## Uncertainty Analysis of the LCA Results of Transport Infrastructure Development by Mode

<u>Ryoko MORIMOTO<sup>1,\*</sup></u>, Hirokazu KATO<sup>1</sup>, and Naoki SHIBAHARA<sup>1</sup>

<sup>1</sup>Nagoya University, C1-2(651) Furo-cho, Chikusa-ku, Nagoya, Aichi, 464-8603, Japan

rmori@urban.env.nagoya-u.ac.jp

#### Abstract

The application of life cycle assessments (LCA) implies treatment of data containing uncertainties. This study aims to develop a methodology for uncertainty analysis in LCA for transport infrastructure development. An analysis of light rail transit (LRT) shows that the influence of LCA results from uncertainties of input data. We identified the probability distribution of the main input data for a) the demand volume of LRT/roads and b) the fuel consumption of passenger cars. The result of an inventory analysis, which is based on the probability distribution shows that the environmental load will be reduced by the LRT project. However, the uncertainty analysis proves that environmental loads will not be reduced in the case where the analysis without uncertainty of input data indicates the reduction of the environmental load.

Keywords: uncertainty analysis, system boundary, transportation system, reliability assessment, interpretation

#### 1. Introduction

The reliability of life cycle assessment (LCA) results increases the effectiveness of decision-making from the perspective of the environmental impact. Both the LCA results, which indicate the environmental load or impact from each proposal project and the information regarding the uncertainty are useful for assessing the reliability of LCA-based decisions. This is because LCA results are affected by various types of uncertainty such as parameters, scenarios, and model uncertainty.

In particular, LCA at the planning phase implies input data with large uncertainties because most data are defined by predictions or estimations. It is difficult to build up highly-accurate predicted data because of the long lifetimes of infrastructure and the impact spanning a wide area. If this fact is not carefully considered, LCA results can be grossly misinterpreted. Nevertheless, such uncertainties have not be analyzed in LCA for the development of transport infrastructure. The methodology used for uncertainty analysis has already been developed by previous studies<sup>[1-3]</sup>. According to Heijungs et al.<sup>[2]</sup>, some case studies analyzed the uncertainty using a methodology called "sensitivity analysis" or "scenario analysis," and several different data sets were investigated to determine the consequences for the LCA results such as high and low emission scenarios. However, the teatment of uncertainties for all the parameter requires a large number of scenarios. It is not an ideal method for the LCA of transport infrastructure, which includes many parameters with large uncertainties. Therefore, this study focuses on another statistical method called the "sampling method"<sup>[2]</sup> that is based on the random variation of uncertain parameters. It requires the specification of a distribution of every parameter for repeated calculations, which will have a distribution of results using the Monte Carlo analysis and other methods. However, this statistical analysis remains unused for the LCA of transportation infrastructure. This is because it is not clear whether or not input data can be treated statistically. The method used to collect statistical uncertainty information is also unclear.

This study aims to develop an uncertainty analysis method in the LCA of transport infrastructure. A case study for light rail transit (LRT) is expected to demonstrate how the uncertainty of input data affect the LCA result. It will also suggest how the reliability of the LCA result can be improved.

Table 1: Input data for LCA for transport infrastructur			
Life cycle stage	Input data	A cause of uncertainty	Type of uncertainty
Mining/extraction, production and construction (Infrastructure, vehicle, etc.)	Amount of materials	- Change in plans of infrastructure construction and operation	Scenario
Use	Demand volume	- Accuracy of model for transport demand forecasting	Parameter
(Operation of rails, driving of cars, etc.)	Amount of fuel consumption of passenger car	- Accuracy of vehicle speed simulation model	Parameter
Maintenance	Amount of maintenance	- Accident and disaster	Scenario
Disposal	Amount of disposal	- Amount of reusing and recycling is unknown	Scenario
Throughout life cycle	Emission factor	<ul> <li>Data quality</li> <li>Representativeness</li> <li>Technology and value in the future</li> </ul>	Data Data Scenario

Table 1: Input data for LCA for transport infrastructure development and factors that might cause uncertainty

### 2. Methodology

#### 2.1 The classification of uncertainties

The input data to be collected for each lifecycle stage in the LCA for transport infrastructure improvement are listed in Table 1 along with the cause of its uncertainties and the classification of uncertainties. This study categorises uncertainties into three different types.

