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전과정평가의 사용단계 모델링을 위한 계산적 프레임워크 연구

Computational Framework for Usage Stage Modeling of Machines in Life Cycle Assessment

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Despite the importance of the usage stage in life cycle assessment (LCA), there is a lack of comprehensive studies on the usage stage modeling. Based on the literature review, this paper establishes a general framework of the usage stage modeling by redefining existing models and proposing new models. The proposed computational framework can provide the overview of the current research as well as lead researchers and practitioners to consider proper modeling techniques. The framework includes the representative usage scenario method, usage context modeling, and time series usage modeling. Also, future research directions are suggested with the proposed computational framework.

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1. Introduction

Environmental sustainability has become a critical global issue since people have started to notice that the speed of resource depletion can surpass the regeneration rate of nature. In order not to compromise the availability of natural resources for future generations, governments and companies are required to be green or environmentally-friendly in their decision making. However, the greenness is difficult to be quantified and evaluated directly. Generally, the evaluation is done by the environmental performance of products that we produce, and life cycle assessment (LCA) is the most widely used technique to provide the potential environmental impact of a product throughout its life cycle.[1-5]

The life cycle of a product consists of manufacturing, usage, maintenance, and end-of-life (EOL) stage,[6] and each stage has its own impact on the environment by utilizing resources directly or indirectly as shown in Fig. 1. The manufacturing stage encompasses extraction and processing of raw materials, transportation, part manufacturing, and assembly. The usage stage operates the manufactured products, and the maintenance stage requires new parts, filters, lubricants, etc. depending on the maintenance cycle and reliability. The EOL stage includes recycling, landfill, and incineration. LCA considers the product life cycle and provides the environmental performance of products by analyzing these activities.

While there are relatively standardized procedures to estimate the environmental impacts of the manufacturing, maintenance, and EOL stage in LCA, modeling of the usage stage has not been actively researched.[7,8] There are some reasons why the usage stage research in LCA has not been conducted actively. First, not only products but also human behavior and usage environment affect the stage. It is not only difficult to collect usage data but also large variations can be observed. Second, the whole usage profile is not always available and predictions from historical data are frequently

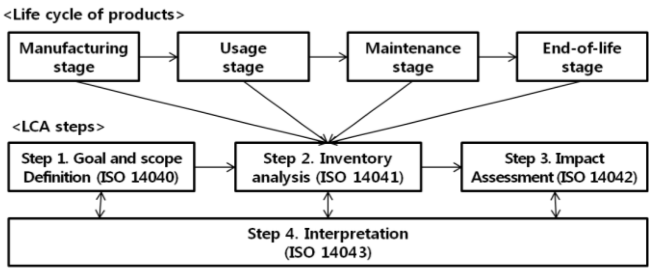

Fig. 1 Product life cycle and LCA steps

required. In contrary, the manufacturing stage is less affected by the human behavior and the life time of a product so that the stage is more controllable than the usage stage in terms of modeling.

Though it is challenging to collect the usage data and model the usage stage, the stage is critical in an LCA study since the majority of the environmental impact can be caused by the stage.[7,9-11] However, despite the importance of the usage stage, only a few studies were conducted and the lack of comprehensive studies on the usage stage modeling motivates this research. The accurate estimation of the environmental performance of products is the basis for sustainable manufacturing.

In this paper, the literature regarding the usage stage modeling in LCA is reviewed and it attempts to establish a computational framework for the usage stage modeling by redefining existing models and proposing new models. The computational framework can not only provide the overview of the current research on the usage stage modeling but also lead the researchers and practitioners to proper modeling techniques. Moreover, future research directions are suggested along with the proposed computational framework.

2. Life Cycle Assessment and Usage Model

2.1 Usage Stage in LCA

With the increased awareness of sustainability, LCA gains popularity as an analytical method to quantify the potential environmental impact of a product system.[8,12] ISO provides international standards[5] for LCA including the four steps in Fig. 1.

The goal and scope definition is the starting point of an LCA study and guides the other steps. It includes the intended application, the purpose of the study, the product system, the system boundary, the functional unit, impact categories, methodologies of impact assessment, data requirements, assumptions, and limitations. The double-headed arrows in Fig. 1 indicate that LCA is an iterative technique. When new data is added or the initial goal and scope of the study are changed, the first step can be revisited. The life cycle inventory (LCI) analysis is the next step, which is the core of an LCA study. It involves collecting data and building an inventory table which quantifies inputs (e.g., energy, raw material, and other physical inputs) and outputs (e.g., releases to air, soil, and water). The life cycle of products can be plugged in this step as inputs. The life cycle impact assessment (LCIA) evaluates the significance of the potential environmental impact from the inventory table with selected impact categories and indicators. As optional elements, normalization and weighting can help the understanding of the impact assessment. Finally, the interpretation step provides recommendations based on the results from the LCIA step. The recommendations can include various opportunities to reduce any adverse environmental impact and decision support for strategic policies.

