Classify and Quantify Cumulative Impact of Change Orders On Productivity Using ANN Models

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요 약

Change is inevitable and is a reality of construction projects. Most construction contracts include change clauses and allowing contractors an equitable adjustment to the contract price and duration caused by change. However, the actions of a contractor can cause a loss of productivity and furthermore can result in disruption of the whole project because of a cumulative or ripple effect. Because of its complicated nature, it becomes a complex issue to determine the cumulative impact (ripple effect) caused by single or multiple change orders. Furthermore, owners and contractors do not always agree on the adjusted contract price for the cumulative impact of the changes. A number of studies have attempted to quantify the impact of change orders on project costs and schedule. Many of these attempted to develop regression models to quantify the loss. However, regression analysis has shortcomings in dealing with many qualitative or noisy input data. This study develops ANN models to classify and quantify the labor productivity losses that are caused by the cumulative impact of change orders. The results show that ANN models give significantly improved performance compared to traditional statistical models.

키워드: Change Orders, Cumulative Impact, Productivity, Claims, ANN Model

1. Introduction

A change order can be defined as "any event, which results in a modification of the original scope, execution time or cost of work" (Ibbs and Allen, 1995). The problem with change orders is that since construction is based upon sequential production, any disruption to a task within the sequence will impact the remaining tasks even if the change order itself does not involve these tasks. This is commonly referred to as "the ripple effect" or "cumulative impact" of changes. Numerous change orders often result in a loss of productivity and, furthermore, can result in a disruption of the whole project due to inefficient labor usage, or the cumulative impact (ripple effect) of multiple change orders.

Many people recognize that there is cumulative impact above and beyond the change itself. However, current korean construction contracts do not typically include adequate language to enable fair and equitable compensation for the unforeseen impact of cumulative change. Often, the contractor fails to foresee, and the owner fails to acknowledge, the "synergistic effect" of the changes on the work as a whole when pricing individual changes. Consequently, projects that exceed cost or schedule targets are likely to lead to claims. Determining the impacts that changes can have on contract price and time can be arduous due to the interconnected nature of construction work and the difficulty in isolating factors for quantification. As a result, it is very difficult for owners and contractors to agree on equitable adjustments, especially for cumulative impact. What is needed is a reliable method (model) to identify and quantify the loss of productivity (cost) caused by the cumulative impact of change orders.

A number of studies have attempted to quantify the impact of change orders on project costs and schedule. Many of these attempted to develop regression models to quantify the loss. However, regression analysis has shortcomings in dealing with highly nonlinear input-output functions. Moreover, regression

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analysis shows limited success when dealing with many qualitative or noisy input variables. Artificial Neural Networks (ANN) are known as a powerful tool to model these complicated problems. This study developed two ANN models to classify projects impacted by change orders and quantify productivity losses.

2. ANN(Artificial Neural Network)

This research uses Multilayer Feed-Forward Back-Propagation Networks, because previous research showed that feed-forward networks have good performance in dealing with pattern classification (matching output class to target class) and approximation (regression, modeling) problems. Also, back-propagation learning algorithms make it possible to optimize weights in a multilayer perceptron, thereby minimizing the estimation error. These two abilities match exactly the purposes of present study. The concept behind this algorithm is that a network tries to minimize its output error (Formula 1) by continuously adjusting network weights.

$$E=\sum_{k=1}^{K}\sum_{i=1}^{N(L)}[e_i(k)]^2=\sum_{k=1}^{K}\sum_{i=1}^{N(L)}[d_i(k)-z_i(k)\text{........(Formula 1)}$$

Figure 1 shows the graphical representation of the feed-forward back-propagation algorithm and a brief summary of algorithm process is as follows:

1) Initialize the weights to small random values.
2) Randomly choose an input pattern.
3) Propagate the input forward through the network
4) Compute the error between output and target.
5) Compute the deltas for the preceding layers by propagating the errors backwards
6) Update weights
7) Repeat the algorithm for the next pattern until the error in the output layer is below a pre-specified threshold or a maximum number of iterations is reached.

