



Article Stochastic Analysis of Embodied Carbon Dioxide Emissions Considering Variability of Construction Sites

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Abstract: The current method of estimating CO_2 emissions during the construction phase does not consider the variability that can occur in actual work. Therefore, this study aims at probabilistic CO_2 estimation dealing with the statistical characteristics in activity data of building construction work, focused on concrete pouring work and based on field data. The probabilistically estimated CO_2 emissions have some differences from CO_2 emissions measured by current deterministic methods. The results revealed that the minimum difference was 11.4%, and the maximum difference was 132.7%. This study also used Monte Carlo simulations to derive information on a probability model of CO_2 emissions. Results of the analysis revealed that there is a risk of underestimating emissions because the amount of emissions was estimated at a level that exceeds the 95% confidence interval of the simulation results. In addition, the probability that CO_2 emissions using the measured activities data were less than the estimated CO_2 emissions using the bill of quantity was 73.2% in the probability distribution model.

Keywords: CO₂ emissions; construction phase; stochastic analysis; Monte Carlo simulation

1. Introduction

The building sector consumes about 40% of the world's annual energy production, which accounts for approximately a quarter of the world's annual CO₂ emissions [1]. Continuous efforts have been made to reduce the amount of CO₂ emitted from buildings. Various technological developments and political measures related to eco-friendly building materials or renewable energy usage have been undertaken in the public and private sectors. However, these have tended to focus on specific phases in the whole life of the building, namely, material manufacturing and operational building phases [2,3]. Previous studies also have mentioned that it is important to deal with the embodied carbon emissions generated in the production, construction, maintenance, and disposal of building materials [4]. Among these phases, the construction phase accounts for approximately 10–30% of the entire building life cycle, even if it represents a short period. The aforementioned highlights the necessity for accurate and detailed estimation of CO₂ in order to devise means of reducing emissions from the construction phase [5].

However, estimating or predicting the amount of CO_2 generated during the construction phase is difficult because there is variability at the construction site. There is much variability in the input of resource types or quantities because construction activities are performed in outdoor environments [6].

Several researchers have utilized bills of quantity or standard productivity information prepared in the design stage, so values were almost fixed by design documents and cannot reflect the actual condition of the construction site.

Therefore, this study aims at probabilistic CO_2 estimation dealing with the statistical characteristic in activity data of building construction work, based on field data and considering variability. According to 2006 Intergovernmental Panel on Climate Change (IPCC) guidelines, variability is an inherent property of the system of nature and not of the analyst [7]. In this study, variability is defined as an inherent characteristic of the construction phase work. In addition, the result of the intrinsic characteristics is judged to be the working time. This study used actual activity data gathered during the construction phase and performed Monte Carlo simulation to determine the probabilistic interval of CO_2 emissions, focusing on concrete pouring work. Activity data were collected by measuring the operating time of concrete pump cars and concrete mixer trucks, which consume fossil fuels and directly emit CO_2 . In this study, correlation analysis is performed to derive the correlation coefficients for the emission amount of each activity and to reflect them in the simulation. We executed the simulation test 10,000 times at a 95% confidence interval.

2. Literature Review

A deterministic CO_2 emission estimation obtained by multiplying the CO_2 emission coefficient with the amount of input material may not be accurate because these inputs do not take into account uncertainties at the construction site. Therefore, a previous study evaluated variability when estimating CO_2 emissions and has presented a prediction method that considers this level of variability [8–12].

This study also considered the most-consumed building materials to perform an analysis of statistical properties. Based on this, it probabilistically predicted the materials' construction stage emissions [8,9]. Other studies analyzed the variability of emission coefficients by evaluating the most-consumed building materials based on accumulated greenhouse gas emissions, as well as the energy emissions coefficient, in order to assess the level of uncertainty and variability when estimating the emissions of the apartment housing construction stage [10,11]. Another study suggested a method of calculating CO₂ emissions by calculating the amount of use of construction equipment on construction sites based on the schedule information of the building construction [12].

