Consequential Life Cycle Assessment With Market-Driven Design

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Consequential Life Cycle Assessment With Market-Driven Design

Development and Demonstration

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Summary

This article describes the development of a consequential life cycle assessment (cLCA) with endogenous market-driven design (MDD). Incorporation of MDD within cLCA (cLCA-MDD) is beneficial because design decisions, influenced by market forces, are a major source of environmental emissions and resource consumption in many life cycle systems. cLCA-MDD captures the environmental impact of these design responses resulting from industrial and policy decisions. We begin by developing the concept of cLCA-MDD, then present a case study that demonstrates how design responses can be endogenously captured in a cLCA analysis. The case study is in two parts: First, we incorporate endogenous design responses into a cLCA of a mid-size vehicle and, second, we conduct a policy analysis using a cLCA-MDD approach. The case study illustrates that cLCA-MDD can capture multiple "ripple effects" resulting from an industrial decision (e.g., downsizing a vehicle's engine) or a policy decision (e.g., raising gasoline taxes) and that these effects significantly influence results. A key challenge of the approach is appropriately managing and communicating uncertainties associated with the choice of economic parameters or models. We discuss sources of uncertainty in cLCA-MDD and demonstrate a presentation scheme to facilitate communication of result sensitivity to uncertainties from input parameters, models, and model structure.

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Introduction

Industrial ecology "focuses on the potential role of industry in reducing environmental burdens throughout the product lifecycle" (Lifset 2006, 18). To enable that focus, life cycle assessment (LCA) characterizes materials, energy, wastes, and emission flows through a product or service system (hereafter referred to as a "product") as well as the resulting impacts on the environment (SETAC 1993; ISO 1997). The industrial ecology and LCA literature has distinguished two types of LCA methodologies: *attributional LCA* (aLCA), which describes the environmentally relevant flows to and from a life cycle, and *consequential LCA* (cLCA), which describes how these flows may change in response to possible decisions (e.g., Ekvall and Weidema 2004; Curran et al. 2005; Finnveden et al. 2009). cLCA extends the boundaries of an aLCA to include not only the flows of the product life cycle of interest but also any flows of other products that are significantly affected. For example, Schmidt and Weidema (2008) presented a cLCA of vegetable oil in which they found that consumption of palm oil displaces the consumption of barley and soybeans. This displacement of competing products reduces the impact of producing palm oil on life cycle flows compared to the case in which no competing product is displaced.

A growing body of literature has advanced the methodology required to incorporate cross-life-cycle effects in cLCAs, including displaced products, price changes of raw materials, and cost reductions due to economies of scale (e.g., Ekvall and Andræ 2006; Sandén and Karlström 2007; Schmidt and Weidema 2008). Researchers still need to develop methods to incorporate product design decisions into cLCA when the environmental flows are substantially dependent on product design, however. For example, the total environmental impact of redesigning the Volkswagen (VW) Touareg line so that the vehicles are smaller and more fuel efficient depends not only on the resulting changes in emissions from the redesigned Touareg's life cycle but also on shifts in sales due to consumers substituting competing vehicles in place of the redesigned Touareg (because they prefer a larger vehicle) and any resulting incentives for manufacturers to change the size of these competing vehicles. Incorporating product design responses endogenously within cLCA can also make a valuable contribution to policy analysis. For instance, the effectiveness of carbon taxes, technology subsidies, and emission standards is influenced by the changes to product designs that may result from the policy.

This article contributes to the development of cLCA by demonstrating a methodology to endogenously determine market-driven design responses to industrial and policy decisions (this approach is referred to here as cLCA-MDD). In particular, we describe techniques to determine design responses in an LCA analysis using economic oligopolistic equilibrium models.[1] We then demonstrate the cLCA-MDD approach using a case study. In the first part of the case study, we analyze changes in life cycle greenhouse gas (GHG) emissions of a mid-size vehicle in response to a decision to reduce the vehicle's engine size, accounting for the equilibrium design responses of competing firms. For clarity, we refer to the products that are the subject of the exogenous decision (the VW Touareg, in the previous example) as the "protagonist products", so that they can be distinguished from competing products that are indirectly affected. In the second part of the case study, we conduct a policy analysis using cLCA-MDD techniques, analyzing the changes in life cycle GHG emissions that result from increases in gasoline taxes, accounting for the equilibrium design responses of all firms in the mid-size vehicle market.

The case study is only meant to be illustrative of the cLCA-MDD methodology. To that end, it has many simplifications and should not be interpreted as a comprehensive characterization of GHG emissions resulting from the decisions analyzed. We note, however, that methods enabling extension of the case study with more realistic submodels (e.g., representations of production costs, demand, and use) are being developed in the economics literature. For example, Whitefoot and colleagues (2011) have developed submodels of passenger vehicle performance and consumer demand that could be incorporated into the cLCA-MDD analysis presented here. Although we focus only on GHG emissions in the case study, the method is equally applicable to a complete inventory of emissions, wastes, and resource utilization.

Additionally, we discuss uncertainty in cLCA and present a scheme of communicating sensitivity of cLCA results to these uncertainties. The existing cLCA literature uses economic parameters, such as elasticities and learning curves, to incorporate cross-life-cycle flows (e.g., Ekvall and Andræ 2006; Sandén and Karlström 2007; Schmidt and Weidema 2008). Evaluating the sensitivity of results to such parameters is essential, given that many of these parameters have large uncertainties. In practice, however, such uncertainty analyses are often not performed. In the case of cLCA-MDD, multiple economic models must be employed, including consumer demand and use functions that are dependent on product design and pricing and cost models that are dependent on design. The need for these input models introduces uncertainty associated with the choice of the specific models and any uncertainty in model parameters. In the case study, we handle this uncertainty by conducting a sensitivity analysis under multiple combinations of available input parameters and models and presenting these results side by side to allow for easy comparison.

The cLCA-MDD approach discussed is relevant to many product categories. The specific methods employed in the automotive case study are directly applicable to energy-using products, such as household appliances or consumer electronics, given the necessary models of demand, use, and cost. More generally, endogenous design responses could be incorporated into LCA in a wide array of product classes, including consumer electronics and "designable" consumables, such as paper products and processed foods.

