

# An input-output approach for the efficient design of sustainable goods and services

Elaine Croft McKenzie · Pablo Luis Durango-Cohen

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## Abstract

**Purpose** We propose a prescriptive framework to support environmentally conscious decision making in the design of goods and services. The framework bridges recent applications of input-output analysis to conduct environmental life cycle assessment (LCA), with seminal work in production economics. In the latter, product design, production planning, and scheduling problems are frequently formulated as input-output models with substitution, and subsequently analyzed and solved as linear programs. The use of linear programming provides an appealing theory and computational framework to support decision making, as well as to conduct sensitivity analysis

**Methods** In this paper, we explore the benefits of integrating LCA within a linear programming (LP) framework and present a case study where we consider a hypothetical advertiser located in the Chicago Metropolitan Area, who wishes to allocate a predetermined budget to place ads in either the print or online versions of a high-circulation, local newspaper. We formulate the problem of finding an advertising strategy that minimizes global warming potential (GWP), subject

to demand and budget constraints. We then solve the problem and evaluate the optimal strategy in terms of discharges of component greenhouse gases, and in terms of requirements imposed on various energy sources. We also analyze the sensitivity of the optimal advertising strategy (and associated global warming potential) to perturbations in the model parameters and constraints.

**Results and discussion** By embedding LCA within an LP formulation, we are able to examine the relationships between economic and environmental factors inherent within decisions to use specific products or services. Specifically, the advertiser finds that each strategy contains tradeoffs among and between environmental and monetary costs. A disaggregate comparison of greenhouse gas release and energy consumption among strategies highlights the variation between these factors and the potential dangers of aggregation. Sensitivity analysis gives us marginal costs (per dollar and per person) of GWP in the optimal solution. These and other managerial insights presented highlight the complex tradeoffs necessary for environmentally conscious, sustainable decision making.

**Keywords** Product design · Environmental life cycle assessment · Production planning and scheduling · Input-output analysis · Linear programming · Print vs. online advertising

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E. Croft McKenzie · P. L. Durango-Cohen (✉)  
Department of Civil and Environmental Engineering,  
Northwestern University, 2145 Sheridan Road,  
A332 Evanston, IL 60208-3109, USA  
e-mail: pdc@northwestern.edu

E. Croft McKenzie  
e-mail: e-croft@northwestern.edu

## 1 Introduction

Input-output (IO) analysis has been used extensively to conduct life cycle assessments (LCAs) of the environmental impact, e.g., greenhouse gas emissions, energy

and water consumption, associated with various industrial/commercial/government processes, goods, services, resources, and policies. The approach was conceived by Leontief (1970). Miller and Blair (1985), Joshi (2000), and Hendrickson et al. (2006) provide an overview of the methodological approach and describe several recent applications of IO analysis in engineering, management, and policy.

Overall, the IO approach involves specifying the direct requirements, i.e., a bill of materials, of goods, and services in terms of demand imposed on sectors of the economy. The IO model, in turn, is used to compute the direct and indirect requirements that satisfying an exogenous demand imposes on the economy as a whole. Subsequently, the model is used to calculate the environmental repercussions associated with the economic activity that is needed to meet the demand. The flexibility, transparency, and accuracy of the methodology explain its broad appeal in the scientific and engineering community, and why it has become an accepted method for conducting LCA, especially among products or services that are not well served by more resource intensive LCA methods (Hendrickson et al. 2006; Lenzen 2001).

Although they have provided much insight, economic IO life cycle assessments (EIO-LCAs) have been used almost exclusively as descriptive tools. That is, EIO-LCA models have not been integrated into a prescriptive framework to support decisions that arise during product/process design or (production) planning. Furthermore, LCAs in general lack the ability to reflect the preference structure or value systems of different stakeholders (Zhou and Schoenung 2007). To address these limitations, we build on literature in production economics, where process/product design, production planning, and scheduling problems are often formulated as IO models with substitution, and subsequently, analyzed and solved as linear programs (cf. Shephard 1953; Hackman and Leachman 1989). Indeed, and as described in Koopmans (1951), these types of problems are among the first applications of linear programming. From a managerial perspective, one of the appealing features of the proposed framework is that linear programming provides a well-established theory, as well as a systematic approach, to conduct sensitivity analysis, i.e., to evaluate the effect of perturbations in the inputs on the results.

