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SiF 2022– The 12th International Conference on Structures in Fire

The Hong Kong Polytechnic University, Nov 30 - Dec 2, 2022

A NOMOGRAM FOR PREDICTING FIRE-INDUCED SPALLING

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ABSTRACT

Concrete, encountering harsh conditions such as fire, is prone to damage. One of the most critical ones is spalling, and this tragic event continues to be a challenging area of research. A thorough examination of the available literature reveals the difficulty of anticipating spalling. As a result, this work proposes a nomogram as a tool to predict spalling of concrete mixtures. The suggested solutions enable interested academics and engineers to visually assess a concrete mixture's susceptibility to spalling without costly laboratory tests. The outcome of this study is a simple tool for practitioners and structural designers to predict spalling in their designed sections disregarding the complex nature of this long-standing problem.

Keywords: Logistic Regression; Spalling, Fire; Concrete; Nomogram.

1 INTRODUCTION

Due to its high tendency not to interact with external conditions, concrete has become one of the two primary materials used in construction. However, in the harsh conditions of fire, concrete will undertake some degree of damage. Such damage is fundamentally correlated to the main components of concrete (including but not limited to aggregates, sand, (water/sand) ratio, (silica-fume/ binder) ratio, fly-ash, etc.) and is controlled by their portion. Spalling is one of the most complicated damages to consider [1, 2].

The spalling phenomenon is a condition in which we have a disintegrated chunk of concrete from one of its member sides. Reduction in size and exposure of crucial elements (such as bars and other reinforcement) to harsh conditions, as well as high-temperature propagation of concrete due to spalling can result in many unexpected failures in structures [3–5].

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Remarkable works and projects have assessed both the traditional and high-strength concrete performance at high temperatures [4, 5]. They have shown that modern concrete (UHPC) is more inclined to spall in comparison to moderate-strength concrete due to the dense microstructure that UHPC concrete has. A deep dive into the open literature [6–9] show that we still suffer from the lack of a reliable and verified procedure by which we can predict the spalling phenomenon. Furthermore, in contrast with many other phenomena in civil engineering, there are limited guidelines and provisions for predicting spalling.

To tackle the difficulties associated with spalling, taking advantage of current computational methods, including artificial intelligence (AI), machine learning, and big data, seems attractive enough to be applied in this project. The fundamental assumption herein is that capturing the correlation through a data-driven analysis could be possible rather than traditional methods[10].

Even though rigorous jobs have been carried out so far to apply AI in engineering, most of these works can be categorized as a black-box procedure (where we have final prediction and output without any insight into the whole process). As a result, we propose to use the logistic regression (LR) algorithm to predict spalling. LR models can demonstrate the correlation between input values and output features in different ways, some of which are graphs or nomograms.

In the current project, we map a path to discover a heuristic nomogram through LR to estimate the appropriate degree of predicting spalling phenomena. In this pursuit, 293 observations from the different tests were gathered and analyzed. Our findings show that predicting spalling through LR has high accuracy and can predict spalling through the model component.

2 DATA COLLECTION AND METHODOLOGY

For the current project, using data from[11], we collected 293 different data samples containing 11 different input variables (ratio of water to binder, ratio of silica-fume to binder, ratio of fly-ash to binder, ratio of GGBS to binder, ratio of fine aggregate to binder, ratio of coarse aggregate to binder, moisture content of concrete mixture, rate of heating per minute, maximum exposure temperature, the maximum size of aggregate, and the characteristic length) and one target variable (this output value categorized as Spalling/No-Spalling) to find a spalling occurrence in concrete sections as a function of different mixtures. Considering Table (1), one can see that the dataset has a balanced and healthy distribution range for identified variables.

Table 1: Concrete mixtures database with statistical features.

