Activity Based Prediction of On-site CO_2 Emissions Containing Uncertainty

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Abstract –

Recently, the importance of reducing embodied carbon has become clear. The construction stages, is the stage where the building production takes place, and a large quantity of embodied carbon is emitted. However, because this stage presents a variety of sources of uncertainty at building sites, it is difficult to compute and predict precise CO_2 emissions. To solve this problem, existing research has estimated emissions amounts by considering the variability of the main materials' carbon emission factor, as well as the variability of the equipment's activity conditions. However, these approaches are unable to reflect uncertainty at activity level, leading to an underestimation of CO_2 emissions. In this research, we perform an analysis by considering the uncertainty of CO_2 emissions in the construction stage at activity level. In addition, from the results, we recognize the relevance of considering uncertainty for each activity. Therefore, we present a CO_2 emission prediction method using a Monte Carlo simulation and confirm its effectiveness. We believe that the outcome of this research advocates for the necessity of considering the uncertainty in each activity and contributes to the prediction and management of on-site emissions.

Keywords –

CO_2; activity based; uncertainty; Monte Carlo simulation

1 Introduction

Recently, as operational carbon emissions (OC) have been reduced, it has gradually become clear that it is important to reduce the embodied carbon emissions (EC), which occur latently during the production, construction, maintenance and discarding of building materials [1]. The construction stage is a good example of the seriousness of EC. In this stage, 10 to 30% of the materials' lifetime CO_2 are emitted within a relatively short time [2]. In addition, the construction stage is the stage in which the usage of the building materials is completed, and thus, mechanical equipment and materials are used, causing a large amount of CO_2 emissions.

However, the CO_2 emissions that occur in the building construction stage are difficult to compute and predict accurately due to various sources of uncertainty that are present at a building site [3]. Choosing and managing goals of CO_2 emission reduction based on uncertain prediction values cause problems in meeting these goals [4]. To solve this problem, existing research has estimated emissions amounts by considering the variability of the main materials' carbon emission factors, as well as the variability of the equipment's activity conditions. However, these approaches are based on resources, not based on activity, so it is possible that the CO_2 emissions will be underestimated. Furthermore, another limitation is the suggestion of only piecemeal reduction methods such as a reduction or replacement of input resources.

To address those limitations, in this research, we aim to analyze the construction stage CO_2 emissions' uncertainty at activity level. We also aim to present a method that can use the analyzed uncertainty data to probabilistically predict CO_2 emissions.

We selected concrete construction as our research target, as it uses a large amount of material and has a high material carbon emission factor. For the uncertainty that can occur in concrete placement, measured equipment operating times of both the concrete pump and the concrete mixer truck were considered. These operating times were converted to CO_2 emissions, and the uncertainty was analyzed by comparing the actual value and the planned emissions based on the equipment operation time. Finally, the analyzed data was used to derive a method to predict CO_2 emissions, which is based on a Monte Carlo simulation, and their effects were verified.

2 Computing the construction stage CO_2

A deterministic emission calculation obtained by multiplying the CO_2 emission factor and the amount of input material can cause problems due to uncertainty. Therefore, existing research has evaluated the uncertainty when estimating carbon emissions and then presented a prediction method that considers this. We reviewed several researches in terms of materials and equipment.

Regarding materials, there is a research that considers the most used building materials to perform an analysis of statistical properties, and based on this, it probabilistically predicts the materials' construction stage emissions [4]. Another research analyzes the variability of emission factor of the most used materials based on accumulated greenhouse gas emissions, as well as energy emissions factor, in order to evaluate the uncertainty when estimating the emissions of apartment housing construction stage [5].

Regarding equipment, there is a research on a simulation technique, which is developed to calculate CO_2 emissions in a road paving work while considering the variability in the amount of fuel consumption according to engine load [6]. Similarly, another research uses a CYCLONE simulation to predict emissions probabilistically while considering the variability of fuel consumption according to the activity of earthwork equipment [7].

