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THE BURNING SEARCH FOR CAUSALITY AND KNOWLEDGE DISCOVERY: BEYOND FIRE TESTS AND EXPLAINABLE ARTIFICIAL INTELLIGENCE

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ABSTRACT

Most of our research effort revolves around uncovering data generating processes (i.e., the how and why phenomena come to be). In this pursuit, we hope that by knowing the *how* and *why*, we can discover new knowledge, or perhaps advance our existing knowledge. This short paper presents a look into causal discovery and causal inference from the lens of fire resistance and then contrasts that to traditional artificial intelligence (AI) methods. Thus, two sets of algorithms are used; causal discovery algorithms are adopted to uncover the causal structure between key variables pertaining to the fire resistance of reinforced concrete (RC) columns, and causal inference algorithms are applied to estimate the influence of key predictors on the fire resistance of the same columns.

Keywords: Causality; Fire; Artificial intelligence; Machine learning.

1 INTRODUCTION

Discovering new knowledge implies the realization of the data generating process (DGP) responsible for creating the phenomena we happen to be interested in [1]. Such realization is often identified via fire tests or experiments. A typical experiment is planned to quantify, for example, the influence of some form of intervention (i.e., changing the construction material from A to B) on the outcome of interest (e.g., fire resistance). Hence, the outcome of such an experiment is thought of as a *cause(s)* → *effect* approach [2].

Once a true DGP is identified, then an engineer may opt to utilize the identified DGP to estimate the outcome of a particular testing intervention. This may, in fact, reduce our heavy reliance on expensive fire tests. At a minimum, a DGP will allow us to complete our understanding of a particular problem or phenomenon. The same could also open the door for new hypotheses and, most importantly, intelligently narrow the vast search space of our problems (rather than relying on outdated information that we do not seem to break free from).

Fire resistance is one such problem that is elemental to structural fire engineers. For example, predicting fire resistance of structural members is a complex problem that remains, and rightfully so, to be confined to the standard fire testing method. It is very likely that the DGP for fire resistance already exists in the thousands of fire tests conducted so far. At the end of the day, many such tests were conducted on specimens of, more or less, similar features (i.e., columns tend to have a practical range of size, length, reinforcement, etc.), which further narrows our search space. This may also ease the identification of possible DGPs.

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For instance, reinforced concrete (RC) columns made from normal strength concrete (NSC) often display good performance under fire conditions. Recent works argue that NSC columns may outperform other columns made from high strength concrete (HSC) and ultra high-performance concrete (UHPC) [3]. Although HSC and UHPC columns inherently have high strength than NSC, such a strength does not correlate to improved fire resistance. Figure 1 illustrates this very point by plotting the relationship between compressive strength and fire resistance of about 100 RC columns. As one can see, there is a weak correlation. Not surprisingly, columns of relatively low grade strength (NSC) do not seem to guarantee achieving high fire resistance.

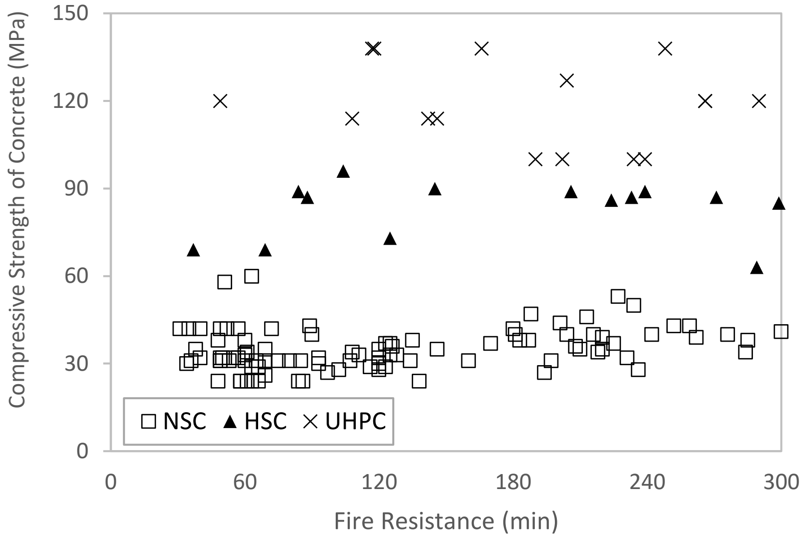

Fig. 1 Examination of compressive strength and fire resistance of fire-tested RC columns

The fire resistance of RC columns can be evaluated through codal charts/tables, or hand calculation methods, or via finite element simulations, and/or artificial intelligence (AI)/machine learning (ML). These methods deliver fire resistance predictions for RC columns *given* a set of variables. Interestingly, these methods do not often agree if applied to a particular and/or a group of columns [4–6]. As such, re-visiting the classical phenomenon of fire resistance of RC columns is of interest to this paper.

