Title
Embedded Temporal Difference in Life Cycle Assessment: Case Study on VW Golf A4 Car

Authors
Yuan, Chris
Simon, Rachel
Natalie Mady
et al.

Publication Date
2009-05-18

Peer reviewed

Embedded Temporal Difference in Life Cycle Assessment: Case Study on VW Golf A4 Car

Chris Y. Yuan, Rachel Simon, Natalie Mady, David Dornfeld

Abstract—**Existing Life Cycle Assessment does not take into account the relative temporal differences in inventory data. The lack of such considerations could lead to an inaccurate analysis of impacts and to incorrect conclusions in the comparative studies of products with comparable inventories but different life cycle times. In this paper, we report on our research of the investigation of the embedded temporal differences in LCA, and propose a simple method to calculate the temporal space of the subject system for life cycle assessment. A case study is performed on VW Golf A4 Car based on previous LCA results. The temporal space of the vehicle, as estimated, is found to be approximately 11.04 years. We establish the emission pattern of CO_2 along the time scale to demonstrate the effects of product life cycle durations on the LCA modeling and the inventory results. The life cycle inventory flow is discounted using a traditional economic discounting method with two discounting rates, 5% and 10%, respectively. The discounted results indicate that significant differences could be achieved on the life cycle inventory results.**

Index Terms— **Life Cycle Assessment, model uncertainty, temporal discounting, time difference**

I. Introduction

It is generally accepted that advancements in green technologies will have the potential to lower environmental emissions in the future. This is true not only on the macro scale but also when considering individual products. Interest in developing such technologies is occurring at both the production and disposal level. These advancements have the potential to lower the emissions of products that are currently being sold on the market. In doing so, such technologies may alter Life Cycle Assessment (LCA) results that were initially conducted for such products. Hence, as concerns for sustainability expand, the results of LCA evaluations will likely become less certain.

The longer the life of the product, the greater the uncertainty is that expected emissions will occur along the temporal scale of the life cycle assessment. For instance, use and end of life phase emissions that are scheduled to take place far into the future may be mitigated by unforeseeable advances in technology. The development of substitute products, complementary goods, and post consumer recovery techniques can all reduce the amount of predicted emissions. Policy may also play a role, as legislation can restrict the use or disposal of items, resulting in changes to those phases, and hence changes to the global warming impacts initially estimated. In addition, as more manufacturers run into financial problems there is a chance that products that are in the process of being made might never even make it to market, especially when items have long production cycles. The likelihood that one of these scenarios will occur is proportional to the amount of time that passes after initial estimations are made.

Researchers have long recognized the need to consider aspects of uncertainty and variability in Life Cycle Assessment models [1]–[4]. Advances in computing abilities have made methods for incorporating data uncertainties possible. As a result, several opportunities for the improvement of the robustness and significance of assessments have been developed. However, aspects of model uncertainty - the ambiguity of outcomes due to variability not incorporated in the models - have remained largely unaddressed. In particular, very little consideration has been paid to the time at which life cycle impacts occur. Several researchers have explicitly indicated a demand for time dependent discounting in life cycle models, so as to incorporate the uncertainty that is inherent with future events [1], [4]-[6].

The lack of time considerations in LCA models not only neglects uncertainties which can improve models, but also can lead to problems in utilizing past literature data for research. For instance, various studies may not relate to one another because they contain data which were collected at different points in time [7]. Also literature may not be applicable to current technologies because past models did not accurately anticipate the possible outcomes of nonexistent technologies. Such is the case with material recycling, where technological advances decrease the flow of product waste to landfills, resulting in lower end of life emissions [8].

The first step in designing a time dependant discounting model is to assess the time frame for product life cycles. This time period, which begins with the mining of raw materials and concludes with post consumption disposal, is also known as the time horizon or temporal space of the product. Current LCA methodologies consider the time at which an emission is generated as largely irrelevant. This is evidenced by the lack of a time consideration in present models, and the direct

This research is conducted in the Laboratory for Manufacturing and Sustainability (LMAS) at the University of California, Berkeley. For more information, please visit: http://lmas.berkeley.edu.

