

EXPLAINING SEISMIC RESPONSE AND FRAGILITY OF RC FRAMES THROUGH MACHINE LEARNING

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by

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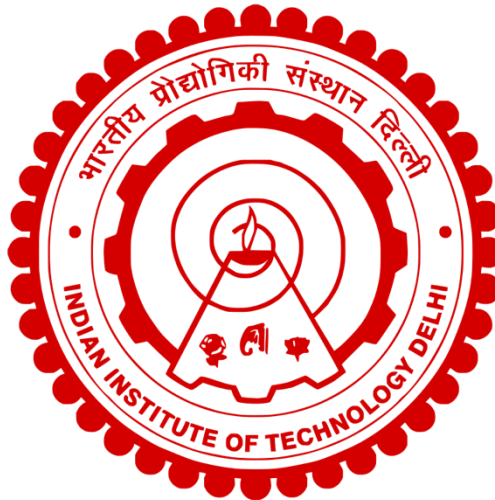
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Submitted

in fulfillment of the requirements of the degree

DOCTOR OF PHILOSOPHY

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NOVEMBER 2024

Dedicated to my family!

CERTIFICATE

This is to certify that the thesis titled “

Explaining Seismic Response and Fragility of RC Frames through Machine Learning

”, is being submitted by Ms. Iqra Latif (2019CEZ8228), to the Indian Institute of Technology Delhi, for the award of the degree of Doctor of Philosophy. This is a bonafide record of research work and is entirely carried out by her under my supervision and guidance. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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DECLARATION

I hereby declare that the thesis contains the work carried out in fulfilment of the requirements for the award of the degree of Doctor of Philosophy under the guidance and supervision of Dr. Arnab Banerjee, Assistant Professor, Department of Civil Engineering, IIT Delhi and Dr. Mitesh Surana, Assistant Professor, Department of Civil Engineering, IIT Ropar. The contents of the dissertation, including text, tables, figures, etc., have not been reproduced from other reports, theses, etc. Wherever reproduction has been made from books, journals, reports, manuals, websites, etc., the sources have been duly acknowledged and referenced appropriately.

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ABSTRACT

Structural engineering and design are key research areas that facilitate construction of safe buildings. Some of the important variables involved in design and assessment of RC buildings are loading conditions, soil type, building typology, material properties, ground motion characteristics, codal provisions, dynamic characteristics including the fundamental period, base shear, fragility curve parameters, in-structure acceleration amplification factor, and spectral acceleration amplification function. Researchers have developed several techniques to simplify different stages of structural analysis to rapidly obtain these design variables. These techniques are based on experimental observations and computationally complex simulations. Because of the development of machine learning models and their applications in structural engineering, researchers have been able to predict static and dynamic response of RC buildings.

However, there exist certain limitations with respect to the use of these models. Due to complexity of machine learning models, they behave as black-box and hence the model predictions are not explainable. Further, the existing works consider only structural and ground motion characteristics as input for training the machine learning models. Hence, there exist the need to incorporate different input features like properties of construction materials, wide range of ground motion characteristics, structural characteristics including fundamental period, level of inelasticity in building to obtain desired predictions for RC frames. The machine learning model explanation method should also be used to provide insights into the effect of input features on model predictions.

In this work, explainable machine learning models are developed for four tasks: fundamental period prediction, seismic fragility curve parameter prediction, in-storey acceleration amplification factor prediction, and spectral acceleration amplification function at fundamental

and second mode vibration period. The dataset for training fundamental period prediction model is prepared by eigen value analysis of 4, 8, and 12 storey buildings modelled in OpenSees by considering 200 sets of material modelling parameters of concrete and reinforcing steel. Overall, 6 parameters (2 for modelling concrete, i.e., unconfined concrete's peak compressive strength and strain, and 4 for modelling reinforcing steel, i.e., yield strength, Elastic modulus, post-yield strain hardening ratio, and curvature variation parameter of Bauschinger curve after each strain reversal) are used to generate 200 sets through Latin hypercube sampling method by considering the appropriate probability distributions as obtained from the literature. The machine learning models trained to predict fundamental period are neural networks and extreme gradient boosting trees, both of which yielded equally good results. SHAP analysis which was performed to explain the effect of input feature on model predictions revealed that fundamental period is governed by unconfined concrete's strength and strain in addition to number of storeys in the RC buildings.

