)	Continuous	12.8	119.0
Flex. reinf. ratio	$\rho_l$	(-)	Continuous	0	3.7
Shear reinf. presence	(-)	(-)	Binary	(-)	(-)
Long. reinf. strength	$f_{st}$	(MPa)	Continuous	0	889
Shear reinf. ratio	$\rho_w$	(-)	Continuous	0	2
Shear reinf. strength	$f_{swd,ef}$	(MPa)	Continuous	0	1095
Fiber presence	-	(-)	Binary	-	-
Fiber vol.	-	(%)	Continuous	0	2
Failure load	$V_s$	(kN)	Continuous	10	5193

## Key findings

A significant finding was that EC2 tends to underestimate punching shear capacity, especially at higher load capacities (see Figure 2). The model we implemented was more accurate at predicting the full range of observed experimental values. The study revealed that the GPR

model shows greater sensitivity to input variations than EC2. For instance, concrete compressive strength has a higher influence on thin slabs without shear reinforcement, while geometrical properties become more influential as slab dimensions increase. The compressive strength influence had a highly non-linear response to the load and column size, as compared to the (presumably oversimplified) relationship stipulated by the governing structural design code EC2 (see Figure 3).

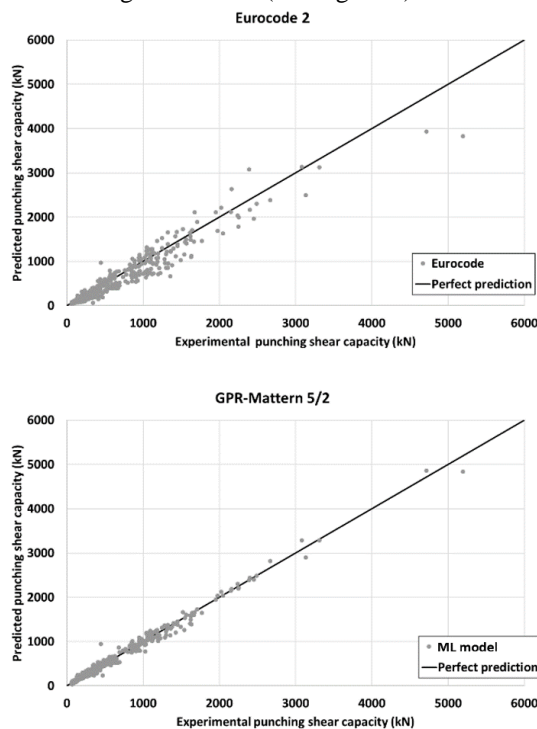


Figure 2: Relative presentation of prediction accuracy (kN)

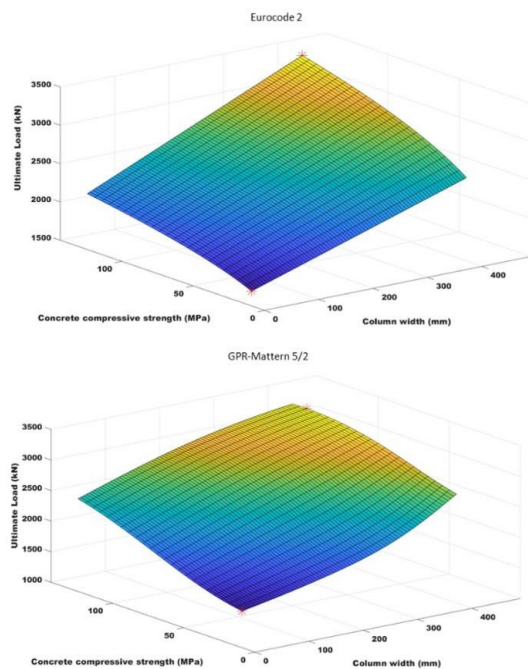


Figure 3: Relative visualization of capacity predictions, against compressive strength and column size variations. Asterisks mark the minimum and maximum values.

## Probabilistic reliability analysis

The study conducted probabilistic reliability analyses using First Order Reliability Method (FORM) and Monte Carlo simulations, following some methodological paradigms by Dubourg et al. (2011). The analyses assessed how various structural parameters influence the overall reliability of flat slabs against punching failure. Four configurational scenarios were evaluated: thin slabs (150mm) with slender columns (300mm) and thick slabs (300mm) with wide columns (600mm), both with and without shear reinforcement. Both models achieved appropriate reliability indices ( $\beta$  values) as prescribed by European standards, but the GPR model generally provided more economical designs while maintaining safety requirements. This was particularly evident for thick slabs with shear reinforcement, where the GPR model was significantly more economical than EC2.

## Conclusions

We concluded that machine learning-based models can effectively predict punching shear capacity and can be implemented within general reliability frameworks for structural design. Their GPR model correlates well with experimental observations and provides more reliable information about failure probability than EC2. The EC2 model is less sensitive to structural and material inaccuracies, which could potentially lead to unconservative designs in some cases. The study demonstrates how machine learning can capture complex relationships between variables in structural engineering applications, potentially leading to more accurate and safer designs. The authors recommend further experimental investigations related to punching shear under axially symmetric loading to expand the database beyond the 501 tests used in this study and to further validate and refine their machine learning approach.

## References

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