PREDICTING THE EXPECTED SERVICE LEVEL AND THE REALISTIC LEAD TIME OF RFI PROCESS USING BINARY LOGISTIC REGRESSION

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This research describes an investigation into the development of predictive Request-For-Information (RFI) performance models, particularly to aid contractors and owners in predicting the expected service level of RFIs and establishing realistic review times. Two quantitative models have been developed and are discussed. Four input variables were developed and employed to construct binary regression logistic models. Results show large discrepancies on average between the contractor-want-time and actual lead time and between the expected CWT and realistic lead time to achieve a particular desired service level. Contractors can use the model to predict the service level for more reliable planning. Owners in turn can use the model to verify the expected RFI process time and to gain a valuable internal benchmark for process improvement. With higher awareness of the possible outcomes of a project and how likely each is to occur, project teams can better determine which options amongst those available are likely to yield the most favourable results.

Keywords: actual lead time, binary logistic regression, contractor-want-time, on-time rate, risk.

INTRODUCTION

As the complexity of a project increases, the likelihood of encountering problems – errors, conflicts, omissions, and ambiguities – and the degree of risk also increase (Zack 1999). One of the essential tools available to reduce risk in the construction industry is the Request For Information (RFI), a formal question or clarification that is submitted to the A/E firm by the contractor regarding details in the plans, drawings or specifications. Any delay in the reviewer's (A/E/ firm) response to an RFI can result in the contractor's delay, consequently resulting in a delay in the project as a whole. Despite the importance of expedient RFI processing, its function and significance have been underestimated in current practice. The RFI process requires information transfer and processing amongst many members of a project team (i.e., subcontractor, contractor, architect and consultant engineer) and is a standard requirement of AIA (American Institute of Architects) contracts. Because most projects in the United States are governed by AIA contracts, the purpose and process for RFIs are well defined as following: "…Before starting each portion of the Work, the Contractor shall carefully study and compare the various Drawings and other Contract Documents relative to that portion of the Work, as well as the information furnished

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by the Owner... These obligations are for the purpose of facilitating construction by the Contractor and are not for the purpose of discovering error, omissions, or inconsistencies in the Contract Documents; however, any errors, inconsistencies or omissions discovered by the Contractor shall be reported promptly to the Architect as a Request for Information in such form as the Architect may require" (AIA 1987). However, it is a common practice for contractors to use the RFI process in a more limited way as a means of discovering design defects and pursuing a claim strategy (Zack 1999). By using RFIs in this way, a contractor is able to assert the claim that the project was not fully designed.

In general, both parties (contractor and owner) agree on a minimum RFI review time before starting a project but the minimum review time is usually determined based on their past experiences. As the findings show, the agreed-upon minimum review time is typically unrealistically short, often rendering the reviewer incapable of meeting the contractor's expectation. As a result, the owner is at risk of encountering legal claims resulting from the late start of tasks caused by late RFI responses while the contractor runs the risk of not completing its job on time. However, another risk to the owner can be introduced by the contractor's abuse of RFI process time. Contractors can intentionally submit their RFIs as late as possible and the owner has no method of proving this late submittal was the contractor's fault. This gives rise to a need for an effective predictive model for expected service levels and realistic lead times.

The first author conducted observations on RFI processing from several projects in different regions in the United States and noted that the on-time rate of RFI process was very low on average (about 50%) and the average response time (lead time) was considerably longer than the contractors typically expected. The individual project selected for this research involves an eight-story college laboratory building located in California in the United States.

One limitation in conducting this research was data availability. Data were available only at the sign in/off dates. The contractor stamps "Date Create" and "Date Answered" on each RFI when RFIs are created and when the responses are received by contractors. As such, these were the only data points the authors could track. Figure 1 represents the RFI review process flow and available data points.