The second aspect of the study investigated the effect of the material properties (same as taken in case of fundamental period prediction) on the fragility curve parameters of RC frames. The fragility curves are an effective tool to evaluate the seismic performance of buildings as the entire structural state can be represented by their two parameters. In this study, 4, 8, and 12 storey RC buildings were subjected to 184 pulse type ground motions to develop fragility curves corresponding to three intensity measures, i.e., peak ground acceleration, 5%-damped spectral acceleration at fundamental period ($Sa(T_1)$), and average spectral acceleration ($Sa_{avg}[T_2, 2T_1]$). The ground motions were scaled from 0.1 g to 1.5 g at a step of 0.1 g to perform nonlinear dynamic analysis. The XGBoost models performed significantly better than the neural network models in predicting the fragility curve parameters. The model predictions were explained using SHAP analysis, revealing that fundamental period, and modelling parameters of unconfined concrete

played important role at all limit states. The importance of material properties of reinforcing steel was lower than other input features like properties of concrete and fundamental period and increased with increase in the severity of limit state.

The third and fourth aspect of this study deals with understanding the effect of 16 input features which comprises of 6 material, 6 ground motion, and 4 structural characteristics on the in-structure acceleration amplification factor (IAAF) and spectral acceleration amplification factors corresponding to fundamental (A_1) and second mode (A_2) period of RC buildings. The 4, 8, and 12 storey buildings with 50 sets of material properties were subjected to 30 ground motions at different levels of inelasticity to obtain IAAF, A_1 and A_2 at each floor. Using this dataset, separate machine learning models were trained to predict IAAF and SAAF where the XGBoost models significantly outperformed neural networks. Through SHAP analysis, it was revealed that structural features are most important followed by ground motion characteristics and then material properties while predicting IAAF, A_1 and A_2 .

Finally, the methodology to train machine learning models was applied to predict fundamental period of bare and infilled RC frames using an existing dataset of more than 4000 buildings. The model predictions were explained through three different model explanation methods like partial dependency plots, additive local explanations, and SHAP analysis. The trained ML models were used as surrogate while optimizing the geometrical and mechanical properties of the frames while targeting desired fundamental periods. Interactive dashboards are developed for providing access to all the ML models developed in this work.

सार

संरचनात्मक अभियांत्रिकी और डिजाइन प्रमुख अनुसंधान क्षेत्र हैं जो सुरक्षित इमारतों के निर्माण की सुविधा प्रदान करते हैं। RC इमारतों के डिजाइन और मूल्यांकन में शामिल कुछ महत्वपूर्ण चर लोडिंग की स्थिति, मिट्टी का प्रकार, इमारत की टाइपोलॉजी, सामग्री के गुण, भूकम्प की विशेषताएँ, कोडल प्रावधान, मौलिक अवधि, बेस शियर, भंगुरता वक्र पैरामीटर, इन-स्ट्रक्चर त्वरण प्रवर्धन कारक और स्पेक्ट्रल त्वरण प्रवर्धन फ़ंक्शन सहित गतिशील विशेषताएँ हैं। शोधकर्ताओं ने इन डिज़ाइन चर को तेज़ी से प्राप्त करने के लिए संरचनात्मक विश्लेषण के विभिन्न चरणों को सरल बनाने के लिए कई तकनीकें विकसित की हैं। ये तकनीकें प्रायोगिक अवलोकनों और कम्प्यूटेशनल रूप से जटिल सिमुलेशन पर आधारित हैं। मशीन लर्निंग मॉडल के विकास और संरचनात्मक इंजीनियरिंग में उनके अनुप्रयोगों के कारण, शोधकर्ता RC इमारतों की स्थिर और गतिशील प्रतिक्रिया की भविष्यवाणी करने में सक्षम हैं।

हालाँकि, इन मॉडलों के उपयोग के संबंध में कुछ सीमाएँ मौजूद हैं। मशीन लर्निंग मॉडल की जटिलता के कारण, वे ब्लैक-बॉक्स की तरह व्यवहार करते हैं और इसलिए मॉडल की भविष्यवाणियाँ व्याख्या योग्य नहीं हैं। इसके अलावा, मौजूदा कार्य मशीन लर्निंग मॉडल को प्रशिक्षित करने के लिए इनपुट के रूप में केवल संरचनात्मक और भूकम्पिये विशेषताओं पर विचार करते हैं। इसलिए, RC फ्रेम के लिए वांछित भविष्यवाणियाँ प्राप्त करने के लिए निर्माण सामग्री के गुण, भूकम्पिये विशेषताओं की विस्तृत श्रृंखला, मौलिक अवधि सहित संरचनात्मक विशेषताएँ, भवन में असंगठितता का स्तर जैसी विभिन्न इनपुट विशेषताओं को शामिल करने की आवश्यकता है। मॉडल भविष्यवाणियों पर इनपुट सुविधाओं के प्रभाव के बारे में जानकारी प्रदान करने के लिए मशीन लर्निंग मॉडल स्पष्टीकरण विधि का भी उपयोग किया जाना चाहिए।