Various life cycle impact indicators have been developed for the easier understanding of the environmental impact and the comparison between products, e.g., Eco-Indicator series, IPCC (International Panel on Climate Change) Global Warming Potential (GWP) series, ReCiPe, Ecosystem Damage Potential, etc. Each impact indicator has unique assumptions and its own objective. For example, while the Eco-Indicator provides a single score from three damage categories (resources, ecosystems, health), the global warming potential is a relative measure of greenhouse gases (e.g., carbon dioxide, methane, nitrous oxide, etc.) with a reference gas, carbon dioxide. In order to help the LCA steps and calculate these indicators, a set of software programs is available such as SimaPro, Gabi, openLCA, Team and Greet.

From the perspective of product life cycle, the environmental impact of a product can be formulated as follows.[10,13] First, the total environmental impact can be expresses as:

$$\sum_{t=i}^{l} I_t^{total} = I^{mfg} + \sum_{t=i}^{l} [I_t^{usage} + I_t^{maint} + I_t^{eol}] \qquad (1)$$

where l is the expected life time starting from time i; I_t^{total}, I^{mfg}, I_t^{usage}, I_t^{maint}, and I_t^{eol} represent the impact of total life cycle, manufacturing, usage, maintenance, and EOL. Note that the impact of the manufacturing stage is a one-time event and is not affected by the life time.

The impact of the manufacturing stage is defined as:

$$I^{mfg} = \sum_r e_r^{raw} N_r + \sum_p e_p^{process} N_p + \sum_s e_s^{trans} N_s \qquad (2)$$

where e_r^{raw}, $e_p^{process}$, and e_s^{trans} represent the unit environmental impact of raw materials (r), manufacturing processes (p), and transportation (s); N_r, N_p, and N_s denote the number of raw materials, manufacturing processes, and transportation.

The impact of the usage stage is defined as:

$$\sum_{t=i}^{l} I_t^{usage} = \sum_{t=i}^{l} e^{energy} N_t + \sum_{q} \sum_{t=i}^{l} e_q^{emission} ER_q \, OH_t \quad (3)$$

where e^{energy} and $e_q^{emission}$ are the unit impact of energy and emissions q; N_t is the amount of used energy; ER_q is the emission rate of emissions q in g/h; OH_t is the operating time in hours. It can be seen that the main emission causes are the expected life time and the type and amount of energy used and produced.

The impact of the maintenance stage is defined as:

$$\sum_{t=i}^{l} I_t^{maint} = \sum_{m} \sum_{t=i}^{l} e_m^{maint} \, N_m \left\lceil \frac{max(OH_t - RC_m, 0)}{RC_m} \right\rceil \quad (4)$$

where e_m^{maint} is the unit impact of manufacturing of maintenance part m; N_m is the number of part m; RC_m is the replacement cycle of part m in hours; the ceiling function gives the number of replacements for part m.

The impact of the EOL stage is defined as:

$$\sum_{t=i}^{l} I_t^{eol} = e_{used}^{eol} + \sum_{m} \sum_{t=i}^{l} e_{replace}^{eol} \, N_m \left\lceil \frac{max(OH_t - RC_m, 0)}{RC_m} \right\rceil \quad (5)$$

where e_{used}^{eol} and $e_{replace}^{eol}$ are the unit impact of EOL processing of the used product and replaced parts.

Among the life cycle stages of a product, the usage stage is one of the most uncontrollable stages for manufacturers since user behavior plays a key role, which makes the stage challenging to be modeled when conducting an LCA study. Furthermore, the ISO 14040 family does not suggest any guidelines on how to model the usage stage.[7] Therefore, many LCA studies only focus on the manufacturing stage which has the most standardized procedure among the life cycle stages.

However, LCA studies report that the usage stage can be the primary contributor to the environmental impacts of consumer products in comparison with the other stages.[7,9-11] For example, the reported proportions of the usage stage impact out of the total environmental impact are as follows: more than 80% for electronic kettles,[14] 80% for washing machines,[15] 70-80% for loaders,[16] 85% for tractors,[17] 90% for surface radar systems,[7] 90% for diesel engines.[18] The proportions are summarized in Table 1. Though the percentage can be varied by assumptions (e.g., life time, usage environment, etc.) and available data, it can be noticed that the usage stage can dominate the total environmental impacts of machines.

Table 1 Usage stage environmental impact of machines

Product	Usage stage impact out of total impact (%)
Electronic kettle	80
Washing machines	80
Loader	70-80
Tractor	85
Surface radar system	90
Diesel engine	90

Also, it is a reasonable assumption that when products run for a long period of time, the environmental impact of the usage stage will be increased since the life time directly affects the usage stage. Therefore, it is expected that large-scale machinery in industry, agriculture, and military generates the dominant environmental impact from the usage stage due to the long life time. These types of machines are the focus of this study though many consumer products can show a similar pattern. The understanding and proper modeling of usage patterns are critical for estimating the potential environmental impacts of machines correctly.