We begin below by describing the development of cLCA-MDD methodology and its relationship to the existing computational framework for life cycle inventory (LCI) analysis. The following section discusses uncertainties and the use of a decision unit in cLCA in addition to a functional unit. We then present the case study in two parts, followed by a summary discussion of the value and practice of cLCA-MDD.

cLCA-MDD Modeling Approach

Modeling Approach

To endogenously incorporate market-driven design responses into LCA, we draw on customary economic concepts of (Nash) equilibrium based on profit maximization of firms and utility maximization of consumers (e.g., Samuelson 1947). A firm's profits depend not only on its own product design and pricing decisions but also on its competitors' decisions. Consequently, firms often have incentives to adjust the designs and prices of their products in response to a change in a competing product's design. We determine these design responses by using an oligopolistic partial-equilibrium model whereby each firm simultaneously maximizes its profits with respect to the prices and designs of its products.[2] Partial-equilibrium models are widely used to study how the incentives of industrial producers influence the results of environmental policies (e.g., Parry 2004; Fischer and Newell 2008), and related equilibrium analyses are increasingly being used to explore the motives behind environmental management decisions (e.g., Lou et al. 2004; Grimes-Casey et al. 2007). Using this approach, we can determine the equilibrium product designs in response to the decision of interest and changes to life cycle flows resulting from these design adjustments.

In principle, other methods of incorporating design decisions could be used besides equilibrium modeling. For example, researchers have proposed that the consequences of economic behavior on LCA results be captured with agent-based modeling (Axtell et al. 2001) and systems dynamics (Mihelcic et al. 2003). These approaches could, indeed, be incorporated into the cLCA-MDD methodology in place of an equilibrium model and consumer behavior models (e.g., for product demand and use). Given the added complexity of these models (e.g., Bouman et al. 2000; Garcia, 2005), we would need to overcome significant computational burdens to adequately account for model and parameter uncertainty.

Figure 1A represents an LCI in which market-driven design decisions, product demand, and design-dependent use-phase behavior are factors

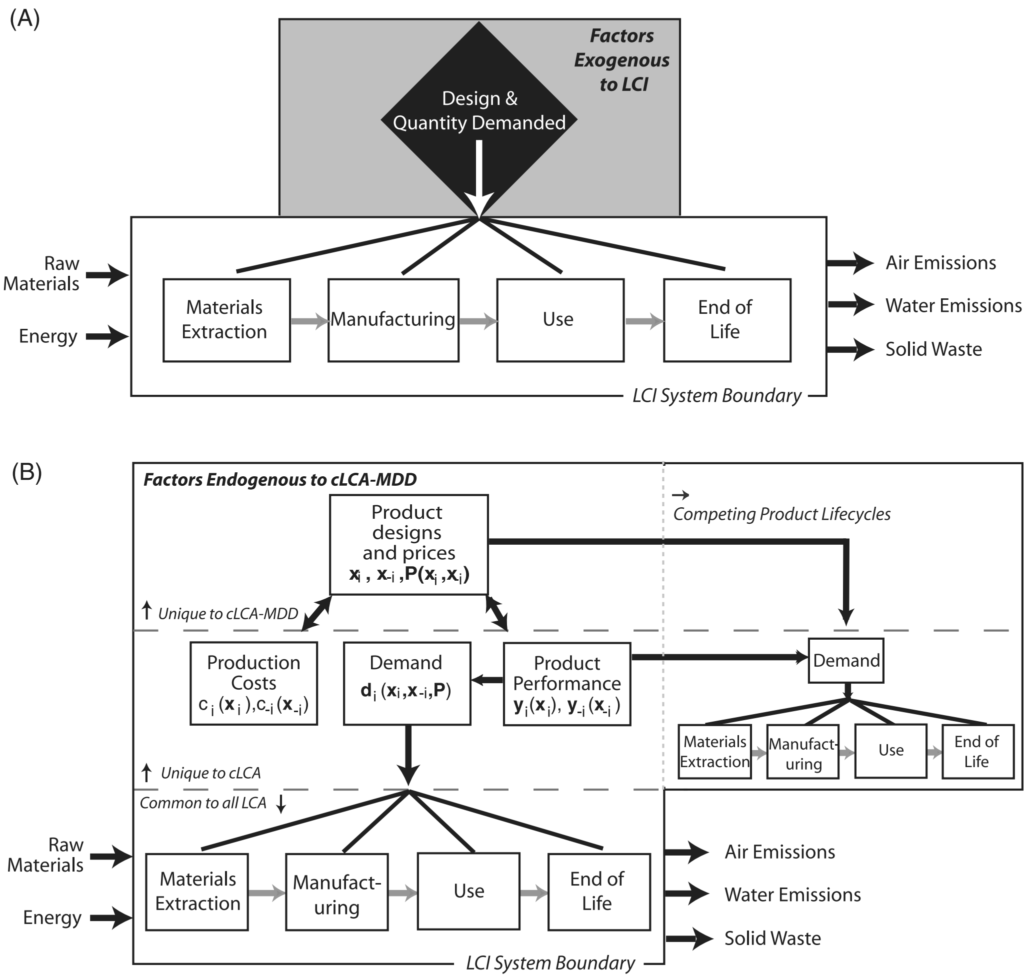

Figure 1 Life cycle inventory (LCI) system boundaries according to (A) an attributional life cycle assessment approach and (B) a consequential life cycle assessment with market-driven demand approach. xi, protagonist design variables; x-i, competitor design variables; P, prices of all products; ci and c-i, the production costs of the protagonist and competitor products, respectfully; yi and y-i, product attributes that consumers care about of the protagonist and competitor products, respectfully; di, demand for the protagonist products.

that are left exogenous to the system boundaries. In this system, we determine life cycle material and energy flows by scaling industrial process data to match exogenously determined demand. For instance, an automotive manufacturer estimating life cycle emissions associated with selecting a specific engine for a vehicle through an LCA would typically assume a fixed number of units sold and fixed vehicle miles travelled (VMT), independent of the engine design. Uncertainty in these assumptions could be characterized with sensitivity analyses, but dependent relationships between these parameters and the engine design would be ignored.

Figure 1B represents an LCI that uses a cLCA-MDD approach in which product designs, demand, and use are computed endogenously and dependent on the decision of interest. The subscript *i* indicates the variables of protagonist products, whereas $-i$ represents variables for competing products; the absence of a subscript indicates variables of protagonist and competing products.