Chris Y. Yuan is with Department of Mechanical Engineering at University of California, Berkeley, CA 94720 USA (e-mail: chrisyuan@berkeley.edu).

Rachel Simon is with Department of Industrial Engineering and Operations Research at University of California, Berkeley, CA 94720 USA (e-mail: rachel@ieor.berkeley.edu).

Natalie Mady is with Department of Civil Engineering at Bristol University, Bristol, U.K. BS8 1TR (email: nm5618@bris.ac.uk)

David Dornfeld is with Department of Mechanical Engineering at University of California, Berkeley, CA 94720 USA (Tel: 510-642-0906; Fax: 510-643-7463; e-mail: dornfeld@berkeley.edu).

comparison of life cycle results between products with very different life spans. However, products with a longer lifetime have a higher chance of yielding fewer emissions than current LCAs indicate, because future emissions are not guaranteed to happen [9]. In existing life cycle assessment techniques all emissions for a product are aggregated, giving no indication of how emissions are distributed across its life cycle and how the impacts are generated within the temporal space of the product. Hence there exists no simple way to superimpose time dependant discounting on current assessments. This indicates the necessity of developing a methodology to assess the temporal space and the distribution of impacts across that space for products.

This paper describes the framework we developed to derive the temporal space of products for life cycle assessment, and presents our results by applying this framework to a case study on a VW Golf A4 automobile. First, a proposed methodology for integrating temporal aspects into life cycle assessments is presented. Then a case study which applies this theoretical framework to empirical data is then presented. Finally, some main conclusions are drawn.

II. METHOD FOR TEMPORAL SPACE AND DISCOUNTING

The aim of developing a time contingent methodology is to provide a more accurate measure of emissions and associated impacts, and thereby increasing confidence in the meaningfulness of LCA results. This is vitally important because LCA has been so widely adopted for assessments of sustainability. Ideally, any modifications to current methodologies will not detract from the overall simplicity of the model, which has been a factor in the proliferation of its use. Additionally any proposed methodology should bear in mind the overall objective of making LCA results easy to interpret by decision makers. Taking these aspects into consideration, the following methodology for calculating the temporal space for LCA studies is proposed. In addition, some preliminary discounting is performed to demonstrate its impacts.

A. Estimating the Temporal Space

In order to develop time dependant discounting, a methodology to assess the expected temporal space of a product's life cycle must first be devised. Fortunately, the basic premise behind such a model is fairly straightforward, involving only the aggregation of data for the process times of the life cycle. An assumption is made that procedural activities can easily be identified and time values associated with these activities can be estimated without difficulty. This supposition is based on the current degree of particularity that is needed in the gathering of life cycle data. The inclusion of variability in duration times would be an interesting extension of the method proposed below and provides an opportunity for further research, but is beyond the scope of this paper. Once data are gathered, the methodology to accurately capture the temporal space of a product will consist of two parts: calculating a singular time for each phase, and summing all of the phase times together.

The duration of each phase can be modeled as a network, in a method similar to calculating job durations for project planning and management. Each life cycle phase will consist of a series of activities, some of which must be performed sequentially and others which can be performed in parallel with other activities. Construction of a network is done based on the identification of these required activities, the recognition of their dependencies, and an outlining of their sequence. We assume that if duration times were integrated into life cycle assessments, actual activity durations can be collected, so that expected values need not be used. Furthermore, any ambiguity in duration times will be due to disruptions, which will be of a length that is relatively inconsequential when compared to the time frame for long-lived products. Hence, a deterministic method with fixed time estimates is employed, and the benefits obtained from incorporating stochastic predictions do not merit the increased complexity for this preliminary assessment.

We begin by summarizing the formulation of the time frame for each life cycle phase. We define the relevant notations in Table I below.