2.2 Usage Model

There are several methods and perspectives for a usage model. In general, usage modeling aims at understanding users, identifying requirements, and improving product's quality in product design, software engineering and human-computer interaction. Users and their interactions are typically emphasized in design philosophies such as human-centered design, user-centered design process and usability engineering.

Usability body of knowledge provides an overview of various methods related to usability: ethnography, persona, contextual inquiry, use case, use scenario, quality function deployment (QFD), GOMS (Goals, Operators, Methods, and Selection), and so forth.[19] Use cases and use scenarios are known as best practices in software engineering.[20] Use cases are a sequential construct in object-oriented modeling for providing users' interactions with a system. Use scenarios provide key tasks in sequence from the work context and usage requirements.

QFD is a structured method to convert the customer needs into engineering parameters or functions for a product. Using the planning tool called the house of quality, customer attributions and design parameters are linked and engineering designers can compare the current product with its competitors. GOMS is a family of user cognitive models consisting of goals, operators, methods and selections rules. There are four basic variants of GOMS: Keystroke-Level Model (KLM), CMN-GOMS, NGOMSL and CPM-GOMS. For example, KLM defines keystroke-level

Table 2 Usage modeling techniques in the framework

Modeling techniques	Advantage	Disadvantage
Representative usage scenario method	Simple and easy to use	Can't explain variation of usage factors and time
Usage context modeling	Can capture variation of usage factors	Difficult to build causal maps
Time series usage modeling	Can capture usage patterns over time	Difficult to reflect various usage patterns

operators such as pressing keys, buttons, and moving mouse and helps to predict task execution time in a human-computer system.

While the aforementioned usage models are useful to systematically understand the users and their usage patterns in design and software engineering, it is rarely discussed that how the usage models can be related to environmental impact. Moreover, instead of presenting a general framework, separate experiments have been conducted. For example, Anjos et al.[21] show the usability of software affects sustainability by having the usability test of 40 participants and calculating energy consumption.

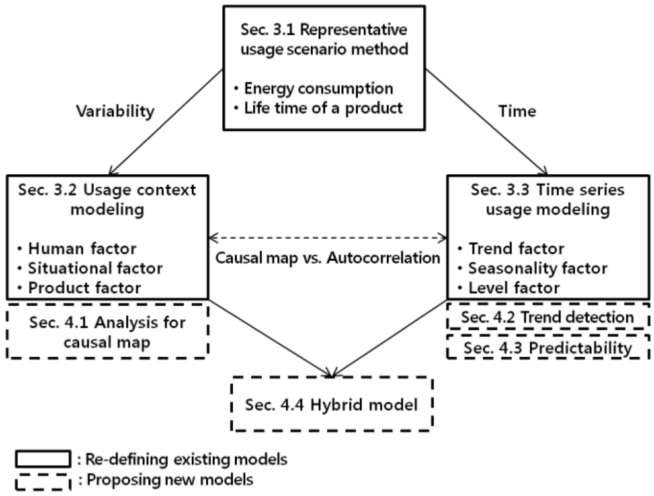

Fig. 2 Computational framework for usage stage modeling

3. Computational Framework of Usage Stage Modeling for LCA

In this section, the computational framework of the usage stage modeling for LCA is presented based on the systematic analysis of related research. Table 2 and Fig. 2 show the proposed computational framework including the representative usage scenario method, usage context modeling, and time series usage modeling. Note that this paper presents new perspectives of each method and their relations. Eq. (3) is the basic equation for calculating environmental impact of the usage stage and it is assumed that the unit impact of energy and emissions in Eq. (3) can be obtained from environmental database such as the Ecoinvent and European reference Life Cycle Database (ELCD), and pollution (emissions) testing.

3.1 Representative Usage Scenario Method

The most widely used method for the usage stage modeling in LCA is the representative usage scenario method though there is no consensus for the name among researchers. The representative usage scenario in this paper indicates a representative usage profile or an average value of different usage modes. As shown in Eq. (3), the energy (fuel, electricity, etc.) consumption, N_t and the life time (or total driving distance), $\sum_{t=i}^{l} OH_t$, are the two key usage parameters affecting the environmental impact of the usage stage.

For example, Li et al.[18] assume the average fuel consumption (25 *l*/100 km) and the total driving distance (300,000 km) for the LCA study of a truck. Then, the potential environmental impact of the usage stage can be calculated from the required fuel production and the emissions from the engine operation. Choi et al.[22] assume the average electricity consumption (94 Wh/week) and the life time (4 years) for the LCA study of a personal computer. Then, similarly the environmental impact can be quantified from the electricity production and consumption.

The representative usage scenario method mainly resorts to the correctness of assumed usage profiles, and most of the studies that use the method do not show how to get the representative scenario. The work of Gustafsson and Rönnblom[7] is the one of the few studies which shows the clear definition of the representative usage scenario. In their LCA study of the surface radar system, eight possible operational profiles are defined first and the representative usage is derived as the average value of energy consumption of the eight different operational profiles. Since the potential environmental impacts of the eight operational profiles differ widely, if one of them is chosen as a representative usage scenario, the total environmental impact of the product can be largely misestimated.

