Predicting Indicators of Design Quality for Cast-in-Place Reinforced Concrete Structures Using Logistic Regression

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Abstract –

This paper presents the application of the information contained in exchange standards to predict indicators of design quality for concrete-in-place reinforced concrete (CIP RC) structures early in the design process. A logistic regression model is applied to each node type of a frame structure: beam-column, slab-column, beam-slab, and beam-beam. All model results present the significance of the variable chosen, as well as the classification table with very high values of prediction accuracy. The results show how well the obtained models fit the data, and therefore may be used to estimate potential construction issues early in the process, based on the parameters of the design intent standard exchanges.

Keywords –

Design computing; Reinforced Concrete; Constructability; Logistic regression

1 Introduction

While there have been multiple studies around the evaluation of design indicators, [1] performed a comprehensive research and categorization effort of most of those available. Using three categories: functionality, build quality and impact, they identified multiple performance indicators of what potentially constitutes a good design, including layout, lighting and ventilation, energy, structural elements, building stability, comfort, and many others. The category that relates the most to the structure of the building from a design and construction standpoint is “Build Quality”. However, these indicators were mostly developed to evaluate the performance of a design after it has been completed, and do not consider the valuable information available during design, particularly the one contained in intermediate model exchanges done during the design process. Regarding the category of build quality, research performed around the efforts of design professionals to purse enhanced effectiveness of their designs during construction, found that most design professionals consider that constructability is a key indicator of the quality of the finished product or building [2].

The concept of “Constructability” or “Buildability” refers to the application of construction knowledge during the planning and design phases to make the construction process more efficient, practical, or sometimes even realistic [3]. This concept has been around for several years, and while the focus has changed through time, a review on the previous, current and future research done around it found that its application today is as important as ever for reasons including increased project complexities, great amount of ambiguous information, new relationships between stakeholders, and increased use of powerful methods and software tools [4]. Constructability can be approached from several angles, and pursue different benefits, including costs, time, labor, efficiency, and others. [5] grouped in seven themes the Construction Industry Institute constructability principles, and conducted a survey to estimate the potential and realized value of each of these groups. The group considering principles about designs that facilitate construction efficiency was ranked amongst the three with the highest potential value, which shows how much industry professionals value the positive impact that informed design decisions may have on the efficiency of the construction process.

Constructability is particularly important for Cast-in-Place Reinforced Concrete (CIP RC) buildings, because as a process that is very labor-intensive, it can benefit greatly from considerations taken during design that lead to a more efficient construction process [6]. [7] developed a constructability adviser system based on an object-oriented enriched CAD tool (a predecessor of BIM tools), to provide constructability feedback for CIP RC structures using criteria such as layout, dimensioning and construction methods. The paper identified two levels of reasoning when performing constructability analyses: reasoning about attributes of objects, and reasoning about relationships between attributes of objects. Although the research focused mostly on elements’ dimensioning and forming methods due to their high impact on the costs, it identifies the most important preliminary design variables that may be constrained or considered for constructability analyses: dimensions of elements, distance between elements, changes in dimensions and distances, concrete strength, quantity and type of reinforcement, and modularity. Out of these, the dimensions of elements and the quantity and type of reinforcement are applicable and relevant if the design intent and construction planning standards want to be used for analysis.

Section 2 of this paper presents a literature review of design indicators and constructability. Section 3 describes the research methodology used, including the data types, the development of the training database, and the development and results of the logistic regression model. Finally, section 4 presents the study conclusions.

2 Literature Review

Most of the research CIP-BIM oriented has focused on the reinforcement optimization of the elements using BIM models as noted in [8], on the assessment and recommendations of BIM capabilities to handle the concrete reinforcement supply chain [9], [10] and on defining the unique requirements CIP RC has regarding its modeling and processes on BIM [11]. In the assessments performed for the BIM capabilities of current tools, from the evaluated categories of design and modeling, editing, project management and interoperability, interoperability proved to be the weakest because of the lack of a standardized way to document and translate the information [9]. Nevertheless, these assessments were performed before the release of the latest ACI 131 documents which propose a standard way to exchange concrete reinforcement information [12]. Furthermore, although in reality CIP RC is monolithic, during the modeling it has to be broken down into members, which means that the delineation between such members is conceptual and not physical. There has also been research focused on reinforcement bars, particularly related to the impact of design on rebar productivity [13], and on optimizing cost by integrating rebar design and construction [14], [15].