Throughout this article, we denote equilibrium variables with an asterisk. As figure 1B illustrates, cLCA can expand the boundaries of aLCA by incorporating the effects of a decision on the demand of a product as well as the demand for competing products and effects on product performance and product costs (Finnveden et al. 2009). cLCA-MDD further expands the system boundaries to include calculation of product designs, and prices dependent on these designs, in response to a decision.

In the engine selection example, a cLCA-MDD analysis would determine the equilibrium horsepower for competing vehicles, $x^*_{-i}(x_i)$, and equilibrium prices for all vehicles, $\boldsymbol{p}^*(x_i, x^*_{-i}(x_i))$, in response to a change in the protagonist vehicle's horsepower, x_i. These equilibrium decisions will depend on submodels characterizing vehicle demand as a function of the designs and prices of competing vehicles and production costs as a function of vehicle design. The resulting demand and VMT, as well as associated emissions, for the protagonist vehicle and its competitors can then be calculated given these equilibrium designs and prices.

Researchers can use the cLCA-MDD methodology to analyze the life cycle environmental impacts of a policy decision by endogenously accounting for design and price responses of relevant products in equilibrium. For example, if the policy decision were a carbon tax, changes to the equilibrium designs and prices of relevant products would be determined in response to the tax. The resulting demand and life cycle flows could then be calculated on the basis of these equilibrium decisions.

cLCA-MDD, unlike aLCA, requires a linkage between equilibrium models and LCI data. To explore this further, we build from the computational framework for ISO-based LCI that is well established in the literature (Heijungs 1994; Heijungs and Suh 2002; Hertwich 2005; Suh and Huppes 2005). In principle, it is also possible to incorporate the MDD approach within the economic input-output LCA (EIO-LCA) framework (e.g., by extending the approach used by Takase et al. [2005]), but this is left to future work.

The construct of LCI as a linear algebraic system of equations (e.g., Heijungs 1994) usually assumes that inventory parameters in the product system are defined by constant factors, as shown in equation (1). The demand vector for the unit process outputs, d, is determined exogenously, whereas the coefficients describing the transformation of j inputs (e.g., raw materials and energy) and outputs (e.g., products and coproducts) through k unit processes represented in the *process matrix* (sometimes called the *technology matrix* or *coefficients matrix*), **A**. Coefficients associated with the output (input) of one unit of material or energy have positive (negative) values. In equation (1), d_i represents the total quantity of aluminum, steel, energy, and generic machined parts required to produce the engine for a hypothetical vehicle model, with all other material inputs excluded for simplicity. Data collected indicate the inputs required to produce a single vehicle part, with the input of steel dependent on the vehicle's designed horsepower, x_1, which is exogenously determined and may be varied in a sensitivity analysis.

$$\begin{array}{l c c c} & \overbrace{\begin{array}{cccc}\text{Energy} & \text{Rolled Al} & \text{Rolled steel} & \text{Machine part}\end{array}}^{\boldsymbol{A}} & & \overbrace{\text{Product demand}}^{\boldsymbol{d}} \\ \begin{array}{l}\text{Energy (MJ)}\\ \text{Al (kg)}\\ \text{Steel (kg)}\\ \text{Machine part}\end{array} & \begin{bmatrix} 1 & -100 & -25 & -500 \\ 0 & 1 & 0 & -20 \\ 0 & 0 & 1 & -0.1x_1 \\ 0 & 0 & 0 & 1 \end{bmatrix} & \times\ \boldsymbol{s} = & \begin{bmatrix} 0 \\ 0 \\ 0 \\ 100 \end{bmatrix} \end{array} \tag{1}$$

The vector $\boldsymbol{s}$ represents the scaling-up of unit processes needed to satisfy the exogenous demand vector, which can be calculated from equation (2) as long as **A** is invertible:

$$\boldsymbol{s} = \mathbf{A}^{-1}\boldsymbol{d} \tag{2}$$

The manufacturing of products and coproducts associated with matrix **A** creates emissions to the environment that can be represented within an *emission factor matrix* (sometimes called the *stressor matrix*), $\boldsymbol{B}$. In our hypothetical example in equation (3), the first and last elements in $\boldsymbol{B}$ indicate that production of one megajoule (MJ) of energy emits 200 grams of carbon dioxide equivalent (g CO_2-eq.) emissions, and the production of one machined part emits 50 g CO_2-eq. for every unit of horsepower.[3] Given the scaling vector, $\boldsymbol{s}$, and an assumed horsepower (100), the cumulative life cycle emissions, $\boldsymbol{v}$, associated with satisfying demand can be calculated with equation (3):

$$\begin{array}{lc} & \overbrace{\begin{array}{cccc}\text{Energy} & \text{Rolled Al} & \text{Rolled steel} & \text{Machine part}\end{array}}^{\boldsymbol{B}} \qquad\qquad \overbrace{\text{Total emissions}}^{\boldsymbol{v}} \\ \text{Emission factors } (\text{kg } CO_2\text{-eq.}) & \begin{bmatrix} 200 & 10{,}000 & 2{,}000 & 50(100) \end{bmatrix} \times \boldsymbol{s} = 77{,}500 \text{ kg} \end{array} \tag{3}$$

The consideration of the interrelated dependencies of $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{d}$ to market-driven design decisions (as in equation 4) is what differentiates aLCA and cLCA-MDD. cLCA-MDD determines the environmental impact of life cycle flows, dependent on an exogenously determined decision, as in cLCA, but also considers the resultant design and demand responses to this decision (equation 5). For example, a cLCA-MDD version of vector $\boldsymbol{d}$ in equation (1) would determine not only the number of machined parts necessary to produce the demanded quantity of the protagonist vehicle but also the reduction of machine parts from competing vehicles displaced by the protagonist vehicle. The cLCA-MDD version of the $\boldsymbol{B}$ matrix in equation (3) would determine not only the emissions intensity factors as a function of the protagonist vehicle's horsepower but also those associated with competing vehicles' equilibrium design characteristics as a function of the protagonist's horsepower.