It has not been discussed but once the representative usage scenario is selected, a hierarchical breakdown structure can be constructed for related activities similar to the concept of keystroke-level model in the GOMS family. The amount of energy consumption can be summed up with a bottom-up approach using the hierarchical breakdown structure.

The representative usage scenario method is simple and easy to use so that many LCA studies use this method. However, the method cannot show the variability of the usage stage, and various usage profiles cannot be generated and tested. To overcome this, the usage context modeling in Fig. 2 can be used. Another limitation of the representative usage scenario method is that the method assumes either the whole usage profile is known or the usage stage is the steady-state process over time. For example, it is not clear how to determine the required period for averaging (e.g., last 10 years or last 5 years) in the representative usage scenario method. Also, it is possible that there is an increasing or decreasing trend in the usage stage, which is the obvious violation of the assumption in the representative usage scenario method. For this issue, the time series usage modeling in Fig. 2 can be used.

3.2 Usage Context Modeling

The usage context modeling is proposed by Telenko and Seepersad[14] in order to deal with operational variability in LCA[23] using probabilistic graphical models (PGMs). The core of this method is to build a probabilistic network of usage context factors instead of utilizing separate scenarios, e.g., A, B, and C in Fig. 3. The usage context factors can be classified as human factors (user's behaviors, skills, habits), situational factors (location, time, weather, goal), and product factors (features and specifications). With this perspective, a scenario can be considered as a set of usage conditions that describes how a product can be used.

The PGM is used to express the conditional dependence structure between the usage context factors as a graph. Each usage context factor is a node in the graph, and an arrow represents a directional dependency. Based on the network structure with sets of conditional and joint probability distributions, operational variability in LCA can be studied. For example, let's assume that the energy consumption of electronic kettles is caused by weather and the types of drinks. Once building a PGM and collecting data for Bayesian inference, a simulation study can be conducted and the final result has a form of distribution. Furthermore, various scenarios can be tested utilizing the built PGM. The mathematical model can be expressed simply as follows:

$$\sum_{t=i}^{l} N_t \sim P(A,B,C) = P(C|A,B)P(B|A)P(A) \qquad (6)$$

which indicates that the life time energy use can be related to the usage context factors, A, B, and C.

The understanding of the relationship between the representative usage scenario method and the usage context modeling is important in the proposed framework. The representative usage scenario method can be viewed as the mean of the distribution of the usage parameter (energy consumption) in the usage context modeling as depicted in Fig. 3. That is, the representative usage scenario method assumes the representative usage condition, which is the specific realization of usage context factors.

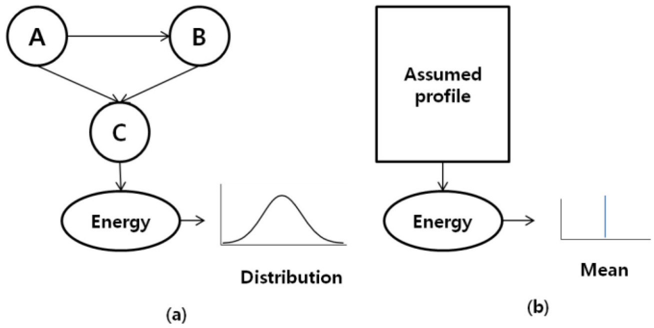

Fig. 3 Relation between usage context modeling (a) and representative usage scenario method (b)

The limitations of the usage context modeling include building a conditional dependence structure and requiring more data than the representative usage scenario method. Identifying causal relations among different usage context factors is challenging or sometimes impossible. Moreover, it can be time-consuming to collect all the necessary data to estimate the sets of conditional and joint probability distributions.

3.3 Time Series Usage Modeling

The time series usage modeling is proposed by Ma and Kim[10] to deal with the issue of time in LCA.[24-26] The method decomposes patterns of usage parameters (e.g., energy consumption and operating hours) as trend, seasonality, and level factors. A trend is a long-term increase or decrease pattern; a seasonality is a repeated pattern with a fixed and known period; a level is remaining values after removing trend and seasonality factors.

The time series usage modeling can capture these usage patterns and model them using time series analysis techniques (e.g., exponential smoothing[27] and ARIMA.[28,29] The mathematical model can be expressed simply as follows:

$$\sum_{t=i}^{l} I_t^{usage} = \sum_{t=i}^{l}\sum_{s=1}^{z} e^{emission} TS_{ts}^{N_t} + \sum_{q}\sum_{t=i}^{l}\sum_{s=1}^{z} e_q^{emission} ER_q TS_{ts}^{OH} \qquad (7)$$

where s is the number of time segments, TS^{Nt} and TS^{OH} are time series models for the amount of used energy and the operation time.

With the advent of sensors and storage technology, operational data can be gathered in real time for a specific usage condition.