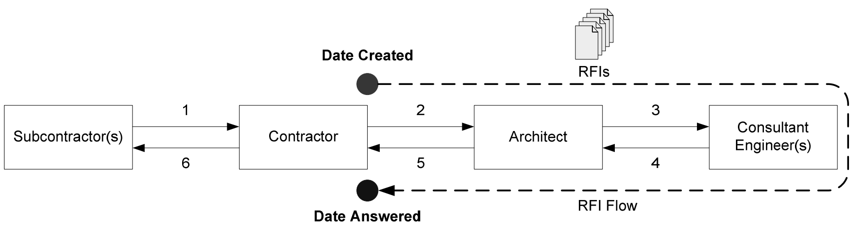

Figure 2: RFI Review Flow Diagram and Available Data Points

In addition, in developing input variables for the binary logistic regression study, rather than exploring all the possible factors, the authors selected only four variables – contractor-want-time (CWT), actual lead time (LT), reasons for RFI and building elements – due to the limitations of data availability. Hence, this research paper describes and summarizes the findings of an investigation into the development of predictive RFI performance models.

CURRENT SERVICE LEVEL

The data set for the research consists of 574 RFIs generated over approximately a seven month period, averaging a daily rate of roughly three RFIs. It is interesting to note that the dates when the contractor expected to receive the responses from the reviewer fell mostly into two time periods – 7 days or 14 days (56% and 28% respectively). The service level of products or services which are activated in response to a customer's requests can be measured as a percentage of jobs that are completed on or before (i.e., within) the time when the customer expects to receive what they requested. These types of products and services are generally assembled, built, fabricated, customized, reviewed or engineered in response to customer's requests (Hill 2002). We can simply measure the service level by calculating the percentage of RFIs that are completed within Contractor-Want-Time (CWT). The data shows that only 274 out of 574 RFIs (48%) were responded to without delay. Table 1 shows the corresponding service levels to each CWT.

Table 1: Service levels of different CWT

CWT (days)	0	1	2	3	4	5	6	7	8	10	11	13	14	16	37	Total
# of RFIs responded within time	2	2	6	6	3	8	4	143	5	1	1	0	92	0	1	274
# of RFIs responded late	5	4	10	2	8	10	7	179	6	0	0	1	67	1	0	300
Total # of RFIs	7	6	16	8	11	18	11	322	11	1	1	1	159	1	1	574
Service Level (%)	29	33	38	75	27	44	36	44	45	100	100	0	58	0	100	48

Figure 2 shows the ranges of actual lead times corresponding to each CWT, indicating that the actual lead times for each CWT varied greatly. For example, actual lead times corresponding to CWTs of 7 days ranged from 1 day to 93 days.

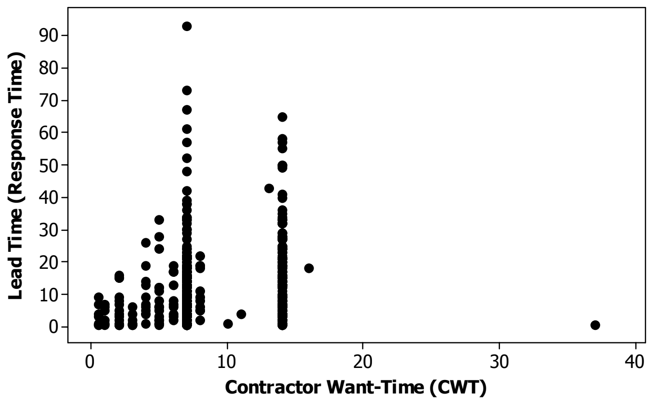

Figure 3: CWT vs. Actual Lead Time

The actual lead time (LT) can be influenced by many factors – reasons for RFI, building elements to be reviewed, the amount of information required for review, quality of contract documents (e.g., drawings and specification), quality of RFI, efficiency of the document control system, the working relationship between contractors and reviewers and so forth. This research, however, considers only the first two of these factors for which data is available: reasons for RFI, and building elements to be reviewed. In order to determine whether variables CWT and LT are correlated, the Pearson correlation test and the fitted line plot were conducted.