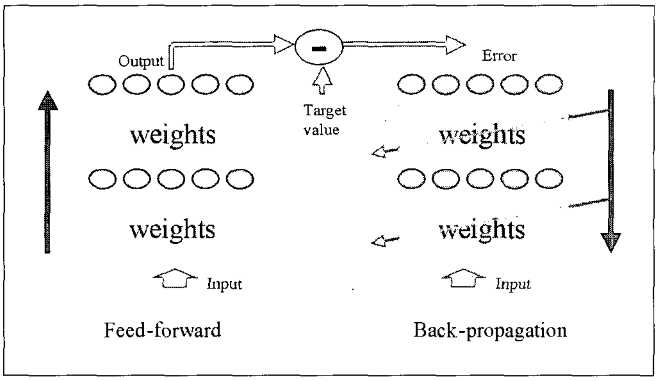


Figure 1. Feed-Forward Back-Propagation

There has been considerable interest in the development of neural network applications to solve problems in diverse fields such as construction. This is attributable to their ability to solve a variety of challenging computational problems with a massively parallel and distributed system along with their capabilities of generalization, fault tolerance, and adaptive performance. Also, their generalization capabilities enable these applications to produce meaningful solutions to problems in which the input data are noisy and uncertain.

3. Research Methodology

Several studies have attempted to develop a quantification model for the cumulative loss of change orders. Leonard et al. (1988) provided a first effort to quantify the effect of change orders on labor efficiency. This study used 90 cases that involved disputes between owners and contractors and showed graphic results that related loss of efficiency to the percentage of changes However, the Leonard study identified percent (%) change as the only factor that impacts project efficiency. Moselhi (1998) expanded Leonard's original work by using trained neural networks. He also showed that approximation accuracy could be improved by adding more factors to the model. Moselhi added three more parameters (total number of change orders, the frequency of the change orders, and the average size of the change orders) to Leonard' s one factor (percent change). By using trained neural networks, Moselhi improved the output (productivity loss approximation) significantly. Even though this study used a limited number of factors, it suggested that the neural network model can be used to quantify change order impact on productivity and can also improve the estimation accuracy.

The Construction Industry Institute (CII) and the University of Wisconsin-Madison change orders research team have conducted the most significant studies using statistical regression modeling methods to classify and quantify the impact of change orders on labor productivity for mechanical and for electrical construction (Hanna, 2001; Hanna et al. 1999(a), (b)). Several regression models were developed to classify projects impacted (by change orders) and estimate the cumulative loss of productivity. These studies developed the term "Delta" in order to calculate the productivity loss associated with change orders. Delta is graphically shown in Figure 2.

Delta is defined as the difference between the actual labor hours needed to complete the project and the budgeted base hours plus the approved change order hours. Delta can take a positive value or negative value. Positive values of Delta indicate that more workhours were used to complete the project than were budgeted, that is that the actual productivity was less than the planned or estimated productivity. On the other hand, negative values of Delta indicate higher efficiency than originally anticipated or budgeted, that is that less actual hours were spent on the project than planned. To ensure that the whole of Delta was a result only of the effect of the change orders on the project, a screening criterion was developed and utilized. Also, the concept of "Percent Delta" was developed to compare projects of varying sizes. Percent Delta (%Delta) is defined as Delta divided by the actual workhours spent to complete the project. Percent Delta can be written as below. Application of the Delta approach allowed a macro-analysis, so that cumulative impact on the project due to change orders could be measured.