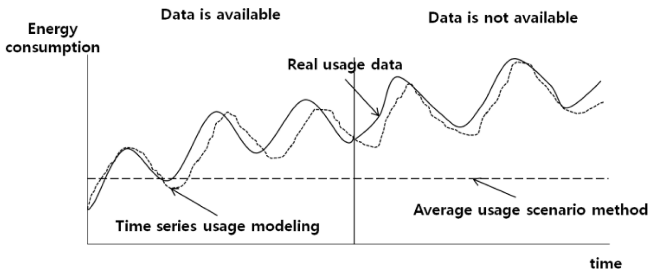

Fig. 4 Relation between time series usage modeling and representative usage scenario method

This data can be an input of the time series usage modeling. Time series analysis is useful when the causal relationships among usage context factors are not easily identified. Therefore, the usage context modeling and the time series usage modeling can be distinguished depending on the availability of the causal map. The time series usage modeling utilizes the autocorrelation of the usage parameters.

It is important to understand the relationship between the representative usage scenario method and the time series usage modeling. The representative usage scenario method can be considered as an equally weighted smoothing (or averaging), which is the simple average of all past data as shown in Fig. 4. Since the weights (e.g., range from 0 to 1) for past data can have various forms (e.g., 1 for only the latest data and 0 for others, or exponentially decreasing weights for older data), the representative usage scenario method is only a special case of the time series usage modeling. The representative usage scenario method smooths a time series using a simple averaging so that it cannot reflect the various usage patterns. The time series usage modeling provides not only the future usage patterns based on trend, seasonality, and level factors but also their variability (i.e., prediction intervals) systematically.

The limitation of the time series usage modeling is requiring more complex modeling procedures than the representative usage scenario method. It should be addressed when the time series usage modeling can be used with the high cost. Finally, a predictability issue should be addressed. It is beneficial to understand the predictability issue and address how to improve the prediction accuracy.

4. Future Research Directions

This section provides some future research directions of the proposed computational framework for the usage stage modeling. Since the representative usage scenario method can be viewed as the special case of the other methods, the research directions mainly focus on the limitations of the usage context modeling and time series usage modeling.

4.1 Data Collection and Analysis for Causal Map

The usage context modeling requires more data than the representative usage scenario method in order to figure out the usage context factors and interactions among them (i.e., causal map). One possible solution is to utilize telematics systems. PRODUCT Link and JDLink are the examples of the telematics systems provided by Caterpillar and John Deere. Information such as locations, work modes, operating hours, energy consumption, and conditions of machines can be stored remotely.

Once the usage data is collected, data mining or machine learning techniques can be applied to relate the usage context factors and usage parameters. Recently, there have been some attempts to identify usage contexts for product design using embedded sensor data.[30,31]

4.2 Trend Detection

The representative usage scenario method is useful when there is no trend. Ma and Kim[10] show that when there is a trend, the simple average method can generate huge errors in LCA. This gives one critical condition when the time series usage modeling can be used. Instead of applying various time series techniques in the beginning, it is important to test whether a trend is detected or not first.

A trend can be observed with the changes of usage context factors. For example, users' behaviors and skills as human factors or fuel price as situational factors can continuously affect the fuel consumption. Therefore, trend detection techniques should be the first step to determine the necessity of the time series usage modeling. Note that seasonality can also be important when an LCA result of a specific time period is required, e.g., the environmental impact of the first quarter in 2018.

Regression analysis and the Mann-Kendall test[32,33] are the popular trend testing techniques as parametric and non-parametric methods. Regression provides the regression slope as an estimator of trend magnitude. Regression analysis assumes that the residuals are independent and normally distributed with a constant variance. The Mann-Kendall test is based on the calculation of Kendall's tau in Eq. (6) with the null hypothesis of no monotonic trend.

$$\tau = \frac{S}{\frac{1}{2}n(n-1)} \tag{8}$$

where n is the total number of time series data points and the statistic S is given in Eq. (7).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \quad (9)$$

where x_j is the data point one time step ahead, x_i is the current data point, and the sign of (x_j - x_i) is given in Eq. (8).

$$sgn = \begin{cases} 1 & if\ \left(x_j - x_i\right) > 0 \\ 0 & if\ \left(x_j - x_i\right) = 0 \\ -1 & if\ \left(x_j - x_i\right) < 0 \end{cases} \quad (10)$$

If there is a seasonality in the time series, the seasonal Mann-Kendall test can be used.[34]

4.3 Predictability

As discussed in Sec. 3.3, the conventional usage modeling technique, representative usage scenario method, can be considered as an equally weighted smoothing over all available past data. When an LCA study is conducted, if only past environmental impact is required and the whole picture of a usage profile during the period is available, the representative usage scenario method can provide fairly accurate modeling for the usage stage. However, in general, future usage patterns should be predicted for LCA within the expected life time of a machine based on the limited past data[10] Therefore, it is also important to understand the predictability of a given time series. The goodness of predictability of a time series depends on how much information the past conveys for the future values of the time series.[35]

The standard approach for predictability is the use of a hold-out strategy.[36] In this strategy, the most recent data points withheld from time series modeling (hold-out data) and a time series model is built only using the remaining data points (training data). The prediction accuracy of the built model is then tested with the hold-out data.