Parameters	Mean	Median	Standard Deviation	Range	Minimum	Maximum	Skewness
Water/binder (W/b)	0.371	0.33	0.124	0.42	0.19	0.61	0.4232712
Coarse aggregate/binder (ca/b)	1.733	1.77	0.900	3.95	0	3.95	0.1084053
Fine aggregate/binder ratio(fa/b)	1.658	1.51	0.653	2.93	0.45	3.38	0.7925641
Heating rate (°C/min)	28.55	5	42.028	239.75	0.25	240	1.7831517
Moisture content of concrete(M)	0.03132	0.04	0.020	0.07	0	0.07	-0.386714
Characteristic distance of the concrete (D)	61.91	50	37.606	180	20	200	2.0872133
Maximum exposure temperature (T-max °C)	568.2	600	246.201	1100	100	1200	0.2212357
Silica fume/binder(sf/b)	0.03297	0	0.062	0.207	0	0.207	1.6677876

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Maximum size of aggregate (Sa)	12.76	13	6.608	31.88	0.12	32	0.1848011
GGBS/binder (G/b)	0.04328	0	0.100	0.458	0	0.458	2.3875603
Fly ash/binder (F/b)	0.02272	0	0.071	0.546	0	0.546	3.4990225

2.1 Nomogram Development

The logistic regression is one the most used algorithm for classifying two different outputs, developed by David Cox[12], is used for developing the nomogram in this study. The LR algorithm uses the *Sigmoid function*. The suggested nomogram was created in the R programming language (version 4.1.2).

The following algebraic form is used to fit the spalling occurrence once the LR algorithm has been properly validated (Eq. 1). This illustration indicates that the occurrence of spalling is determined using the collected database's specified characteristics. A logistic, *Sigmoid* equation is then used to determine the likelihood that spalling will occur (Eq. 2). Equation 2 returns two distinct values, one for no spalling equal to zero and the other for spalling equal to one, respectively. To build the nomogram and determine the likelihood of spalling, the sigmoid function from the R Toolbox and the *rms* (regression modeling strategy) R package [13]are specially utilized.

$$Spalling \sim W/b + Ca/b + Fa/b + H + M + D + T + Sf/b + Sa + G/b + F/b \qquad \text{Eq. 1}$$

$$Propensity\ \text{of}\ Spalling = \frac{1}{1 + exp^{-(\beta 0 + \beta 1 X1 + \beta 2 X2 + \cdots)}} \qquad \text{Eq. 2}$$

Where β_0, β_1, etc., are coefficients[3] derived during the training process, and X_1, X_2, etc., are the features identified in our database (and those listed in Eq. 1).

3 FINDINGS AND DISCUSSION

3.1 Validation metrics

For the current project, the collected data set has passed the split procedure in which it has separated into train and test sets that start from 70% in the train set and corresponding 30% in the test set. For the validation assessment, test sets were used. Also, the confusion matrices, which encompass three main elements, are considered for data analysis, usually used for binary and multi-classification problems. The three metrics elements are 1- True Positive Rate (TPR) or Sensitivity or Recall (TP), 2- True Negative Rate (TNR) or Specificity, and 3- Accuracy (ACC). The metrics above define as 1- actual positive cases correctly identified, 2- actual negative cases correctly identified, and the assessment ratio of correct predictions to the total number of samples, respectively. All the metrics formulas are described hereunder[14].

$$\text{True Positive Rate (TPR) =Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \qquad (1)$$

$$\text{True Negative Rate (TNR) =Specificity} = \frac{\text{TN}}{\text{TN+FP}} \qquad (2)$$

$$\text{Accuracy (ACC)} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \qquad (3)$$

---

[3] *Spalling=-9.6005W/b+0.3444Ca/b+1.2066Fa/b+0.0089H+40.3826M+0.0224D+0.0070T+14.2181Sf/b-0.1055Sa+4.2498G/b+0.3490F/b-6.1001*

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3.2 Logistic regression result

R programming language (R version 4.1.2 (2021-11-01)) was used, and all the compiled, as well as the compiled dataset were then input into the R for analysis. Additionally, for data training, the logistic regression modeling algorithm adopted a data set formerly divided into train and test. Then, 10-fold cross-validation is used for the train set to avoid any biases stemming from data ordering. Lastly, confusion matrices were calculated to visualize the model performance in different sub-dataset from the original dataset.

