STATISTICAL EVALUATION OF A MACHINE LEARNING MODEL AS SHEAR STRENGTH PREDICTION ON REINFORCED CONCRETE BEAM

By

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Chair : Assoc. Prof. Sumarni Ismail, PhD
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The shear strength (Vs) computation of reinforced concrete (RC) beams has been a major topic in structural engineering. Several methodologies have been introduced for the Vs prediction; however, the modeling accuracy is relatively low owing to the complex character of the resistance mechanism involving the dowel effect of longitudinal reinforcement, concrete in the compression zone, the contribution of the stirrups if existed, and the aggregate interlock. It is difficult, if not impossible, to shear design RC beams with and without stirrups utilizing laboratory trials. The span-to-depth proportion, web width, and reinforcement proportion are only a few of the various factors that must be considered concurrently. Additionally, empirical techniques for shear design are developed within the confines of their testing regimes owing to the complicated shear failure process. As a result, these methodologies have limited generalizability and application. To overcome this problem, this work applies machine learning strategies for shear design. The current thesis is adopting the developing the Random Forest (RF) model as a robust machine learning (ML) predictive model for Vs prediction for reinforced concrete beams. The proposed ML model is developed based on collected experimental data 349, including the beam geometric and concrete properties parameters. Nine input combinations are constructed based on the associated input parameters for the proposed predictive model. The validation was conducted against the support vector machine (SVM) model, considered a well-established ML model introduced in the literature. In addition, several empirical formulations (EFs) are calculated for comparison. Research findings evidenced the potential of the proposed RF model for modeling the Vs reinforced concrete beams. Based on quantitative metric for the testing phase modeling, the RF model achieved the best results of the seventh input combination with root mean square error (RMSE = 89.68 KN), mean absolute error (MAE = 35.59 KN), mean absolute percentage error (MAPE = 0.16). The modeling accuracy performance comparison with the established ML models and the EFs confirmed the capacity of the proposed model. Results indicated that all the parameters utilized beam geometric and concrete properties are significant for the development of the predictive model. However, the model structure

emphasizes the incorporation of seven predictors by excluding (beam flange thickness and coefficient). In general, the research provided a reliable a robust soft computing model for Vs of RC beams computation that contributes to the basic knowledge of structural engineering design and sustainability.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

PENILAIAN STATISTIK MODEL PEMBELAJARAN MESIN SEBAGAI RAMALAN KEKUATAN RICIH PADA RAS KONKRIT BERTETULANG

Oleh

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Pengiraan kekuatan ricih (Vs) rasuk konkrit bertetulang (RC) telah menjadi topik utama dalam kejuruteraan struktur. Beberapa metodologi telah diperkenalkan untuk ramalan Vs; walau bagaimanapun, ketepatan pemodelan adalah agak rendah disebabkan oleh ciri kompleks mekanisme rintangan yang melibatkan kesan dowel tetulang membujur, konkrit dalam zon mampatan, sumbangan rakap jika wujud, dan pasak agregat. Sukar, namun tidak mustahil untuk memotong reka bentuk rasuk RC dengan dan tanpa rakap menggunakan ujian makmal. Perkadaran rentang kedalaman, lebar jaringan dan perkadaran tetulang adalah antara beberapa faktor yang perlu dipertimbangkan secara serentak. Selain itu, teknik empirikal untuk reka bentuk ricih dibangunkan dalam lingkungan rejim ujian mereka kerana proses kegagalan ricih yang rumit. Akibatnya, metodologi ini mempunyai kebolehgeneralisasian dan aplikasi yang terhad. Oleh itu, strategi pembelajaran mesin untuk reka bentuk ricih digunakan bagi mengatasi masalah ini. Tesis semasa diterima pakai mengenai pembangunan model Random Forest (RF) sebagai model ramalan pembelajaran mesin (ML) yang mantap untuk ramalan Vs serta rasuk konkrit bertetulang. Model ML yang dicadangkan dibangunkan berdasarkan data eksperimen yang dikumpul 349 termasuk parameter sifat geometri rasuk dan konkrit. Terdapat sembilan kombinasi input yang dibina berdasarkan parameter input yang berkaitan, dibuat untuk model ramalan yang dicadangkan. Pengesahan telah dibuat terhadap model mesin vektor sokongan (SVM) kerana dianggap model ML mantap yang diperkenalkan melalui literatur. Di samping itu, beberapa rumusan empirikal (EF) dikira untuk perbandingan. Penemuan penyelidikan membuktikan potensi model RF yang dicadangkan untuk memodelkan rasuk konkrit bertetulang Vs. Berdasarkan metrik kuantitatif untuk pemodelan fasa ujian, model RF mencapai keputusan terbaik bagi kombinasi input ketujuh dengan ralat purata kuasa dua akar (RMSE = 89.68 KN), min ralat mutlak (MAE = 35.59 KN), min ralat peratusan mutlak (MAPE = 0.16). Perbandingan prestasi ketepatan pemodelan dengan model ML dan EF yang telah ditetapkan, mengesahkan keupayaan model yang dicadangkan. Keputusan menunjukkan bahawa semua parameter sifat geometri