Previous research [16], [17] shows that constructability of the design can be seen as a good quality indicator for CIP RC design and planning, particularly because it can use the information available during design intent and construction planning model exchanges, to contribute to efficiently achieve the intent during construction. Since the information about connectivity, dimensions and design intent reinforcement is something that is now available as part of the exchange models in a standard way, the congestion of the reinforcement, particularly in the areas between interacting elements, appears as an excellent alternative to measure the constructability of the design and planning, and to use as an indicator to develop predictions on potential future issues the design may encounter once it reaches more detailed stages. Current design tools allow the engineer to use the design intent to perform reasoning about attributes of objects as shown in blue in Figure 1 (such as a column, or a beam), but do not typically perform reasoning about relationships between attributes of objects such as the ones shown in yellow and red (beam-column or beam-slab interactions for instance). These are types of analyses that could be performed now that the design intent is available as part of a BIM model that holds the information about objects' connectivity and interacting volumes.

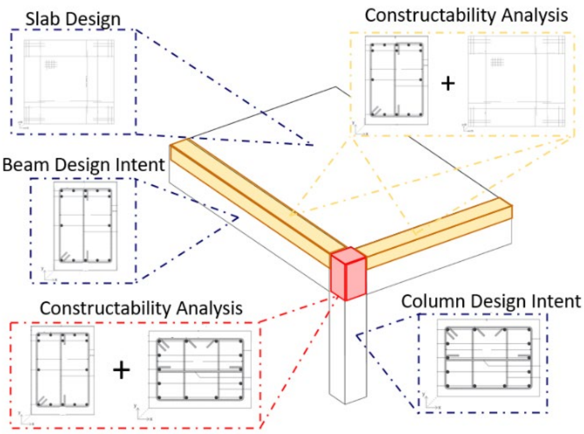


Figure 1. Types of design intent constructability analysis

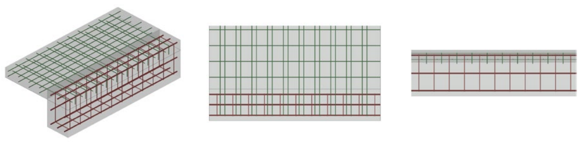
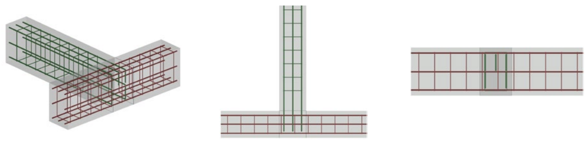
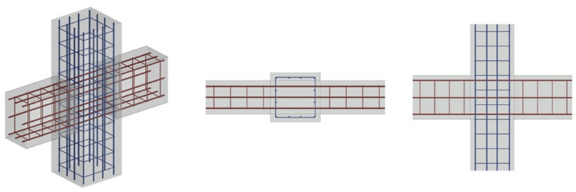
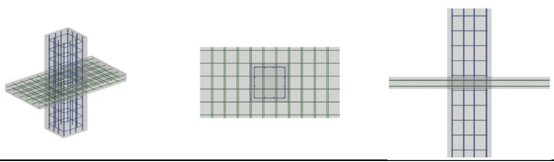
Since the steel reinforcement ratio is typically a design decision based on code requirements and load demands, it is not a variable that can be modified for enhanced constructability. However, the way the steel ratio is achieved through the selection of diameter of bars, number of bars and bar separation is something more easily modifiable that has a direct impact on constructability; the use of fewer bars for a same ratio would derive in arrangements of larger diameters and spacings, thus reducing congestion and making the number of bars per volume of concrete a good estimator of congestion [18]. Therefore, the design indicator selected, "Constructability", will be estimated in terms of congestion as done by [18]. To create an estimating method applicable to several types of occurrences (element interaction types) with varying concrete element dimensions and steel distribution, the number of bars alone is not enough. Consequently, a similar concept to the steel volumetric ratio is proposed as the independent variable but using the number of bars per volume of concrete, thus accounting for most of the parameters aforementioned.