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Pearson correlation of Lead Time and CWT = 0.167
P-Value = 0.000

The regression equation is
Lead Time = 7.595 + 0.5107*CWT

S = 11.6768   R-Sq = 2.8%   R-Sq(adj) = 2.6%
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Since the p-value is less than 0.05, it appears that there is a statistically significant relationship between CWT and LT at a 95% confidence level. However, the R-Squared statistic indicates that the model as fitted explains just 2.8% of the variability in Lead Time. Hence, the correlation coefficient 0.167 with small R-Square value indicates a relatively weak relationship between the variables. This is because the determination of the "CWT" was not dependent on the LT required for the reviewers to respond to the RFIs, but on contractor's on-demand expectation.

STRATIFICATION OF RFI DATA

If a sample is formed by combining units from several lots having different properties, the sample distribution will show a concentration or clumping about the mean value for each lot: this is called stratification. In other words, stratification is a way of looking at data in multiple layers of information such as what (types, complaints, etc.), when (month, day, year, etc.), where (region, city, state, etc.), and who (department, individual) (Hill 2002). With the given data set, each RFI was stratified into 5 subgroups as to the "Reasons" for RFI in order to see multiple properties of given RFI data and Table 2 represents the result of stratification of RFIs by "Reasons."

Table 2: Stratification of RFIs by "Reasons"

Code	Reasons	Description	# of RFIs	%	Avg. CWT	Avg. LT
OE	Omissions or errors in contract documents	Omissions - clarification resulting from omission by design team (A/E) (e.g. lack of dimensions; lack of elevations; missing sections; details omitted etc); Errors - Clarification about the information provided erroneously (e.g. wrong dimensions, wrong elevations etc)	226	39.37	8.08	12.17
H	Hidden /Unexpected field condition	Site conditions different from the information provided in the contract documents (e.g. water table, sudden rock layers, existing pipe found etc)	23	4.01	8.00	11.59
I	Inconsistency	Inconsistency (discrepancy) in contract documents (e.g. different pipe location between structural drawing and MEP drawings etc)	43	7.49	9.36	13.72
CC	Changes requested by the contractor	Changes made for the constructability issue (e.g. changes in construction sequences or construction joint etc)	14	2.44	4.96	5.36
CF	Just confirm	Just confirm if information provided or previously discussed is correct (e.g. material selection, welding method etc)	268	46.69	9.10	11.86
	Total		574	100		

Other than the "Reason" category, the RFI data can be stratified by another category, "Building elements", as represented in Table 3. This category was developed based upon the UniFormat II system which is commonly used in the United States construction industry (NIST 1999). Unlike the Stratification by "Reasons", we could not find any significant factors among the building elements except V (Services) and O (Others) which account for 22% and 26% of the total RFIs generated, respectively.

Table 3: Stratification of RFIs by "Building Elements"

Code	Building elements	Description	# of RFIs	%	Avg. CWT	Avg. LT
ER	Earth work	Excavation, disposal & filling	6	1.05	6.00	3.17
F	Foundations	Footing, grade beam, others all related to foundation	34	5.92	8.18	10.41
B	Beams	Superstructure components	54	9.41	8.11	10.00
C	Columns		32	5.57	7.97	8.17
S	Slabs & decks		26	4.53	7.23	11.85
N	Connections		21	3.66	7.86	8.69
E	Exterior & roofing	Exterior enclosure & roofing	17	2.96	11.35	9.97
I	Interior	All related to interior construction (including finishing and stairs)	40	6.97	9.55	15.83
V	Services	Conveying, plumbing, HVAC, fire protection, electrical	124	21.60	9.48	14.54
Q	Equipment & furnishings	Equipment & furnishings	21	3.66	9.33	14.71
SC	Special constructions	Not included in the above category but major building elements of the project (e.g. soil nailing)	50	8.71	5.12	6.78
O	Others	Other components not included in the above	149	25.96	9.11	13.04
	Total		574	100.00		

Based on the input variables developed, we conducted the binary logistic regression. We could have conducted this study with the entire sample but chose to do so only with the major two Reasons (CF and OE) and their secondary categories (building elements). This simplifies the analysis and is still meaningful given that these two major Reasons (CF and OE) account for about 86% of the total RFIs produced.