$$\begin{aligned}&\boldsymbol{A}(x_i)\,\boldsymbol{s}(x_i, x^*_{-i}(x_i))\\ &\quad = \boldsymbol{d}(x_i, x^*_{-i}(x_i), \quad \boldsymbol{p}^*(x_i, x^*_{-i}(x_i)))\end{aligned} \tag{4}$$

$$\boldsymbol{B}(x_i)\,\boldsymbol{s}(x_i, x^*_{-i}(x_i)) = \boldsymbol{v}(x_i, x^*_{-i}(x_i)) \tag{5}$$

The dependency of life cycle flows on endogenous design responses allows cLCA-MDD to capture many direct and indirect "ripple effects," as characterized by Hertwich (2005). For example, the economics literature has recognized that automotive firms have an incentive to decrease the fuel efficiency of their vehicles in favor of larger size, in response to a decrease in size (and increase in fuel efficiency) of a competing vehicle (e.g., Jacobsen 2010; Whitefoot et al. 2011). This indirect effect can be captured in cLCA-MDD, along with direct effects, such as the classical energy-economics concept of rebound effects, whereby energy use increases as a result of fuel efficiency improvements (or fuel price decreases).

Equations (4) and (5) present at least two challenges for cLCA-MDD. The first is the parameterization of the process matrix $\boldsymbol{A}(x_i)$ and the emission factor matrix $\boldsymbol{B}(x_i)$ as functions of all relevant design variables. Although this certainly is not trivial, similar data have been collected and analyzed in sensitivity analyses of design choices (e.g., Keoleian 1998). The second issue is the need for models of consumer behavior (e.g., product demand and use functions) to determine $\boldsymbol{d}(x_i, x^*_{-i}(x_i), \boldsymbol{p}^*(x_i, x^*_{-i}(x_i)))$ and an equilibrium simulation to determine $x^*_{-i}(x_i)$. These issues increase the data requirements and computational costs of cLCA-MDD.

Relevant consumer behavior submodels to determine $\boldsymbol{d}$ in equation (4) include consumer utility models of product demand (e.g., how consumer demand for a particular vehicle changes with the vehicle's design and pricing) and use (e.g., how demand for VMT changes with vehicle horsepower). Determining equilibrium design responses, x^*_{-i}, and prices, $\boldsymbol{p}^*$, also requires submodels of production costs, $\boldsymbol{c}(x)$, and product performance (e.g., fuel economy as a function of engine horsepower), $\boldsymbol{y}(x)$, in addition to a model of product demand. Given these models, one can determine equilibrium prices and competing product designs by simulating a partial-equilibrium model in which firms maximize profits with respect to the design variables and prices of their products, given the prices and design variables of competing products. This process is outlined in detail and implemented by Michalek and colleagues (2004). We also refer the reader to other publication examples (e.g., Shiau and Michalek 2009; Frischknecht et al. 2010; Whitefoot et al. 2011) that provide recent applications of oligopolistic equilibrium models to product design.

Functional and Decision Unit

Implementing cLCA-MDD requires the same goal definition and scoping stage as implementing aLCA. Issues such as the purpose, scope, functional unit, and boundaries for the system must be considered. Unit processes must be defined and populated with the most representative data available, after a detailed and transparent analysis of the data. The complexity of accounting for flows through possibly hundreds of processes and managing the inventory of coproduced wastes (Heijungs and Suh 2002) must be rigorously addressed through model simplification and careful consideration of system boundaries and allocation methods.

During goal definition and scoping in cLCA, we have also found it necessary to clearly specify a *decision unit* along with a *functional unit*. For example, a decision unit for the VW example in the introduction could be "downsizing the VW Touareg model by 10%." In the same way that the functional unit is useful to help determine which life cycle unit processes can be excluded from the analysis (e.g., on the basis of contribution to overall emissions or consumption), the decision unit helps the researcher justify the inclusion or exclusion of specific models and assumptions. In a cLCA, in which impacts of a decision on the environment can cascade through countless indirect impacts on other products and consumer behavior, the significance of including a parameter or model to characterize these effects is usually not evident from the functional unit alone, without a decision unit also specified.

Life Cycle Assessment Uncertainties

Given perfectly accurate data and models of firm and consumer behavior, cLCA could reduce uncertainty compared to aLCA because the systematic relationships between input parameters are defined. Even with sufficient validation of the individual input models and parameters, however, multiple models and parameters often exist, and validation of the interaction of several submodels is very challenging and not generally possible (see the work of Frischknecht et al. [2010] for a discussion of submodel evaluation). As a result, we would expect that cLCA adds significant uncertainties to those already present in LCA (see the work of Ross et al. [2002] for a review). With respect to the inventory stage, four categories of uncertainty that must be managed in both aLCI and cLCI are (1) structural uncertainty, (2) model uncertainty, (3) parameter uncertainty, and (4) variable uncertainty. Below, we define these four categories of uncertainty as they are used later in the article. We do not consider the uncertainties involved with translating LCI results to environmental impacts (see Lenzen 2006).

Structural uncertainty concerns the interconnections between models, embodying questions regarding the appropriateness of the overall modeling approach and assumptions of how submodels are interconnected. For instance, questions of structural uncertainty in cLCI could focus on what types of competing products are considered, what parameters are considered exogenous, and whether it is reasonable to assume that firms behave as though they are in partial equilibrium. Structural uncertainty questions common to both cLCI and aLCI include the definition of the functional unit and the incorporation of unit processes inside and outside the system boundary and have previously been addressed with computation-based, hybrid input-output LCI (Lenzen 2001; Williams et al. 2009).

Model uncertainty considers the appropriateness of the selected models to determine required outputs. The selection of a product performance model to convert design variables, x (e.g., horsepower) into consumer observable attributes, y (e.g., fuel economy) would be classified under model uncertainty, as would selection of models characterizing life cycle flows in the absence of direct measurements.

Parameters are exogenous to the LCA study (e.g., elasticities) and often have uncertainties expressed by distributions, confidence intervals, or discrete values. Variables are endogenous to the study and may also have uncertainty if they are generated by stochastic models (e.g., fuel economy dependent on random traffic conditions). Uncertainty associated with parameters and variables with known distributions can be treated with standard methods, such as interval assessment, bootstrapping, and Monte Carlo analysis (Lloyd and Ries 2008). Parameter uncertainty deriving from discrete values, however, presents additional challenges. For example, many different estimates of the elasticity of gasoline demand have been produced from the econometrics literature (Graham and Glaister 2002). This cross-study uncertainty cannot as easily be analyzed with distributional assumptions.