3 Research Methodology

A logistic regression model is developed, allowing the use of rich data contained within the exchange standards to estimate design indicators that inform the design and coordination processes of potential design issues during the exchanges. The focus of this application consists of identifying indicators that could be estimated from typical parameters available in the exchange files, create a database to train the model, and use it to inform the design process early on about issues that may arise during further phases of the project.

The study considers the intersections of pairs of elements for framed structures, including beams, columns, and slabs. The specific interactions considered are beam-column, beam-slab, beam-beam, and column-slab, and are shown in Table 1.

Table 1. 3D Visualization of Intersection Cases

3D view	Top View	Side View
Beam – Slab Intersection		
		
Beam – Beam Intersection		
		
Column - Beam Intersection		
		
Column - Slab Intersection		
		

The beam-slab interaction considers all the beam longitudinal and transversal reinforcement, up to the thickness of the slab, plus the slab reinforcement that enters and anchors in the beam. The beam-beam interaction considers all the mean beam longitudinal and transversal reinforcement, up to the heigh of the secondary beam, plus the secondary beam longitudinal reinforcement that enters and anchors in the main beam. The column-beam interaction considers all the column reinforcement, plus the beam longitudinal reinforcement that continues through the column. The column-slab interaction considers all the reinforcement of both elements. The same method considered for slabs could be easily extrapolated to footings and pile caps, since the reinforcement distribution is not that different between these elements. The properties required to estimate the congestion of the intersection are the number of bars each element contributes, and the volume of the intersection itself. As shown in the simplified data structure on Figure 2, the number of bars is derived from the design intent property set containing the design intent reinforcement information, and the volume intersection is derived from the geometric representation of the elements.

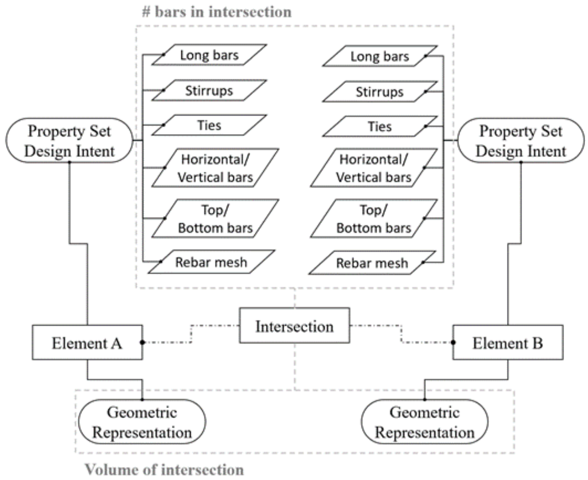


Figure 2. Data structure of parameters required for indicator estimation

These properties could be easily extracted from an IFC file because of the way they have been standardized as proposed and aligned with ACI efforts. Different types of elements will have some of the properties listed that contribute to the number of bars (for example, slabs will have top and bottom bars and rebar mesh, while beams will have longitudinal bars, stirrups and ties). The following sections provide the detail of what reinforcement and parameters are considered for each type of intersection to estimate the indicator.

3.1 Training Database

The first step to generate the database was to define a representative number of reinforcement distributions for each element. Three beam sections were considered: small, medium, and large. For each of these sections, several options were generated varying the top and bottom reinforcement ratio (in one and two lines), the stirrup spacing, and the number of vertical legs. Combinations of these parameters were based on typical occurrences in practice, for example: stirrup spacings will typically be smaller where top reinforcement ratios are higher, which is near the supports. For each ratio, two alternatives were proposed: more smaller bars, or fewer bigger bars. This is a concept directly related to constructability: several times it will be more constructible to use fewer bigger bars that allow more spacing and lead to less congestion. Table 2 shows the three slab thicknesses considered: small, medium, and large. For each of these sections, several options were generated varying the top and bottom reinforcement ratios (assumed equal in both directions). Combinations of these parameters were based on typical occurrences in practice. For each ratio, two alternatives were proposed: more smaller bars, or fewer bigger bars.