The only datum that can be used to quantify the environmental impact of equipment in the construction process is the daily report on the type and quantity of equipment that is deployed at the worksite. However, this data source lacks detailed information on equipment usage. To calculate CO_2 emissions using traditional life cycle impact assessment metrics and methods, historical performance data must be compiled with an accurate construction inventory (i.e., materials and equipment used for construction and maintenance work) [13,14]. Previous studies estimating CO_2 emissions have used simulation methods. The CO_2 of equipment used in road construction was calculated by measuring the engine load of the equipment. Moreover, the measured data were applied to the simulation considering the variability of the engine load [15–17]. Regarding equipment, simulation studies also exist. Similarly, other studies used CYCLONE simulation to predict emissions probabilistically while considering the variability of fuel consumption according to the activity of earthwork equipment [18,19].

However, the previous studies mentioned above have limitations, since they focus only on materials, or there is a lack of consideration of activity data, such as the operation time of construction equipment at the activity level. Previous studies have estimated only the amount of CO₂ emissions from construction equipment based on the amount of oil the equipment consumes. In addition, the variability in embodied carbon emissions of various building types has been explored [20,21]. However, there is still a lack of statistical information for the activity data for construction. In particular, the distribution type, parameters, and correlations required as input variables for Monte Carlo simulation have not been investigated yet [22].

Therefore, in this study, we gathered actual data about the operating time of construction equipment used at the activity level. Moreover, this study presents an estimation method using probabilistic CO_2 emissions for analyzing the variability during the construction phase.

3. Analyzing Variability in CO₂ Emissions

3.1. Overview of Activity Data Collection

In order to estimate CO_2 emissions, it is necessary to estimate the amount of oil consumption by measuring construction equipment operation time and equipment specification information. Therefore, data were collected on equipment operation time at the activity level (Table 1).

	Content
Project	K Research Building (new construction)
Location	Seongbuk-gu, Seoul, Korea
Land area	130,606 m ²
Building area	33,521 m ²
Gross floor area	22,910 m ²
Structure type	Reinforced concrete
Floors	Six floors and two floors underground
Building use	Office building (education and research facility)

Table 1. Overview of the construction site with activity data collected.

This study collected data about concrete work for a typical floor slab. In this study, it was difficult to collect activity data for all tasks. Therefore, this study collected data focused on heavy equipment, which uses heavy oil in concrete pouring work; we installed a camcorder and a stopwatch to measure the operating time of each piece of construction equipment, namely, concrete pump cars and concrete mixer trucks.

Based on the specifications of the construction equipment, this study surveyed the equipment that meets the applicable standards of construction machinery expenditure as illustrated by Korean professional construction association information.

3.2. Calculating Emissions from Equipment Operation Times

In this study, one work cycle of concrete pouring work was defined from when a concrete mixer truck enters to when the truck leaves the construction site. A total of 37 work cycles were measured. However, interrupted working hours during the work cycle were excluded from the measurement.

The equipment operation time for each detailed task was measured, and 21 data sets were acquired in five categories and used in the analysis. The work of a concrete mixer truck was classified into four detailed tasks: Stopping after entering, waiting after stopping, pouring concrete, and leaving. The detailed work of the concrete pump cars was classified as a single task: Pumping concrete.

To estimate the working time of a concrete pump car for one concrete mixer truck (6 m³), we referred to the average productivity value of the amount pumped per hour (87.5 m³/h) provided in the Construction Equipment Cost Estimates Table (CECET). The CECET is an annual national standard released by the Construction Association of Korea (CAK) and the Ministry of Land, Infrastructure and Transport (MOLIT) and is calculated and published using data on the hourly hire of machines, miscellaneous materials, and drivers of construction machines listed in the standard production unit system. In this study, the concrete mixer trucks and concrete pump cars used at the construction site were collected through the CECET.

In this study, the CO_2 emission coefficients of materials and equipment were used according to the data presented in the 2006 IPCC guidelines [23]. The IPCC provides CO_2 emission coefficients through its own data surveys and reports submitted by each country. Recently, each country has used IPCC guidelines to calculate CO_2 emission coefficients that fit the situation for that country [17].