TABLE I
NOTATION FOR LIFE CYCLE PHASE DURATION

Symbol	Meaning
k	indicator of the life cycle phase
A_k	the set of precedence relations in phase k, where activity pairs (i, j) indicates that activity j cannot start before job i is completed
$d_{k,i}$	the duration of activity i in phase k
d_k	The duration of phase k
$X_{k,h}$	the hth path of phase k
$t_{k,i}$	the time that activity i begins in phase k
s_k	artificial activity, of duration zero, indicating the beginning of phase k
f_k	artificial activity, of duration zero, indicating the conclusion of phase k
(s_k, i_k)	artificial precedence relations, added to set A_k, to included the beginning relation in phase k
(i_k, f_k)	artificial precedence relations, added to set A_k, to included the concluding relation in phase k
P	the temporal space, or duration of a product's lifetime

The proposed approach to calculating the temporal space consists of estimating the duration for each of the life cycle phases, and then summing all phase durations together to obtain one life cycle period length. For any given product, here we assume that there are five life cycle phases associated with its lifetime: mining; material production; manufacturing; use; and end of life. Here, k is used to represent the life cycle phase, and is assigned a value from one to five to represent each of the respective phases. The generalized methodology for estimating the length of any phase, k, is outlined below.

According to the precedence relation, signified by membership in the set A_k, all predecessor activities must be completed before an activity can begin. Let $t_{k,i}$ be the time that activity i begins in phase k, and let $d_{k,i}$ be its duration. Then, the time that any activity starts must adhere to the precedence relation as formulated as follows

$$t_{k,i+1} \geq t_{k,i} + d_{k,i} \tag{1}$$

Considering the different production patterns of a good, the temporal space is calculated by estimating the minimum and maximum phase duration times. The phase duration is assumed to be a value within this range. A specific singular value is approximated by taking the mean of the two extremes. Symbolically the phase duration is represented by d_k, or equivalently

$$d_k = t_{k,f} - t_{k,s} \quad (2)$$

Production flow paths are used to find the minimum value of the phase duration time. A path is defined as a continual succession of activities, starting at the beginning node, denoted s_k, and ending with terminal node f_k. If $X_{k,h}$ is the duration of the h^{th} path of phase k, then the minimum length of phase k is the maximum duration of all possible paths (the greatest sum of $d_{k,i}$'s that correspond to a path), that is

$$d_k \geq Max\{X_{k,h}\} \quad (3)$$

This path which produces the maximum elapsed time is known as a 'critical path,' and all nodes which are part of that path are known as 'critical activities.' Critical activities have zero slack, meaning that any delay in their completion will cause a delay in the duration of the entire phase. The critical path represents the minimum time necessary to complete the life cycle phase. Thus, the critical path signifies the minimum time that must elapse to include all activities of a phase.

The minimum phase time is achieved when the production time of a phase is optimized, and will be longer when it is not. Optimization can easily be executed with a linear model whose objective is to minimize the phase duration as demonstrated in equation (2). When subjected to the constraint (1), the dual of this problem is easily solvable. A phase duration can be longer if production planning is not optimized or if parallel processes are not taken advantage of. An instance in which this may occur is if a company is vertically integrated but does not have the capacity to conduct all parallel activities simultaneously. In this case a maximum can be calculated by summing the duration of all of the activities of any phase k:

$$d_k \leq \sum_{i=1}^{n} d_{k,i} \quad (4)$$

where n is the number of activities in the phase k being considered.

The duration of the phase is then a value between its minimum value (the critical path), and the maximum value (the sum of all activity durations). To simplifying the method, a single value is estimated by taking the average of the minimum and the maximum. In the analysis, the value used for the duration of the each phase is:

$$\overline{d_k} = \frac{Max\{X_{k,h}) + \sum_{i=1}^{n} d_{k,i}}{2} \quad (5)$$

After the duration of each phase is calculated as previously discussed, the temporal space of a product can then easily be construed, by summing the length of all of the phases together. Here we consider the LCA phases which are comprised of 5 stages (mining, material production, manufacturing, use, and end-of-life). If we let P indicate the temporal space, it could be defined through the following formula:

$$P = \sum_{k=1}^{5} (t_{k,f} - t_{k,s}) = t_{5,f} - t_{1,s} \quad (6)$$

B. Estimating Emissions over the Temporal Space

The actual distribution of emissions over each time period can be modeled in several different ways. However such modeling would require an investigation of each process in the life cycle, and a variety of distributions may be equally suitable [10]. Also, such investigations would to some degree be particular to each product – as different processes and machinery achieve the same end result - and may not be easily applicable to other products. So any added benefits from such investigations may not warrant the added level of complexity, the burdens of which LCA practitioners would have to bear. Furthermore, since the probability that an emission will be mitigated can also be thought of as the probability that an innovative disruptive technology will be developed. Such events occur rather infrequently, with the assumption that truly ground-breaking improvements occur at the annual scale.

Once the temporal space has been obtained, a method for distributing the emissions over that duration is outlined below. For every path in each phase, a slack time is obtained by calculating the difference between the mean phase time and the minimum phase time. For each activity, a range of times in which that activity can occur is calculated by assuming the first activity in the path starts sometime between the start time of the phase and the slack time. Subsequent activities are found in a similar manner, with the starting time of the activity occurring sometime between the earliest possible time (where no slack has previously occurred) and the earliest time plus the slack time. Then the expected time that an emission takes will be the midpoint of the range of the process period, as calculated in the previous step, plus and minus the expected phase duration time. The distribution of the impacts across the phase can be modeled in many various ways. Here it will be modeled according to the method most appropriate for the discounting technique employed, as outlined below.

C. Temporal Discounting Methodologies

One danger inherent in a time dependent discounting methodology is that it will ultimately result in reductions in the assessment of emissions. Since the model fundamentally represents the potential risks that are associated with each individual emission (i.e. greenhouse gases), great care should be taken to thwart the dangers of under-accounting. Undervaluing of the environmental effects of, say, global warming, can have far worse consequences than an overestimation. Thus any theoretical conceptions of how to integrate temporal discounts into models should be tempered by these considerations. In the context of this paper discounting is used to explore its possible effects on life cycle assessments. Although we recognize the need to develop proper discounting methods, such endeavors deserve a more thorough analysis, and thus are beyond the scope of this paper.

The concept of temporal discounting is to get a more accurate picture of the current value of present and future emissions by lowering the value of subsequent events that take place in the future [11]. This technique is widely used in finance and economics to discount future costs and benefits to a common present value, so that they can be made comparable. In the context of the environmental LCA, discounting is a way of quantifying the impacts or damages that occur over different time periods [12]. For environmental emissions, temporal discounting is suggested by assigning an increasingly lower weighting factor to emissions that occur farther into the future. The rationale behind the application of this theory to emissions is that the impacts caused by future events are less certain and can perhaps be mitigated [9]. This makes the assumption that it takes different lengths of time for the influence of an event to be realized and that some certain consequences of an action may take as long as a decade to fully develop [11]. Such an approach has been put forth in LCA best practice guidelines established by SETAC, The Society of Environmental Toxicology and Chemistry – Europe [9]. Even though there have been abundant studies relating to discounting in finance, healthcare, and consumer purchasing, there is, at present, limited research on environmental discounting. Unfortunately, the conclusions reached in discounting literature in other fields do not necessarily apply to environmental discounting.

The research that has been done on temporal discounting for environmental problems has been limited in its scope and technique. One method which has been employed is temporal cut-off discounting, where emissions are counted in full for a specified time horizon (i.e. the discount rate is zero), and then are completely mitigated after the cut-off point of that horizon (i.e. the discount rate is infinity). Such methods have been used in the application of landfill emissions [13][14]. Another method that has been proposed for landfill emissions is discrete compound discounting, to calculate the net present value of emissions in a method similar to economic discounting principles [8]. These two techniques encompass the proposed methods that have been put forth for emissions discounting in the LCA analysis.