The contribution of our work is, therefore, (1) to combine the two literature streams of environmental life cycle assessment and production economics, and (2) to provide a practical, prescriptive framework to support the design of environmentally conscious goods and services. To illustrate the proposed framework,

we analyze the problem of designing an advertising strategy. In particular, we consider an environmentally conscious advertiser in the Chicago Metropolitan Area, wishing to allocate a predetermined budget to place ads in either of two media outlets: print vs. online versions of a high-circulation, local newspaper. We assume that the advertiser's objective is to minimize environmental impact, i.e., global warming potential, while reaching a target population.<sup>1</sup> We use the proposed framework to find an optimal advertising strategy, and then evaluate and compare the strategy to two benchmarks in terms of discharges of component greenhouse gases, and requirements imposed on various energy sources. Finally, we analyze the sensitivity of the optimal advertising strategy and associated environmental impact to perturbations in the budget, size of the target population, relative costs to place ads, and relative environmental impact associated with each medium.

The remainder of the paper is organized as follows: Section 2 reviews approaches to carry out environmental LCAs, as well as frameworks to optimize the design of goods, services, or processes while accounting for environmental impact metrics. In Section 3, we provide an overview of the use of IO analysis to address problems related to design and production of goods or services. In Section 4, we apply the proposed framework to the problem of designing an environmentally friendly advertising strategy. Concluding remarks appear in Section 5.

## 2 Related work

In this section, we position the proposed framework in relation to alternative methods of environmental LCAs. We also consider approaches to optimize the design of goods, services, or processes that explicitly account for environmental impact metrics, e.g., that include restrictions that limit pollution.

In the early 1990s, *sustainable development* emerged as an all-encompassing, integrative concept/philosophy to simultaneously capture and address economic, social, and environmental concerns that began to dominate the world-wide political landscape. As defined by the World Commission on Environment and Development,

<sup>1</sup>We recognize that a single advertising campaign does not have a significant effect on the environmental footprint of different media types. However, because ad revenue is one of the main sources of income for many media types, an increase or decrease of advertising dollars could affect their long-term viability, and thus their environmental impact.

sustainable development refers to “development that meets the needs of the present without compromising the ability of the future to meet its needs” (Mihelcic et al. 2003). These concerns spearheaded significant work in the development, adaptation, and application of numerous methodologies to conduct environmental LCAs, i.e., to quantitatively evaluate the environmental impact of a variety of goods and services over their life cycle and over their supply chain. Finkbeiner et al. (2006) summarizes the series of international standards in place to consolidate procedures and methods of LCA throughout businesses and organizations (ISO 14040:1997, ISO 14041:1999, ISO 14042:2000, ISO 14043:2000, ISO 14040:2006, ISO 14044:2006).

Over the past two decades, different types of LCAs have emerged. Hertwich (2005) reviewed different approaches to conduct LCAs, and classified them as either “classical product/process models” or as “economic IO models”. In process models, the objective is to establish a causal link between activities that take place over a product’s life cycle, i.e., raw material extraction, fabrication, distribution, sales, utilization, disposal, and the associated environmental stresses. In their purest form, the specification and application of such models requires detailed descriptions of the aforementioned activities, and relies on identification and understanding of the physical/chemical/engineering processes that take place during their execution, i.e., chemical reactions, mass/energy/heat transfer, etc. The broad adoption of process models stems from the thoroughness of the analysis, coupled with the fact that the US government spells out standards for the development of such models under a framework created by the Society of Environmental Toxicology and Chemistry and the Environmental Protection Agency.

The main limitations of process models also relate to the thoroughness of the analysis and comparability between studies. In particular, following Hendrickson et al. (2006) and others, we note that because they are data and analysis driven, process models are extraordinarily resource intensive. This may render the approach inefficient or impractical in many situations. Furthermore the data sources and variations in methodology necessary to conduct a process analysis by different firms or organizations may in some cases limit the comparability of products or services. Finally, defining the scope of a process model places an artificial and subjective boundary on the supply chain impact of the good, service, or process being analyzed, which, in turn, can lead to significant errors (Lenzen 2001; Suh et al. 2004).