This study does not consider the working time of concrete mixer trucks at the work planning phase because the number of concrete mixer trucks is calculated at the time of work planning. The working time of the concrete pump car was estimated using the formula (Equation (1)) proposed in the standard for reinforced concrete construction estimation [24]:

$$T_p = t_p \times f_1 \times f_2 \times Q \tag{1}$$

where:

 T_p : Concrete pump car working time;

 t_v : Reference time, estimated time it takes for the concrete pump car to pour 1 m²;

*f*₁: Facility type consideration coefficient;

 f_2 : Concrete mixer truck entry condition coefficient; and

Q: Workload.

In this study, a reference time (t_p) value was applied—1.25 min corresponding to 15 cm of the reinforced concrete slump—by referring to the information provided on the site where the activity data were collected [24]. The working time was calculated under the conditions that f_1 is normal (1.2) and f_2 is good (1.0) [24].

The average and the standard deviation of the measured equipment operation time are shown in Table 2. The planned equipment operation time is expressed as a single value. The variation of work time was the largest for waiting after stopping and was relatively low for stopping after entering and leaving. The average measured operation time of concrete pumping work was calculated to about 50 s longer than the value given by the machine cost calculation table. In addition, the concrete pumping work was more than twice the average measurement time in the case of the bills of quantity.

Activity	Stopping after Entering	Waiting after Stopping	Pouring Concrete	Leaving	Pumping Concrete	Cycle
Average of the measured	36.3	190.5	343.8	9.3	299.6	879.4
equipment operation time (standard deviation)	(27.3)	(243.2)	(95.5)	(3.5)	(83.2)	(279.35)
Planned equipment operation time	36.3	190.5	343.8	9.3	246.9	826.8

Table 2. Measured operation time and planned operation time (in seconds).

3.3. Estimating CO₂ Emissions

In this study, CO_2 emissions from the oil consumption of construction equipment were estimated. The oil consumption was calculated using the measured working time at the construction site, the fuel efficiency of the construction equipment, and the engine load factor of construction equipment (Equation (2)):

$$F = T \times FE \times LF \tag{2}$$

where:

F: Oil Consumption by Work;

T: Working time;

FE: Fuel efficiency of construction equipment;

LF: Engine load factor of construction equipment.

The fuel consumption of the construction equipment is based on the equipment specification information (Table 3). The engine load factors are: Low (20–30% output, short distance travel); medium (30–40% output); waiting after stopping (when output is idling at 10%); and acceleration (100% output

and continuous acceleration) [24]. When output is 40–50%, it indicates that the slope has suddenly changed, or there was a long distance of high driving resistance.

	Stopping after Entering	Waiting after Stopping	Pouring Concrete	Leaving	Pumping Concrete
Engine load factor	Low (25%)	Waiting (10%)	Acceleration (100%)	Low (25%)	Acceleration (100%)

Table 3. Engine load factor by detailed operation.

Using the estimated amount of oil consumption, CO_2 emissions for detailed tasks were calculated using Equation (3):

$$CO_2 = F \times TE \times CF \times \frac{44}{12} \tag{3}$$

where:

TE: Petroleum conversion coefficient; and

CF: Carbon emission coefficient.

In this formula, the type of oil consumed is converted to equivalent oil consumed using an oil conversion factor, since the amount of CO_2 consumed differs depending on the type of oil. The converted value is multiplied by the CO_2 emission factor to estimate the CO_2 emission. The carbon molecular weight ratio to the carbon atom is multiplied by the constant 44/12 to calculate the final CO_2 emitted. In this study, the diesel oil conversion factor is 0.000845 toe/ton, and the emission factor is 0.837 ton-C/toe (where toe is ton of oil equivalent).

3.4. Comparative Analysis of Emissions

The average CO_2 emissions calculated based on the measured operating time and the planned operating time of the equipment were compared. Concrete mixer trucks do not have planned emissions, so they cannot be compared with actual CO_2 emissions. A descriptive analysis of the CO_2 emissions for the activities and the whole cycle was conducted to examine the variability of CO_2 emissions data (Table 4).