To calculate the net present value of all emissions, discounting will be applied using discrete discounting which is compounded annually. This discount rate represents the probability of an emissions mitigating technology being developed. Since such technologies are developed rather infrequently, and emissions associated with activities are often fixed once they commence, the discounting rate does not continuously improve. Here, events that occur within the year are weighted at that year's rate. Longer activities, which span more than one year, will be assumed to have emissions which are released uniformly across their duration, then the amount of annual emissions are assigned their respective year's discount rate.

III. CASE STUDY

In order to illustrate the methodology in developing temporal space for life cycle assessment, here we apply it in a case study on the VW Golf A4 car. Our study is based on a 4 door Otto, which carries a 1.4l, 55kW petrol engine, and LCA data is based on the work of Schweimer and Levin [15]. As is conventional in LCA work, additional assumptions for emissions based on energy consumptions and power ratings were made for information that is typically lacking. Such assumptions were necessary to develop a detailed timescale and associated life cycle phase emissions for the car. Each of the life cycle phases for the Golf A4 were evaluated to obtain the temporal space of the vehicle.

Since this calculation is being done long after the initial life cycle analysis was conducted, process steps and their estimated time were best approximated using data that are available. Therefore, the following case study is the best calculation that can be made for an analysis that is done after the fact. The accuracy of such estimates may be improved if time data is gathered simultaneously with life cycle data.

A. Mining Phase

As shown in the work of [15], the VW golf A4 car is made from 12 primary groups of materials. As prescribed by the methodology, each of these materials is indicated by *h*, where:

$$h=\begin{cases}1 \text{ indicates processes associated with Platinum group ore}\\ 2 \text{ indicates processes associated with Iron ore}\\ 3 \text{ indicates processes associated with Zinc-lead ore}\\ 4 \text{ indicates processes associated with Limestone } (CaCO_3)\\ 5 \text{ indicates processes associated with Rock salt } (NaCl)\\ 6 \text{ indicates processes associated with Copper}\\ 7 \text{ indicates processes associated with Titanium ore } (0.6\%\ Ti)\\ 8 \text{ indicates processes associated with Bauxite } (Al_2O_3)\\ 9 \text{ indicates processes associated with Sand}\\ 10 \text{ indicates processes associated with Dolomite } (CaMg(CO_3)_2)\\ 11 \text{ indicates processes associated with Spar (Aluminum silicates)}\\ 12 \text{ indicates processes associated with Chrome ore}\end{cases}$$

The mining phase consists of serial process for each of these materials, resulting in 134 different activities that were identified. The longest duration of these parallel processes (i.e. the critical path) is found as outlined in (3) of the previously put forth methodology:

$$d_1 \geq \text{Max } \{X_{1,h}\}$$

This critical path, Max $\{X_{1,h}\}$, is the processes associated with zinc-lead ore. The extraction of this material involves 15 steps, including: blasting; loading/hauling; crushing; transport to ground; 2nd crushing/mixing; beneficiation; froth flotation; filtering; annealing; transport to shipping place; waiting for shipping; loading to ship; transport to port; waiting & discharging; in storage & transport to the mill. The total time of these events is estimated as the sum of the duration, $\boldsymbol{d_{1,i}}$'s, of all of these activities at 0.112 years. This is the minimum duration of the mining phase.

The maximum time for the mining phase is calculated as outlined in (4) in the model formulation.

$$d_1 \leq \sum_{i=1}^{n} d_{k,i} = \sum_{i=1}^{134} d_{1,i} = 0.776 \text{ years.}$$

The phase duration is calculated, as outlined in (5), as the mean value of the minimum and maximum duration times. This represents the value of the temporal space of the mining phase, equaling 0.44 years.