To address uncertainties associated with discrete parameters and models, we generate results under multiple combinations of selected submodels and parameters within models, referred to as *scenarios*. Structural uncertainty could similarly be handled under such a system but is not addressed in the case study. Uncertainty associated with input parameters with assumed or estimated distributions is captured with confidence intervals within each scenario, generated from bootstrap samples. Multiple scenarios can be arranged together in matrices, which we call *scenario landscapes*, to facilitate easy comparison. This presentation scheme complements the uncertainty analysis discussed by Huijbregts and colleagues (2003). Although the authors suggest assigning a probability of "faith" in models and discrete parameters to generate confidence intervals, we avoid this aggregation, instead illustrating result sensitivity to specific input parameters and models. This type of analysis can be used in cLCA to interpret the integrity of results over a range of scenario landscapes that are appropriate to the goals and scope of the analysis. We believe that this approach increases the transparency of system boundary decisions and overall study conclusions.

Case Study Part 1: Industrial Decision

Goal and Scope

This study investigates the change in life cycle GHG emissions resulting from a decision to downsize the engine of a mid-size vehicle by 25% (in terms of horsepower). In particular, we evaluate the hypothesis that this level of engine downsizing will reduce life cycle GHG emissions associated with the mid-size vehicle market by at least 10%. The scope of the study includes the effects of this decision on equilibrium design adjustments to competing vehicles, changes in demand for the protagonist and competing vehicles, and changes in the VMT of these vehicles. Endogenous design variables considered include the horsepower and final drive ratio (the gear ratio between the transmission and wheels) of competing vehicles and the final drive ratio of the protagonist vehicle. The study includes the effects of these design variables and the protagonist vehicle's horsepower on production costs, fuel economy, 0 mph to 60 mph acceleration time, and the mass of the vehicle body needed to support the engine. All other aspects of the vehicle are assumed to be fixed and equivalent to the mid-size vehicle considered by Keoleian and colleagues (1998). Decisions on engine horsepower affect upstream material and manufacturing emissions, downstream end-of-life unit processes, and use-phase emissions associated with consumer demand for VMT based on the operating cost of the vehicle. The effect of changes to final drive ratios on life cycle flows and production costs are negligible and so are not considered.

A number of additional ripple effects are not considered in the boundary of this particular case study. For instance, decreases (increases) of vehicle prices in response to the decision analyzed may increase (decrease) the money consumers have available for other purchases. Consumption (or avoided consumption) of additional goods due to this change would have environmental consequences that are not considered. Macroeconomic effects, such as the relationship of producer welfare to industrial investment, wages, or tax receipts, are also not considered. Such economic shifts also lead to changes in consumption that are outside the boundaries of this case study. These effects could be included in a cLCA-MDD analysis and are already included in some large-scale policy analyses (U.S. Energy Information Administration 2010).

The following subsections summarize the life-cycle unit processes and models employed in the case study. In the interest of brevity and focus, many of the details are provided in the references and the supporting information on the Journal's Web site. The descriptions are only meant to demonstrate how submodels of product performance, demand, and use can be incorporated into cLCA. The results of the case study are not intended to accurately describe the affects of the decisions analyzed but provide a useful demonstration of the cLCA-MDD approach.

Unit Processes

The process and emission factor matrices are based on a generic vehicle LCI from the U.S.

Automotive Materials Partnership (Keoleian et al. 1998) that estimates the material and energy profile for a mid-size vehicle with a gasoline engine (3 liters [L], 140 horsepower [hp]). The baseline vehicle material inputs are listed in Table 1 of the supporting information on the Web and represent 90% of the body mass, 86.5% of the powertrain mass and 97% of the suspension mass; excluded components are not significantly affected by the design decisions. To determine the relationship between horsepower and engine mass, we combine power-displacement data from Arnold and colleagues (2005) with the displacement-mass data from Messner (2007). The relationship between engine weight and the weight of the vehicle frame and body necessary to support the engine is accounted for with a weight-compounding factor of 0.5, from Lave and colleagues (2000). The study assumes that energy inputs for engine manufacture are independent of engine horsepower and that energy used in body manufacture varies with body mass. A suspension system of constant size is also manufactured with materials and energy, as modeled according to the work of Keoleian and colleagues (1998). Vehicles are assembled from the manufactured systems with additional inputs of materials (no other systems manufacturing is modeled) and energy. After production, the new vehicles are driven for their useful life and then sent to a shredder, which recovers metals and sends nonmetals to a landfill. Additional nonmetal inputs and transportation between processing facilities are not included in the analysis.

Partial-Equilibrium Model

We model the market for mid-size vehicles as an oligopoly in partial equilibrium. Five producers are modeled, but the qualitative results of the case study do not change as a result of this assumption. Firms maximize profit with respect to the horsepower (between 100 and 210 hp), final drive ratio (between 0.2 and 1.3), and prices of their vehicles, with demand and costs calculated dependent on these variables from submodels described below. We computed the equilibrium by sequentially optimizing each firm's profits given fixed competitor vehicle designs and prices until convergence. Additional details can be found in the work of Skerlos and colleagues (2005) or Hu and Ralph (2007).

Vehicle Performance Model

The relationship between design variables and product performance attributes (fuel economy and acceleration performance) is taken from the work of Michalek and colleagues (2004). This model approximates results from the vehicle simulation software, ADVISOR (AVL LIST GmbH, Austria). ADVISOR calculates a vehicle's fuel economy and 0 mph to 60 mph acceleration time[4] on the basis of input driving cycles, engine maps, and vehicle parameters (including the final drive ratio and scaling of the engine horsepower).

Product Demand Model

A logit model, based on the model estimated by Boyd and Mellman (1980), determines consumer demand for vehicles on the basis of price and performance attributes. This model, although dated, provides the simplicity and convenience appropriate for demonstrating the cLCA-MDD approach in the case study. The model does not account for heterogeneity of consumer preferences. The possibility that consumers may not choose any of the product offerings is included, modeled as an "outside good." In this study, we assume the outside good is an old vehicle that has a fuel economy of 21.8 miles per gallon (mpg),[5] equivalent to the average on-road passenger vehicle in 1994 (U.S. Energy Information Administration 1995). For a discussion of contemporary product demand modeling, see the work of Louviere and colleagues (2000) and Train (2003).