Table 4. Descriptive statistics of CO_2 emissions for measured operation time (g CO_2).

Activity		Stopping after Entering	Waiting after Stopping	Pouring Concrete	Leaving	Pumping Concrete	Cycle
	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
Emissions for measured	Standard Deviation	64.0	227.8	894.2	8.1	1061.4	1877.2
equipment operation time	Coefficient of variation	0.8	1.3	0.3	0.4	0.3	0.3
	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	11,333.1
Emissions for planned equipment operation time		85.1	178.4	3219.7	21.7	3442.6	6947.5

The standard deviation, similar to the mean value, appeared to have a large value in the order of pumping concrete, pouring concrete, waiting after stopping, stopping after entering, and leaving. However, the coefficient of variation had the largest value of 1.3 for waiting after stopping, followed by stopping after entering with 0.8, leaving with 0.4, and pouring and pumping with 0.3. Therefore,

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the variation was relatively small in pouring concrete, pumping concrete, and leaving, while it was relatively large for waiting after stopping and stopping after entering. On the other hand, the coefficient of variation for the whole cycle was similar to that of pouring concrete and pumping concrete. Similarly, this is the reason why the emissions of both activities have a high emission rate.

Overall, the amount of CO_2 emissions during pouring works is influenced by the high emission ratios of pouring and pumping. Thus, the distribution of emissions and the total emissions from these two activities represent a relatively regular form of distribution. However, since the coefficient of variation exceeds 0.3 for both the detailed and the complete work, the analyzed deviation is relatively large. Moreover, several activities showed a relatively high coefficient of variation and a biased distribution in the emission data even though the emission rate was low. Thus, the estimation of CO_2 emissions using a single value may cause a significant error due to an insufficient reflection of the variability. In order to increase the reliability of CO_2 emission estimation, it is necessary to consider the variability of CO_2 emissions for each activity.

4. Predicting CO₂ Emissions Using a Monte Carlo Simulation

4.1. Monte Carlo Simulation

In this study, Monte Carlo simulation was adopted for probabilistic estimation of CO_2 emissions. Monte Carlo simulation was used because it is one of the essential techniques used for probabilistic analysis and it generates a stochastic model for uncertain variables and presents statistical results from the simulated experiment [25]. These statistical results enable effective decision-making under uncertain conditions.

In this study, Crystal Ball software was used to effectively perform Monte Carlo simulations. This software supports probabilistic model analysis and simulation testing of the data required for Monte Carlo simulations. For the application of Monte Carlo simulations in this study, CO_2 emissions of one work cycle were set as the result value. In addition, the variables that affect the resultant value were set at CO_2 emissions for each activity. Afterward, the Kolmogorov–Smirnov (K–S) test was performed on the activity data to derive the probability distribution model for CO_2 emissions from the activities. A correlation analysis was performed between the CO_2 emission data for each activity. The simulation was performed by generating random numbers using the correlation analysis results. As a result, the probability model of the resultant value was derived, and the CO_2 emissions were analyzed for each activity.

4.2. The Kolmogorov–Smirnov (K–S) Test

In this study, the K–S test was used to focus on a typical situation where the number of observations is higher than in certain situations where the equipment takes a long time to run. Comparing the K–S test with the Anderson–Darling test, the K–S test has the advantage that it is more sensitive in the middle distribution than in the tail [26]. In the K–S test, 14 types of probability distributions are available in the Crystal Ball software. The K–S test was used to test the goodness-of-fit of the emissions data from the measured operation time.

Since the test statistic of the critical value has a significance level of 0.05 and an N value of 21, it is confirmed to be 0.287 for the K–S test for goodness of fit [27]. The test results indicated that the null hypothesis of the K–S test method adopted in Table 5 for all the sub-tasks is lower than the critical value of 0.287. Therefore, the probability model of each variable derived from this section sufficiently reflects the distribution of actual data. Analysis showed that the distributions for stopping after entering, waiting after stopping, and leaving activities followed a log normal distribution, whereas pouring concrete followed a logistic distribution, and pumping concrete followed an extremum value distribution (Figure 1).