B. Material Production

The material production phase similarly consists of parallel serial processes for multiple materials. The materials that were considered are those listed as the car's contents, including: iron, steel, synthetics (polymer), oil, light metals, tires and rubber, glass, electric motors, base metals, insulation, paints, and all other material. In total 75 activities were identified. The critical path for this phase is again obtained based on equation (3). This figure is associated with the production of light metals, which is calculated to be:

$$d_2 \geq \text{Max } \{X_{2,h}\} = 0.146 \text{ years.}$$

The processes for light metals consist of storage, waiting for smelting, transit and preparing for smelting, smelting, forming, baking, rodding, electrolysis, casting, finishing and packaging, storage and transit time, and the transport process to car manufacturing plant. The upper bound for the material production phase duration is:

$$d_2 \leq \sum_{i=1}^{n} d_{k,i} = \sum_{i=1}^{75} d_{2,i} = 0.912 \text{ years.}$$

As a result, the average duration for the material production phase is 0.53 years, which is again the average of the maximum and the minimum.

C. Manufacturing

The manufacturing of the car is modeled from the processes that take place at Volkswagen's Wolfsburg Plant in Germany. At this location, a series of activities takes place for the component manufacturing, general assembly, painting, and quality control for the car. However, several parts of the car are manufactured at different locations and at different times. The activities at the Wolfsburg plant consists of only one serial process involving: material storage time; parts manufacturing, painting, assembly, quality check and waiting for shipping, transport to the market. Since there is only one path of activities, the minimum, maximum, and average duration of the manufacturing phase all take the same value

$$d_3 = Max\{X_{3,1}) = \sum_{i=1}^{6} d_{3,i} = 0.0586 \text{ years}$$

D. Usage

Meanwhile, the use phase only consists of one activity, namely the utilization of the car. The expected use time is estimated in the Life Cycle Inventory for the Golf A4 as ten years [15]. With only one activity, the minimum, maximum, and average duration of the use phase all take the same value here as the expected lifetime in [15]:

$$d_4 = Max\{X_{4,1}) = \sum_{i=1}^{1} d_{4,i} = 10 \text{ years}$$

E. End of Life

The end of life activities are based on recycling processes for the recovery of vehicles. Current car recyclers are the best source for such data. Accordingly, the process for recycling was modeled on a UK based company CarTakeBack, where cars can be recycled at the end of their useful life. Process steps and time estimates are comprised of manual labor and machinery that are used to dismantle, shred and dispose of the vehicle. This information was obtained through direct correspondence with the company [16]. In total, an eight step serial process was identified for car recycling which is comprised of: transport, storage, disposal of fluids, dismantle (manually), loading, shredder, media separation, and disposal. With one series of activities, the minimum, maximum, and average duration of the end of life phase all take the same assessment:

$$d_5 = Max\{X_{5,1}) = \sum_{i=1}^{8} d_{5,i} = 0.0117 \text{ years}$$

F. Temporal Space of the Golf A4

Having calculated the duration of each phase, as previously discussed, the temporal space of the vehicle can easily be obtained by using the equation (6) as elucidated in the previous section. The lengths of all the phases are summed together, to obtain P, the temporal space as follows:

$$P = \sum_{k=1}^{5} (t_{k,f} - t_{k,s}) = 11.04 \text{ years}$$

G. Emissions over the Temporal Scale

Once a temporal scale is obtained, emissions can be modeled across the duration of each phase in the whole life cycle of the vehicle. The method for benchmarking emissions and point along the life cycle temporal space at which they occur has been previously outlined in the section II (B). Since our aims here are to illustrate the technique, we only consider the carbon dioxide emission as a demonstration of the life cycle emission pattern along the temporal scale of the Golf A4 vehicle. The CO_2 emissions from mining and material processing of various materials are modeled based on the steel and iron production process, which makes up the majority of the car, accounting for 59.9% of its 1059kg total weight [15]. The mining process of iron is modeled on operational temporal sequence data from the LKAB Kiruna mine in Northern Sweden, the largest iron ore reserve in the world [17]. The steelmaking process is modeled on the operational activities of the Rautaruukki Steel Company which is based in Finland [18].