A similar approach was followed for beams, where three typical section sizes were considered, each with three top and three bottom reinforcement ratios (minimum, average, and maximum), each with three to four typical stirrup spacings for the section, and each with one to two number of legs, for a total of 64 combinations (beams). For columns, three typical section sizes were considered, each with three reinforcement ratios (minimum, average, and maximum), each with three typical stirrup spacings for the section, and each with one to three number of tie legs, for a total of 54 combinations (columns). See Table 2. The combinations of the parameters were based on typical occurrences in practice, for example higher number of legs for higher reinforcement ratios on columns, or smaller stirrup spacings for higher top reinforcement ratios on beams.

Table 2. Representative Slab Sections and Parameters for Database

Slabs			Beams						Columns				
Thick	ρ (%)	# of slabs	Section	Top ρ (%)	Bott. ρ (%)	Stirrup space	Vert. legs	# of beams	Section	ρ (%)	Tie space	Tie legs	# of col.
4”	0.5	9	8”x12”	0.5	0.5	3”	2	16	12”x12”	1.5	2”	2	18
	1.0			1.0	1.0	6”				5.0	4”		
	1.5			2.0	2.0	12”				8.0	6”		
6”	0.5	9	16”x24”	0.5	0.5	3”	3	24	18”x18”	1.5	2”	2	18
	1.0			1.0	1.0	6”	3			5.0	4”	3	
	1.5			2.0	2.0	12”	4			8.0	6”	4	
						24”							
8”	0.5	9	24”x36”	0.5	0.5	3”		24	24”x24”	1.5	3”	3	18
	1.0			1.0	1.0	6”	4			5.0	6”	4	
	1.5			2.0	2.0	12”	5			8.0	12”	5	
						24”							

Afterwards, logical occurrences of intersections of these elements were created. If, for example, the 8”x12” beam section was combined with the 12”x12” column section, this generated 16 x 18 = 288 possible interactions. Some combinations were not considered because they would not normally occur in practice, such as a 24”x24” column with a 4” slab. Once the database was built, the value of congestion as defined previously (number of bars in the intersection divided by the concrete volume of the intersection) was calculated for each of the interactions, using the parameters and relationships illustrated in Figure 2. Since these points will constitute the base to build the model, it is necessary to identify whether or not each of them is considered to have or not constructability issues.

A value of 1 is assigned to those occurrences with constructability issues, while a value of 0 is assigned to those without constructability issues. Table 3 presents the total number of interactions evaluated, the number of interactions considered to have constructability issues per criteria, and number of interactions without issues. The next sections explain in detail the three criteria used to determine whether each of these interactions was constructible or not.

Table 3. Database interactions classification

Interaction	Total Inter-actions	Interactions with Constructability Issues				Interactions without Issues
		Smin Criteria	ρ min Criteria	Visual Criteria	Total	
Beam-Col	2,736	144	120	208	336	2,400
Col-Slab	1,134	150	0	333	414	720
Beam-Slab	1,440	164	54	75	245	895
Beam-Beam	2,752	128	0	224	322	2,430

3.1.1 Minimum Separation (Smin)

This criterion evaluated for each of the interactions that the reinforcement could physically and logically fit within the node, by ensuring minimum spacing was provided in critical cases. For the beam-column interaction, it was evaluated whether the longitudinal beam reinforcement could fit through the column reinforcement and ties, with a 1/8” tolerance. For the column-slab interaction, it was evaluated whether the slab reinforcement could fit through the column reinforcement and ties, with a 1/8” tolerance. For the beam-slab interaction it was evaluated whether the spacing between beam stirrups and anchoring slab reinforcement was at least 1”, to allow the concrete to be placed and the largest size of aggregate to pass. For the beam-beam interaction, it was evaluated if the secondary beam anchoring reinforcement would fit through the main beam reinforcement and stirrups, with a 1/8” tolerance. Any interaction that did not satisfy these conditions, was assigned a value of 1, thus classifying it as an interaction with potential constructability issues.

3.1.2 Maximum Volumetric ratio (ρmin)

This criterion was based on the ACI maximum ratio for column reinforcement. The ACI sets a maximum 8% steel ratio reinforcement in columns for longitudinal rebars mainly because above this number they consider the element to be hardly constructible [19]. If this limit is added to the maximum shear reinforcement caused by the minimum allowed separation, a value between 16% to 20% is obtained. Therefore, any intersection with a volumetric steel ratio greater than 16%, was assigned a value of 1, thus dimming it as an intersection with potential constructability issues.

