Computational Intelligence for Engineering Design Applications: A Case Study in Structural Engineering

Emergent Research Forum (ERF)

Anuja Kamat
Wentworth Institute of Technology
Boston, MA, USA
kamata@wit.edu

Amit V. Deokar
University of Massachusetts Lowell
Lowell, MA, USA
amit_deokar@uml.edu

Abstract

In this interdisciplinary study, we present a framework for applying computational intelligence techniques to address structural engineering design problems that are ill-structured and do not have well-established and tested theoretical models. The framework is presented as a design artifact that is validated through a case study in structural engineering using a large set of experimental data on shear failure of reinforced concrete beams.

Keywords

Machine learning, structural engineering, shear failure, concrete beams.

Introduction

Advances in computational intelligence techniques present opportunities for applications across varied industry sectors. In this interdisciplinary study, we demonstrate a unique application of computational intelligence techniques for supporting knowledge workers in the structural engineering domain. Despite advancements in theory development and testing, there are several engineering design problems that do not have well-tested theoretical models. In these situations, empirical models are regularly used by practitioners. These empirical models are developed by researchers through rigorous experimentation and are guided by an intuitive understanding of physical behavior of materials. For example, in structural engineering, several empirical models have been proposed for predicting shear failure in concrete beams. Eventually, these empirical models in various forms are adopted across different countries within their respective professional design codes. For instance, in the Unites States, Federal Emergency Management Agency (FEMA) defines professional design codes as "sets of regulations governing the design, construction, alteration, and maintenance of structures. They specify the minimum requirements to safeguard the health, safety and welfare of building occupants." A key issue observed in practice is that the eventual designs (i.e., designs of structures) created based on these varied professional codes vastly differ in terms of expected failure values compared to each other. Ironically, when retrospectively compared to the experimental values, these codes cannot accurately predict failure points. This discrepancy presents a practical problem of non-reliability of professional design codes when it comes to such ill-problems.

Through an intelligent information system, machine learning models can be built and tested to accurately predict failure points in case such complex problems. Computational models developed for such problems can not only provide accurate predictions for problems, but also serve as a guide for development of new theoretical models. Toward this end, in this study, we present a case study in the field of structural engineering to test the feasibility of the idea. We use a knowledge base of experimental tests conducted by researchers for shear failure problem in reinforced concrete beams. This knowledge base with large number of observations provides a testbed for machine learning models for predicting shear failure in these beams.

This study aims to make the following contributions. Taking an interdisciplinary approach, we present a machine-learning based analysis framework aimed at tackling structural engineering design problems lacking theoretical models. We illustrate the value of the framework through highly accurate predictive models developed for the case study in structural engineering domain.

The remainder of the paper is organized as follows. The research methodology is discussed next, followed by the proposed framework. Next, the case study is presented. Relevant literature is discussed in the research methodology and case study sections as appropriate. Lastly, concluding remarks are discussed.

Research Methodology and Framework

We adopt the design science research methodology. Design science research methodology proposed by Peffers et al. (2008) provides systematic guidelines for researchers to incorporate the design science principles, practices, and procedures proposed earlier in the literature by researchers including Nunamaker Jr., et al. (1991) and Hevner et al. (2004). In this methodology, four six key steps are listed, namely problem identification, definition of objectives of a solution, design and development, demonstration, evaluation, and communication of the design artifact to key stakeholders. In this stepwise methodology, it is emphasized that there may be varied entry points that may be possible. These include the entry points being either problem-centered, objective-centered, design and development centered, or client/context centered.

In this study, the entry point is design and development centered. The key design artifact is a proposed framework that uses principles of machine learning in creating a data-analysis pipeline that can address unique structural engineering design problems lacking theoretical models. The novelty of the framework is in the application of machine-learning approach for predictive modeling that has not been applied prior to design problems in structural engineering. The proposed framework is part of an ongoing interdisciplinary project involving application of data-driven methods to improve structural engineering design. The framework is implemented in Python using open source data science libraries including numpy, pandas, scikit-learn, and auto-sklearn.