This paper presents a casual approach to discovering and inferring the causal mechanism responsible for the DGP of the fire resistance of RC columns. Then, this paper compares the newly discovered knowledge against domain knowledge and traditional machine learning. For completion, a companion discussion on causality can be found in a recent paper from the author’s group [7].

2 CAUSAL APPROACH

In a traditional sense, a regression-based approach can be used to *predict* an outcome, *Y*, through a set of predictors. In such an approach, a predictive expression does not imply that the predictors are causes of *Y* but rather notes the outcome can be predicted using the predictors. On the other hand, a causal analysis strives to establish if a set of predictors are likely to cause *Y*. A look into Fig. 2 showcases a visual depiction of how regression differs from causation.

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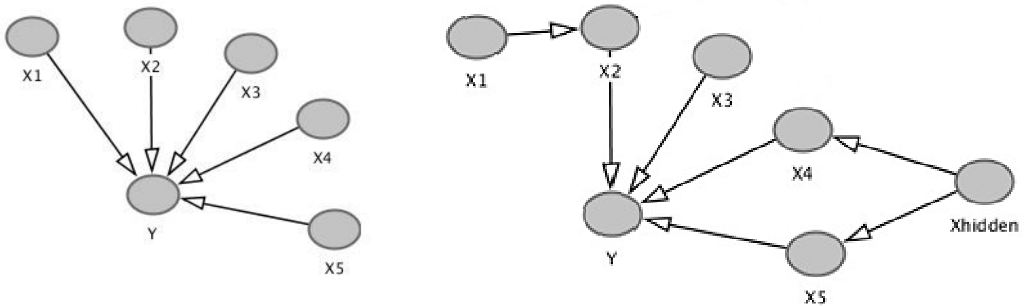

Fig. 2 Regression vs. causation

A causal approach comprises four primary steps (see Fig. 3):

1) Collecting data on the phenomena of interest.
2) Causal discovery to uncover the underlying DGP by satisfying causal principles. These principles include the Markov causal assumption, the causal faithfulness assumption, and the causal sufficiency assumption. Following such assumptions lead to the creation of a direct acyclic graph (DAG). Full details on such assumptions can be found elsewhere [8–10].
3) Causal inference is applied to infer how the output (i.e., fire resistance) would change by intervening on a predictor. An intervention equates to *setting* $X = x$ (what is the fire resistance of a RC column if its width is *increased* to 300 mm?) vs. *observing* $X = x$. (what is the fire resistance of a RC column, *given* it has a width of 300 mm?).
4) Finally, the outcome of the causal analysis can be compared to that of existing methods.

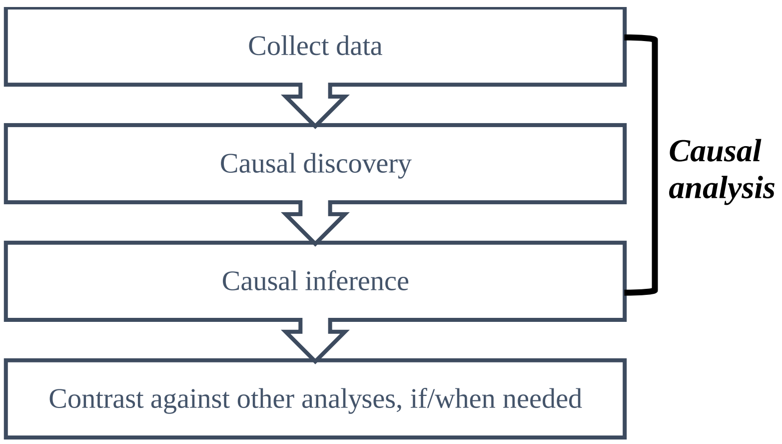

Fig. 3 Flowchart of the proposed approach

3 DATABASE

The database used in this short study compiles information on 144 fire-exposed RC columns that were tested at full scale and under standard fire conditions. The following predictors were collected 1) column width, *W*, 2) steel reinforcement ratio, *r*, 3) column length, *L*, 4) concrete compressive strength, f_c, 5) column effective length factor, *K*, 6) concrete cover to steel reinforcement, *C*, 7) the magnitude of applied loading, *P*, and 8) fire resistance time, *FR*.