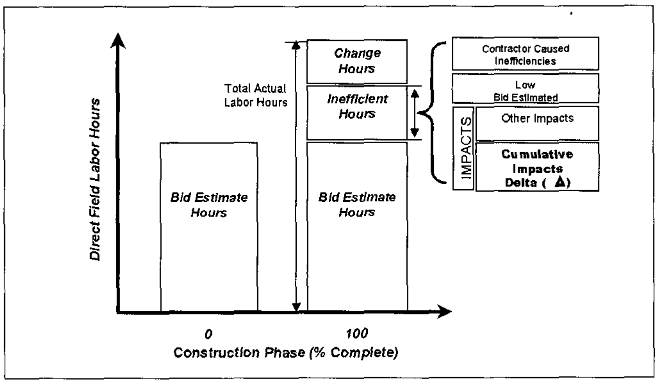


Figure 2. Definition of Delta

These studies also developed a definition of an "impacted" project. The contractors classified projects as either "on budget" or "over budget" based on their budgeted workhours at the data collection stage. These initial contractor classifications of projects as impacted or unimpacted were then compared to a cutoff line drawn at 5% Delta. Since a conservative estimate of a contractor' s estimating ability is 5%, this was set as the lower limit for impacted projects.

The problem with these studies is even though these studies found several more factors which impact productivity, it is still difficult to validate developed models with high classification and prediction accuracy for new cases because of the low R2 (quality of regression model). The reason is that there are still other factors which significantly impact productivity and that these factors are interconnected with a highly nonlinear structure. Also, many of them are qualitative in nature rather than quantitative. Usually, regression analysis has limited success when dealing with many qualitative or noisy input variables.

The present researches have acquired two groups of case studies from electrical and mechanical specialty contractors through a study conducted by the principal investigator of a Construction Industry Institute research report (Hanna, 2001). The first group includes 140 case studies for developing an "impact model" (classifying whether a project was impacted by change orders or not). The second group includes 64 case studies which were impacted by change orders to develop a "change order loss (%Delta) model" (quantifying the cumulative productivity loss). The two groups of data were further divided into a training group and a testing group. These case studies have potentially 70 independent factors (Input) that may impact project performance. Many of them are qualitative factors and are difficult to model using traditional statistical (regression) techniques.

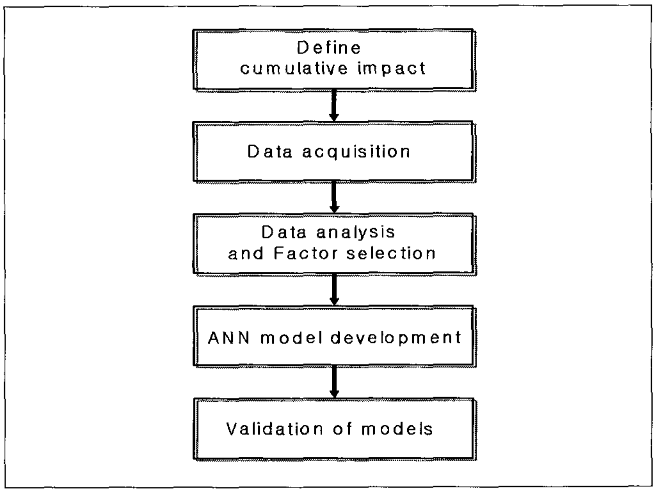


Figure 3. Research Process (methodology)

This research included statistical significance testing to find and determine significant factors and used these factors to develop trained ANN models. Furthermore, the ANN models were validated by testing with new case studies. Research process shows in Figure 3.

4. Change Order "Impact Model"

A "change order impact model" is defined as a trained ANN model to determine that a project was impacted by change orders or

$$\%\text{DELTA} = \frac{\text{Total Actual Direct Labor Hours - (Budgeted Hours + Change Order Hours)}}{\text{Total Actual Direct Labor Hours}} * 100$$