3.1.3 Visual/Manual Inspection

Finally, the remaining intersections were visually inspected to determine whether the node or edge would present constructability issues based on the number of bars. It was found that intersections tend to present constructability issues at numbers greater than 60 bars per cubic feet. These intersections found to have potential constructability issues were assigned a value of 1.

3.2 Design Indicator Estimating Model

The model selected was logistic regression, because it fits the goal of the study: to estimate whether there will be an issue or not with an indicator based on parameters obtained from the standardized exchange models. More specifically, to estimate the probability that for a certain type of intersection, there will be a constructability issue based on the design intent. The procedure finds the best fitting curve by transforming the y-axis, odds of congestion, to a transformed logarithm log(odds of congestion / (1 – odds of congestion)). This new axis now goes from -infinity to +infinity, with all the data, previously lying at 1 or 0, now lying at +infinity and -infinity. Then a line is fit to this data, and its coefficients are determined based on a linear model using the transformed y-axis. To transform the line from the transformed y-axis to the initial y-axis, the transformation y= e^log(odds)/1+e^log(odds) is used. After this transformation, the line becomes an s-shaped curve. To find the best fitting line, the method uses the concept of maximum likelihood. The procedure projects the original data points (located at – and + infinity) onto the candidate line, and is then transformed to the original axis. The likelihood of the line is the sum of the probabilities of the points after being projected onto the curve and transformed to the original axis. This line is rotated multiple times recording its likelihood, after which the best fitting line is obtained by selecting the model with the highest likelihood. Finally, since this is a classification problem (1 or 0), a threshold value, typically 0.5, is used to classify a new point as 1, congested, or 0, not congested. Based on this threshold value a weighted accuracy is calculated, which indicates the accuracy of the model to predict the points in the database as they were defined.

3.2.1 Beam-Slab Model

Figure 3 shows the logistic regression model for the beam-slab intersection.

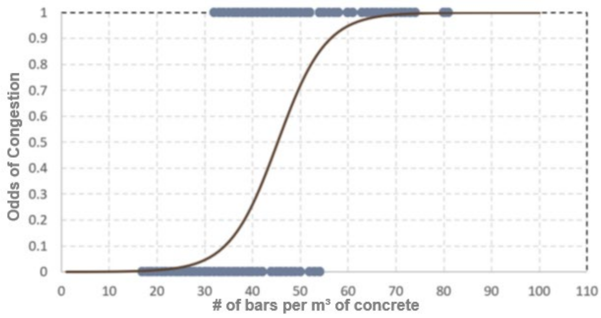


Figure 3. Logistic regression model for beam-slab intersection

The coefficients of the regression are shown in Table 4, along with the standard error, the Wald number (a measurement of the precision of the estimate), and the p-value.

Table 4. Regression Coefficients for Beam-Slab Intersection Model

	# Iter		20		Alpha		0.05
	coeff	*s.e.*	*Wald*	*p-value*	*exp(b)*	*lower*	*upper*
intercept	-9.001	0.486	342.367	0.000	0.000		
var 1	0.199	0.012	283.554	0.000	1.220	1.192	1.249

These values show that the variable chosen (number of bars per CF of concrete at the intersection) is statistically significant for this model. Equation 1 describes the model (best fitted curve), and can be used to calculate the probability of congestion, PC, based on the number of bars per cubic feet at the intersection, n. In other words, this model allows to estimate the probability that the intersection will present a constructability issue, which is the selected indicator.

$$\boldsymbol{PC(n)} = \frac{e^{(-9.001\,+\,0.199n)}}{1+e^{(-9.001\,+\,0.199n)}} \tag{1}$$

Table 5 shows the classification table for the model, based on a cutoff value of 0.5. This value is the threshold value, above which points are classified a success, or with constructability issues, and below which points are classified a failure, or without constructability issues. The values shown correspond to a typical cutoff value of 0.5 or 50%. The weighted accuracy of the model at predicting success and failure is 88%, which is a good indicator of how well the model fits the behavior of the data.

Table 5. Classification Table for Beam-Slab Intersection Model

	Obs Succ	Obs Fail	Total
Pred Succ	180	72	252
Pred Fail	108	1080	1188
Total	288	1152	1440
Accuracy	63%	94%	88%
Cutoff	0.5		
AUC	0.944		

3.2.2 Beam-Column Model

Figure 4 shows the logistic regression model for the beam-column intersection.