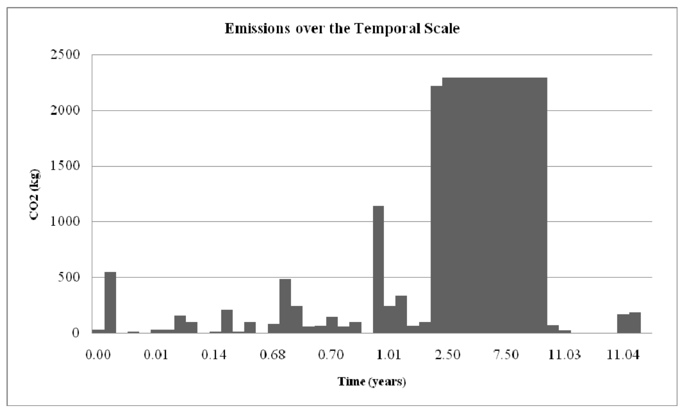

Fig.1 Distribution of CO_2 Emissions over the Temporal Scale

H. Significance of Temporal Discounting

Discounting for this case study is briefly discussed to demonstrate its potential impacts on the life cycle inventory analysis. In our analysis, two separate discrete compound discounting rate of five and ten percent annually are used to show the impacts on the total emission inventory of CO2, when compared with the results of non-discounted emissions. Results are shown in figure 2 below. Here we can see that a 5% annual discounting rate, results in roughly 5,500 kg less CO2 emission over the life time of the vehicle, while a 10% annual discounting rate could result in a difference of 9,200 kg.

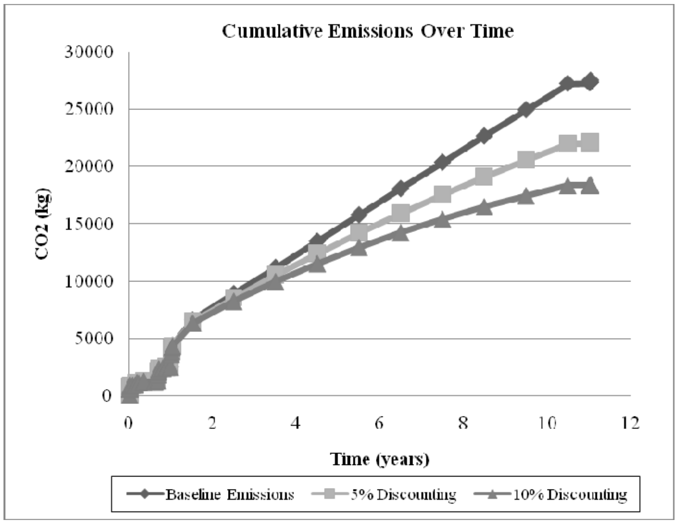

Fig.2 Impact of Temporal Discounting on Emissions

IV. CONCLUSION

Life cycle assessment does not presently take the relative time at which respective emissions occurs into consideration. Therefore each of the individual emissions that take place over the course of a product's life are treated with the same magnitude. As the emissions are aggregated over the product's life cycle, the inventory results could lead to inaccurate analysis of impacts and incorrect conclusions in the comparative studies of products with comparable inventories but different life cycle times.

Integration of temporal aspects into life cycle assessments is necessary to provide robust decision-support in environmental management and to improve modeling accuracy. In this paper, we reported on our research investigating the embedded temporal difference in LCA, and proposed a simple method to calculate the temporal space of the subject system for life cycle assessment. The LCA temporal space considered here was composed of five stages: mining, material production, manufacturing, use and end-of-life. Research was carried out to break down each life cycle stage into individual steps to separate the different emissions. The time of production, transportation, storage and distribution were all considered for each life cycle stage in the analysis. Accordingly, the time length of each stage was quantified and the emissions were allocated according to the corresponding activities in each LCA stage.

A case study was performed on the VW Golf A4 based on the LCA results of [15]. The temporal space of the vehicle, as estimated, was found to be approximately 11.04 years. We establish the emission pattern of CO_2 along the time scale to demonstrate the effects of product life cycle durations on the LCA modeling and the inventory results. Then the life cycle inventory flow was discounted using a traditional economic discounting method with two discounting rates, 5% and 10%, respectively. The differences of life cycle inventory data are investigated between the results with and without temporal discounting.