was not. This model used 140 case studies (training: 130 cases; testing: 10 cases), and the training group had 69 unimpacted (normal) projects and 61 impacted projects (by change orders). Each case study is composed of 70 potential input features (independent variables) and one output feature (dependent variable). Input features include numerical, binary, and categorical inputs. In addition, the output feature possesses a binary case only (1: the project was impacted by change order; 0: was not impacted). The first step in the model development was to find significant input features (factors). Some of the factors showed significant differences between impacted and unimpacted projects' characteristics while some did not. There are two steps in determining significant features. The first step is "irrelevant feature reduction" (removing un-correlated features), and the second step is "redundant feature reduction" (if the value of a feature is linearly dependent on the remaining features, then this feature can be removed). To perform these feature dimension reductions, this study used statistical methods. We can use statistical significance tests to detect significant features, which have a strong relationship with the output feature, by performing the null hypothesis (H_o) test so irrelevant features can be removed. Also, statistical correlation tests can calculate the correlation values between features so that redundant features can be reduced. These tasks were performed using the statistical software Minitab, and a summary of selected test values (correlation value and p-value) is shown in Appendix-A.

The test values demonstrate that projects impacted by change orders have a greater number of change orders; higher ratios of peak over average manpower; longer change order processing times; more design errors; and higher absenteeism, overtime, and overmanning. However, a project that has adequate coordination and support between the architect and engineer, adequate productivity tracking, and a large percentage of the project manager's effort (time) devoted to the job site is less likely to be impacted by change orders. These results are consistent with industry intuition.

Two ANN models were developed to classify the impact of change orders. Model ANN-8 comprises the same factors (8 factors) that were used for the impact (logistic regression) model (Hanna-CII,2001) for comparison purposes. Model ANN-18 extends the number of factors to 18 to include not only quantitative factors but also some of the significant qualitative factors. Appendix-A shows a summary of selected factors for the ANN-8 and ANN-18 models along with a brief description of each factor.

This study used the mathematical computing software Matlab to perform the neural network execution. Many sub-routine programs were developed and run in Matlab with a back-propagation algorithm. To develop well-trained neural networks, one needs to optimize the number of hidden layers and neurons to use, the learning rate (α), the momentum value (υ), the activate function, and the number of epochs to run. Network performances are varied through these parameters, and we can find optimized values of each parameter by the "trial and error" method. After many repetitions of the network execution, we found that the ANN-8 model optimized under a three layer perceptron network (8-5-3-1) with five hidden neurons in the first hidden layer and three hidden neurons in second hidden layer. Also, we found a learning rate (α=0.01) and a momentum value (υ=0.8) with the sigmoid activation function after 1000 iterations of the epochs. Figure 4 shows a graphical representation of the ANN-8 model design.

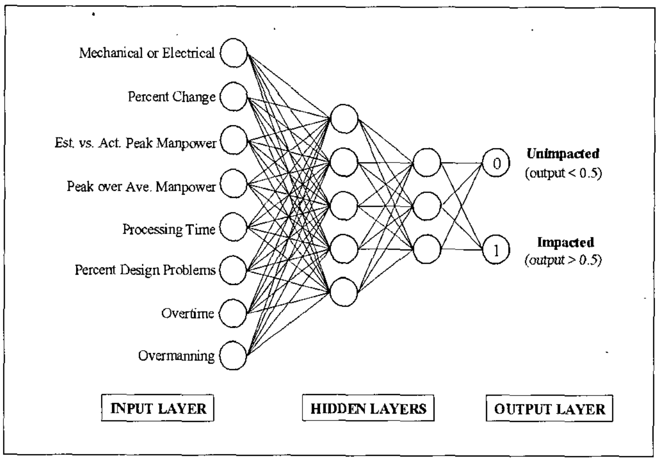
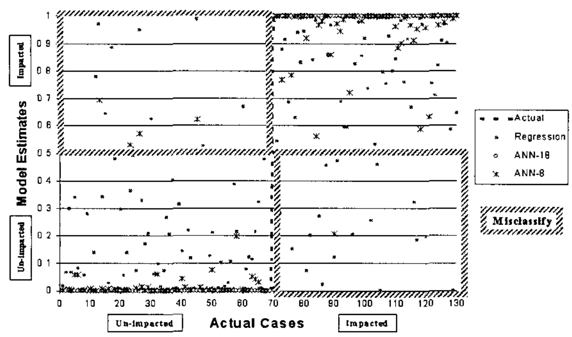


Figure 4. A Network Design for ANN-8 Model

The ANN-18 model shows optimized performance with a one hidden layer perceptron network (18-10-1) with ten hidden neurons. The rest of the settings (learning rate, momentum value, activation function, and epoch size) used the same values as the ANN-8 model.