At the beginning of the training procedure, the model accuracy was relatively poor (nearly 70%). Therefore, using the ML validation technique can enhance the model's accuracy and prevent overfitting. Also, 10-fold cross-validation was used to increase the data accuracy for the 70/30 ratio and boost the accuracy from 70% to 89%. For the same purpose of increasing data accuracy, the same procedure has been carried out three times to have a better result for 80/20 and 90/10 ratios. Lastly, for the 90/10 split ratio, 96.6% accuracy of the corresponding test set has been achieved, and its nomogram developed. As mentioned earlier, confusion matrices encompassed predicted and actual classes and explored the logistic regression model performance. Entries in diagonal and off-diagonal of these matrices indicate the model's true and false prediction of spalling phenomena. Confusion matrices on the test set based on maximum accuracy for three different split ratios are presented in Tables 2-4.

Table 2: confusion matrix for Spalling (Considering highest accuracy for 70/30 split ratio)

True classes	Predicted classes ('Positive' Class: not spalling)		True sum
	not spalling	spalling	
not spalling	31	7	38
spalling	2	49	51
Sum	33	56	89
Error (%)	0.06	0.12	0.1

Table 3: confusion matrix for Spalling (Considering highest accuracy for 80/20 split ratio)

True classes	Predicted classes ('Positive' Class: not spalling)		True sum
	not spalling	spalling	
not spalling	21	2	23
spalling	1	35	36
Sum	22	37	59
Error (%)	0.04	0.05	0.05

Table 4: confusion matrix for Spalling (Considering highest accuracy for 90/10 split ratio)

True classes	Predicted classes ('Positive' Class: not spalling)		True sum
	not spalling	spalling	
not spalling	10	0	10

spalling	1	19	20
Sum	11	19	30
Error (%)	0.09	0	0.03

The pooled results of different test-train ratio approaches are summarized in Table 5, including sensitivity (precision of model in predicting not spalling classes), and Specificity (precision of model in predicting spalling cases), and accuracy.

Table 5: Sensitivity, Specificity, and Accuracy for the three main test-train split (70%-80%-90% Train and 30%-20%-10%Test)

Performance measure results of LRM models for different split ratio			
Split ratio	Sensitivity	Specificity	Accuracy
70/30%(Train-Test)	0.9394	0.8750	0.8989
80/20%(Train-Test)	0.9545	0.9459	0.9492
90/10%(Train-Test)	0.9091	1.0000	0.9667

3.3 Variable Importance

The importance of variable for the 11-input variables was computed in this analysis. The result is summarized in Figure 1 to visualize the feature's importance. As can be seen, the four most significant variables are the maximum exposure temperature, water/binder ratio, heating rate, and moisture content of concrete correspondingly. On the contrary, the fly ash/binder ratio has the least significance in spalling occurrence, which means that it has the least interaction in any reaction regarding the increasing void pressure in concrete. Furthermore, to eliminate the multiplicity of independent variables, the top five significant variables chose and assigned to the logistic model to find the model with the least variable. The result shows that less than 5% differentiation exists between all and most significant variables, which can be ignored for simplicity in future studies.