There have been other studies to estimate the predictability of time series. Diebold and Kilian[35] propose a measure of relative predictability which is based on the ratio of short-run accuracy relative to long-run accuracy. For example, if a time series is white noise, relative predictability is zero since short-run forecasts are as accurate as long-run forecasts. If a time series is generated from a random walk, relative predictability will decline as the forecast horizon increases. Garland et al.[37] focus on the inherent complexity of real-world time series such as the dimension, nonlinearity, noise, etc. Based on the concept of entropy (e.g., white noise have maximal entropy rates while well structured time series have low entropy rates), predictability can be quantified. These methods are useful in that a single value related to the complexity of given time series can be suggested.

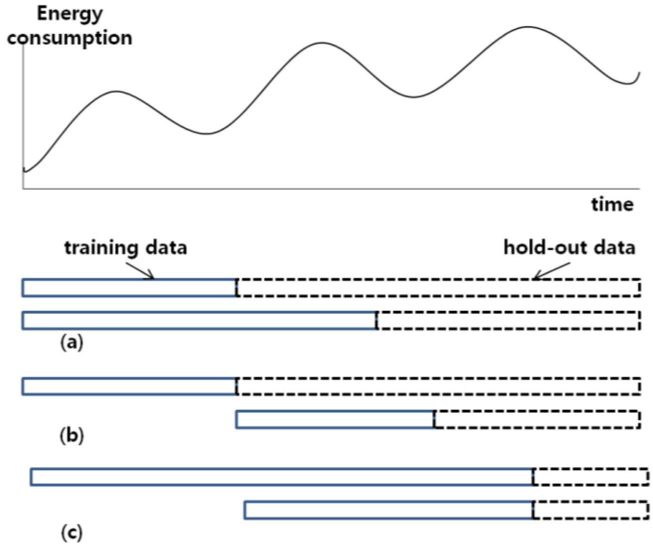

Fig. 5 Three different ways in the visualization method[38]

Instead of quantifying predictability using a single value, a visualization method is proposed to help the understanding of factors which can affect predictability.[38] The visualization method basically uses the hold-out sampling strategy but extends the basic strategy more systematically as shown in Fig. 5.

The first way (in Fig. 5(a)) aims to get a historic insight by extending the length of training data. The second way (in Fig. 5(b)) tries to detect where predictions work well or not in time series, and analyze systematic patterns that cause the result. The length of training data keeps constant and moves towards the hold-out data. The third way (in Fig. 5(c)) provides the extent the recent data affects prediction results by varying the starting point of training data while the length of hold-out data keeps constant.

4.4 Additional Prediction Techniques

The previous study on the time series usage modeling proposes that the two most popular time series analysis techniques, exponential smoothing and ARIMA, can be used to model a time series in an LCA study.[10] Two additional prediction techniques are possible to improve the prediction accuracy for LCA.

The first candidate is the dynamic regression model.[28,29,39] Time series analysis techniques can utilize time series dynamics and provide predictions systematically. However, even though some causal factors can be identified, the time series analysis techniques in the previous study[10] cannot include the information. The dynamic regression model allows external variables with time series modeling, and this can be viewed as the combination of the time series modeling and the usage context modeling in Fig. 2.

The regression model with ARIMA errors is the example of the dynamic regression model[29]

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \cdots + \beta_k X_{k,t} + n_t$$
$$\left(1 - \varphi_1 B - \cdots - \varphi_p B^p\right)(1 - B)^d n_t = c + (1 + \theta B + \cdots + \theta_q B^q) e_t \quad (11)$$

where Y_t is a time series (e.g., energy consumption); there are the k predictor variables at time t ($X_{k,t}$); the error series n_t is assumed to follow the ARIMA (p,d,q) model; B represents a backward shift operator, e.g., $BY_t = Y_{t-1}$; the first parenthesis is an autoregressive (AR) model of order p with coefficients φ; the second parenthesis is an integration (or differencing operation); the third parenthesis on the right-hand side is a moving average (MA) model of order q with coefficients θ; e_t is white noise. The dynamic regression model also can have lagged external variables. The lagged predictors can provide more dynamic nature of predictive structure, e.g., $X_{1,t}$, $X_{1,\,t-1}$, $X_{1,t-2}$, and so on.

The second candidate is the artificial neural network model. The neural network model can be very useful when prediction accuracy is mainly focused. Though the model cannot explain how the prediction is made, complex nonlinear relationships between input and output variables can be modeled.

A neural network is a network of neurons connected in layers. When it has the simplest form, the neural network is equivalent to linear regression. When there are multiple layers, inputs can be modified nonlinearly based on observed data to predict outputs. With time series data, lagged values of outputs can be directly used in a neural network autoregression.[29] A hybrid approach is also proposed to combine the neural network and ARIMA model[40]. The hybrid approach considers a time series composed of autocorrelated linear and nonlinear components. Once the ARIMA model is fitted for the autocorrelated linear portion, the residuals can be modeled nonlinearly using the neural network model.