rasuk dan konkrit yang digunakan adalah penting untuk pembangunan model ramalan. Walau bagaimanapun, penekanan struktur model dalam penggabungan tujuh peramal dengan mengecualikan (ketebalan bebibir rasuk dan pekali). Secara amnya, penyelidikan menyediakan model pengkomputeran lembut yang teguh dan boleh dipercayai untuk Vs pengiraan rasuk RC yang menyumbang kepada pengetahuan asas reka bentuk kejuruteraan dan kelestarian.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfillment of the requirement for the degree of Master of Science . The members of the Supervisory Committee were as follows:

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
Vs	Shear Strength
SF	Shear Failure
RC	Reinforced Concrete
SCC	Steel Concrete Composite
DTF	Diagonal Tension Failure
SCF	Diagonal Tension Failure
SSF	Splitting Shear Failure
Efs	Emoirical formulations
ML	Machine Learning
SVM	Support Vector Machine
ANN	Artificial Neural Network
SFRC	Seare Fiber Reinforced Concrete
USS	Ultimate Shear Strength
LGP	linear genetic programming
FRP	Fiber-Reinforced Polymer
FIS	Fuzzy Inference System
NSM	Near Surface Mounted
PSO	Particle Swarm Optimization
ANFIS	Adaptive Neuro-Fuzzy Inference System
HSC	High Strength Concrete
GMDH	Group Method of Data Handling
RF	Random Forest

SFA	Smart Firefly Algorithm
LSSVR	Least Squares Support Vector Regression
GB	Gradient Boosting
XGBoost	Extreme Gradient Boosting
NMR	Non-linear Multiple Regression
GCV	Generalised Cross-Validation
SRM	Structural Risk Minimisation
*R*2	Determination Coefficient
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
NASH	Nash–Sutcliffe Efficiency
MD	Modified Index of AgreementNMR
MOP	Meta-model of Optimal Prognosis

CHAPTER 1

INTRODUCTION

1.1 Research Background

Early in the 1990s, intelligent agents became the focus of artificial intelligence research. These intelligent agents may be utilised for web surfing, online shopping, and news retrieval services. Agents or bots are other names for intelligent agents. They have increasingly transformed into chatbots and digital virtual assistants with the aid of Big Data applications. The solving of nonlinear problems is developed by using machine learning, a branch of artificial intelligence. It still serves as a building element for AI even though it has grown into a different sector, doing jobs like taking phone calls and giving a small selection of suitable replies. Deep learning and machine learning are now crucial components of artificial intelligence.

In its widest definition, the phrase "artificial intelligence" (AI) refers to a machine's capacity to carry out the same kinds of tasks that distinguish human intellect. As alternatives to more traditional or classical methodologies, a number of artificial intelligence techniques are being applied more often. They have been utilised to resolve challenging real-world issues in a variety of fields, including engineering, economics, medical, the military, marine, etc., and are gaining popularity today. They have been effectively incorporated into the field of structural engineering in a number of domains, including structural analysis and design (Zhang and Subbarayan, 2002a, 2002b), damage assessment (Levin and Lieven, 1998; Perera et al., 2009a, 2007), and constitutive modelling (Zhao and Ren, 2002).