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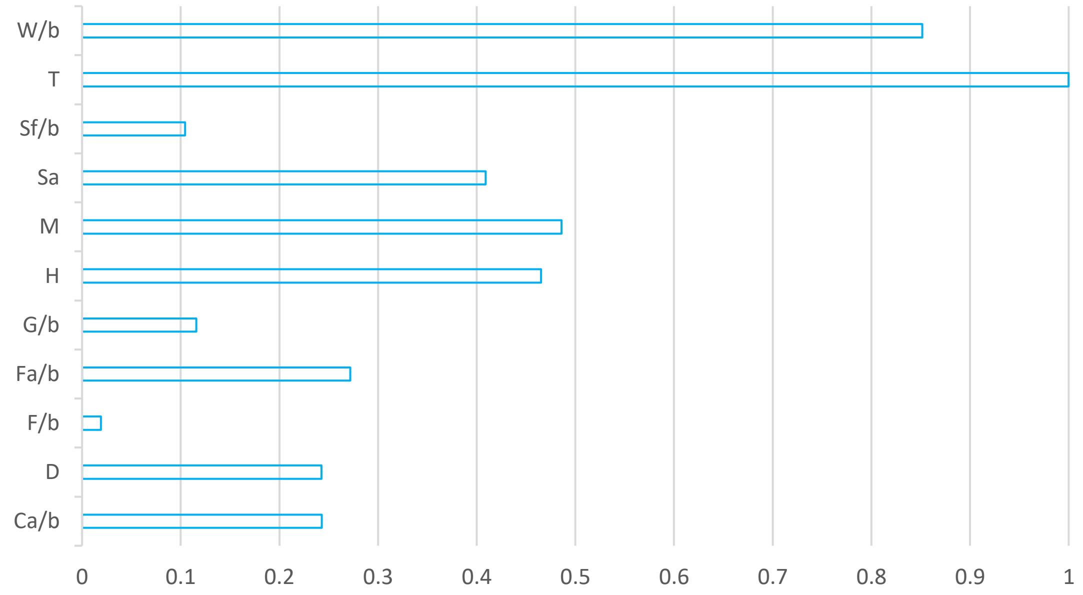

Figure 1: Feature Importance

3.4 Nomogram

Like the previous part, we begin by assessing the logistic regression model, which had an area under the curve metric of 92% and 100% in training and testing, respectively. Additionally, the model's sensitivity, Specificity, and accuracy scores were 0.910, 1.000, and 0.961, respectively; as the data shows, the model has excellent performance.

3.4.1 Development of Nomogram

In Fig. 2, the created nomogram is shown. Based on receiving a total amount of points, this nomogram determines a certain concrete mixture's propensity to spall based on its characteristics (ranging from 0-100). This total number of points is also used to calculate the likelihood of spalling, which is the arithmetical sum of the points allotted to independent features. As one can see, each feature must be scaled separately; hence the scale of the points associated with each feature must also be done correctly. This nomogram shows the possibility of spalling with varying degrees of confidence for concrete mixes with a total summation of numbers starting from 133 for the zero probability (no spalling) and 251 for the one probability(spalling).

Table 6, which includes a list of all the variables and their associated scaled points, is also a companion to the nomogram. As a result, rather than using the nomogram to discover points, a user can refer to Table 6 to determine whether the required concrete mixture will be spalled or not. Please refer to the Appendix for a complete solved example.

Table 6: Companion to the developed nomogram

Water-binder ratio	Points	Coarse aggregate/ binder ratio	Points	Fine aggregate/ binder ratio	Points	Heating rate	Points	Moisture content	Points	Characteristic distance of the concrete	Points
0.15	**62**	0	**0**	0	**0**	0	**1**	0	**0**	20	**0**
0.2	**56**	0.5	**2**	0.5	**8**	20	**2**	0.005	**3**	40	**6**

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0.25	**50**	1	**4**	1	**16**	40	**5**	0.01	**5**	60	**12**
0.3	**43**	1.5	**7**	1.5	**23**	60	**7**	0.015	**8**	80	**17**
0.35	**37**	2	**9**	2	**31**	80	**9**	0.02	**10**	100	**23**
0.4	**31**	2.5	**11**	2.5	**39**	100	**11**	0.025	**13**	120	**29**
0.45	**25**	3	**13**	3	**47**	120	**14**	0.03	**16**	140	**35**
0.5	**19**	3.5	**16**	3.5	**54**	140	**16**	0.035	**18**	160	**41**
0.55	**12**	4	**18**			160	**18**	0.04	**21**	180	**46**
0.6	**6**					180	**21**	0.045	**23**	200	**52**
0.65	**0**					200	**23**	0.05	**26**		
						220	**25**	0.055	**29**		
						240	**28**	0.06	**31**		
								0.065	**34**		
								0.07	**36**		