However, the above-mentioned research has the limitation of being mainly focused on materials and earthwork equipment. We perceived a lack of research on building construction equipment, which is a direct source of emissions at the building site. Also, we analyzed existing research is not considering uncertainty at activity level. Therefore, in this research, we evaluate uncertainty in CO_2 emissions focusing on building construction equipment at activity level, and then present a prediction method that considers our analysis.

3 Evaluating and analyzing uncertainty in CO_2 emissions

3.1 Measuring and analyzing equipment operation time

To analyze the uncertainty sources in carbon emissions, we estimated fuel consumption according to measured equipment operation time and planned equipment operation time to obtain CO_2 emissions, and then compared these values. To analyze at activity level, we measured on-site data about equipment operation times (Table 1). For the information of used equipment, we referred to the report from the Korea Specialty Contractors Association [8], which contains the standard measurements for construction machines in Korea(Table 2).

Table 1. Overview of measuring equipment operation time

Components	Contents
Facility type and scale	1 education research facility, 2 stories underground/6 stories aboveground
Total area	22,910 m^2
Location	Seongbuk-gu, Seoul, Korea
Measurement target process	Concrete slab placement work
Data gathering date	2017-3-10

Table 2. Information of used equipment

Used equipment	Concrete mixer truck	Concrete pump
Type	6 m^3	36 m
Activity amount	6 m^3	80-95 m^3/h
Fuel efficiency(l/hr)	13	17.7
Fuel type	Diesel	Diesel

We analyzed the measured equipment operation time in the following way. A single concrete mixer truck entering the site and leaving was set as one activity cycle. Our analysis did not include the start and end of the depositing work or the periods of time when the activity was suspended. In this research, we analyzed a total of 21 activity cycles. We then set the detailed activities for each piece of equipment. For the concrete mixer truck, we considered four activities; stopping after entering the site, waiting after stopping, pouring concrete, and leaving. For the concrete pump, only one activity was considered; pumping the concrete. Following this, we measured the equipment operation time for each activity, and obtained a total of 21 data sets with the five activities.

However, the planned equipment operation time is not calculated for the defined activity units; therefore, in this research, we used several processes to estimate the values. For concrete pump cars, the time spent to digest the concrete (6m^3) of a concrete mixer truck was calculated based on the average value of the pump amount per hour (87.5m^3/hr) which isprovided in [8]. In the case of the concrete mixer truck, we did not present any specific activity time information, and assumed the average equipment operation time to be the planned equipment operation time (Table 3).

3.2 Calculating emissions from equipment operation times

This section describes the process for calculating CO_2 emissions by estimating fuel consumption from equipment operation times. The fuel consumption for each activity was calculated via Equation (1). For the fuel efficiency, the equipment data presented in Table 2 was used. The load factor reflects the equipment's fuel consumption according to the activity. We used the load factors analyzed in [7], and the load factors for each activity were Low (25%) for stopping after entering and leaving, Idle (10%) for waiting after stopping, and Accelerated (100%) for pouring concrete and pumping concrete.

Fuel consumption (l) = Equipment operation time (s) × Fuel efficiency (l/hr) × Load factor (%) × 1/3600 (hr/s) (1)

The fuel consumption calculated in Equation (1) was used along with Equation (2) to calculate the CO_2 emissions for each activity. In this research, we used the data provided in [9]; the oil conversion factor is 0.000845, the fuel carbon emission factor is 0.837. Here, the constant of 44/12 is the ratio of CO_2's molecular weight to carbon's atomic weight, and the constant of 10^6 converts the emission unit from tons to grams.

CO_2 emissions (gCO_2) = Fuel consumption (l) × Oil conversion factor (toe/T) × Fuel carbon emission factor (T×C/toe) × 44/12 (Carbon conversion) × 10^6(g/T) (2)

3.3 Comparative analysis of emissions

Through the process above, emissions based on measured times and emissions based on planned times were calculated. The results for the calculated emissions are shown in Table 4. The emissions based on measured time are shown along with descriptive statistic values for the emissions of each activity, whereas the emissions based on planned time are shown as specific values.