There has been a diverse engineering structural applications using the reinforced concrete (RC). For instance, urban infrastructures, buildings, industrial facilities and thus protective structures may be subjected to different types of loadings. In recent decades, due to the demand for higher safety and better sustainability, more reliable and robust design of RC structures has become a necessity. Reinforced concrete beams are used for load distribution in a wide range of structures; for example, in tall buildings, offshore gravity structures, as transfer girders, pile caps, folded plates, and foundation walls.

The production of reinforced concrete beams involves the embedding of steel reinforcing bars into concrete mixtures to resist bending, shear, and tensile failures (Ruan et al., 2020; Shioya et al., 1990). During the design of reinforced concrete (RC) beams, one of the important parameters considered is the shear behaviour of the concrete structural members (Wu et al., 2021). Shear failure (SF) is mostly happened due to a lack of ductility and minor deflections and occurs suddenly without any early marks and observation for failure (Babar et al., 2015; Jumaa’h et al., 2019).

SF which is the most critical failure mode is induced by a combination of shear force, axial loads and moments (G. Zhang et al., 2020). Before the SF, almost little or no warning can be identified. This is unlike flexural failure that is caused by the gradual development of deflection upon yielding of the rebars (Abambres and Lantsoght, 2020; Abdulrahman and Mahmood, 2019; Institute, 2012). The share transfer mechanism after shear cracks initiation is uncertain. The possible consequences of SF of any component of RC may include structural collapse, disasters, casualties, and loss of properties (Abdulrahman et al., 2020; Carino et al., 1983). It is there expected that an RC beam should exhibit a high level of shear resistance that can support the flexural failure not the SF.

SF is a complicated process that involves several parameters whose impact makes the mechanism of SF a debatable matter. Until now, empirical methods are being used to derive the guidelines and design codes for the shear strength of RC beams (Committee and Standardization, 2008); such empirical methods are limited in physical simulation as practice, paving the way for the development of an effective mathematical technique that will provide better estimates of the accuracy of the shear strength of RC beams (Ibrahim et al., 2019; Majdzadeh et al., 2006). Generally, several methods introduced over the literature to design the shear strength that are incorporated a trial batches in the laboratory to satisfy the required shear strength (Mahmood and Mohammad, 2019; Shahnewaz et al., 2020). For instance, by assuming the essential shear strength is 200 kN, this purpose can be achieved by combining series of influencing variables arbitrarily. However, despite the high number of influencing variables involved, time and money will still be wasted in the preparation of several samples that will be tested for shear strength.

It is worth to mention that, in the field of structural engineering, some of the nagging problems encountered are the analysis of beam behaviour, beam response to loading, analysis of beam SF; these problems require the prediction of the behaviour of the system using few laboratory observations (Birtel and Mark, 2006; Mahmood and Mohammad, 2019; Najafgholipour et al., 2017). Most of the time, mathematical models are developed for the prediction and analysis of the performance of the system through scientific extrapolation of the laboratory test results on an undefined system (Shiohara, 2001). These problems can be solved using artificial intelligence (AI) based machine learning algorithms which are mathematical tools that can detect patterns in a given dataset and extract such patterns for analysis purposes.

The complex nature of the theoretical studies in this domain drives the use of some simplified techniques for practical designs. However, only the deformed shape is considered in the first vibration mode of this method (Quasi-static). The application of this method is only restricted to the determination of the flexural response of simple structures like beams and slabs due to its over-simplification (Reddy, 1997). Furthermore, the use of this method to analyse a structure can only provide the history of the structures' maximum displacement time at the critical point without providing any information about the stress distribution in the other parts of the structure (Saatci and Vecchio, 2009). As such, it has been the view of many scholars that, for high impulsive loads, the maximum shear force prediction at the supports using the simplified techniques may produce inaccurate results (Hart-Smith, 1998; Mangalathu and Jeon, 2018; van Wees and Peters, 1995).