Once the network is optimized, we can obtain the model estimate (network output) and compare it with the expected actual output. Since this study used the same data as in previous research (Hanna-CII,2001), it is reasonable to compare the performances. Figure 5 shows a comparison of performance between actual and estimated values for each model. From the confusion matrix comparison, both the ANN-8 and ANN-18 models show superior performance over the statistical regression method. The previous logistic regression model classified 77.7% of the cases correctly, but the ANN-8 model shows about a 95% classification rate and the ANN-18 model shows a 100% classification rate in the training stage.



Confusion matrix comparison

		Regression		ANN-8		ANN-18	
		Unimpacted	Impacted	Unimpacted	Impacted	Unimpacted	Impacted
Actual	Unimpacted (69 projects)	58	11	64	5	69	0
	Impacted (61 projects)	18	43	1	60	0	61
Classification rate		77.70%		95.38%		100%	

Figure 5. Impact Model Performance Comparison

5. Change Order "Loss (%Delta) Model"

The "change order loss (%Delta) model" is a trained ANN model that quantifies productivity losses caused by the cumulative impact of change orders. This study used 64 case studies that were impacted (experienced a productivity loss) by change orders. These case studies were divided into two groups: 57 case studies for the training set and 7 case studies for testing and validation. The training data (57 case studies) include 70 potential input features (independent variables) and one output feature (%loss of productivity). Input features include numerical, binary, and categorical inputs. The output feature is a numerical form of a productivity loss percentage (from 0% to 100%).

Again, model development started with the selection of significant input features (factors). Some of the factors have a relationship with productivity loss, but some do not show a correlation. A summary of selected factor values (correlation value and p value) is shown in Appendix-B. The statistical tests show that a project is more likely to experience productivity losses if it is larger, has more change orders, manpower fluctuations and shortages, longer change order processing time, higher absenteeism, turnover, and overmanning. However, the cumulative productivity losses caused by change orders are reduced in a project that has adequate coordination and support between the architect and engineer, adequate productivity tracking, a larger portion of owner initiated change orders, a properly updated CPM schedule, and a large percentage of the project manager' s effort(time) on the job site.

Two ANN models were developed to quantify the loss of productivity due to the cumulative impact of change orders. Model ANN-6 contains the same factors (6 factors) that were used for the previous regression model (Hanna-CII, 2001) to allow comparison of their performance. Model ANN-20 extends the number of factors to 20 to allow development of a more rigid model.

This study used the same back-propagation programs that were developed for previous models and repeatedly executed them in Matlab to optimize the parameter settings. The ANN-6 model optimized under a three layer perceptron network (6-4-3-1) with four hidden neurons in the first hidden layer and three hidden neurons in the second hidden layer. In addition we found a learning rate (α =0.01) and a momentum value (υ=0.8) with a sigmoid activation function after 1000 iterations of the epochs. Figure 6 shows a graphical representation of the ANN-6 model design.

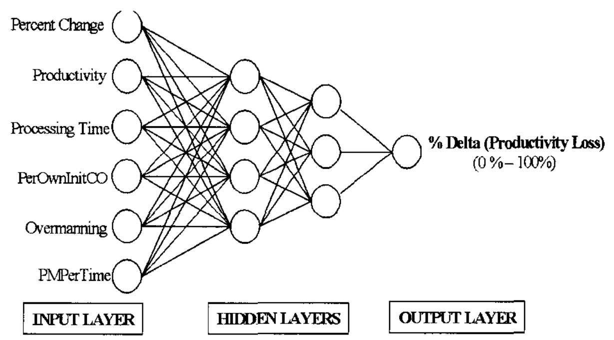


Figure 6. A Network Design for ANN-6 Model

The ANN-20 model showed optimized performance with a two hidden layer perceptron network (20-10-5-1). The rest of the settings (learning rate, momentum value, activation function, and epoch size) used the same values as the ANN-6 model.