5. Conclusion

In this paper, the studies about the usage stage modeling in LCA are reviewed. Despite the importance of the usage stage in LCA, there is a lack of comprehensive studies on the usage stage modeling. The proposed computational framework can not only provide the overview of the current research but also lead the researchers and practitioners to proper modeling techniques. The framework of the usage modeling includes the representative usage scenario method, the usage context modeling, and the time series usage modeling based on the analysis of the reviewed literature. The representative usage scenario method is the most widely used method but it has some critical limitations. The usage context modeling and the time series usage modeling can overcome some aspects of the limitations in the representative usage scenario method. The relationships among these usage modeling approaches show that the representative usage scenario method can be considered as a special case of the other methods.

Furthermore, the future research directions are suggested along with the proposed computational framework. First, automatic data collection and analysis methods can enhance the applicability of the usage context modeling. Second, trend detection is suggested to be the first condition to use the time series usage modeling over the representative usage scenario method. Third, predictability of a time series is important since the modeling of the usage stage requires prediction unless only past environmental performance is needed. Fourth, the dynamic regression model and the artificial neural network model are suggested to improve the prediction accuracy. In the future, the future research directions should be validated with real data sets.

REFERENCES

1. Bhander, G. S., Hauschild, M., and McAloone, T., “Implementing Life Cycle Assessment in Product Development,” Environmental Progress, Vol. 22, No. 4, pp. 255-267, 2003.

2. Chiu, M.-C. and Chu, C.-H., “Review of Sustainable Product Design from Life Cycle Perspectives,” International Journal of Precision Engineering and Manufacturing, Vol. 13, No. 7, pp. 1259-1272, 2012.

3. Costa, D., Quinteiro, P., and Dias, A. C., “A Systematic Review of Life Cycle Sustainability Assessment: Current State, Methodological Challenges, and Implementation Issues,” Science of the Total Environment, Vol. 686, pp. 774-787, 2019.

4. Curran, M. A., “Life Cycle Assessment: A Review of the Methodology and Its Application to Sustainability,” Current Opinion in Chemical Engineering, Vol. 2, No. 3, pp. 273-277, 2013.

5. ISO 14040, “Environmental Management - Life Cycle Assessment - Principles and Framework,” 2006.

6. Ma, J. and Kim, N., “Optimal Product Design for Life Cycle Assessment (LCA) with the Case Study of Universal Motors,” International Journal of Precision Engineering and Manufacturing, Vol. 17, No. 9, pp. 1229-1235, 2016.

7. Gustafsson, I. and Rönnblom, A., “Life Cycle Assessment of a Surface Radar System: A Case Study at Saab Electronic Defense Systems,” M.Sc. Thesis, Linköping University, Sweden, 2015.

8. Rebitzer, G., Ekvall, T., Frischknecht, R., Hunkeler, D., Norris, G., et al., “Life Cycle Assessment: Part 1: Framework, Goal and Scope Definition, Inventory Analysis, And Applications,” Environment International, Vol. 30, No. 5, pp. 701-720, 2004.

9. Domingo, L. and Rio, M., "Linking Use Stage Life Cycle Inventories with Product Design Models of Usage," Procedia CIRP, Vol. 48, pp. 342-347, 2016.

10. Ma, J., and Kim, H. M., "Predictive Usage Mining for Life Cycle Assessment," Transportation Research Part D: Transport and Environment, Vol. 38, pp. 125-143, 2015.

11. Oberender, C., Weger, O., Birkhofer, H., and Sauer, J., "Ecological Design for the Usage Phase: An Interdisciplinary Approach to Design for Environment," Proc. of 2nd International Symposium on Environmentally Conscious Design and Inverse Manufacturing, pp. 71-76, 2001.

12. Finnveden, G., Hauschild, M. Z., Ekvall, T., Guinée, J., Heijungs, R., et al., "Recent Developments in Life Cycle Assessment," Journal of Environmental Management, Vol. 91, No. 1, pp. 1-21, 2009.

13. Kwak, M. and Kim, H., "Economic and Environmental Impacts of Product Service Lifetime: A Life-Cycle Perspective," in: Meier, H., (Ed.), Product-Service Integration for Sustainable Solutions, Springer, pp. 177-189, 2013.

14. Telenko, C. and Seepersad, C. C., "Probabilistic Graphical Modeling of Use Stage Energy Consumption: A Lightweight Vehicle Example," Journal of Mechanical Design, Vol. 136, No. 10, Paper No. 101403, 2014.

15. ETH Sustainability, "Washing Machine," ETH Sustainability Summer School, http://webarchiv.ethz.ch/sustainability-v2/lehre/Sommerakademien/so2011/washies_report.pdf (Accessed 28 OCT 2019)

16. Kwak, M., Kim, L., Sarvana, O., Kim, H. M., Finamore, P., et al., "Life Cycle Assessment of Complex Heavy Duty Equipment," Proc. of ASME/ISCIE International Symposium on Flexible Automation, pp. 625-635, 2013.