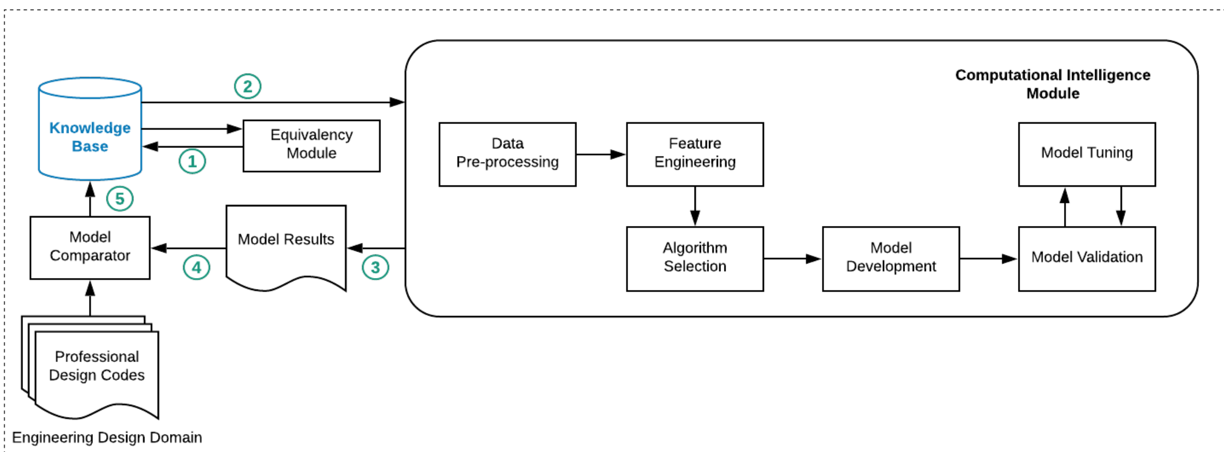

Figure 1. A Computational Intelligence Framework for Structural Engineering Design

Figure 1 shows the proposed framework for structural engineering design tasks which lack systematically proven theoretical models. The knowledge base forms a repository for recording empirically conducted test results along with rich set of parameters (e.g., material properties, size, etc.) about the test. The knowledge base organization relies heavily on engineering domain experts in the project. In our study, structural engineering design applications strength testing results for beams of different types are stored. However, conceptually, the knowledge base in other similar engineering projects would be analogous. For example, in mechanical engineering design applications, fluid mechanics related experimental test results may be stored. A key component of the framework is the equivalency module in which the test results are converted in semantically and mathematically comparable observations for eventual computational model generation. This module involves ensuring that the units for various measurements are converted appropriately and recorded in a standardized manner. Also, using domain-specific information about the physical behavior of test components, the module allows for recording observations even though the test conditions may be different. For example, some tests may use a rectangular beam for shear failure testing, whereas others may use beams of another cross-section. The equivalency unit converts them into a uniform manner. This module is conceptually similar to the Extract-Transform-Load (ETL) in data warehousing but is distinct from the data pre-processing step in data analysis because of its objective of developing and maintaining the knowledge base that contains comparable data for any subsequent analysis.

The computational intelligence module is then engaged through multiple submodules. This includes pre-processing module for tasks such as feature scaling and normalization. Feature engineering is a related module to the pre-processing that is focused on generating any relevant derived features with inputs from domain experts. It can also create multiple feature sets to be tested during model development. The algorithm selection module analyses the data types of features to semi-automatically select the best suited machine learning algorithms for the prediction problem at hand. Model development include multiple steps. First, it involves systematically sampling the data through cross-validation techniques for most effective use of data while ensuring model validation on unseen data. Second, the selected subset of algorithms are then applied using grid search technique for model tuning. Grid search allows for selecting the values of model hyperparameters to achieve empirically best results. For numeric predictions in supervised learning, which is the case in most engineering design problems, root mean square error (RMSE) is used as optimization metric. However, other metrics may be suitably selected.

The selected model is then used to compute predicted values and recorded in the database. The model comparator operator uses existing professional design codes to compute predicted values as prescribed through each of the individual codes, and further computing comparison metrics for comparing the machine learning model prediction in relation to the engineering code-based predictions. This information is used to further enhance the knowledge base.

Case Study

The machine-learning based framework described above is instantiated in the context of particular structural engineering design problem of shear failure of reinforced concrete beams. The shear behavior of concrete beams is very complex. To improve the understanding, numerous studies were independently conducted throughout the world. If these studies are combined, a resulting database would provide additional insight in the problem. Hence, the development of a comprehensive database of shear test results was initiated (Kuchma et al. 2004). The resulting database is the largest database thus far created and is therefore being utilized to gain new insight into the factors that affect shear strength as well as to evaluate and compare models for shear behavior. In the creation of this database, 95 papers or reports, summarizing the results of experimental research on the shear resistance of concrete beams has been processed to date (Kuchma et al. n.d.; Reineck et al. 2003). The data is further described next.