The first category is "scenario uncertainty," which is caused by the long lifetime of transport infrastructure. In the course of several decades, there could probably be accidents, disasters, changed plans, and introduction of new technologies, which were not assumed when the LCA calculations were made. These types of uncertainties cannot be described statistically.

The second category is "data uncertainty." Data quality and the representation of background data are included in this type. There are already some emission data such as "eco invent," which disclose uncertainty data along with software that provides analysis tools of for this type of uncertainty.

The third category is "parameter uncertainty." Some of the parameters for LCA provided by forecast models or simulations will include some distribution and enable statistical analysis. In our study, we focus on this type. These parameters are likely to belong to the "use" stage, and the analysis of this uncertainty is very important because the environmental load from the "use" stage is generally larger than that of other stages<sup>[4]</sup>.

# 2.2 Application of the uncertainty analysis method to this study

This study applies Monte Carlo analysis using the following procedure. First, the main input data: a) the demand volume and b) the fuel consumption of a passenger car are subjected to uncertainty analysis, its probability distribution is identified. Monte Carlo analysis uses this probability distribution. The distribution of the LCA outcomes is calculated by running the model 10,000 times with randomly selected parameters being represented.

Then, the following three sets of uncertainty information are disclosed from the outcomes. 1) A bar chart, which shows the life-cycle environmental load before and after the project.  $\triangle E$  indicates that the reduction of the life cycle environmental load of the project is used as a decision-making index. When  $\triangle E$  is positive, the life cycle environmental load is reduced by the project. 2) A distribution of  $\triangle E$ , which shows the variability and robustness of LCA outcomes without considering uncertainties. For environmental decision-making, this study provides a percentage of the reduction of the life-cycle environmental load of the project from this distribution. 3) Countermeasures for increasing the reliability of the LCA results are proposed from the information in 1) and 2).

### 2.3 Providing uncertainty data for demand volume

The LCA analysis requires data such as demand volume of each traffic mode and their routes before and after the improvement. The available data are only the forecast data for LCA in the planning phase, but they could probably differ from the actual volume, which is measured after starting the operation.

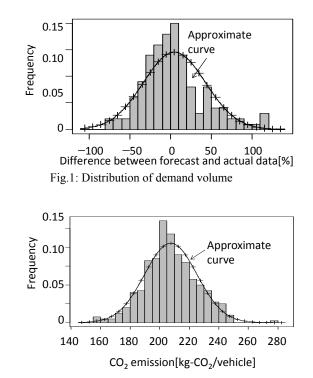


Fig.2: Distribution of the fuel consumption of the passenger car

Table 2: Assumptions made for the case study		
LRT	Length : 5[km] LRT Station : 38 Passengers (two-way) : 7,000[person/day] The number of LRT per day : 278	
Bus	Length : 5[km] Bus Stop : 38 Passengers (two-way) : 5,000[person/day] The number of Bus per day : 305	
A road along LRT	Traffic volume before and after improvement [vehicle /day] : 20,000→16,000* * 2000 to LRT, 2000 to alternative road	
An alternative road	Traffic volume before and after improvement [vehicle /day] : 20,000→22,000** ** 2000 from the road along LRT	

The Ministry of Land, Infrastructure, Transport, and Tourism has published the changes in the demand volume of several road development projects in the past<sup>[5]</sup>. They includes the difference between the forecast data that were predicted before the projects commenced with actual data that were measured more than 5 years after starting the operation. It enables us to obtain a distribution of the difference between the forecast and actual data, which is expressed as a percentage of the amount of forecast data shown in Eq.(1).

$$D = (F - A) / F \times 100 \tag{1}$$

where *D*: Difference [%],

F: Forecasted demand volume [vehicles/day],

A: Actual demand volume [vehicles/day]

The distribution is illustrated in Fig.1. The number of samples is 139. The Chi-squared test shows that the distribution can be considered as a normal distribution with a mean value of 4.7 and a standard deviation of 38.