इस कार्य में, चार कार्यों के लिए व्याख्या योग्य मशीन लर्निंग मॉडल विकसित किए गए हैं: मौलिक अवधि पूर्वानुमान, भूकंपीय भंगुरता वक्र पैरामीटर पूर्वानुमान, इन-स्टोरी त्वरण प्रवर्धन कारक पूर्वानुमान, और

मौलिक और द्वितीय मोड कंपन अवधि में वर्णक्रमीय त्वरण प्रवर्धन कारकों का पूर्वानुमान। मौलिक अवधि पूर्वानुमान मॉडल के प्रशिक्षण के लिए डेटासेट कंक्रीट और मजबूत स्टील के सामग्री मॉडलिंग मापदंडों के 200 सेटों पर विचार करके ओपनसीज़ में मॉडल किए गए 4, 8 और 12 मंजिला इमारतों के आइजेन मूल्य विश्लेषण द्वारा तैयार किया गया है। कुल मिलाकर, 6 पैरामीटर (कंक्रीट मॉडलिंग के लिए 2, यानी, असीमित कंक्रीट की अधिकतम संपीड़न शक्ति और तनाव, और मजबूत स्टील मॉडलिंग के लिए 4, यानी, यील्ड शक्ति, लोचदार मापांक, यील्ड के बाद तनाव कठोरता अनुपात, और प्रत्येक तनाव उलटने के बाद बॉशिंगर वक्र का वक्रता भिन्नता पैरामीटर) साहित्य से प्राप्त उचित संभाव्यता वितरण पर विचार करके लैटिन हाइपरक्यूब नमूनाकरण विधि के माध्यम से 200 सेट उत्पन्न करने के लिए उपयोग किए जाते हैं। मौलिक अवधि की भविष्यवाणी करने के लिए प्रशिक्षित मशीन लर्निंग मॉडल न्यूरल नेटवर्क और एक्सट्रीम ग्रेडिएंट बूस्टिंग ट्री हैं, जिनमें से दोनों ने समान रूप से अच्छे परिणाम दिए। मॉडल भविष्यवाणियों पर इनपुट फीचर के प्रभाव को समझाने के लिए किए गए SHAP विश्लेषण से पता चला कि मौलिक अवधि RC इमारतों में मंजिलों की संख्या के अलावा असंबद्ध कंक्रीट की ताकत और तनाव द्वारा नियंत्रित होती है।

अध्ययन के दूसरे पहलू ने आरसी फ्रेम के नाजुकता वक्र मापदंडों पर सामग्री के गुणों (मूल अवधि की भविष्यवाणी के मामले में लिया गया समान) के प्रभाव की जांच की। नाजुकता वक्र इमारतों के भूकंपीय प्रदर्शन का मूल्यांकन करने के लिए एक प्रभावी उपकरण हैं क्योंकि संपूर्ण संरचनात्मक स्थिति को उनके दो मापदंडों द्वारा दर्शाया जा सकता है। इस अध्ययन में, 4, 8 और 12 मंजिली RC इमारतों को तीन तीव्रता उपायों, यानी, चरम भूमि त्वरण, मूल अवधि में 5%-मंद स्पेक्ट्रल त्वरण ($S_a(T_1)$), और औसत स्पेक्ट्रल त्वरण ($S_{avg} [T_2, 2T_1]$) के अनुरूप नाजुकता वक्र विकसित करने के लिए 184 पल्स प्रकार के भूकम्पों के अधीन किया गया था। गैर-रेखीय गतिशील विश्लेषण करने के लिए भू-गति को 0.1 g के चरण में 0.1 g से 1.5 g तक बढ़ाया गया था मॉडल पूर्वानुमानों को SHAP विश्लेषण का उपयोग करके समझाया गया, जिससे पता

चला कि मौलिक अवधि और असंबद्ध कंक्रीट के मॉडलिंग मापदंडों ने सभी सीमा स्थितियों में महत्वपूर्ण भूमिका निभाई। प्रबलित स्टील के भौतिक गुणों का महत्व कंक्रीट के गुणों और मौलिक अवधि जैसी अन्य इनपुट विशेषताओं की तुलना में कम था और सीमा स्थिति की गंभीरता में वृद्धि के साथ बढ़ता गया।