Table 5. Kolmogorov–Smirnov (K–S) test of CO₂ emissions by activities.

Figure 1. The plots of distribution by activities.

4.3. Correlation Analysis

In this section, correlation analysis is performed to derive the correlation coefficients for the emission amount of each activity and to reflect them in the simulation. The correlation analysis indicated the magnitude of the correlation among the activities through a correlation coefficient. The correlation coefficient range is from -1 to +1, and the signs of the coefficients indicated whether the relationship of the two variables is proportional or inversely proportional. The absolute value of the coefficient indicates the strength of the relationship. Thus, any value close to +1 or -1 indicates a strong correlation.

This study investigated the correlation between each variable, determined through the Spearman correlation coefficient. The Spearman correlation coefficient is a non-parametric measure of the degree of qualitative correlation of the increase or decrease when the distribution of two successive variables fits a normal distribution or provides rank-scale data. Therefore, the application of Spearman's correlation coefficient can be suitably considered a detailed work-specific fit distribution model that was verified in the previous section.

As a result of the correlation analysis with a significance level of 0.05, it was confirmed that the correlation between stopping after entering and pouring concrete, stopping after entering and leaving, pumping concrete and waiting after stopping, pumping concrete and pouring concrete was significant

(Table 6). The highest correlation was found between pumping concrete and pouring concrete with a correlation coefficient of 0.806 because the concrete pump car can pump concrete while concrete pouring work is underway. The correlations between pouring concrete and stopping after entering (0.524), and between stopping after entering and leaving (0.469) appeared to be strongly positive. The reason for the two positive correlations is that these activities are particularly affected by the proficiency of handling the equipment at a busy construction site and of the concrete mixer truck driver. The correlation between waiting after stopping and pumping was -0.469, indicating a strong negative correlation. This is because the waiting time is longer as the concrete pumping work is delayed.

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

Table 6. Results of correlation analysis between activities.

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

4.4. Simulation Test Results and Analysis

In this study, we executed the simulation test 10,000 times at a 95% confidence interval. To calculate the confidence interval, instead of a mathematical formula, we used an analytical bootstrapping method [28]. The simulation tests were performed by taking into account the probability distribution model obtained from the fit and the calculated correlation coefficient. The random values were generated considering the correlation to the probability distribution of a particular activity, and the results were obtained stochastically. The upper and lower limits of emissions were determined by adjusting the confidence interval.

The results of the simulation were similar to the corresponding figures of the measured operating time-based emissions data (Table 7). However, in the case of kurtosis and skewness, a significant difference was noticed in the corresponding figures in the CO_2 emission data based on the measured operating hours. The significant differences are because the tendency in the form of CO_2 emission distribution was strongly reflected by the performance of the repeated imitating experiment. The degree of deviation was significantly different from the corresponding values of the emission data based on the measured operating time of equipment.

As a result of the simulation, the CO_2 emission probability model of the pouring work follows the log normal distribution (Figure 2). At a 95% confidence interval, the lower limit of emissions is 4171.7 g CO_2 , the upper limit is 11,705.4 g CO_2 , and the average is 7329.7 g CO_2 .

This study analyzed CO₂ emissions estimated by current deterministic methods as a single value using the derived probability distribution model. The results of the analysis of the estimated current CO₂ emissions were outside the 95% confidence interval of the probability distribution model or about 20% different from the mean value (Figure 3). In the probability distribution model, the probability of CO₂ emissions being less than those estimated by the CECET was found to be about 0.6% (i). Therefore, it is estimated that there is a risk of underestimating emissions because the level of emissions was estimated at a level that exceeds the 95% confidence interval of the simulation results. In addition, the probability of actual measured CO₂ emissions being less than the estimated CO₂ emissions using a bill of quantity was 73.2% in the probability distribution model. However, it is considered that the CO₂ emission calculation method using a bill of quantity may over-calculate compared to actual CO₂

emissions because the corresponding probability differs by more than 20% from the average value of the probability distribution model.