Economic IO models constitute an alternative approach to conduct LCAs, while addressing the afore-

mentioned difficulties. Rather than mapping processes in detail, the IO approach involves specifying the direct requirements, i.e., a bill of materials, of a product in terms of demand for economic sectors, e.g., transportation, construction, financial services, etc. This demand is (usually) expressed in monetary value, i.e., US dollars. The model, in turn, is used to compute the level of economic activity and environmental repercussions associated with satisfying the given demand for the product. Because all sectors represented in the economy are linked, there is no effective boundary on the scope of the analysis. The number and diversity of LCAs employing IO analysis has greatly increased since the late 1990s as a result of the methodology’s flexibility, simplicity, and, importantly, the availability of online tools to support the analysis (cf. The Green Design Institute 2008). Examples can be found in the fields of waste disposal (Kondo and Nakamura 2004), transportation (Facanha and Horvath 2007) urban studies (Norman et al. 2006), energy (Hendrickson et al. 2006), and service industries (Rosenblum et al. 2000).

The main criticisms of the Economic IO-based LCAs (EIO-LCAs) are related to estimation biases introduced by aggregation and linearity. Suh and Nakamura (2007) lists the most common limitations of EIO-LCAs along with relevant work to overcome these limitations. One of the main arguments by critics is that monetary values used to represent demands and flows in the economy are not a good representation of (physical) processes or their environmental repercussions. Also, the use of flows across the national economy, as well as nation-wide, average discharges per economic sector may not be representative of a process taking place in a specific location using a particular technology.

While research to validate the use of EIO-LCA models has shown that the results are comparable to those using process models (see Hendrickson et al. 2006 and the references therein), the aforementioned weaknesses have motivated work to improve the precision of EIO-LCAs. Yi et al. (2007), for example, describe the development of a *regional* IO LCA model. We also note the work of Joshi (2000), who describes a number of techniques to exploit the flexibility of IO models, leading to more detailed representations/maps of goods, services or processes. The ensuing models are referred to as *hybrid LCA* models.

Hybrid type models which incorporate elements from both process-based and IO-based LCA models. Although hybrid LCA models can still include error inherent in IO models, such as aggregation and linearity, Lenzen (2001) demonstrates that these errors are often significantly lower than errors caused by the subjective boundaries in process LCAs. Similar in

function to the hybrid model is the ecological-economic model proposed by Suh (2004), which interconnects physical and commodity based systems in order to reduce the error for subjective boundaries and improve the ability to conduct analysis and supply chain management. The approach used by the authors in this paper (see Section 3) is also similar in function to hybrid LCA models.

Much of the work on LCA has focused on improving the data sources and the modeling structures needed to produce more precise measurements of the life cycle impacts of a product. Less work has been done to integrate environmental LCA models with quantitative frameworks to optimize the design of sustainable goods, services, or processes. However some research has been done to develop integrated frameworks. Zhou and Schoenung (2007) proposed an Integrated Industrial Ecology Function Deployment model to incorporate environmental impact assessment within industrial management tools and focus on incorporating the preferences of different stakeholders into the analysis. Within the chemical engineering system design literature, Azapagic and Clift (1995, 1999), and related works provide a good starting point in the context of generic approaches to study the tradeoffs between environmental, economic, and social factors in product/process design. In Azapagic and Clift (1999), they propose a multi-objective optimization model to identify Pareto optimal policies that satisfy both economic and environmental criteria for sustainable performance of a system over its life cycle. Similar to other (earlier) works, they take a process model perspective to assess impact.