From the data based on activity cycles, the calculated value present emissions based on planned time were around 3.0 $kgCO_2$ more than the minimum and were 4.4 $kgCO_2$ less than the maximum, respectively. In terms of error rate, the differences were -42.7% and 63.1% respectively. When we compare the average values for the emissions based on planned time and the emissions based on measured time, the error is around 5%, which is smaller than the difference between maximum and minimum.

If emissions are predicted as deterministic values, a relatively accurate calculation with less than 5% error is obtained from the average values of the equipment data and measured data. However, this approach does not create acceptable predictions. As can be seen from the comparative results in Table 4, this is because the emissions obtained from measurements present a broad range of deviation. This can cause problems in managing emissions related to underestimation or overestimation of the CO_2 emissions in the planning stage. Therefore, in order to make realistic emission predictions, we must consider the uncertainty of each activity.

4 Predicting CO_2 emissions using a Monte Carlo simulation

4.1 Monte Carlo Simulation

This section presents a method of predicting CO_2 emissions probabilistically by using a Monte Carlo simulation. The Monte Carlo simulation is one of the main techniques used in probabilistic analysis. It creates a probabilistic model of variables' uncertainty, and it

Table 3. Measured equipment operation time and planned equipment operation time

Activity	Stopping after entering	Waiting after stopping	Pouring concrete	Leaving	Pumping concrete	Cycle
Average measured equipment operation time (Standard deviation)	36.3 (27.3)	190.5 (243.2)	343.8 (95.5)	9.3 (3.5)	299.6 (83.2)	879.4 (279.35)
Planned equipment operation time	36.3	190.5	343.8	9.3	246.9	826.8

* The unit of all items is sec.

presents statistical results from simulated experiments [10]. These statistical results allow for more effective decision-making in situations where the effects of uncertainty are clear.

In this research, we used the Crystal Ball program, which is an effective tool to execute Monte Carlo simulations. Crystal Ball supports probabilistic model analysis and simulation tests of the data needed for a Monte Carlo simulation. A method for making predictions using Crystal Ball follows the next steps. First, use Crystal Ball to perform a goodness of fit test on the data for the emissions based on measured time. To take the uncertainty at activity level into account, perform the goodness of fit test for each activity. Next, use the analyzed test result values to construct a model of the probability distribution for each activity. In addition, analyze the correlations between emissions for each activity in order to perceive the relation between the different activities. Finally, perform simulation tests that reflect the correlations in the constructed probability model, and analyze the results.

4.2 Goodness of fit test

For the goodness of fit test on the emission data obtained from the measured times, we used the Kolmogorov-Smirnov (K-S) test. When we compared the K-S test to the Anderson-Darling test, which is also a goodness of fit test, the former showed a more sensitive tendency in the median area of the distribution than the tail areas [11]. In this research, the K-S test was used to focus on the general situation where the number of observations is larger than the specific situation where the equipment operation time is measured long.In the test, we considered 14 types of probability distributions supported by the Crystal Ball program.

The results of the test for each activity are shown in Table 5. Test values (D) were below the rejection value of 0.287 at a significance level of 0.05 when N was 21. Therefore, we accepted the null hypothesis of the K-S test, which means the emission data fit well in specific distributions.

Analysis showed that the distributions for stopping after entering, waiting after stopping, and leaving activities follow a log normal distribution, whereas pouring concrete follows a logistic distribution, and pumping concrete follows an extreme value distribution.

4.3 Correlation analysis

To consider the relationship between activities' emissions in the simulation test, we calculated their Pearson correlation factors. The emission correlation factors are shown in Table 6. Through the analysis, we found 4 significant relationships.