Table 6 (continued)

Maximum exposure temperature	points	Silica fume/binder ratio	Points	Maximum aggregate size	Points	GGBS/binder ratio	Points	Fly ash/binder ratio	Points	Total Points*	Probability of spalling occurrence
100	**0**	0	**0**	0	**48**	0	**0**	0	**0**	**133**	**0.01**
200	**9**	0.02	**4**	5	**41**	0.05	**3**	0.05	**0**	**178**	**0.25**
300	**18**	0.04	**7**	10	**34**	0.1	**5**	0.1	**0**	**192**	**0.5**
400	**27**	0.06	**11**	15	**27**	0.15	**8**	0.15	**1**	**206**	**0.75**
500	**36**	0.08	**15**	20	**20**	0.2	**11**	0.2	**1**	**251**	**0.99**
600	**45**	0.1	**18**	25	**14**	0.25	**14**	0.25	**1**		
700	**55**	0.12	**22**	30	**7**	0.3	**16**	0.3	**1**		
800	**64**	0.14	**26**	35	**0**	0.35	**19**	0.35	**2**		
900	**73**	0.16	**29**			0.4	**22**	0.4	**2**		
1000	**82**	0.18	**33**			0.45	**25**	0.45	**2**		
1100	**91**	0.2	**37**			0.5	**27**	0.5	**2**		
1200	**100**	0.22	**40**					0.55	**2**		

*The values of 192 is expected to spall.

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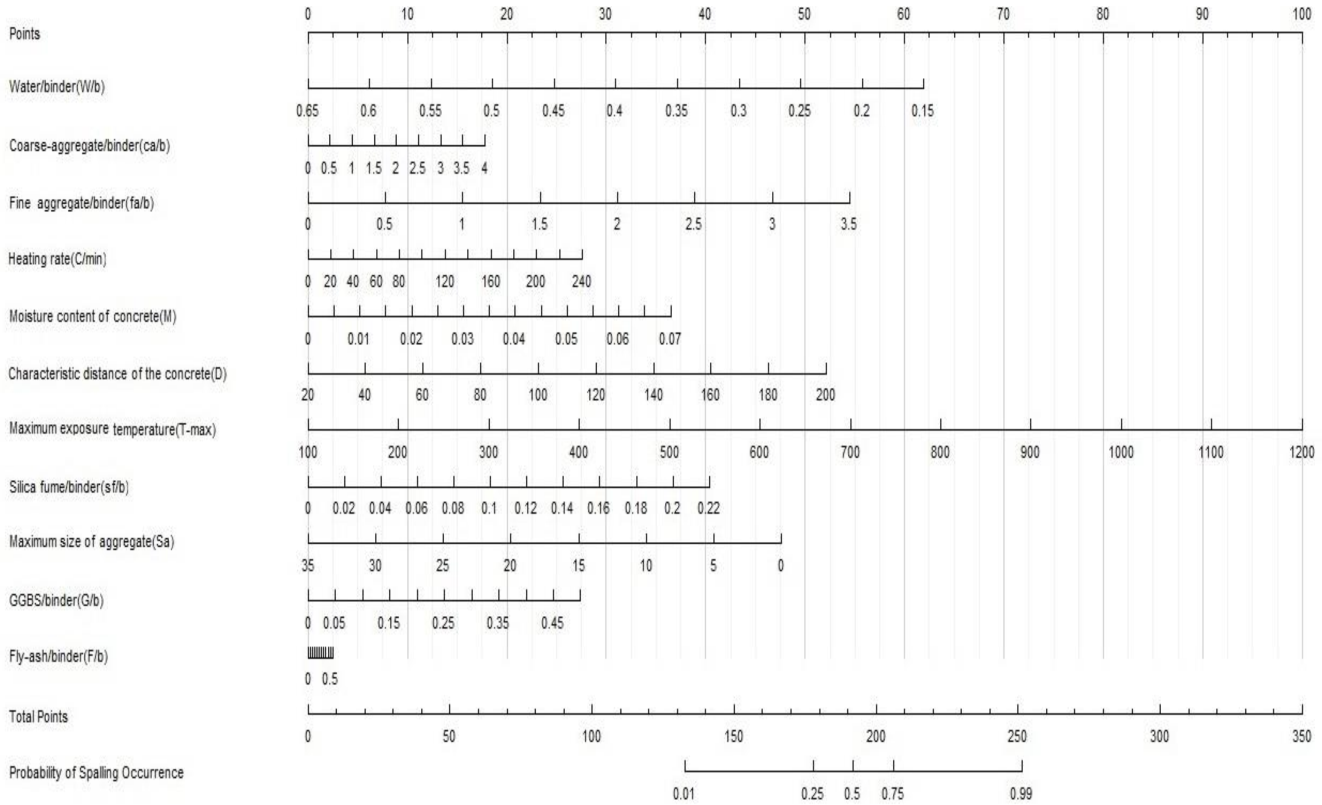