BINARY LOGISTIC REGRESSION

Binary Logistic Regression is one type of logistic regression analysis and a valuable tool to utilize when the response Y is binary (two levels) and the predictor Xs are either discrete or continuous (Pyzdek 2003). The results are summarized in terms of the probability of the discrete event. The Binary Logistic Regression provides a model to predict the probability (p) for the occurrence of a specific event for Y. The logistic regression equation is expressed as:

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n$$

Note that α is called the "intercept (constant)" and $\beta 1$, $\beta 2$, $\beta 3 \ldots \beta n$, are called the "regression coefficients" of X1, X2, X3…Xn, respectively. In a given particular setting of X, the probability of occurrence can be computed by reversing the equation to the following form:

$$p(X) = \frac{e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n}}{1 + e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n}}$$

Figure 3 represents the logic of the Binary Logistic Regression model for the selected case. The response is discrete (Yes or No) and the predictors include one continuous data (either CWT or lead times) and two discrete data (reasons for RFIs and building elements). By relating these predictors to the corresponding response statistically, we can estimate the probabilities of on-time RFI response or the realistic lead time as to different combinations of predictors.

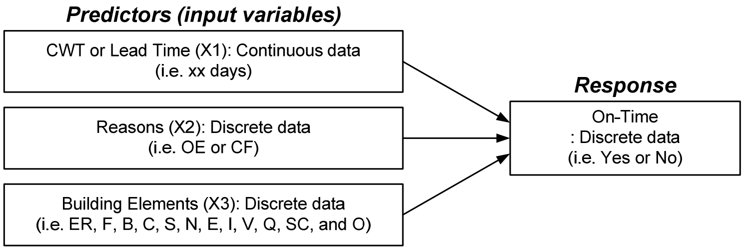

Figure 4: Logic of Binary Logistic Regression

PREDICTING EXPECTED SERVICE LEVELS

Once the key input variables (Xs) were identified, the logit equation was constructed using Minitab software, one of most reliable commercial software packages. The following represents the results of the binary logistic regression generated by Minitab.

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Link Function: Logit

Response Information

Variable  Value  Count
On Time   Yes      238  (Event)
          No       256
          Total    494

Logistic Regression Table
                                                      Odds     95% CI
Predictor           Coef    SE Coef      Z       P  Ratio  Lower  Upper
Constant        -1.34312   0.368461  -3.65   0.000
CWT            0.0818354  0.0273190   3.00   0.003   1.09   1.03   1.14
Category
 CF             0.417464   0.198571   2.10   0.036   1.52   1.03   2.24
Bldg Element
 B              0.594136   0.369885   1.61   0.108   1.81   0.88   3.74
 C               1.00926   0.437865   2.30   0.021   2.74   1.16   6.47
 E              0.819066   0.608957   1.35   0.179   2.27   0.69   7.48
 ER              2.03827    1.15699   1.76   0.078   7.68   0.79  74.14
 F               1.02159   0.457018   2.24   0.025   2.78   1.13   6.80
 I            -0.0362725   0.404173  -0.09   0.928   0.96   0.44   2.13
 N              0.200465   0.506622   0.40   0.692   1.22   0.45   3.30
 O              0.387902   0.278534   1.39   0.164   1.47   0.85   2.54
 Q             0.0648852   0.514223   0.13   0.900   1.07   0.39   2.92
 S             -0.272476   0.510614  -0.53   0.594   0.76   0.28   2.07
 SC             0.166826   0.413542   0.40   0.687   1.18   0.53   2.66