First, the activities with the highest correlation were concrete pouring and concrete pumping, with an emission correlation coefficient of 0.854, which is a relatively high value. This correlation is present because the concrete is being poured and pumped at the same time. Second, leaving and waiting after stopping had a significant correlation value of 0.617. This is caused by the delays in the concrete pouring activity and delays in moving vehicles due to crowding around the concrete pump. Stopping after entering and concrete pumping had a correlation of 0.387, while stopping after entering

Table 4. Calculation results for CO_2 emissions according to equipment operation time

Activity		Stopping after entering	Waiting after stopping	Pouring concrete	Leaving	Pumping concrete	Cycle
Emissions for measured equipment operation time	Average	85.1	178.4	3219.7	21.7	3819.7	7324.4
	Median	63.2	112.4	3118.4	18.7	3664.9	7220.7
	Standard Deviation	64.0	227.8	894.2	8.1	1061.4	1877.2
	Kurtosis	12.4	5.7	1.6	1.8	-0.2	0.4
	Skewness	3.3	2.5	1.0	1.4	0.4	0.6
	Min. Value	44.5	9.4	1947.9	14.0	1879.6	3984.3
	Max. Value	334.8	889.6	5637.5	44.5	5903.4	11333.1
Emissions for planned equipment operation time		85.1	178.4	3219.7	21.7	3442.6	6947.5

* The unit of all items except kurtosis and skewness is gCO_2.

and concrete pouring had a correlation of 0.339, which are similar values. The reasons for these correlations are that parking and concrete pouring can be slowed down by the skill of the mixer truck driver, which also influences pumping.

4.4 Simulation test results and analysis

The simulation test was performed considering the probability distribution models obtained via the goodness of fit tests and the calculated correlation coefficients. In the simulation test, the results were obtained probabilistically by generating random values that consider the correlations for the probability distribution of a specific activity. The upper and lower bounds for the emissions can be determined by adjusting the confidence level. In this research, we executed the simulation test 10,000 times at a 95% confidence level.

From the test results, Figure 1 shows the probabilities of the emissions that occur during a single activity cycle. The outcomes suggest that a log normal function is the most fitting probability distributions. An analysis of the results shows that the probability of emitting less CO_2 than the planned emissions amount is 46.2%, which means that the probability of obtaining more emissions than planned is higher. Therefore, we can see that for the planned emissions, the CO_2 emissions that occur during the activity are underestimated.

Table 5. Goodness of fit test results by activity

Goodness of fit test (Kolmogorov-Smirnov test)					
Activity	Stopping after entering	Waiting after stopping	Pouring concrete	Leaving	Pumping concrete
Fit distribution	Log normal	Log normal	Logistic	Log normal	Extreme value
D	0.108	0.108	0.137	0.158	0.076

* At a significance level of 0.05 when N = 21, the rejection value is 0.287

Table 6. Results of analysis of correlation between activities

Activity	Stopping after entering	Waiting after stopping	Pouring concrete	Leaving	Pumping concrete
Stopping after entering	1				
Waiting after stopping	-0.040	1			
Pouring concrete	0.339*	-0.079	1		
Leaving	0.284	0.617**	0.140	1	
Pumping concrete	0.387*	-0.298	0.854**	0.110	1

* Significant at 0.05 level of significance
** Significant at 0.01 level of significance