Activity		Stopping after Entering	Waiting after Stopping	Pouring Concrete	Leaving	Pumping Concrete	Cycle
	Average	86.1	186.4	3164.6	22.4	3871.1	7329.7
	Median	64.4	98.4	3168.6	18.7	3.668.7	7165.1
Simulated test	Standard Deviation	74.8	316.6	875.1	11.8	1186.3	186.9
emissions	Coefficient of variation	0.9	1.7	0.3	0.5	0.3	0.3
	Kurtosis	107.7	226.5	4.2	47.4	6.0	3.5
	Skewness	7.58	10.5	0.0	4.8	1.2	0.5
	Lower *	45.0	11.0	1428.1	13.9	2152.3	4171.7
	Upper *	262.6	890.2	4941.6	53.5	6694.1	11,705.4
Emissions base equipment op	d on planned eration time	85.8	175.1	2718.2	21.6	3448.2	6831.4

* 95% confidence interval.

Table 7. Simulated test results (units are gCO₂).



: The average of CO_2 emissions (7,329.7 g CO_2) (2)

(3) : The upper limit of CO_2 emissions (11,705.4 g CO_2)

* Standard Deviation : 186.9 gCO₂

Figure 2. The probability model of CO₂ emissions in concrete pouring work according to simulation results.

Consequently, using actual measured data, probability-based estimation and analysis of CO₂ emissions will be more realistic and accurate for the construction planning phase as well as for the construction phase. The current methods of estimating CO₂ emissions are analyzed to have differences with actual CO₂ emissions, so further verification or improvement of the current methods of estimation is needed. It is also possible to assess quantitatively whether CO₂ emissions are likely to be over- or under-estimated by reviewing the probability distribution model for specific construction work.



(1) : The lower limit of CO_2 emissions (4,171.7 g CO_2)

- (2) : The average of CO_2 emissions (7,329.7 g CO_2)
- (3) : The upper limit of CO_2 emissions (11,705.4 gCO₂)
- (i) : CO₂ emissions as calculated by Construction Equipment Expense Calculation Table (3,147.5 gCO₂, 0.6%)
- (ii) : Amount of emissions equal to 50% of the probability model (7,134.8 gCO₂, 50.0%)

(iii) : CO_2 emissions as calculated by the bills of quantity (8,262.3 gCO₂, 73.2%)



5. Conclusions

This study gathered data on the operation time of construction equipment at the activity level and performed a probabilistic analysis using Monte Carlo simulations to determine the variability of CO₂ emissions during the construction phase.

This study used actual activity data to account for variability in the construction phase, and probabilistic estimation showed that the current deterministic methods are insufficient to predict CO_2 emissions at the planning and design phases. It is suggested that actual activity data collection and probabilistic analyses for activity data are necessary to present highly reliable CO_2 emission estimation. Risk information from the probabilistic emission calculation methods presented in this study may support decision makers to establish more realistic reduction goals in developing greenhouses gas and energy consumption reduction strategies.

This study dealt with the CO_2 emissions of the construction process stage within the life-cycle assessment (LCA) system boundaries. The CO_2 emissions from the construction process stage are known to account for less than those of the operational use stage in the building life cycle. Thus, the variability of the construction phase covered in this study may not have a significant impact on the CO_2 emissions of the whole life cycle. Nevertheless, the importance of embedded carbon, including CO_2 emissions from the current construction process stage, has been emphasized. In particular, according to the zero-energy building concept, which has recently become a reality, CO_2 emissions from the construction process stage will be close to zero in the future, and the calculation of carbon emissions from the construction process stage will be important.

However, this study was limited to the activity data gathered from concrete work only and considered variability at the activity level only in terms of construction equipment operation time. In future studies, we will gather further actual activity data during the construction process. In addition, we will derive the additional factors affecting CO_2 emissions during the construction phase and calculate the derived weights of the factors. The CO_2 emissions from the construction process will also be implemented as a probabilistic model with calculated weights.

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