Log-Likelihood = -326.602
Test that all slopes are zero: G = 30.969, DF = 13, P-Value = 0.003
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The above logistic regression table shows that the odds ratio of CWT was 1.09 (= e^0.0818354) indicating that the odds of on-time response increases by a factor of 1.09 as the CWT increases by one day. The coefficient labelled "Constant" (-1.34312) is the value for α, and the coefficients labelled "CWT", "Reasons" and "Bldg Element" are the values for βn in the binary logistic regression equation. However, the factor “OE” in the Category predictor and the factor “V” in the Bldg Element predictor do not appear here because these two factors were selected as default values (i.e. reference levels) when constructing the regression model. For category “CF”, the coefficient 0.417464 indicates that the RFIs that are of the “CF” category tend to have a higher on-time rate than that of the default “OE.” Other coefficients also can be interpreted in the same manner. With the parameters estimated, hence, we can write the logit equation as following:

ln[p/(1-p)] = -1.34312 + 0.0818354*CWT + 0.417464*(Reason=CF) + 0.594136*(Bldg Element=B) + 1.00926*(Bldg Element=C) + 0.819066*(Bldg Element=E) + 2.03827*(Bldg Element=ER) + 1.02159*(Bldg Element=F) - 0.0362725*(Bldg Element=I) + 0.200465*(Bldg Element=N) + 0.387902*(Bldg Element=O) + 0.0648852*(Bldg Element=Q) – 0.272476*(Bldg Element=S) + 0.166826*(Bldg Element=SC)

Validity of the Regression Model

In order to decide whether the constructed model is statistically valid, we should make sure that the model meets the following two requirements. Firstly, the p-value for the G statistic: The p-value for testing that all slopes are zero is 0.003. Considering an α-level of 0.05, a p-value less than 0.05 indicates that there is a significant relationship between the response and at least one of the predictor variables (Minitab Inc. 2004). Radio tests were then conducted to determine whether or not the model could be simplified. The highest p-value for the likelihood ratio tests is 0.1057, belonging to Bldg Element. Because the p-value is greater or equal to 0.05, meaning it has little significance on the model, we can consider removing Bldg Element from the model altogether.

Likelihood Ratio Tests

Factor	Chi-Square	Df	P-Value
CWT	9.45166	1	0.0021
Category	4.45331	1	0.0348
Bldg Element	17.0756	11	0.1057

Secondly, the p-value of the "Goodness of Fit" Tests should be greater than 0.05: "Goodness-of-fit" tests should be conducted to see whether the model adequately fits the actual situation (Minitab Inc. 2004). Low p-values indicate a significant difference of the model between the model results and the observed data from the observed data. Hence, the p-values should be above 0.05 to show that there are no significant differences. In this model, the p-value of Deviance is less than 0.05 but other p-values are all greater than 0.05, which signifies that the model doesn’t represent the data well.

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	88.093	80	0.251
Deviance	106.757	80	0.025
Hosmer-Lemeshow	4.598	7	0.709

Final multiple logistic regression fit after backward elimination

As discussed, the building elements are not significant variables in the original regression model. Hence, we will eliminate this input variable from the model. The resulting goodness of fit tests were much more favourable than that of the original model (i.e. p-value for Deviance changed from greater than 0.05 to less than 0.05) and all the goodness of fit tests achieve p-values of greater than 0.05), providing an excellent description of this data. With the parameters estimated, we can then write the logit equation as follows:

ln[p/(1-p)] = -0.887527 + 0.0741050*(CWT) + 0.322544*(Reason=CF)

From this regression model we can determine the expected service level (on-time rate) given two predictors (CWT and Reasons). For instance, suppose that the contractor found errors (i.e. "OE") on the drawing related to the structural column of superstructure (i.e. "C") and expects a RFI response in 14 days in the current system. The probability of on-time response can be estimated by:

$$p(X) = \frac{e^{-0.887527 + 0.0741050*(14) + 0*(Reason=OE)}}{1+e^{-0.887527 + 0.0741050*(14) + 0*(Reason=OE)}}$$