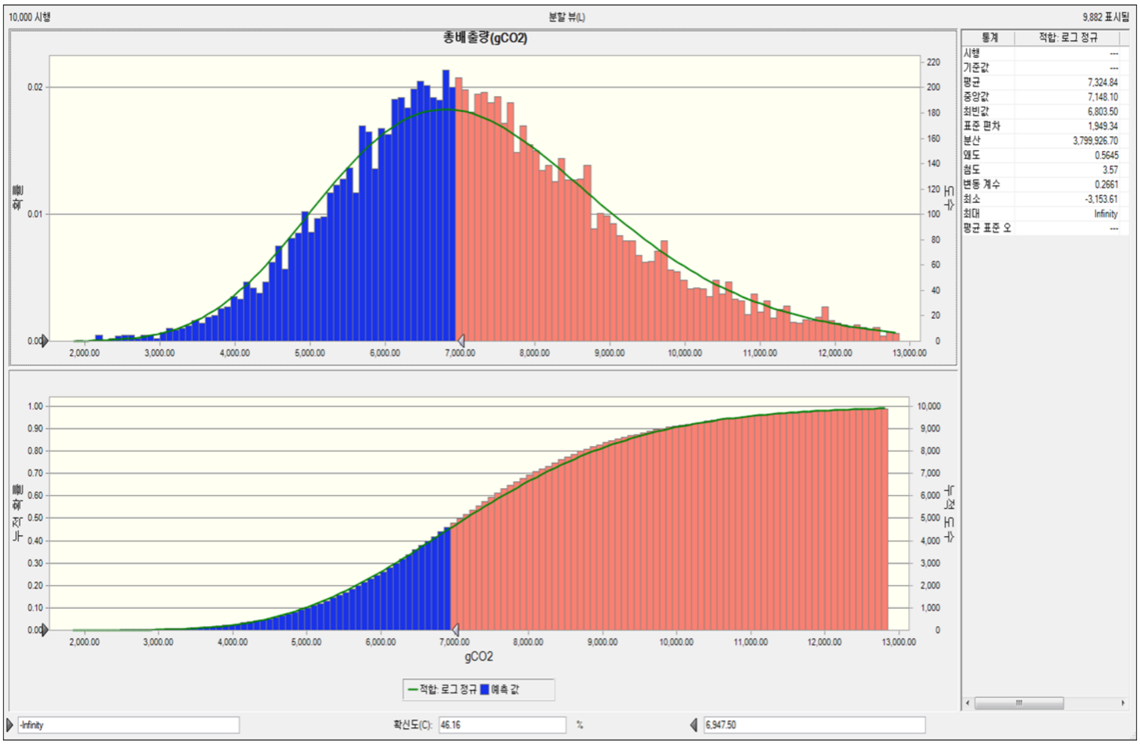

Figure1. Probability view of simulation results (based on activity cycle)

Based on an activity cycle (Table 7), the lower bound for emissions was 4039.8 gCO_2, and the upper bound was 11833.9 gCO_2 at a confidence level of 95%. For each value, when the emissions were compared to those obtained from the planned equipment operation time, there was a 70.3% to - 41.9% difference. From this, it is possible to predict with 95% of confidence that the actual emissions will be within 70.3% to - 41.9% of the planned emissions. In addition, the average value of the simulation was 5.5% higher than the planned value, at 7324.8 gCO_2. This gives a smaller error than the comparison with the bound values.

From the results by activity (Table 7), concrete pouring and concrete pumping have lower kurtosis and skewness than other activities so they follow a gradual distribution, but they present a high emission ratio. In both activities, the equipment is practically working, so the load factor is high and the activity time is long and it causes high amount of emissions. In addition, we think that the activity timespan is determined by the equipment that present relatively uniform work speeds; therefore, the distribution is relatively gradual.

On the other hand, in the case of stopping after entering, waiting after stopping, and leaving, the emission ratio is low but the kurtosis and skewness are both large. We consider that this result occurs because the activities load factor is low and the activity timespan is short. The reason for the kurtosis of these activities to be high is that they are relatively simple activities so they are often completed within a fixed amount of time. Sometimes, however, due to the delay in former activity and preparations for tasks, the activity timespan is extremely long. These extreme value causes an increase in the degree of skewness.

Based on this analysis, reducing activity deviation and improving activity efficiency of equipment can be good methods to both increase prediction accuracy and reduce emissions. However, in order to consider uncertainty effectively, the activities must be considered from a management perspective. Looking at waiting after stopping, the emissions show a difference of more than five times with respect to the average. In addition, the difference between the upper and lower bound amounts to 87 times. That is, as the activities are being performed, certain activities have extreme time increases that can cause an increase in emissions and prediction error. Therefore, we believe that to increase prediction accuracy and reduce emissions, such activities must be well identified and managed.