Again, we can compare the different models' estimates since the models were developed from the same data set. Figure 7 show the comparison of performance (output) between the actual and estimated values of each model.

Both the ANN-6 and ANN-20 models show superior performance over the statistical regression method. The regression model shows 53% of average %error, but the ANN-6 model shows 5.11% and ANN-20 shows only 2.83% error for the training cases. The ANN models show significant improvements in approximation.

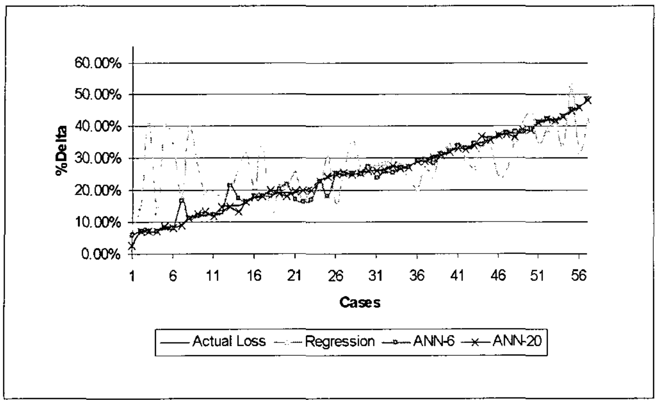


Figure 7. %Delta Model Performance Comparison

6. Model Testing and Validation

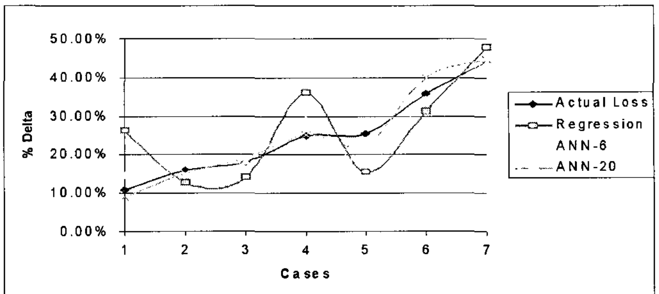
Once the trained neural networks are developed, we can apply them to new projects. At the beginning stage, we divide all the data into two sets: one for training and the other for testing. Testing data were randomly selected from the original data set and were not included in the training data set.

This study tested the impact model first. Testing data were composed of five electrical and five mechanical projects, and three in each category were impacted projects. To test the reliability of the trained network, we input the testing data (10 projects) into each trained network (ANN-8, ANN-18) and determine how well the network classified the impacted projects. Table 1 shows the comparison of testing results between the different models. The logistic regression model (Hanna-CII, 2001) shows only a 60% classification rate, but both neural network models show a 100% classification rate. The neural network models classify all testing projects correctly. These results validate that the developed ANN models provide a fairly reliable output.

Table 1. Testing Result for Impact Models

Case Study				Statistical Model	ANN-8 Model	ANN-18 Model
Testing Data (10 Projects)	Electrical	E071	Impacted	*Unimpacted*	Impacted	Impacted
		E201	Impacted	Impacted	Impacted	Impacted
		E341	Impacted	Impacted	Impacted	Impacted
		E352	Unimpacted	Unimpacted	Unimpacted	Unimpacted
		E161	Unimpacted	Unimpacted	Unimpacted	Unimpacted
	Mechanical	3172	Impacted	*Unimpacted*	Impacted	Impacted
		3301	Impacted	*Unimpacted*	Impacted	Impacted
		3012	Impacted	Impacted	Impacted	Impacted
		3081	Unimpacted	Unimpacted	Unimpacted	Unimpacted
		3061	Unimpacted	*Impacted*	Unimpacted	Unimpacted
Classification rate				60%	100%	100%

The change order loss (%Delta) models were tested in the same fashion. Actual productivity losses in the testing data varied from 10% to 50% of actual labor hours. To test the trained network, we input the testing data (7 projects) into each trained-network (ANN-6, ANN-20) and determined how well the network estimated each project's productivity loss. Figure 8 shows the comparison of the testing results between the different models. The regression model shows 41.17% of average %error, but the ANN-6 model shows 15.12% and the ANN-20 model shows only 7.49% of average %error. The neural network models show superior accuracy in productivity loss approximation.