Note that the predictor "C" was discarded because the building elements input variables were the least significant as discussed previously. This then gives a result of p(X) = 0.54 (54%). The result can be interpreted as there being a 54% probability that the contractor will receive the response from the reviewer on time within 14 days for the given combination of predictors. The event probability for all the possible combination of categories could be calculated using either the reversed logistic regression equation or the Minitab software. Next a scatterplot was constructed to illustrate the overall probability of on-time vs. CWT. Figure 4 clearly shows that as the CWT increases, the probability of an on-time response increases, i.e. the contactor can expect a higher probability of on-time by increasing CWT. The regression line was placed on the scatterplot to show the calculated line of best fit. Two further sets of lines (confidence intervals and prediction intervals) are also presented. The confidence intervals indicate the interval within which one can be 95% confident what the process average will occur while the prediction intervals indicate the interval within which one can expect 95% of the process output (data points) to occur (Minitab Inc. 2004). The results can be interpreted as: "the probability of on-time increases to around 90 percent if the CWT increases to around 35 days." The fitted line plot shows that the R-Squared (R-Sq) value is 90.3% indicating that 90.3% of the variation in the process output is accounted for by the model, which means the regression model is well fitted.

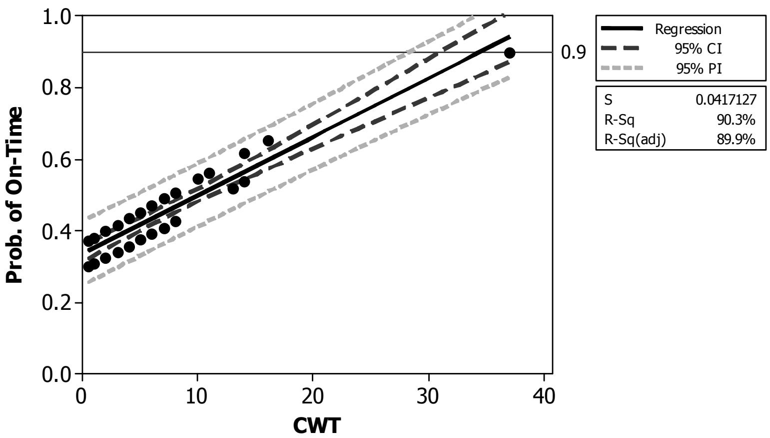

Figure 5: Fitted line plot of Probability of In-Time vs. CWT

PREDICTING REALISTIC LEAD TIMES

In comparison to the service level prediction model, the realistic lead time should be computed by relating LT to responses considering all possible combinations of the predictors. As described previously, this is because the CWTs are arbitrarily set by the contractor without knowledge of the actual lead time so that there is no strong correlation between CWT and LT. In order to construct the binary logistic regression model, the Minitab was run in the same manner as for the service level prediction modelling. As with the service level prediction model, the model validity was also evaluated. Looking first at the p-value for the G statistic – the resulting p-value for testing that all slopes are zero is 0.000. The result of likelihood radio tests indicates that the highest p-value is 0.6315, belonging to Reason. As explained previously, we can consider removing the predictor "Reasons" from the model because it has least significance. Secondly, the p-value of the "Goodness of Fit" Tests is greater than 0.05 – The model has no test results indicating a significant difference, i.e., the regression model is valid.

Final multiple logistic regression fit after backward elimination

As discussed in the previous section, the Reasons are not significant variables in the regression model to estimate the realistic lead time. Hence, we will eliminate this input variable from the model. Having estimated parameters for the final multiple logistic regression fit after backward elimination of the Reasons input variable from the original model, the goodness of fit test was conducted. The result indicates slightly better results of goodness of fit test than that of the original model. Additionally, all the goodness of fit tests had p-values greater than 0.05, providing an excellent description of this data. With the parameters estimated, we can write the logit equation as follows:

ln[p/(1-p)] = 6.83259 - 0.618123*LT - 0.840562*(Bldg Element=B) - 1.43504*(Bldg Element=C) + 1.09041*(Bldg Element=E) - 1.25662*(Bldg Element=ER) - 2.22361*(Bldg Element=F) - 0.425901*(Bldg Element=I) - 2.16348*(Bldg Element=N) - 1.20532*(Bldg Element=O) - 0.314616*(Bldg Element=Q) – 2.21372*(Bldg Element=S) – 3.89901*(Bldg Element=SC)