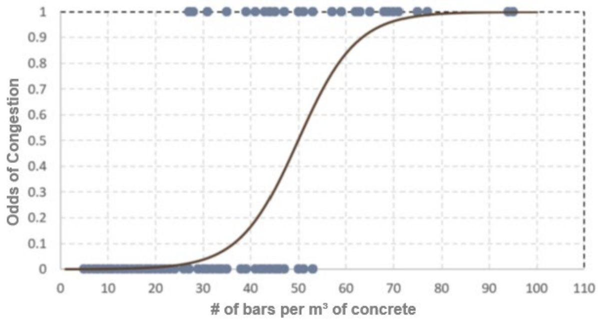


Figure 4. Logistic regression model for beam-column intersection

The coefficients of the regression are shown in Table 6, along with the standard error, the Wald number, and the p-value.

Table 6. Regression Coefficients for Beam-Column Intersection Model

	# Iter		50		Alpha	0.05	
	coeff	*s.e.*	*Wald*	*p-value*	*exp(b)*	*lower*	*upper*
intercept	-8.163	0.391	435.032	0.000	0.000		
var 1	0.164	0.008	381.940	0.000	1.178	1.159	1.197

These values show that the variable chosen (number of bars per CF of concrete at the intersection) is statistically significant for this model. Equation 2 describes the model (best fitted curve), and can be used to calculate the probability of congestion, PC, based on the number of bars per cubic feet at the intersection, n. In other words, this model allows to estimate the probability that the intersection will present a constructability issue, which is the selected indicator.

$$\boldsymbol{PC(n)} = \frac{e^{-8.163 + 0.164n}}{1+e^{-8.163 + 0.164n}} \tag{2}$$

Table 7 shows the classification table for the model, based on a cutoff value of 0.5. The weighted accuracy of the model at predicting success and failure is 94%, which is a good indicator of how well the model fits the behavior of the data.

Table 7. Classification Table for Beam-Column Intersection Model

	Obs Succ	Obs Fail	Total
Pred Succ	252	84	336
Pred Fail	84	2316	2400
Total	336	2400	2736
Accuracy	75%	97%	94%
Cutoff	0.5		
AUC	0.977		

3.2.3 Column-Slab Model

Figure 5 shows the logistic regression model for the column-slab intersection.

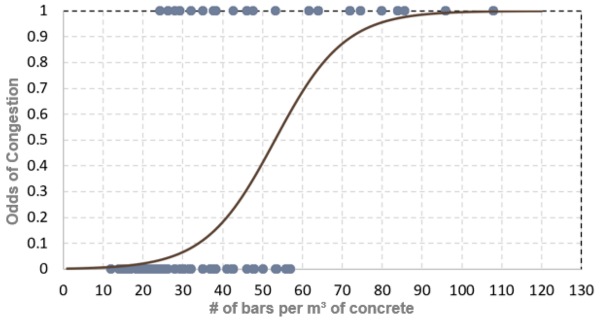


Figure 5. Logistic regression model for column-slab intersection

The coefficients of the regression are shown in Table 8, along with the standard error, the Wald number, and the p-value.

Table 8. Regression Coefficients for Column-Slab Intersection Model

	# Iter		20		Alpha	0.05	
	coeff	*s.e.*	*Wald*	*p-value*	*exp(b)*	*lower*	*upper*
intercept	-6.094	0.329	342.209	0.000	0.002		
var 1	0.115	0.006	318.458	0.000	1.122	1.107	1.136

These values show that the variable chosen is again statistically significant for this model. Equation 3 describes the model for this intersection type and can be used to calculate the probability that the intersection will present a constructability issue.

$$\boldsymbol{PC(n)} = \frac{e^{-6.094 + 0.115n}}{1+e^{-6.094 + 0.115n}} \tag{3}$$

Table 9 shows the classification table for the model, based on a cutoff value of 0.5. The weighted accuracy of the model at predicting success and failure is 94%, which is a good indicator of how well the model fits the behavior of the data.