Advanced mathematical models, such as machine learning (ML) approaches, can be used to significantly resolve the problems of the simplified methods in this domain and facilitate the theoretical study of the detailed structural responses. With this, it will be possible to critically examine failure modes & stiffness deterioration; it can also enable the determination of the time history of stresses and strains in different regions of an element. Despite the capability of ML models to analyse structures with varying geometries and load case dynamics, scholars are still striving towards building the ML models of the dynamic response of RC, especially the shear mechanism of RC (Ben Chaabene et al., 2020). Meanwhile, ML models can serve as alternative tools to the experimental studies (which are more costly) of the impacts of different parameters, such as concrete strength, different geometries, and boundary conditions, as well as placement and amount of reinforcement on the shear strength (V_s) response of RC beams. The performance of such models can serve as a guide for the development of simplified methods and design guidelines for practical design purposes.

1.2 Statement of Problem

The RC beam shear strength resistance is considered as critical shear element in the RC beam what it is defined over the literature as a challenging issue in the structural and architectural engineering (Mansouri et al., 2021). It is yet an interesting subject in the academic domain to be studied and better understood its phenomenal (Hassan and Elmorsy, 2021). As a matter of fact, RC beam shear behavior is totally stochastic and not easily can be comprehended owing to the influence of several parameters including the dimensional, and concrete properties, which define the whole system as interdependency and complicated issues (Zhao et al., 2021). Over the literature, several EFs have been introduced to solve the shear strength problem. However, those EFs have shown several limitations on solving this complex engineering problem such as the shortcoming on the understanding the shear behavior due to the variance of the concrete properties, beam dimensions, loading types and direction. Hence, this problem has brought a serious attention for the structural engineers and designers to find better and reliable solution for shear strength determination.

Empirical or semi-empirical approaches and code guidelines are mostly used these days to predict V_s due to the complex nature of SF in RC beams. Hence, these approaches are not capable of mimicking or providing the physical explanation of the SF mechanism encountered in practice; therefore, they are only used in testing the regimes they were derived from. Considering these limitations, this study proposed a more advanced technology that can suit any type of concrete, reinforcement, and geometry for better explanation and simulation of the shear pattern of RC beams. The suitability of the proposed method in the quantification of the V_s of RC beams using different parameters was also evaluated in this work.

With the great development of modern computer aid and computational models, computational science and engineering have accomplished a massive success in the structural engineering. AI models have profound application in structural engineering owing to the ability to provide remarkable solutions (Flood and Kartam, 1994; Ly et al., 2020; Solhmirzaei et al., 2020). AI models can provide solutions to problems associated with high stochasticity, non-linearity, and non-stationarity. They can be used to map incomplete system data into a description state of the system (Khalaf et al., 2021). In structural engineering, incomplete and unorganized datasets are interpreted and recognized for the formulation of problems. One common example is the detection of damage in a structure with numerous components via the collection of data at different locations on the structure (Avci et al., 2021; Figueiredo et al., 2011). This is considered an inverse problem and requires that a state should be determined from the observed system behaviour (Ben Chaabene et al., 2020). The problems are first analyzed before finding the solution that will aid in achieving the desired system behavior while those that will not improve performance are filtered out (Solhmirzaei et al., 2020). AI models can be used to map the behavior of a given system to a space of system attributes that can guarantee the expected behavior. Hence, it is required that system engineers be able to predict the behavior of the complex systems based on the known system configuration and the external loads that the system is subjected to. This implies a problem of mapping the cause to effect, this is achievable using AI models.

To the best knowledge of the current thesis, the feasibility of newly explored machine learning model called random forest (RF) was tested to predict the V_s of reinforced concrete beams. The validation of the proposed model was conducted in comparison with support vector machine (SVM) and EFs. A deep analysis and prediction accuracy comparison were performed.