From this regression model we can determine the realistic lead time for the reviewer to complete the RFI review in order to achieve a desired level of service level. Given the same RFI condition used in the previous service level prediction model (i.e. RFI with errors (i.e. "OE") on the drawing related to the structural column of superstructure (i.e. "C")), if the reviewer wishes to complete the review of the RFI with 90% of probability of on-time, we can compute the realistic lead time as follows:

$$\ln\left(\frac{0.9}{1-0.9}\right) = 6.83259 - 0.618123*(\text{Lead Time}) - 1.43504*(\text{Bldg Element=C})$$

Solving for Lead Time gives 5.18 days. As with the service level prediction model, the predictor "OE" was discarded because the "Reason" input variables are least significant to the model. The result can be interpreted as such: the RFI should be reviewed by the reviewer(s) within 5.18 days to attain a 90% probability of on-time response by the contractor under the current system status. If the reviewer's actual lead time exceeds 5.18 days, the response cannot attain the desirable 90% service level.

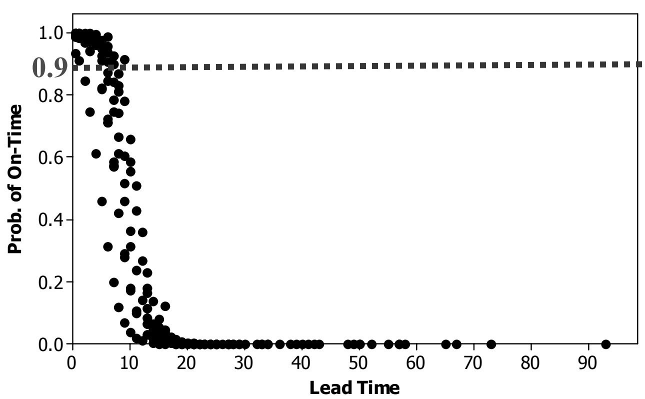

Figure 6: Scatterplot of probability of On-Time vs. Lead Time

The event probabilities for all the possible combination of categories (Lead Time and building elements) were calculated. Figure 5 clearly shows that as the Lead Time decreases there are more on-time responses. As with the service level prediction model, the regression line could have been placed on a scatterplot along with confidence and prediction intervals, but this will not be discussed herein due to space constraints.

LIMITATIONS

In this study, four input variables were used in building the predictive models. As described earlier, the research could have developed such factors as the amount of information required for review, quality of contract documents (e.g., drawings and specification), quality of RFI, efficiency of document control system, working relationship between contractors and reviewers and so forth. However, these are not included due to the need to define each variable and establish a standard form of measurement. These variables are qualitative in nature and require further investigation. A model that includes these qualitative variables will enable the model users to yield the best results.

CONCLUSION

The purpose of this research was to develop a quantitative tool to assist in predicting the RFI service level and realistic response time in advance of an actual RFI submission. The models are based on four key input variables: contractor-want-time (CWT), actual lead (response) time (LT), reasons for RFI, and building elements. Relationships were discovered pertaining to predicting the effects of increasing/decreasing or including/excluding specific variables contained in the models. Results demonstrate that these key input variables affect the probability of on time response and the realistic RFI processing time in different ways. The research revealed large time intervals between CWT and LT and between the expected CWT and realistic lead time required to achieve a particular desired service level. As illustrated, in order to achieve a 90% service level, the contractor would require a much longer CWT (about 35 days) than the current CWT while the reviewer should make efforts to reduce the review time (to about 7 days).

Contractors can employ the model to predict the service level (RFI on-time rate) and consequently plan more favourable courses of action. Owners in turn can employ the model to verify the expected RFI process time and to gain an internal benchmark for process improvement by having knowledge of the realistic lead time necessary to achieve a certain service level.

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