Case Study Projects								Model Estimate		
Case Number	% Change	PM %Time	%Own InitCO	Productivity	Over manning	Process Time	Actual Loss	Regression	ANN-6	ANN-20
1	32.32%	100%	90.0%	Yes	No	5	10.85%	26.09%	14.54%	9.05%
2	27.84%	100%	91.4%	Yes	Yes	2	15.75%	12.61%	18.60%	15.14%
3	48.28%	30%	90.0%	Yes	Yes	4	17.97%	14.10%	18.13%	19.09%
4	51.59%	20%	59.1%	No	No	2	24.82%	36.01%	28.98%	25.16%
5	18.40%	100%	74.7%	Yes	Yes	5	25.33%	15.31%	17.18%	22.51%
6	8.08%	14%	100.0%	No	No	5	35.77%	31.15%	34.30%	39.92%
7	7.10%	14%	0.0%	No	No	5	43.95%	47.76%	44.01%	44.68%
Average %Error	$\%Error = \frac{\lvert X_e - X_d \rvert}{X_d} \times 100$							41.17%	15.12%	7.49%

Figure 8. Testing Result for Productivity Loss Models

7. Summary and Conclusion

This study developed artificial neural network models to classify and quantify productivity loss caused by change orders for electrical and mechanical projects. First, it showed significantly related factors for each model. This study employed the same factors used in previous research (Hanna-CII regression models, 2001) for an impact model (ANN-8) and a productivity loss model (ANN-6) and obtained, and added, additional factors to include qualitative aspects. The ANN-18 model was developed for an impact model with 18 factors and ANN-20 was developed for a change order loss model with 20 factors.

The developed models show significant improvements in classification and estimation accuracy not only for the training performance but also at the testing stage as compared to previous statistical regression models. At the training stage, the ANN-8model shows 95% and the ANN-18 model shows 100% classification accuracy, whereas the regression model shows only 77.7% accuracy. Also, for the change order loss (%Delta) model, ANN-6 shows

5.11% and ANN-20 shows 2.83% of average %error, but the regression model shows about 50% error. In the validation (testing) process, the regression model shows only 60% classification accuracy, but both neural network models show 100% accuracy. Also, for the change order loss (%Delta) model, ANN-6 shows 15.12% and ANN-20shows 7.49% of average %error but the regression model shows an average of 41.17% error. These results encourage the use of the Artificial Neural Network approach in that it can provide improved performance compared to traditional statistical methods in the field of construction data management, which has characteristics of noisiness and uncertainty. This methodology could also be applied to other problems for which solutions are generated based on analogy with previous cases rather than deduction and deep reasoning.

Computer and web-based interface applications are recommended for further tasks, thereby allowing stakeholders easy access to apply their project case. Also, a web-based interface will make it possible to build more rigid models through collecting more data from the industry.

Finally, since the study was conducted in US construction environment, the application of this study outside of US should be careful. Without solid productivity data acquisition and maintenance system, proposed methodologies can not be applied. Especially, Korean construction industry have weakness in this aspects. Development of productivity management system should be preceeded prior to application of proposed methodology.

Acknowledgement

This paper was developed based on the data collected for research funded by the Construction Industry Institute (CII) research group(RR 158-11), and special thanks go to the electrical and mechanical contractors who supplied the data for this study.