Use Demand Model

To determine demand for VMT per year, we use two econometric models that were originally derived to explain fuel consumption trends for light-duty vehicles in the United States (Jones 1993; Goldberg 1998). These models are compared to U.S. Department of Transportation VMT data in the supporting information on the Web. Demographic and transportation infrastructure variables that factor into these models are assigned constant average values from 1990s data to align with the input LCI data. Vehicle operating costs and purchase prices are determined from the partial-equilibrium model. The lifetime of all vehicles is assumed as 15 years; the possibility that vehicles could be driven for fewer or more than 15 years is not modeled.

Comparison of aLCI, cLCI, and cLCI-MDD

To illustrate some of the differences of taking an aLCA, cLCA, or cLCA-MDD approach, we compare LCI results using the data and models used in this case study. Figure 2A shows life cycle GHG emissions using an aLCI approach. The results assume that VMT for each vehicle is identical and independent of fuel economy but subject to sensitivity analyses. The figure illustrates the results of varying both VMT (5,000 to 30,000 miles/vehicle-year) and engine horsepower (100, 140, and 200 hp). Results qualitatively match the work of Keoleian and colleagues (1998), although values differ slightly due to the vehicle system boundary simplifications defined earlier. Figure 2B illustrates how the life cycle CO_2-eq. emissions are broken down by life cycle stage for the case in which VMT per year is 11,200 miles and the selected engine is 140 hp.

Figure 3A illustrates LCI results for the same vehicle model using a simple cLCA approach, in which VMT is calculated as a function of fuel price and affects use-phase emissions. The vehicle's engine is assumed 140 hp. Figure 3B illustrates a cLCA-MDD approach, whereby both equilibrium design variables (horsepower and final drive ratio) and VMT are calculated on the basis of fuel price. Here, emissions from all life cycle stages are affected by the design variable decisions in addition to use-phase emissions from VMT. The figures include evaluation of model uncertainty through the comparison of VMT models by Jones (1993) and Goldberg (1998) and an assumed insensitivity of VMT to fuel price. Because both the demand and the cost models in this simple example do not represent heterogeneity across firms, all firms have the same vehicle design variables in equilibrium in figure 3B.

Unlike the aLCA approach shown in figure 2, the cLCA-MDD approach accounts for the correlation of VMT and engine horsepower due to their mutual dependency on fuel prices. Contrasting figure 3A with figure 3B illustrates how endogenously determining design responses within an LCA can capture important ripple effects. The cLCA-MDD results suggest that lifetime GHG emissions are significantly lower at

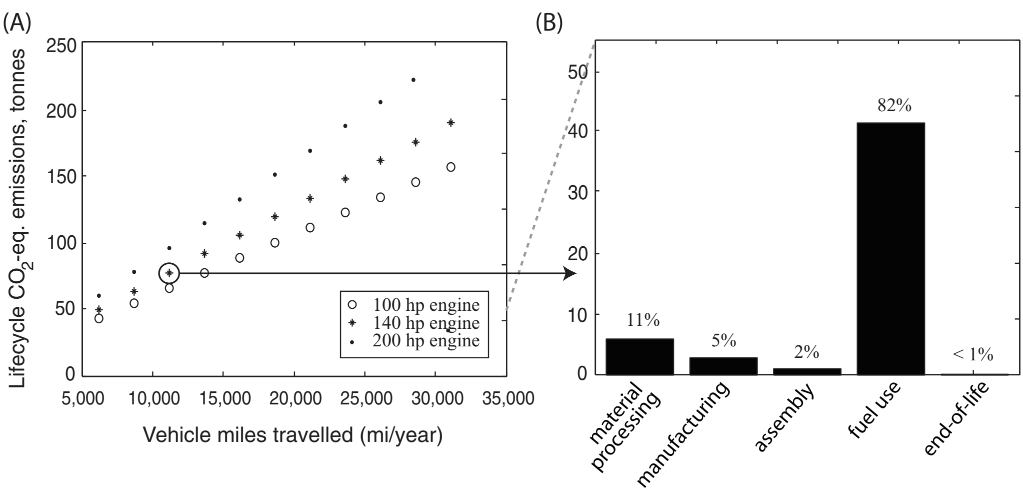

Figure 2 (A) Effect of varying vehicle miles travelled on life cycle equivalent carbon dioxide emissions (CO_2-eq.) using an attributional life cycle assessment approach. (B) Emissions from the 140-horsepower (hp) vehicle with 11,200 vehicle miles travelled, broken down by life cycle stage. mi = miles.

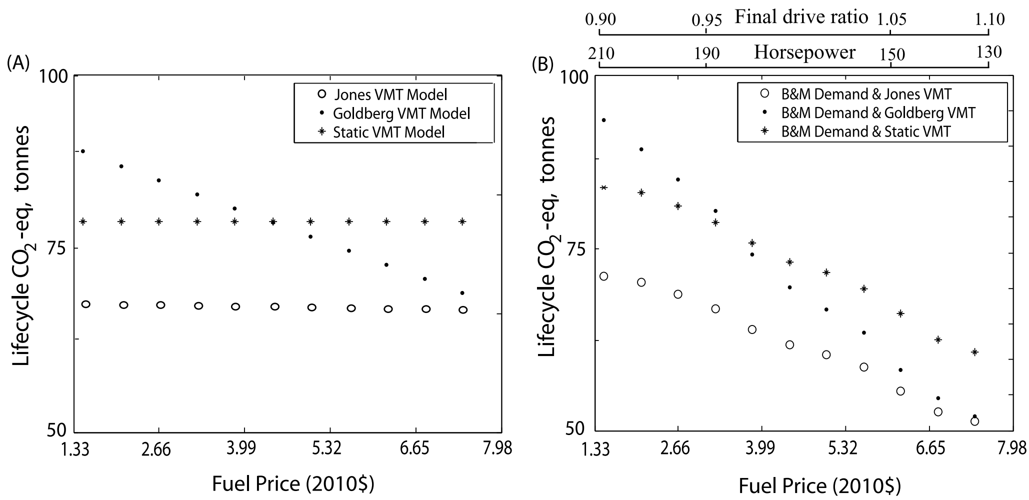

Figure 3 Life cycle greenhouse gas emissions as a function of fuel price according to (A) a consequential life cycle assessment approach, whereby vehicle design is fixed but vehicle miles travelled (VMT) is a function of fuel price, and (B) a consequential life cycle assessment with market-driven demand approach, whereby both vehicle miles travelled and equilibrium engine horsepower are dependent on fuel price. CO_2-eq. = carbon dioxide equivalent; B&M Demand = use of the demand model published by Boyd and Mellman in 1980.

high gas prices than the cLCA without MDD. The cLCA-MDD results suggest that automotive manufacturers downsize their vehicles' engines in response to higher fuel prices and, even given the rebound effect of VMT increasing due to better fuel economy, this downsizing decreases life cycle GHG emissions.