# 2.4 Providing uncertainty data for fuel consumption of passenger car

To quantify the fuel consumption of a passenger car, the vehicular speed is important. It is obtained using a vehicle-driving simulation in the LCA during the planning phase. Therefore, input data regarding the fuel consumption of passenger cars can be used to confirm the uncertainty based on the accuracy of the simulation model.

This study attempts to determine the error in the observation of the vehicle speed, which is obtained using simulation software<sup>[6]</sup>. A simulation is repeated under the same conditions such us traffic volume, traffic signals, and vehicle performance on the same virtual road.

These repeated simulations provide the vehicular speed every 0.1 second for each vehicle while driving through the simulation area. It enables the fuel consumption and  $CO_2$  emission to be calculated using Eq. (2)<sup>[7]</sup>.

$$FC = 0.3T + 0.028I + 0.056\Sigma \left(\delta_k \left(v_k^2 - v_{k-1}^2\right)\right)$$
(2)

where FC: fuel consumption[cc],

- T: total trip time [sec],
- I: total distance [m],
- k: measurement cycle (k = 1, 2, ..., K),
- *K*: *T* / 0.1 [sec],
- $v_k$ : instantaneous velocity at each cycle,
- $\delta_k$ . If a vehicle is running with a driving force:  $\delta = 1$ , without it:  $\delta = 0$

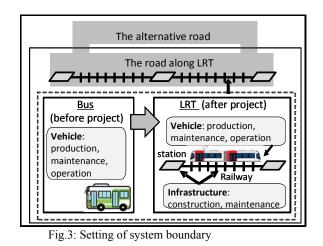
The number of samples is 370. The frequency distribution of these data provides a distribution of fuel consumption calculated by the vehicle speed, which is estimated by the simulation model. The distribution is shown as Fig.2. The Chi-squared test shows that the distribution can be considered to be a normal distribution, for which the mean value is the average speed of all vehicles estimated using simulations, and where the standard deviation is 8.6% of the mean value.

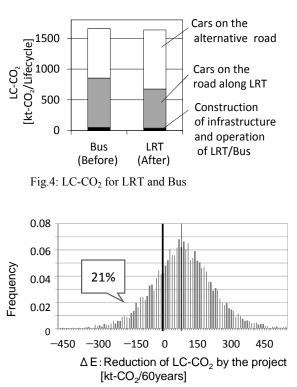
#### 3. Case Study

The case study for LRT is based on the study done by Watanabe et al.<sup>[4]</sup>. They already estimated LC-CO<sub>2</sub> for each part of the LRT and bus systems such as rails, stops and operation processes.

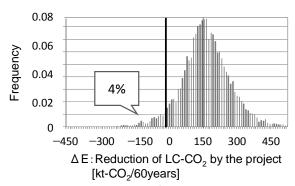
The assumption is made that the existing bus system is abandoned and a new LRT system is developed on the same route as the abandoned bus system. In addition, we assume that passengers of the abandoned bus and a subset of the passenger car users will change their traffic mode to LRT. This leads to a change in the demand volume of each traffic mode, as shown in Table 2.

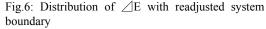
The system boundary involves the construction of the infrastructure and operation of the LRT system, passenger cars on the road beside the LRT railway, and also on another alternative road, which is connected to the road along the LRT route (see Fig.3). In this analysis, the estimated emission of the environmental load is limited to carbon dioxide ( $CO_2$ ) emissions. The life time of this project is assumed to be 60 years.