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Table 1 Statistics on collected database

	W (mm)	***r*** (%)	***L*** (m)	f_c (MPa)	***C*** (mm)	***P*** (kN)	***FR*** (min)
Minimum	203	0.9	2.1	24	25	0	55
Maximum	610	4.4	5.7	138	64	5373	389
Average	350.4	2.1	3.9	55.7	42.4	1501.8	176.6
Standard Deviation	105.3	0.5	0.5	33	7.1	1168.6	82
Skewness	1.1	1	-0.5	0.9	-1	1.3	0.4

4 METHODOLOGY

This paper starts by creating a machine learning (ML) ensemble for the above dataset. Then, this paper applies a common causal discovery algorithm and then compares its result to that of a previously used interpretable machine learning model [11].

The selected ensemble contains three algorithms: random forest (RF), extreme gradient boosted trees (ExGBT), and deep learning (DL). The RF algorithm randomly generates multiple decision trees to analyze the dataset [12]; such that:

$$Y = \frac{1}{J}\sum_{j=1}^{J} C_{j,full} + \sum_{k=1}^{K}\left(\frac{1}{J}\sum_{j=1}^{J} contribution_j(x,k)\right) \quad (1)$$

where, J is the number of trees in the forest, k represents a feature in the observation, K is the total number of features, c_{full} is the average of the entire dataset (initial node).

The ExGBT algorithm re-samples the collected observations into decision trees, where each tree sees a boostrap sample of the database in each iteration. ExGBT shares some aspects with RF, except that it fits successive trees to the residual errors from all the previous trees combined (see Eq. 2).

$$Y = \sum_{k=1}^{M} f_k(x_i)\,, f_k \in F = \left\{f_x = w_{q(x)}, q: R^p \to T, w \in R^T\right\} \quad (2)$$

where, M is additive functions, T is the number of leaves in the tree, w is a leaf weights vector, w_i is a score on i-th leaf, and $q(x)$ represents the structure of each tree that maps an observation to the corresponding leaf index [13]. The RF algorithm incorporates 50 leaf nodes, with a minimum of 5 samples to split an internal node.

Deep learning algorithm contains a number of layers that are connected via nonlinear activation functions e.g., *Logistic*, *PReLu*, etc. [14]. This algorithm aims to achieve a general and primarily implicit representation that best exemplifies a phenomenon; such that:

$$net_j = \sum_{i=1}^{n} In_i w_{ij} + b_j \quad (3)$$

$$Y = f(net_j) \quad (4)$$

where, In_i and b_j are the ith input signal and the bias value of jth neuron, respectively, w_{ij} is the connecting weight between ith input signal and jth neuron, and f is a *PReLu* activation function. The number of used layers are 64, with 3% learning rate, and *Adam* optimizer to enhance the processing of observations.

Finally, the causal analysis carried out in this short paper starts by disregarding the effects of all predictors on each other and assuming that they only have an influence on *FR* as shown in the DAG listed in Fig. 4. As one can see, this DAG also represents how a typical machine learning model assumes the relationships with *FR* and the one used in an earlier study [11].

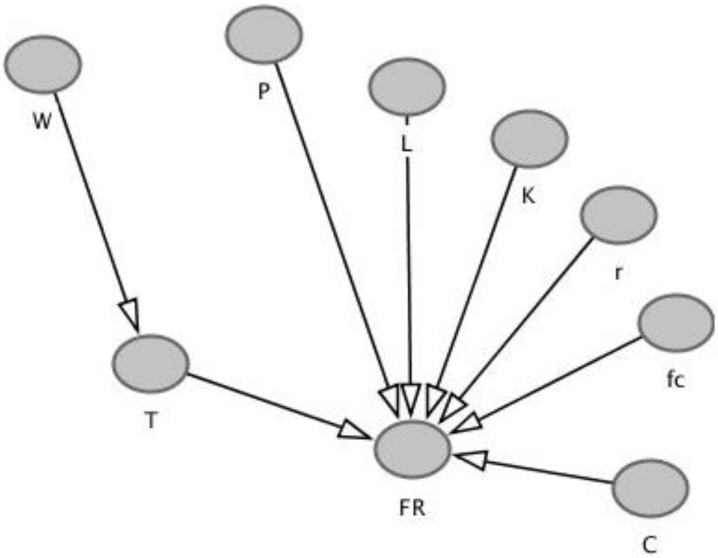

Fig. 4 Hypothetical model [Note: T: intervention/treatment, FR: fire resistance]

5 RESULTS AND DISCUSSION

This section highlights the main findings of this short paper.