Table 6. Simulated test results

Activity		Stopping after entering	Waiting after stopping	Pouring concrete	Leaving	Pumping concrete	Activity cycle
Simulated test result emissions	Average	85.4	187.7	3699.1	22.5	3864.5	7325.8
	Median	64.2	99.5	3152.8	18.7	3663.0	7112.0
	Standard Deviation	75.7	286.1	866.5	13.4	1186.7	1973.8
	Kurtosis	155.0	65.8	4.3	142.7	6.0	0.8
	Skewness	9.0	5.79	0.2	7.7	1.3	5.1
	Lower**	45.0	10.9	1445.1	13.8	2158.7	4039.8
	Upper**	257.2	945.6	4940.0	55.0	6711.7	11833.9
Emissions based on planned equipment operation time		85.1	178.4	3219.7	21.7	3442.6	6947.5

* The unit of all items except kurtosis and skewness is gCO_2.

** 95% confidence level

5 Conclusion

In this research, to analyze the uncertainty in CO_2 emissions in the construction stage at activity level, we gathered data about equipment operation time by activity and used this to analyze the related uncertainty. The results were used to show the need for considering uncertainty at activity level, as well as to propose a CO_2 emission prediction method using a Monte Carlo simulation and verify its outcomes.

The conclusions obtained from this research are the following. First, we propose that in order to make a realistic prediction of CO_2 emissions in the building construction stage, it is important to consider uncertainty at activity level. Second, we obtained a realistic emission prediction by presenting a probabilistic method of predicting CO_2 emissions using activity data. Third, by analyzing emissions by activity, we presented a plan to increase the accuracy of emissions predictions and reduce emissions.

We believe that the results of this research will emphasize the need for considering uncertainty at activity level and assist in the prediction and management of on-site emissions. In the future, we will consider plans at activity level and gather additional data at activity level in order to increase the accuracy of predictions and expand the use of the proposed method.

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References

[1] Ibn-Mohammed T. Greenough R. Taylor S. Ozawa-Meida L. and Acquaye A. Operational vs. embodied emissions in buildings—A review of current trends. *Energy and Buildings*, 66:232-245, 2013.

[2] Daewoo E&C. 2014 *Daewoo E&C sustainability report*, volume 1. Daewoo E&C, 75, Saemunan-ro, Jongno-gu, Seoul, Republic of Korea, 2014.

[3] González V. and Echaveguren T. Exploring the environmental modeling of road construction operations using discrete-event simulation. *Automation in Construction*, 24:100-110, 2012.

[4] Monahan J. and Powell JC. An embodied carbon and energy analysis of modern methods of construction in housing: A case study using a lifecycle assessment framework. *Energy and Buildings*, 43(1):179-188, 2011.

[5] Kang G. Kim T. Kim YW. Cho H. and Kang KI. Statistical analysis of embodied carbon emission

for building construction. *Energy and Buildings*, 105:326-333, 2015.

[6] Zhang H. Simulation-based estimation of fuel consumption and emissions of asphalt paving operations. *Journal of Computing in Civil Engineering*, 29(2): 04014039, 2014.

[7] Yi CY. Gwak HS. and Lee DE. Stochastic carbon emission estimation method for construction operation. *Journal of Civil Engineering and Management*, 1-13, 2016.

[8] Korea Specialty Contractors Association. *Machine cost report of construction machinery 2017*, volume 1. Korea Specialty Contractors Association, 15, Boramae-ro 5-gil, Dongjak-gu, Seoul, Republic of Korea, 2017.

[9] IPCC. *2006 IPCC guidelines for national greenhouse gas inventories*, volume 2. IGES, 2108 –11, Kamiyamaguchi, Hayama, Kanagawa, Japan, 2006.

[10] Touran A. and Wiser EP. Monte Carlo technique with correlated random variables. *Journal of Construction Engineering and Management*, 118(2):258–272, 1992.

[11] Huynh VN. Nakamori Y. Lawry J. and Inuiguchi M. *Integrated uncertainty management and applications*, volume 68. Springer Science & Business Media, Heidelberger Platz 3, 14197, Berlin, Germany, 2010.