Data

2187 individual beam test results were extracted and subsequently utilized to evaluate the strength relationships used in evaluation. This database was then used for comparison of various shear models as well as in code provisions and other empirical equations (Kuchma et al.; Reineck et al. 2003). Of the 2187 concrete beams, 1444 beams were reinforced concrete beams and the rest were prestressed concrete beams. Only reinforced concrete beams were considered in this study. 166 beams had insufficient data. Of these 1278 members, 1219 beams were rectangular, 4 were I–shaped, and 55 were T–shaped; 321 beams had stirrups while 957 of them did not. Most of the tests (1135 of 1278, or about 90%) consisted of simply supported beams subjected to one or two concentrated loads. In 55 loading cases, they consisted of simply supported beams subjected to uniform loads; while in 88 cases they consisted of continuous beams subjected to point loads. Of the 1278 test results, it should be noted that only 347 of them were for beams which had a concrete strength greater than 8000 psi and only 15 of them were for beams with a depth greater than 30 inches. Almost half of the beams had a shear span to depth ratio (a/d) of less than 2.4. Such beams are generally considered as deep beams, and only 151 beams contained less than 1% longitudinal reinforcement. The variables used in the evaluation are:

h	(in)	Height of beam
d	(in)	Effective depth
b_w	(in)	Width of web
A_g	(in^2)	Gross area of the cross-section of the beam
I_g	(in^4)	Inertia of moment of Non-composite section

a_d	(-)	Shear span to depth (moment-shear-force) ratio
M_V_d	(-)	M/V_d ratio at maximum location
f_{pc}	(psi)	Cylinder compressive strength of concrete
agg	(in)	Maximum diameter of aggregate
A_s	(in2)	Area of reinforcement steel
f_y	(ksi)	Yield strength of Longitudinal steel
ρ_l	(%)	Longitudinal reinforcement Ratio
A_v	(in2)	Area of shear reinforcement within a distance s
f_{vy}	(ksi)	Yield strength of transverse steel
s_v	(in)	Spacing of transverse reinforcement
rhov	(%)	Transverse reinforcement Ratio
V(test)	(kips)	Ultimate shear force from test results
V(ACI)	(kips)	Ultimate shear force predicted using the ACI (American) code
V(LRFD) (kips)	Ultimate shear force predicted using the LRFD (American) code	
V(Japan) (kips)	Ultimate shear force predicted using the Japanese code	
V(German)	(kips)	Ultimate shear force predicted using the German code
V(Euro)	(kips)	Ultimate shear force predicted using the European code

The variables also include predicted shear force for each of the test beams computed using professional design codes. Particularly, the following five codes most commonly used around the world are included in this study: ACI (American) code (ACI Committee 318 2002), LRFD (American) code, Japanese code (JSCE Standards 1986), German code (DIN 1045-1 2001), and European code (EN 1992-1-1 2002).

Analysis and Results

In applying the framework, the equivalency module is first employed on the experimental results recorded in the knowledge base. The equivalency module is responsible for SI units conversion as well as applying a shape conversion to ensure that the results recorded for test beams of different shapes and sizes can be compared equivalently. The updated experimental results are recorded back to the knowledge base. As this stage, the CI module is employed in a systematic manner. The data pre-processing module applies normalization transformations to the numeric features. Next, feature engineering module allows us to create multiple feature sets with the help of domain experts. An example of feature engineering in this context is the computation of derived variables such as longitudinal reinforcement ratio, which is a ratio of the area of the reinforcement steel (A_s) to the gross area of non-composite beam section (A_g). Inclusion of such meaningful features clearly relies on professional expertise. For this case study, the algorithm selection module is used to semi-automatically select the candidate set of algorithms listed in Table 1.