Results of discounting are significant for the insights which they provide. They are useful for understanding the temporal aspects of LCA. Additionally, they could assist in further exploratory efforts in developing the scientific temporal discounting method for the life cycle assessment.

REFERENCES

[1] M. Huijbregts. "Application of Uncertainty and Variability in LCA. Part I: A general Framework for the Analysis of Uncertainty and Variability in Life Cycle Assessment." International Journal of Life Cycle Assessment, 3 (5), pp. 273–280, 1998.

[2] A.E. Björklund. "Survey of Approaches to Improve Reliability in LCA." International Journal of Life Cycle Assessment, 7(2), pp. 64-72. 2002

[3] R. Heijungs and M. A. J. Huijbregts. "A review of approaches to treat uncertainty in LCA. In Complexity and integrated resources management." Proceedings of the 2nd biennial meeting of the International Environmental Modelling and Software Society (iEMSs), edited by C. Pahl-Wostl et al. Manno, Switzerland: International Environmental Modelling and Software Society. 2004.

[4] S. M. Lloyd and R. Ries. "Characterizing, propagating, and analyzing uncertainty in life-cycle assessment: a survey of quantitative approaches." Journal of Industrial Ecology, 11, pp.161–179, 2007.

[5] J. W. Owens. "Life cycle assessment: Constraints on moving from inventory to impact assessment." Journal of Industrial Ecology 1(1), pp. 37–49, 1997.

[6] B. P. Weidema and M. S. Wesnæs. "Data quality management for life cycle inventories—An example of using data quality indicators." Journal of Cleaner Production 4(3–4): 167–174, 1996.

[7] A. Riva, S. D'Angelosante, C. Trebeschi. "Natural Gas and the Environment Results of Life Cycle Assessment," Energy, 31, pp.138-148, 2006.

[8] S. Hellweg, T. B. Hofstetter, K. Hungerbühler. "Discounting and the Environment: Should Current Impacts be weighted Differently than Impacts Harming Future Generations?" International Journal of LCA 8(1), pp. 8-18, 2003.

[9] H. A. Udo de Haes. "Best Available Practice Regarding Impact Categories and Category Indicators in Life Cycle Impact Assessment," International Journal of LCA 4 (2), pp. 66-74, 1999.

[10] F. Rugrungruang, S. Kara, H. Kaebernick. "Lifetime Modeling of Products for Reuse: Physical and Technological Life Perspective," proceedings of the 14th CIRP International Conference on Life Cycle Engineering, Tokyo, Japan, June 11-13, 2007.

[11] L. Hendrickx and S. Nicolaij. "Temporal Discounting and Environmental Risks: The Role of Ethical and Loss-Related Concerns," Journal of Environmental Psychology, 24, pp. 409-422, 2004.

[12] S. Hellweg. Time-and Site-Dependent Life Cycle Assessment of Thermal Waste Treatment Proceses. Ph.D. dissertation, Swiss Federal Institute of Technology, 2000.

[13] P. H. Nielsen and M. Hauschild. "Product Specific Emissions from Municipal Solid Waste Landfills; Part I: Landfill Model." Int J LCA 3 (3) pp. 158-168, 1998.

[14] R. Heijungs and G. Huppes. Inventory Modelling in the Dutch LCA Methodology Project. In: Guinée J, eds. Danish-Dutch Workshop on LCA Methods. Leiden (NL), 1999.

[15] G. W. Schweimer and M. Levin, Life Cycle Inventory for the Golf A4, Research, Environment and Transport, Volkswagon AG, Wolfsburg, 2000.

[16] J. Tromans. (Feb 14, 2008), CarTakeBack company in U.K. Personal communications.

[17] Kiruna Iron Ore Mine. Sweden. http://www.miningtechnology.com/projects/kiruna/index.html#kiruna1(accessed on May 5th 2008).

[18] The Rautaruukki Corporation, Steel Manufactures of Finland, <http://www.ruukki.com> (accessed on May 7th 2008).