Results

We employ the cLCA-MDD methodology to examine the changes in GHG emissions resulting from the decision to reduce the protagonist vehicle's horsepower. To do this, we compare the life cycle GHG emissions from a baseline case, in which all firms choose the equilibrium design variables (as in figure 3B), to a case in which the protagonist vehicle horsepower is 25% lower than in equilibrium. The final drive ratio of the protagonist vehicle, equilibrium designs for competing vehicles, and all prices are determined in response to this decision. Figure 4 shows the results of this analysis using Jones's (1993) VMT model and assuming a fuel price of $2.60. This figure illustrates that the cLCA-MDD approach captures a negative ripple effect: Competing firms increase the horsepower of their vehicles in response to the protagonist's decision to decrease horsepower to attract more consumer demand (see Jacobsen 2010; Whitefoot et al. 2011). GHG emissions directly associated with a protagonist vehicle decrease by 11.4 tonnes CO_2-eq., but the redesign also induces an increase in life cycle emissions of each competing vehicle by 3.3 tonnes CO_2-eq.

Sensitivity Analysis Under Parameter and Model Uncertainty

We evaluate results, on the basis of the hypothesis that a 25% reduction in the (equilibrium) horsepower of a mid-size vehicle can reduce the associated life cycle GHG emissions by at least 10%, considering uncertainty in the fuel price and in the VMT model. Figure 5 illustrates a landscape of eight scenarios. We create the scenarios by varying the baseline (before carbon tax) gasoline price at four discrete levels from $1.40 to $5.00 and using two different VMT models (Jones 1993; Goldberg 1998).

Ninety percent confidence intervals are shown in parentheses in figure 5, calculated from 1,000 bootstrap samples of input demand-model parameters. Light shaded scenarios indicate that the hypothesis is supported; mid-shade regions

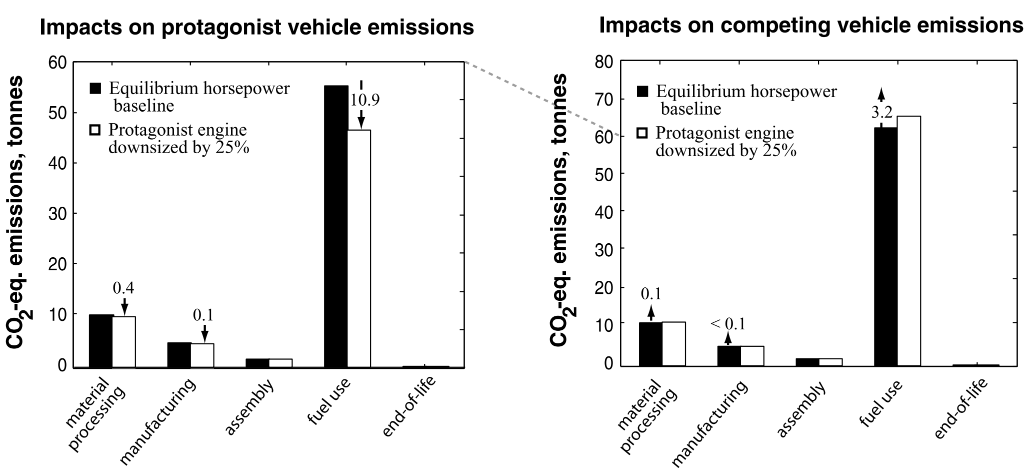

Figure 4 Changes in life cycle greenhouse gas emissions associated with a mid-size vehicle (the protagonist) as a result of the decision to downsize the vehicle's engine. CO_2-eq. = carbon dioxide equivalent.

	\$1.40	\$2.60	\$3.80	\$5.00
B&M Demand Jones VMT	**-17.69%** (-17.70,-16.49)	**-16.25%** (-16.41-14.08)	**-11.58%** (-16.61,-10.86)	**-8.01%** (-12.10,-7.97)
B&M Demand Goldberg VMT	**-18.13%** (-18.14,-16.96)	**-16.85%** (-16.99,-14.93)	**-13.28%** (-17.20,-12.69)	**-11.06%** (-13.85,-11.04)

Fuel Price (2010$)

Figure 5 Greenhouse gas emission results evaluated over scenarios of fuel price parameter and vehicle miles travelled (VMT) model. The shade of the scenario indicates acceptance (light), rejection (dark; none shown in this figure), or neither (mid-shade) of the case-study hypothesis. Confidence intervals are shown in parentheses. B&M Demand = use of the demand model published by Boyd and Mellman in 1980.

indicate that it is not supported or rejected. Percentage reductions of GHG emissions are smaller for higher fuel prices because the 25% reduction of engine power from equilibrium is smaller.