Model	**RMSE**	**MAE**	**R^2**	**CV**
Gradient boosted trees regressor	7.0025	3.1424	0.9728	0.1332
Support vector regressor	8.5065	4.4046	0.9601	0.1460
Random forest regressor	11.1662	4.4889	0.9319	0.1572
K-nearest neighbors regressor	14.8778	7.6993	0.8762	0.2638
Neural network regressor	25.2465	14.9000	0.6526	0.6001

Table 1. Model Comparison Results

The results generated following the model development and model tuning process with 10-fold cross validation are reported in Table 1. Root mean squared error (RMSE), mean absolute error (MAE), R^2 , and coefficient of variation (CV) are shown for comparison. Based on these results the gradient boosted trees regressor was selected as the best predictive model. Two key hyperparameters for this model are (a) the learning rate, i.e., the rate at which the model is used to fit the data, and (b) the number of trees the model is allowed to fit. Grid search reveals the best hyperparameters as learning rate of 0.05 and 1000 trees.

Next, the predicted results are used by the model comparator to compare the predictions of the selected model to the those predicted through numerous engineering design codes. Table 2 presents the comparative results of this analysis. The comparison metric is based on the ratio of V(test)/V(predicted) that is commonly used in the structural analysis domain. V(predicted) is based on whether the predictions of the tuned model are used or the code-based prediction is used. It is expected that this ratio have a value of 1 and a standard deviation of 0. Coefficient of variation (CV), which is the ratio of standard deviation to mean is used for comparison of predicted values. Ideally, we would expect the best model to have a CV of zero.

Table 2 shows that the computational model generated is far superior to the existing professional design codes for shear failure prediction in reinforced concrete beams. This demonstrates the efficacy of the framework and its value for professionals in the structural engineering domain.

Model or Code	**CV**
Gradient boosted trees regressor	0.1332
ACI (American) code	0.6397
LRFD (American) code	0.3633
Japanese code	0.3974
German code	0.4913
European code	0.4694

Table 2. Comparison of Selected Model with Professional Design Codes

Conclusion

In this interdisciplinary study, we present a unique application of computational intelligent techniques in the form of a framework that can be used to generate predictive models for ill-structured structural engineering design problems that do not have well-established theoretical models. The study uses design science research principles in developing and validating the framework as a design artifact. The efficacy of this framework is shown using a case study with real data gathered from large pool of experimental results from structural engineering researchers. The computational model developed and fine-tuned by applying the framework are shown to be superior in terms of predictive power in comparison to existing professional design codes. The results from the study are very promising not only for the professional structural design practitioner community, but also for civil engineering researchers who can use the importance of features in their computational models to arrive at novel theoretical models in future.

REFERENCES

ACI Committee 318. 2002. "Building Code Requirements for Reinforced Concrete (ACI 318-02) and Commentary(ACI 318 R-02): An ACI Standard," Farmington Hills, MI.

DIN 1045-1. 2001. "Deutsche Norm: Tragwerke Aus Beton, Stahlbeton Und Spannbeton – Teil 1: Bemessung Und Konstruktion S.1-148 (Concrete, Reinforced and Prestressed Concrete Structures – Part 1: Design)," Berlin, Germany.

EN 1992-1-1. 2002. "Eurocode 2: Design of Concrete Structures – Part I: General Rules and Rules for Buildings. (PrEN 1992-1-1)."

Hevner, A. R., March, S. T., Park, J., and Ram, S. 2004. "Design Science in Information Systems Research," *MIS Quarterly* (28:1), pp. 75–105.

JSCE Standards. 1986. "Specification for Design and Construction of Concrete Structures: Design – JSCE Standard Part I," Tokyo, Japan.

Kuchma, D. A., Kim, K., Kim, S., Sun, S., Kamat, A. G., and Hawkins, N. 2004. "Simplified Shear Design of Structural Concrete Members," in *Proceedings of the Second Annual Concrete Bridge Conference*, Charlotte, NC.

Kuchma, D., Kim, K. S., Kamat, A. G., and Reineck, K. H. (n.d.). "Establishment and Mining of an Experimental Database of Shear Tests on Structural Concrete Members."

Nunamaker Jr., J. F., Chen, M., and Purdin, T. D. M. 1991. "Systems Development in Information Systems Research," *Journal of Management Information Systems* (7:3), pp. 89–106. (https://doi.org/10.1016/0950-5849(91)90136-Y).

Peffers, K., Tuunanen, T., Rothenberger, M. A., and Chatterjee, S. 2008. "A Design Science Research Methodology for Information Systems Research," *Journal of Management Information Systems* (24:3), pp. 45–77.

Reineck, K. H., Kuchma, D. A., Kim, K., and Marx, S. 2003. "Shear Database for Reinforced Concrete Members without Shear Reinforcement," *ACI Structural Journal* (100), pp. 240–249.