In order to further highlight the accuracy of the developed ensemble, fire resistance predictions obtained herein are also compared against Eurocode 2 [15], as plotted in Fig. 5. This figure infers the good predictions from the ensemble and the adequacy of Eurocode 2 predictions for columns within the 60-240 minute range beyond which these predictions seem to be underestimated.

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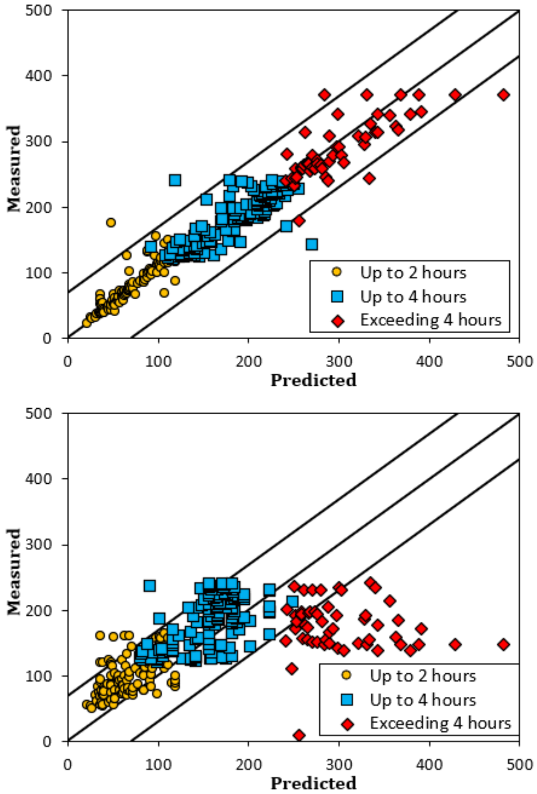

(a) Predictions from ensemble

(b) Eurocode 2 method

$$R = 120\left(\frac{R_{fi}+R_a+R_l+R_b+R_n}{120}\right)^{1.8}, \text{ and } R_{fi} = 83\left(1-\mu_{fi}\frac{1+\omega}{\frac{0.85}{\alpha_{cc}}+\omega}\right), \ \omega = \frac{A_s f_{yd}}{A_c f_{cd}}$$

where,
R = fire resistance of column (min),
α_{cc} = coefficient for compressive strength,
$R_a = 1.6(a-30)$; a is the axis distance to the longitudinal steel bars (mm); 25 mm $\leq a \leq$ 80 mm,
$R_l = 9.6(5-l_{o,fi})$; $l_{o,fi}$ is the effective length of the column under fire conditions; 2 m $\leq l_{o,fi} \leq$ 6 m; values corresponding to $l_{o,fi}$ = 2 m give safe results for columns with $l_{o,fi}$ < 2 m,
$R_b = 0.09b'$; $b' = A_c/(b+h)$ for rectangular cross-sections or the diameter of circular cross sections,
$R_n = 0$, if 4 rebars are used, and 12 for more than 4 rebars.
Performance metrics: $R = 0.7$, $R^2 = 0.49$

Fig. 5 Comparison of fire resistance prediction in RC columns

The ML ensemble can also be used to identify the importance of each predictor. The analysis shows that the following predictors C (100%), P (63%), K (54%), e_x (52%), and b (39%), are the most impactful features. Figure 6 shares additional insights into the impact of each of these features on the increased possibility of improved fire resistance (when all other features remain constant). For example, larger columns are expected to have higher fire resistance.