Figure 2: The developed nomogram for predicting spalling in concrete mixtures

4 CONCLUSION

Fire-induced spalling is a challenging issue. This study proposes the LR technique for developing a nomogram. A set of fire tests gathered from 293 observations was assembled and examined to build the suggested techniques. The analysis's conclusion demonstrates the simplicity and possibility of creating one-shot AI-based solutions for challenging structural fire engineering issues.

REFERENCES

1. Buchanan, A.H., Abu, A.K.: Fire Safety in Buildings. In: Structural Design for Fire Safety (2016)
2. Kodur, V., Naser, M.: Structural Fire Engineering. McGraw Hill Professional (2020)
3. al-Bashiti, M.K., Naser, M.Z.: Verifying domain knowledge and theories on Fire-induced spalling of concrete through eXplainable artificial intelligence. Constr. Build. Mater. 348, 128648 (2022). https://doi.org/10.1016/j.conbuildmat.2022.128648
4. Khoury, G.A.: Effect of fire on concrete and concrete structures, Prog. Struct. Eng. 2, 429–447 (2000). https://doi.org/10.1002/pse.51
5. Liu, J.-C.C., Tan, K.H., Yao, Y.: A new perspective on nature of fire-induced spalling in concrete, Constr. Build. Mater. 184, 581–590 (2018). https://doi.org/10.1016/j.conbuildmat.2018.06.204
6. Hertz, K.D.D.: Limits of spalling of fire-exposed concrete, Fire Saf. J. 38, 103–116 (2003). https://doi.org/10.1016/S0379-7112(02)00051-6
7. Kalifa, P., Menneteau, F., Quenard, D.: Spalling and pore pressure in HPC at high temperatures, Cem. Concr. Res (2000)

8. Jansson, R.: Fire spalling of concrete - A historical overview, in: MATEC Web Conf. 2013,. https://doi.org/10.1051/matecconf/20130601001
9. Hertz, K.D., Sørensen, L.S.: Test method for spalling of fire exposed concrete, Fire Saf. J (2005)
10. Naser, M.Z.: Mechanistically Informed Machine Learning and Artificial Intelligence in Fire Engineering and Sciences. Fire Technol. 1–44 (2021). https://doi.org/10.1007/s10694-020-01069-8
11. Tapeh, A.T.G., Naser, M.Z.: Discovering Graphical Heuristics on Fire-Induced Spalling of Concrete Through Explainable Artificial Intelligence. Fire Technol. 58, 2871–2898 (2022). https://doi.org/10.1007/s10694-022-01290-7
12. Cox, D.R.: The Regression Analysis of Binary Sequences, J. R. Stat. Soc. Ser. B (1959)
13. Regression, T., Strategies, M.: Package ' rms .' (2022)
14. Naser, M., Alavi, A. Insights into Performance Fitness and Error Metrics for Machine Learning. Under Rev. (2020)