1.3 Research Significant and Motivation

The shear forces always behave in the form of combination with other types of loads such as flexure, axial load and sometimes torsion, further complicating the problem. Therefore, precise determination of shear capacity (SC) is paramount since SF is catastrophic and could occur without warning. The existence of the uncertainty, nonlinearity, and nonstationary characteristics in the engineering structural problems, have necessitated the analysis of nonlinear systems with stochastic parameters, input, and boundary conditions. Stochastic methodologies present a rational basis for system analysis and sustainable design. Consequently, the advancement on the utilization of theoretical research has been an essential motivation toward simulating the stochastic behavior of complex system, prediction, and the nonlinear dynamic phenomena. Implementing and adopting new theoretical methodologies can offer a robust and reliable tool for diverse engineering applications.

Although the shear design of a RC beam is considered a straightforward process, its accurate prediction is quite difficult unlike flexural strength; hence, it is yet to be perfectly understood (Michael P Collins et al., 2008; Fenwick and Paulay, 1968) by engineers as they are most times unable to justify the results of their designs and cannot explain what such results represent. Shear design is a complicated 2D problem that differs significantly from flexural design as it deals with the response of the web region of beams over multiple sections while flexural design deals with the analysis of just one or a few numbers of critical sections of the beam. SF can occur suddenly without warning, unlike flexural failure which develops gradually. This is more significant for RC beams that contain little or no shear reinforcement where the chances of a brittle failure mechanism are high (Kuo et al., 2010).

The importance of shear can best be demonstrated by the 1955 event at the Wilkins Air Force Warehouse where there was a collapse of the rigid frame section (Anderson, 1957). More insights on the failure modes and crack patterns of three RC beams with different levels of shear reinforcement are provided in Figure 1.1. The first two beams displayed in Figs. 1.1a and b exhibited only a small level of ductility before their sudden and brittle failure. On the other hand, the beam displayed in Fig. 1.1(c) exhibited a ductile failure mode due to the yielding of the tension steel (flexural failure). Hence, flexural failure can be considered a favourable failure mode (should a beam fail at all) while SF must be prevented.

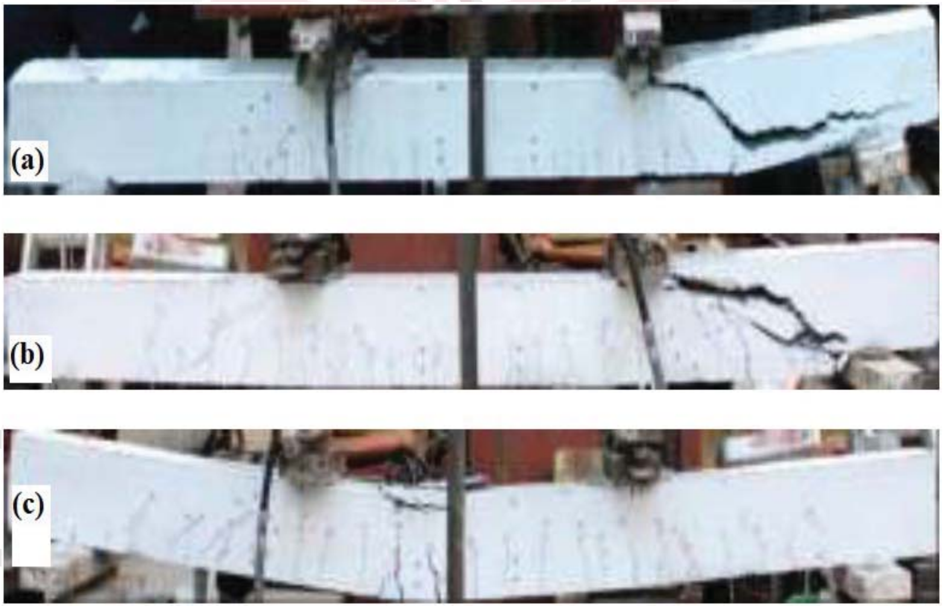

Figure 1.1: (a) Shear failure in a reinforced concrete beam containing no shear reinforcement; (b) shear failure in a reinforced concrete beam with improper shear detailing; and (c) typical flexural failure. Note the large residual deflection sustained by the beam shown at the bottom (Suryanto et al., 2016)

1.4 Research Questions

i. What is the capacity of exploring new machine learning model called Random Forest (RF) for predicting the shear strength (V_s) of reinformed concrete beam?

ii. What is the influence of the geometric and concrete properties parameters on the V_s prediction?

iii. What is the prediction accuracy of the proposed model against the support vector machine (SVM) and several well-established EFs?