17. Lee, J., Cho, H.-J., Choi, B., Sung, J., Lee, S., and Shin, M., "Life Cycle Assessment of Tractors," The International Journal of Life Cycle Assessment, Vol. 5, No. 4, pp. 205-208, 2000.

18. Li, T., Liu, Z.-C., Zhang, H.-C., and Jiang, Q.-H., "Environmental Emissions and Energy Consumptions Assessment of a Diesel Engine from the Life Cycle Perspective," Journal of Cleaner Production, Vol. 53, pp. 7-12, 2013.

19. Usability Body of Knowledge, http://www.usabilitybok.org (Accessed 9 OCT 2019)

20. Riedemann, C. and Freitag, R., "Modeling Usage: Techniques and Tools," IEEE Software, Vol. 26, No. 2, pp. 20-24, 2009.

21. Anjos, T. P., Matias, M., and Gontijo, L. A., "The Usability of a Product Can be an Ally of Sustainability," Work, Vol. 41, No. 1, pp. 2117-2121, 2012.

22. Choi, B.-C., Shin, H.-S., Lee, S.-Y., and Hur, T., "Life Cycle Assessment of a Personal Computer and Its Effective Recycling Rate," The International Journal of Life Cycle Assessment, Vol. 11, No. 2, pp. 122-128, 2006.

23. Reap, J., Roman, F., Duncan, S., and Bras, B., "A Survey of Unresolved Problems in Life Cycle Assessment. Part 1: Goal and Scope and Inventory Analysis," International Journal of Life Cycle Assessment, Vol. 13, No. 4, pp. 290-300, 2008.

24. Collet, P., Lardon, L., Steyer, J.-P., and Hélias, A., "How to Take Time into Account in the Inventory Step: A Selective Introduction Based on Sensitivity Analysis," The International Journal of Life Cycle Assessment, Vol. 19, No. 2, pp. 320-330, 2014.

25. Levasseur, A., Lesage, P., Margni, M., Deschenes, L., and Samson, R., "Considering Time in LCA: Dynamic LCA and Its Application to Global Warming Impact Assessments," Environmental Science & Technology, Vol. 44, No. 8, pp. 3169-3174, 2010.

26. Memary, R., Giurco, D., Mudd, G., and Mason, L., "Life Cycle Assessment: A Time-Series Analysis of Copper," Journal of Cleaner Production, Vol. 33, pp. 97-108, 2012.

27. Hyndman, R., Koehler, A. B., Ord, J. K., and Snyder, R. D., "Forecasting with Exponential Smoothing: The State Space Approach," Springer Science & Business Media, 2008.

28. Cryer, J. D. and Chan, K.-S., "Time Series Analysis: With Applications in R," Springer Science & Business Media, 2008.

29. Hyndman, R. J. and Athanasopoulos, G., "Forecasting: Principles and Practice," OTexts, 2018.

30. Ghosh, D., Olewnik, A., and Lewis, K., "Application of Feature-Learning Methods Toward Product Usage Context Identification and Comfort Prediction," Journal of Computing and Information Science in Engineering, Vol. 18, No. 1, Paper No. 011004, 2018.

31. Ghosh, D., Olewnik, A., Lewis, K., Kim, J., and Lakshmanan, A., "Cyber-Empathic Design: A Data-Driven Framework for Product Design," Journal of Mechanical Design, Vol. 139, No. 9, Paper No. 091401, 2017.

32. Kendall, M. and Gibbons, J. D., "Rank Correlation Methods," Oxford University Press, 5th Ed., 1990.

33. Mann, H. B., "Nonparametric Tests Against Trend," Econometrica: Journal of the Econometric Society, Vol. 13, No. 3, pp. 245-259, 1945.

34. Hirsch, R. M. and Slack, J. R., "A Nonparametric Trend Test for Seasonal Data with Serial Dependence," Water Resources Research, Vol. 20, No. 6, pp. 727-732, 1984.

35. Diebold, F. X. and Kilian, L., "Measuring Predictability: Theory and Macroeconomic Applications," Journal of Applied Econometrics, Vol. 16, No. 6, pp. 657-669, 2001.

36. Schorfheide, F. and Wolpin, K. I., "On the Use of Holdout Samples for Model Selection," American Economic Review, Vol. 102, No. 3, pp. 477-481, 2012.

37. Garland, J., James, R., and Bradley, E., "Model-Free Quantification of Time-Series Predictability," Physical Review E, Vol. 90, No. 5, Paper No. 052910, 2014.

38. Turkay, C., “Visualizing Time Series Predictability,” Proc. of IEEE VIS 2014 Workshop on Visualization for Predictive Analytics, Paris, France, 2014.

39. Ma, J. and Kim, H. M., “Predictive Model Selection for Forecasting Product Returns,” Journal of Mechanical Design, Vol. 138, No. 5, Paper No. 054501, 2016.

40. Zhang, P., “Time Series Forecasting using a Hybrid ARIMA and Neural Network Model,” Neurocomputing, Vol. 50, pp. 159-175, 2003.

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