Appendix(A): Impact Model Factors

Factor	P-value	Correlation	Interpretation ... is more likely to be impacted.	ANN-8	ANN-18
MorE	0.882	0.013	indicator Variable (Mechanical or Electrical Projects)	*	*
Percent Change	0.002	0.137	A project with more change ···	*	*
Percent Extended	0.014	0.216	A project that is extended ···		*
Est. vs. Act. Peak Manpower	0.004	−0.154	A project with a lower ratio of estimated to actual manpower ···	*	*
Est. vs. Act., Peak over Ave. Manpower	0.06	−0.132	A project with a lower ratio of estimated to actual peak over average manpower ···		*
Peak over Average Manpower	0.029	0.177	A project with a higher ratio of peak to average manpower···	*	*
Extension Requested	0.009	0.219	A project where an extension was requested ···		*
AE Coordination Prior to Construction	0.058	−0.134	A project without adequate coordination of the trades ···		*
AE Support During Construction	0.003	−0.252	A project without adequate AE support during construction ···		*
Manpower Shortage During Construction	0.077	0.124	A project with a manpower shortage during construction ···		*
Processing Time	0	0.187	A project with a longer processing time ···	*	*
Percent of Submitted Change Order Hours Approved by Owner	0.002	−0.199	A project with a low percentage of the change order hours approved by the owner ···		*
Percent of Change Orders Resulting from Design Problems	0.08	0.15A	project with more change orders resulting from the design changes or errors ···	*	*
Absenteeism	0.003	0.189	A project with a high absenteeism rate amongst the craftsmen ···		*
Overtime	0.014	0.203	A project where overtime is used for change orders ···	*	*
Overmanning	0	0.378	A project where overmanning has occurred ···	*	*
Productivity	0.081	−0.148	A project without adequate productivity tracking···		*
PMPerTime	0.045	−0.172A	project has less PM's effort (time) on the job···		*

Appendix(B): Productivity Loss Model Factors

Factor	P-value	Correlation	Interpretation	ANN-6	ANN-20
Project Size	0.013	0.239	Larger projects have a higher %Delta than smaller projects.		*
Percent Change	0.062	0.181	More change leads to a higher %Delta.	*	*
Percent Extended	0.05	0.19	Projects that were extended a longer period of time showed a larger %Delta.		*
Estimated over Actual					
Average Manpower	0.005	-0.271	As the ratio of estimated to actual manpower decreases, the %Delta increases. These variables are related to site congestion and overmanning.		*
Peak Manpower	0	-0.34			*
Peak over Average Manpower	0.005	-0.27			*
Extension Requested	0.057	0.185	Projects where an extension has been requested are more likely have a higher %Delta.		*
AE Coordination	0.067	-0.179	If the AE did not provide adequate coordination of the trades during the design phase, a higher %Delta is likely on the project.		*
AE Support	0.034	-0.206	If the AE did not provide adequate support during construction, a higher %Delta is likely on the project.		*
Productivity	0.031	-0.209	If the contractor does not track their productivity, a higher %Delta can be expected.	*	*
Manpower Shortage	0.032	0.207	If there is a manpower shortage during construction, the %Delta is expected to be increased.		*
Processing Time	0.002	0.292	The longer the processing time of change orders the higher the expected %Delta.	*	*
PerOwnInitCO	0.008	-0.26	The more change orders initiated by the owner, the lower the expected %Delta.	*	*
Absenteeism	0	0.368	The more absenteeism there is on the project, the higher the %Delta.		*
Turnover	0.029	0.215	The more turnover there is on the project, the higher the %Delta.		*
Overmanning	0.012	0.224	If overmanning is used, the %Delta is expected to be increased.	*	*
Industrial	0.061	0.243	Indicator factor		*
UPCPM	0.017	-0.216	Updating the CPM schedule properly during construction can lower the expected %Delta.		*
PMPerTime	0.014	-0.238	If the project manager provides more effort (time) on the job, the %Delta is expected to be decreased.	*	*

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논문제출일: 2005.03.10
심사완료일: 2005.07.12