Table 9. Classification Table for Column-Slab Intersection Model

	Obs Succ	Obs Fail	Total
Pred Succ	340	83	423
Pred Fail	74	637	711
Total	414	720	1134
Accuracy	82%	88%	86%
Cutoff	0.5		
AUC	0.938		

3.2.4 Beam-Beam Model

Figure 6 shows the logistic regression model for the beam-beam intersection.

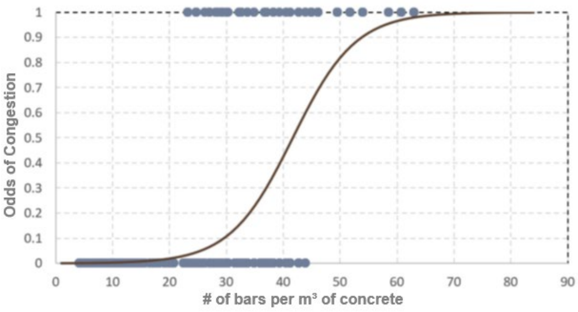


Figure 6. Logistic regression model for beam-beam intersection

The coefficients of the regression are shown in Table 10, along with the standard error, the Wald number, and the p-value.

Table 10. Regression Coefficients for Beam-Beam Intersection Model

	# Iter	20		Alpha	0.05		
	coeff	*s.e.*	*Wald*	*p-value*	*exp(b)*	*lower*	*upper*
intercept	-7.587	0.339	501.575	0.000	0.001		
var 1	0.182	0.009	417.556	0.000	1.200	1.179	1.221

These values show that the variable chosen is again statistically significant for this model. Equation 4 describes the model for this intersection type and can be used to calculate the probability that the intersection will present a constructability issue.

$$\boldsymbol{PC(n)} = \frac{e^{-6.094\,+\,0.115n}}{1+e^{-6.094\,+\,0.115n}} \tag{4}$$

Table 11 shows the classification table for the model, based on a cutoff value of 0.5. The weighted accuracy of the model at predicting success and failure is 94%, which is a good indicator of how well the model fits the behavior of the data.

Table 11. Classification Table for Column-Slab Intersection Model

	Obs Succ	Obs Fail	Total
Pred Succ	230	42	272
Pred Fail	92	2388	2480
Total	322	2430	2752
Accuracy	71%	98%	95%
Cutoff	0.5		
AUC	0.960		

4 Conclusions

This paper presented the application of the information contained in the exchange standards to predict indicators of design quality for CIP RC structures early in the design process.

The paper started with a review of applicable design indicators for CIP RC related to the design intent and construction planning communication. Based on the review, constructability was found to be a good indicator of design quality, given that it relates the design result to how efficient is it to achieve it during construction and ensure the good performance of the structure as specified by the design.

To measure the constructability the parameter of congestion was proposed, given that more congested nodes tend to be harder to fabricate and place. Congestion is defined as the number of bars in the node per unit of volume of the node. This parameter can be calculated based on the parameters and properties shared during the design intent and construction planning exchanges. Afterwards, a database of representative beams, columns and slabs was generated to train the predictive algorithm. For each node in the database, geometric, volumetric, and engineering criteria were used to define whether the node was likely to have issues with construction, which constitutes a binary classification model.

Finally, a logistic regression model was applied to each node type of a frame structure: beam-column, slab-column, beam-slab, and beam-beam. All model results presented the significance of the variable chosen, as well as the classification table with very high values of prediction accuracy. The results obtained show how well the obtained models fit the data, and therefore may be used to estimate potential construction issues early in the process, based on the parameters of the design intent standard exchanges.

Future work involves the development and inclusion of further exchange models used in other parts of the CIP RC supply chain. The methodology can also be applied to other projects and CIP RC structures in order to extend the reach of the findings and develop more comprehensive implementation methods, and size-base estimations of the value of implementation. The methods are easily extensible to other tools and platforms, since they are developed with a generic approach and only the testing is done using specific tools. Furthermore, these methods may be adapted to other contexts, such as countries where BIM implementation has not been as advanced as it has in companies with heavy IT capabilities; or CIP RC bridges, where the development of standards poses other challenges and requirements. The model for prediction of constructability issues may be extended to include more CIP RC element interactions, and further refined as it is used in practice and more data becomes available.

5 References

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