1.5 Research Aim and Objectives

The current research aims to present a statistical evaluation of a machine learning model as shear strength prediction on reinforced concrete beam using two algorithms SVM and RF models using 349 data set.

In order to obtain the aim of the thesis, the following objectives could be stated to:

i. To propose a new computer aided model called Random Forest (RF) to predict shear strength of reinforced concrete beams simulation.

ii. To investigate different input combinations that include different associated parameters of concrete properties and beam geometry based on correlation statistical analysis.

iii. To validate the proposed model against support vector machine (SVM) to several well-established EFs called from the literature.

1.6 Research Scope and Limitation

The random forest (RF) technique, one of several ML algorithms, offers numerous benefits over other models and is often used to resolve issues in structural engineering. Furthermore, because only two hyperparameters need to be modified, RF is quite simple to implement. In classification and regression issues, the random forest model (RF) is often employed; it builds a number of random trees and depends on the bootstrapping technique. In regression tasks, the RF's responsibilities include breaking up the input variables into smaller sections and calculating the difference between the actual and projected values. Each portion's sum of squared errors (SSE) is calculated, and the best part is chosen based on the lowest SSE. The samples are picked at random during the training process, and those that were not chosen are referred to as out-of-bag samples. These samples are used to determine the most important variable based on how accurately the output is predicted.

A supervised technique for determining the input-output connection while developing predictive models is the support vector machine (SVM). The SVM's kernel function, lack of local minima as a result of the learning process, and control mechanism using arranged support vectors and margin value are its key peculiarities. Using a nonlinear kernel function, the input variables for SVM are converted into a high-dimensional space. This transformation enables the algorithm to choose the ideal hyperplane (($Y_i = \omega_0 + \sum_{i=1}^{m} \omega_i \, \phi(x)$)) for separating the data set. SVM can now handle both linear and nonlinear functions thanks to this functionality. When compared to another algorithm, such as ANN, the SVM model has shown its capacity to reach the ideal point in the learning process. The SVM model does have certain limitations when dealing with huge data sets; these limitations relate to the need for memory and the choice of kernel functions. SVM was first suggested by for use in classification problems. But the addition of the - insensitive loss function by increased the SVM's usefulness to regression problems.

Therefore, the scope of the current thesis is to applied the two indicated algorithms random forest (RF) and support vector machine (SVM) to predict the concrete shear strength for different concrete types and conditions.

The limitation of the current research mainly resulting from mathematical relationships between RC shear strength and the influencing variables (Mathey and Watstein, 1963). Also, the nonlinear relationship of the shear strength with the number of influencing variables makes the determination of the parameters of these models difficult. Furthermore, the lack of sufficient experimental data and the presence of missing variables are among the factors that limit the use of empirical or semi-empirical models in the design of the code provisions (Abuodeh et al., 2020; Song et al., 2010). This makes it possible to get different prediction results from different models. Hence, shear strength prediction of RC beams is a recurring task that is yet to be addressed.

1.7 Expected Contribution

The current study expected contribution is to find a robust and reliable emerging technology based on computer aid models to simulate the beam shear strength. Based on the use of the open source of experimental dataset, the proposed methodology was initiated and inspected for its reliability. In conclusion, the finding of the thesis is expecting to come up with handful tool that can help structural engineers for beam design and optimal structure sustainability.

1.8 Thesis Outlines

The thesis is established consisted five main chapters. First chapter is exhibited the research background on the studied shear strength of RC beam, problem of statement, limitation and scope of the study, research significant and motivation and research objective. The second chapter is revealed the introduced related EFs established for the shear strength calculation in addition to the adopted machine learning based models related studies. Based on the reported literature review, several aspects were assessed and evaluated. Research gap identification was reported as well. Chapter 3 is reported the methodological and data explanation. Chapter 4 is described the application results, analysis and discussion. Finally, chapter 5 is stated the research conclusion, limitation of the current study and possible future research.

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