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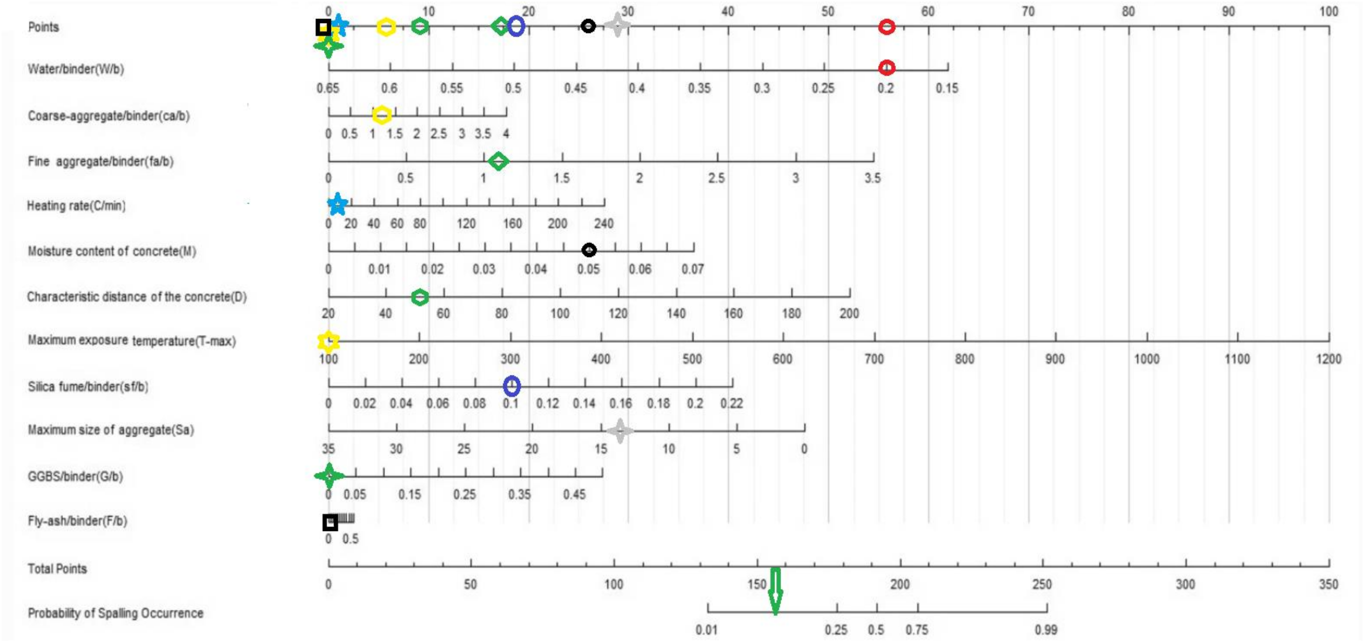
APPENDIX A

This section provides an illustration and step-by-step instructions for utilizing the Logistic-Nomogram to assess a typical concrete mixture's propensity to fire-induced spalling. In this investigation, the concrete piece has spalled and possesses the following characteristic:

Note: The problem's probability close to 0 will be considered as a not spalled model, and a probability close to 1 as a spalled model.

- W/b (water to binder) ratio =0.2
- Ca/b (Coarse aggregate to binder ratio) =1.28
- Fa/b (Fine aggregate to binder ratio) =1.11
- Heating rate Hr (°c/m) = 5
- Moisture content=0.05
- Characteristic length of specimen D(mm)=51
- Maximum exposure temperature T-max(°c) =100
- Silica fume/binder ratio=0.1
- Maximum aggregate size Sa(mm)=13
- GGBS/binder ratio=0
- Fly ash/binder ratio=0



The total score for all 11 independent variables is 159.5, which, when shown on the probability axes, has a rate of about 14%. (Spalling did not happen for the concrete mixture).

(Please help with the dot formatting for the Above figure to show the one-shot Nomogram application)

Using the complementary table, the same conclusion could have been reached.

Total points = 56+5.5+15+1.5+26+9+0+18+28+0+0 = 159.5 points < 192 and is about 14% then No-Spalling is expected.