#### 4. Results

#### 4.1 LC-CO<sub>2</sub> under assumption of this case study

The Life Cycle CO<sub>2</sub> (LC-CO<sub>2</sub>) is estimated both before and after the development of the LRT system, as shown in Fig.4.  $\triangle E$  is estimated without considering that the uncertainty equals 90 [kt-CO<sub>2</sub>/lifetime].  $\triangle E > 0$  means that this LRT project can reduce the LC-CO<sub>2</sub> based on the assumptions made in this case study. Moreover, the CO<sub>2</sub> emitted from passenger cars are responsible for the largest portion of the LC-CO<sub>2</sub>.

### 4.2 Distribution of ∠E

The probability distribution of  $\bigtriangleup E$  is shown in Fig.5. The result of the uncertainty analysis (Fig.5) shows that  $\bigtriangleup$ E has a negative value 21% of the time. In other words, this project has a 79% chance of reducing CO<sub>2</sub> emissions. This probability indicates the reliability of the LCA result. If the decision maker uses this result to determine that a project should proceed on the basis of the environmental load, he has to make reference to this reliability. The adequacy of this reliability should be discussed.

# 4.3 The counter measure to improve reliability of LCA results

If the reliability of the LCA result is not sufficiently high, it cannot be used for the evaluation even if the transportation improvement project could probably improve the environmental conditions. For example, if decisionmakers require a reliability that is at least 90%, the result of this case study cannot be used for decision-making.

This study proposes to employ two countermeasures to increase reliability. One is to perform an additional survey to decrease the uncertainty of the input data by collecting data or using a more accurate model, among others. However, a lack of knowledge, appropriate software, time, and funds sometimes prevents additional surveys from being carried out and hence a reduction in uncertainties.

The second counter measure is, in such cases, the necessary exclusion of large amounts of uncertainty data in the LCA analysis in order to ensure a result with a high reliability. A larger system boundary requires more complicated and numerous estimation models, and the uncertainty of the input data increases. As a result of setting a large system boundary, almost all changes affected by the project can be included in the calculation. On the other hand, the LCA result could probably decrease the reliability due to uncertainties. Therefore, another counter measure is that the system boundary. However, this new result is very definitive, and requires careful consideration when being interpreted and used to make assessments.

For this case study, if the system boundary is readjusted to include only the LRT railway and passenger car on the road along the side of the LRT railway (i.e., the alternative road is removed), the reliability could probably increase. From the calculations with the new system boundary, the  $\angle$ E that is estimated using the represented value equals 170 [kt-CO<sub>2</sub>/lifetime], and the reliability of this result increases to 96% (Fig.6). Because the system boundary reduces, the uncertainty of the data decreases. Moreover,  $\angle$ E being larger than the former estimation increases the reliability.

#### 5. Conclusion

This study developed an uncertainty analysis method in LCA for transport infrastructure. First, input data and its uncertainties are listed together with the classification of uncertainty. A suitable methodology is discussed regarding each type of uncertainty. Then, this study focuses on two main sets of input data: a) demand volume and b) the fuel consumption of a passenger car. For these two sets of data, the probability distribution is identified. The distribution was used in a Monte Carlo analysis. This study provides three sets of uncertainty information from the results of the uncertainty analysis: 1) the life cycle environmental load without considering uncertainties, 2) the distribution of the LCA outcomes, and 3) countermeasures to increase the reliability of the results.

A case study for LRT was conducted to demonstrate how the uncertainty of the input data affects the LCA result. The result of the inventory analysis based on data without considering uncertainties proves that the environmental load will be reduced by the development of the LRT. However, the uncertainty analysis indicates that there is 21% chance that the environmental load will not be reduced. We then proposed a way to improve the reliability.

If the reliability of the LCA result is not sufficiently high, the result cannot be used for evaluation and decisionmaking. Then, two countermeasures for improving the reliability were suggested. 1) To develop additional futher surveys and accurate models, etc. to decrease the uncertainty of the input data, and 2) to readjust the system boundary so that it has a sufficient reliability, and determine the new result with the new system boundary.

#### 6. Acknowledgement

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