Case Study Part 2: Policy Decision

Goal and Scope

This part of the case study investigates the life cycle GHG emissions of the mid-size vehicle market resulting from the decision to add a carbon tax on gasoline of \$25/tonne CO_2. In particular, we determine life cycle GHG emissions for the mid-size vehicle market, modeled as in the *Results* section, with and without a carbon tax on gasoline of \$25/tonne CO_2. We evaluate the hypothesis that this level of carbon tax on gasoline will reduce total life cycle GHG emissions associated with the mid-size vehicle market by at least 5% relative to a 1994 baseline when average gasoline prices were \$1.64 (adjusted to 2010 prices according to the consumer price index). The scope of the study includes the effects of this decision on equilibrium design adjustments to all mid-size vehicles and the VMT associated with these vehicles. Endogenous design variables

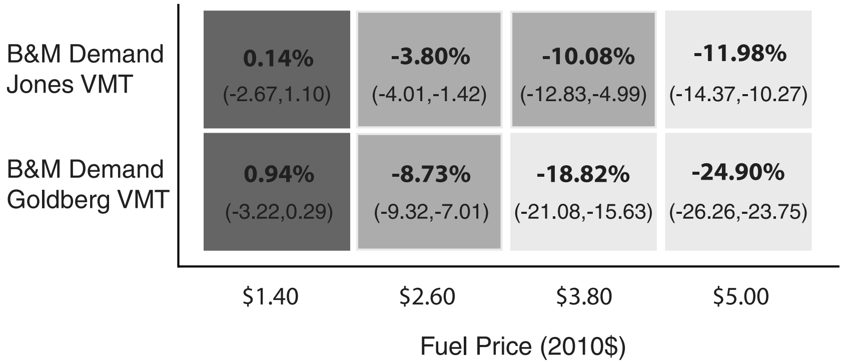

Figure 6 Greenhouse gas emission results evaluated over scenarios of fuel price parameter and vehicle miles travelled (VMT) model. The shade of the scenario indicates acceptance (light), rejection (dark), or neither (mid-shade) of the case-study hypothesis. B&M Demand = use of the demand model published by Boyd and Mellman in 1980.

considered are the horsepower and final drive ratio of all mid-size vehicles. The process and emission factor matrices and selected submodels are the same as in the first part of the case study.

Results

Incorporating endogenous design decisions in the analysis gives significantly larger estimates of lifetime GHG reductions from mid-size vehicles due to the carbon tax. For example, when we use Jones's (1993) VMT model and assume that pre-carbon-tax gasoline prices are $2.60, results indicate that the carbon tax leads to a reduction of life cycle emissions by 3.8% (90% confidence interval [CI] = 1.38, 5.03). The equilibrium horsepower of the mid-size vehicles was reduced from 210 hp in the baseline case to 200 hp with the carbon tax, and the equilibrium final drive ratio increased slightly. If we ignore these design changes, the results indicate a reduction of only 0.50% (90% CI = 0.48, 0.51) of life cycle emissions in response to the tax.

Sensitivity Analysis Under Parameter and Model Uncertainty

Similar to part 1 of the case study, we generate results over scenarios of the fuel price parameter and the VMT model, shown in figure 6. The shade of the scenario indicates acceptance (light), rejection (dark), or neither (mid-shade) of the case study hypothesis: A carbon tax of $25/tonne CO_2 ($0.08/gallon) can reduce total life cycle GHG emissions of the mid-size vehicle market by at least 5% compared to a 1994 baseline at which average gasoline prices were $1.64.

Summary and Conclusions

This article contributes to the methodology of cLCA, which is a valuable framework to study the impact of industrial and policy decisions on life cycle emissions, by presenting an approach to account for MDD responses (cLCA-MDD). The application of LCA methods for future product or policy design has long been recognized as an important tool for sustainable development (Keoleian and Menerey, 1994; Ehrenfeld, 1997), but a comprehensive quantitative design framework has been lacking. This article has introduced the concept for a cLCA-MDD approach, demonstrated its feasibility, and illustrated its applicability with a simplified case study. Although cLCA-MDD can, in principle, be accomplished with other methods, such as agent-based modeling or systems dynamics, in this article, we performed cLCA-MDD using equilibrium analysis. That is, an oligopolistic equilibrium model endogenously determined the vehicle powertrain designs and prices, as well as consumer demand and VMT, that resulted from specific industrial and policy decisions. A comparison between life cycle inventory results from aLCA, cLCA without MDD, and cLCA-MDD approaches illustrated the importance of capturing design responses to industrial and policy decisions. We have also illustrated a scheme for presenting results under scenarios of input parameters and models, which communicates uncertainties in the analysis.

Much of the research to convert the simplified case study presented into a more thorough analysis has already been accomplished. For instance, research that is required to improve the demand models (e.g., Whitefoot et al. 2011), vehicle performance models (e.g., Frischknecht 2009; Whitefoot et al. 2011), and simulation approaches (Morrow 2008) has reached the literature. Instead of incorporating these more sophisticated models into the present article, we simplified the discussion to focus on a basic blueprint for cLCA-MDD, with the goal of inspiring future research in this area within the LCA and industrial ecology community. We expect the resulting discussion will advance cLCA and further increase its relevance and practicality to the sustainable design of products and the design of policies intended to promote sustainable development.

The fundamental relationship between design decisions and environmental impacts is evident in industrial ecology: "Technology, combined with improved design, can greatly aid the quest for sustainability. Indeed, the notion that technological choice is crucial for environmental improvement lies at the core of industrial ecology" (Chertow 2000, 15). Clearly, design decisions regarding the products and services we use have a close link with our effect on the environment. Equally clearly, simply making available the technology or design options that can reduce environmental impacts is not sufficient. We also need to understand the various factors that facilitate or hinder their deployment and how these factors are influenced by industrial or policy decisions. The development of an LCA approach that accounts for design decisions made in response to market forces is a step in this direction.

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Notes

1. An equilibrium in economics is defined as a set of decisions from which no agent (firm, in this case) has a profitable incentive to deviate (e.g., Samuelson 1983).
2. The model represents a partial equilibrium because the prices and design decisions of the mid-size vehicle market are in equilibrium, but the price of gasoline is specified as an input parameter and not necessarily in equilibrium.
3. One gram (g) = 10^{-3} kilograms (kg, SI) ≈ 0.035 ounces (oz).
4. One mile per hour (mph) ≈ 1.61 kilometers per hour (km/h).
5. One mile per gallon (mi./gal.) ≈ 0.425 kilometers per liter (km/L).

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Supporting Information

Additional supporting information may be found in the online version of this article:

Supporting Information S1: This supporting information describes the data and submodels used in the demonstration of consequential life cycle assessment with market-driven design (cLCA-MDD). It details the life cycle data and modeling that characterizes the material and energy flows associated with the life cycle of a mid-size vehicle. It also describes the sources of submodels of consumer demand and production costs and their associated assumptions, as well as the assumptions and formulation of the equilibrium model. Finally, the supporting information describes assumptions of vehicle use used to generate greenhouse gas (GHG) calculations per mile and vehicle miles travelled (VMT) as a function of fuel price.

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