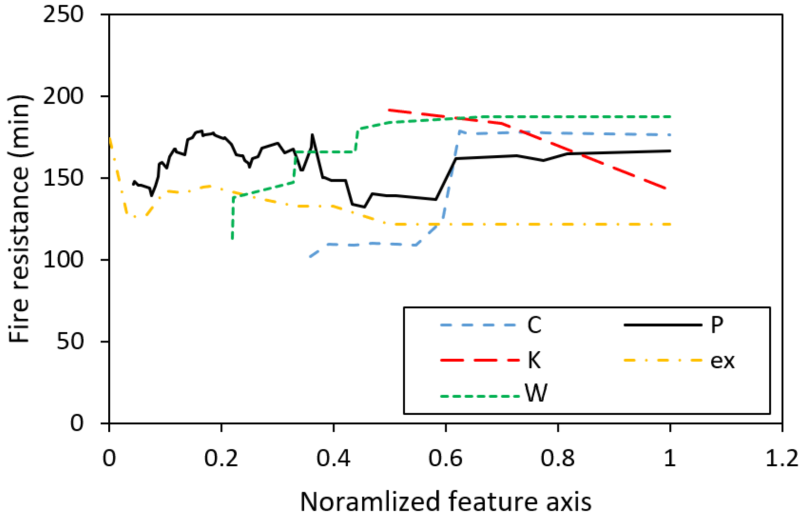

Fig. 6 Insights into key factors influencing fire resistance of RC columns

Since machine learning predictions cannot account for intervention as they are based on observational distribution, then a comparison is drawn between ensemble predictions and the causal algorithm. Figure 7

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shows how intervening by substituting the average value of a given predictor into the ensemble does not turn well. In other words, the ensemble is used to estimate *FR* for a given column with predictors having a value equal to the average value noted in Table 1. This action leads to shifting in each of the method's predictions which can be explained by the reliance on the association of both methods to minimize the variance of the outcome instead of displaying the actual causal mechanism tying each variable to the fire resistance of RC columns.

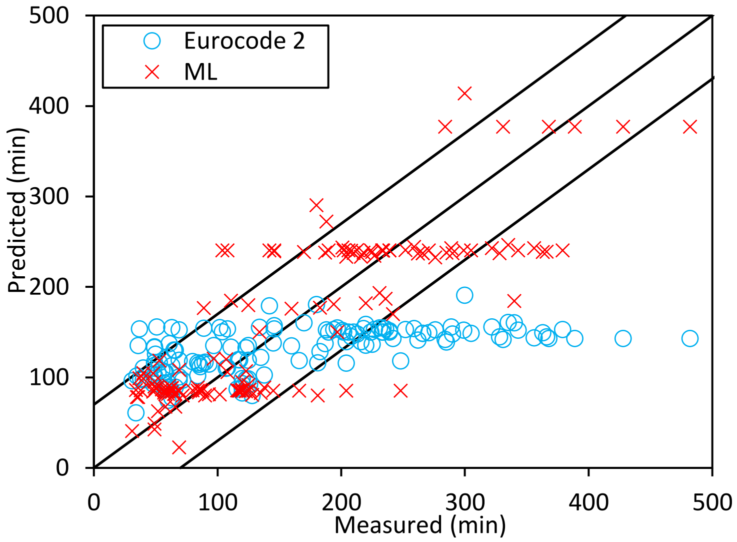

Fig. 7 Comparision applied due to interventions

On the other hand, Table 2 shows that when all variables are assessed for their interventional impact on *FR*. For example, positive interventions/treatments negatively influence *FR* for *W*, *L*, and *K*, whereas they positively influence *FR* for *r*, f_c, *C*, and *P*. In this instance, having a RC column with average steel reinforming ratio (2.1%) will increase FR by about 19 min, while having the same column with an average concrete cover (42.4 mm) will increase FR by 87.8 min.

Table 2 Results of analysis for fire resistance (min)

Treatment variable	Estimate	
	Mean value	*p*-value
W	-245.0	0.11
r	19.0	0.76
L	-82.0	0.97
f_c	40.9	0.85
K	-81.1	0.02
C	87.8	5.8e-9
P	36.3	0.004

6 CONCLUSIONS

This paper presents a look into causal discovery and causal inference to quantify the magnitude of interventions on the fire resistance of RC columns. The following list of inferences can also be drawn from the findings of this study:

- Integrating causality can further accelerate knowledge discovery in our domain.

- Interventions are seen to be highly influential in terms of column width, column length, and concrete cover. Interventions on the level of applied loading and/or reinforcement ratio did not significantly alter fire resistance.
- Unlike traditional ML analysis, the causal analysis provides us with the most realistic predictions as it can accommodate interventions (without needing new tests or experiments).

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