इस अध्ययन का तीसरा और चौथा पहलू 16 इनपुट विशेषताओं के प्रभाव को समझने से संबंधित है जिसमें 6 सामग्री, 6 भूकम्पिये, और 4 संरचनात्मक विशेषताएं शामिल हैं जो RC भवनों के मूलभूत (A_1) और द्वितीय विधा (A_2) अवधि के अनुरूप इन-स्ट्रक्चर त्वरण प्रवर्धन कारक (IAAF) और वर्णक्रमीय त्वरण प्रवर्धन कारकों पर प्रभाव डालती हैं। सामग्री गुणों के 50 सेटों वाली 4, 8 और 12 मंजिला इमारतों को प्रत्येक मंजिल पर IAAF, A_1 और A_2 प्राप्त करने के लिए विभिन्न स्तरों पर 30 भूकम्पों के अधीन किया गया। इस डेटासेट का उपयोग करते हुए, IAAF और SAAF की भविष्यवाणी करने के लिए अलग-अलग मशीन लर्निंग मॉडल को प्रशिक्षित किया गया जहां XGBoost मॉडल ने न्यूरल नेटवर्क से काफी बेहतर प्रदर्शन किया। SHAP विश्लेषण के माध्यम से, यह पता चला कि IAAF, A_1 और A_2 की भविष्यवाणी करते समय संरचनात्मक विशेषताएं सबसे महत्वपूर्ण हैं, इसके बाद भूकम्पिये विशेषताएं और फिर सामग्री गुण हैं।

अंत में, 4000 से अधिक इमारतों के मौजूदा डेटासेट का उपयोग करके इंफ़िल दीवारों से युक्त तथा विहीन RC फ्रेमों की मौलिक अवधि की भविष्यवाणी करने के लिए मशीन लर्निंग मॉडल को प्रशिक्षित करने की पद्धति लागू की गई। मॉडल भविष्यवाणियों को आंशिक निर्भरता प्लॉट, योगात्मक स्थानीय स्पष्टीकरण और SHAP विश्लेषण जैसे तीन अलग-अलग मॉडल स्पष्टीकरण विधियों के माध्यम से समझाया गया था। प्रशिक्षित एमएल मॉडल को वांछित मौलिक अवधियों को लक्षित करते हुए फ्रेम के ज्यामितीय और यांत्रिक गुणों को अनुकूलित करते हुए सरोगेट के रूप में उपयोग किया गया था। इस कार्य में विकसित सभी एमएल मॉडल तक पहुँच प्रदान करने के लिए इंटरैक्टिव डैशबोर्ड विकसित किए गए हैं।

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List of Abbreviations

<i>RC</i>	Reinforced-concrete
<i>4S</i>	4-Storey
<i>8S</i>	8-Storey
<i>12S</i>	12-Storey
<i>EDP</i>	Engineering demand parameter
<i>MIDR</i>	Maximum inter-storey drift ratio
<i>GM</i>	Ground motion
<i>IM</i>	Intensity measure
<i>IO</i>	Immediate occupancy
<i>LS</i>	Life safety
<i>CP</i>	Collapse prevention
<i>LHS</i>	Latin hypercube sampling
<i>PGA</i>	Peak ground acceleration
<i>SFC</i>	Seismic fragility curve
<i>PFA</i>	Peak floor acceleration
<i>PGV</i>	Peak ground velocity
<i>IAAF</i>	In-structure acceleration amplification factor
<i>SAAF</i>	Spectral acceleration amplification function
<i>R</i>	Strength ratio
<i>NOS_t</i>	Number of storeys
<i>NOS_p</i>	Number of spans
<i>SL</i>	Span length
<i>OR</i>	Opening ratio
<i>K</i>	Masonry wall stiffness
<i>EV</i>	Expected value

List of Symbols

T_{actual}	The actual fundamental period of the building
$T_{predicted}$	The predicted fundamental period of the building
$T_{optimized}$	The fundamental period of the building after optimization
$T_{average}$	The average effect of the feature on fundamental period of buildings in PDP plots.
T	The ALE value respective feature w.r.t its value for a given ML model
ε_p	Difference between the actual and predicted fundamental period of the building
ε_o	Difference between the actual and optimized fundamental period of the building
μ	Mean
σ	Standard deviation