In contrast, we propose to integrate optimization and analysis methods with a (hybrid) economic IO model perspective. Using this modeling structure allows us to not only avoid the limitations of process LCAs, but also exploit synergies with models of product/process design from the production economics literature. This perspective is more in line with the work of Kondo and Nakamura (2005), who propose a LP extension of their Waste-IO model. Both the model presented herein and the model in Kondo and Nakamura (2005) exploit the ability of IO models to be integrated into LP, and subsequently examine optimal solutions and tradeoffs. However, the research differs in scope. The focus of the cited research is optimal strategies using IO models where waste management options are integrated into the matrix structure and subsequently solved as a LPs. Our focus is to use EIO-LCA as a tool to integrate the concepts of environmental impacts and sustainability into a traditionally economic decision making framework that can be used in a wide variety of applications.

### 3 Proposed framework: application of IO analysis to support the design of sustainable goods and services

In this section we provide an overview of the methodological tools used in the framework for environmental decision making. First, we describe the use of IO analysis and linear programming to support decisions that arise in the design of goods, services, and processes. To do so we adopt terminology and conventions appearing in references such as Hackman and Leachman (1989) and Hopp and Spearman (2000). We then describe how the approach is used to calculate the environmental repercussions associated with satisfying a demand for a given product or process.

We define a product or process as a collection of  $n$  items/steps that are associated in order to deliver a functional purpose. For example, we consider an end-product or process, labeled “A”, that consists of components/sub-assemblies labeled “B–E”. The relationships and requirements between the  $n = 5$  items are captured in the product structure trees presented in Fig. 1.

In this case, we consider two alternative designs of A captured in the product structure trees. The root node in each of the trees corresponds to the end-product. The components are represented as nodes on the tree. The numbers that appear next to the arcs represent the number of components that are needed to manufacture the preceding item/assembly. For example, product A requires three B’s and each B requires one D, under either of the product structure trees. These requirements can also be represented in matrix form as follows:

$$B_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 3 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 \\ 0 & 1 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}; \quad B_2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 4 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (1)$$

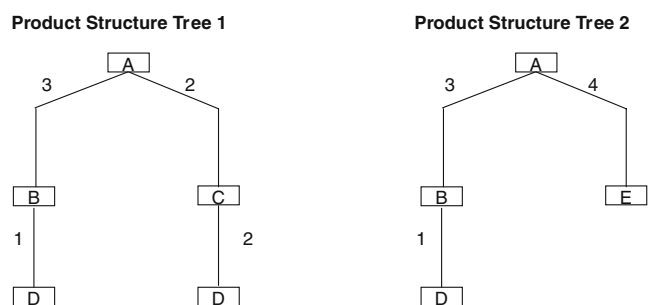


Fig. 1 Product structure trees for product A

The matrices,  $\mathbb{B}_r, r = 1, 2$  are the Bills of Material (or IO matrices) corresponding to the product structure trees presented above. Entry  $i - j$  in the above matrices, denoted  $b_{ij}^r$  for  $r = 1, 2$ , represents the amount of input  $i$  needed to produce one unit of output  $j$  under bill of materials  $r$ . In our example, the rows and columns are for items A–E. They are arranged in alphabetical order; that is, row 1 (and column 1) is for item A, row 2 is for item B, etc.

### 3.1 Calculating the gross requirements to satisfy demand for a product or process: an example

Prior to describing the approach to calculate the gross requirements associated with a product or process, we consider a scheme to classify a product’s components into various *levels*. The scheme uses the product structure trees, where end-products are classified as *Level 0* items. The direct requirements for end-products are classified as *Level 1* items. For example, items B and C are the Level 1 items in product structure tree 1. This scheme is applied iteratively by assigning the direct requirements of Level  $k$  products to Level  $k + 1$ .<sup>2</sup>

For a given product structure tree,  $r$ , we address the issue of calculating the gross requirements needed to satisfy an exogenous demand. The exogenous demand is represented as a vector  $\mathbf{y}$  with components that correspond to the demand for each of the items. We may, for example, be interested in calculating the gross requirements associated with a demand for item A of 5 units, i.e.,  $\mathbf{y}' = [5, 0, 0, 0, 0]$ . (The notation  $\mathbf{y}'$  represents the transpose of vector  $\mathbf{y}$ .) The gross requirements of all level  $k$  items that are needed to deliver  $\mathbf{y}$ , under bill of materials  $r$ , are obtained by considering the expression  $[\mathbb{B}_r]^k \mathbf{y}$ . Under bill of materials 1, the gross requirements to deliver  $\mathbf{y}$  are as follows:

$$\text{Level 0 Requirements: } [\mathbb{B}_1]^0 \mathbf{y} = \mathbb{I}\mathbf{y} = [5, 0, 0, 0, 0]' \quad (2)$$

$$\text{Level 1 Requirements: } [\mathbb{B}_1]^1 \mathbf{y} = [0, 15, 10, 0, 0]' \quad (3)$$

$$\text{Level 2 Requirements: } [\mathbb{B}_1]^2 \mathbf{y} = [0, 0, 0, 35, 0]' \quad (4)$$

For  $k = 3, 4, \dots$ ,

$$\text{Level } k \text{ Requirements: } [\mathbb{B}_1]^k \mathbf{y} = [0, 0, 0, 0, 0]' \quad (5)$$

where  $\mathbb{I}$  is an  $n \times n$  identity matrix.

The total gross requirements associated with satisfying  $\mathbf{y}$  under  $r$  are obtained by adding the gross requirements across all levels. Letting  $\mathbf{x}_r \equiv [x_1^r, x_2^r, \dots, x_n^r]'$  de-

note the total gross requirements for the  $n$  items under  $r$ , we have that:

$$\mathbf{x}_r = \sum_{k=1}^{\infty} [\mathbb{B}_r]^k \mathbf{y} = (\mathbb{I} - \mathbb{B}_r)^{-1} \mathbf{y} \quad (6)$$

where vector component  $x_i^r$  represents the total gross requirements for item  $i$  that are needed in order to meet the exogenous demand  $\mathbf{y}$ .<sup>3</sup> In the example,  $\mathbf{x}_1 = [5, 15, 10, 35, 0]'$ .

Allowing for substitution, as is done in the context of product/process design or of production planning/scheduling, implies the existence of alternatives to meet the exogenous demand,  $\mathbf{y}$ . In the example, there is flexibility to meet the demand for end-product A under either of the two product structure trees presented earlier. Letting  $\tau_r$  be the number of units produced using each product structure, we have:

$$\mathbf{x}_r = (\mathbb{I} - \mathbb{B}_r)^{-1} \tau_r \quad (7)$$

where:

$$\sum_{r=1}^2 \tau_r = \mathbf{y} \quad (8)$$

We define  $\mathbf{x} \equiv \sum_{r=1}^2 \mathbf{x}_r$ , i.e., as the total gross requirements to meet  $\mathbf{y}$ . In the example, if  $\tau_1 = [3, 0, 0, 0, 0]'$  and  $\tau_2 = [2, 0, 0, 0, 0]'$ , then  $\mathbf{x} = [3, 9, 6, 21, 0]' + [2, 6, 0, 6, 8]' = [5, 15, 6, 27, 8]'$ .

A key observation of Dantzig (1949), Koopmans (1951), Wagner (1957) is that demand met under each product structure can be obtained by solving a linear program, thereby providing an analytical and computational approach to support the optimal design of a production strategy (to satisfy the demand for end-product A). The approach is widely used to address various problems that arise in production economics. For example, Hackman and Leachman (1989) consider the problem of satisfying demand over a finite set of periods, and formulate a linear program to find a production schedule that minimizes the total discounted inventory-holding costs. In this problem, referred to as *Material Requirements Planning* or *MRP*, the substitution alternatives are related to feasible production schedules. As described below, the methodology can be easily adapted to address problems related to the design and production of sustainable goods and services. For example, one could consider a problem to minimize (production and operation) costs subject to limiting

<sup>2</sup>In general, product structure trees can be cyclic, and therefore an item can be assigned to multiple levels.

<sup>3</sup>Conditions that guarantee the result presented in Eq. (6) are not restrictive. For instance, the expression holds when  $\lim_{k \rightarrow \infty} [\mathbb{B}_r]^k = 0$ , as is the case in the example.

environmental discharges, or, as is done in Section 4, to minimize discharges subject to meeting requirements and not exceeding available resources. In the remainder of this section, we explain how the above scheme is extended to account for the environmental repercussions associated with goods and services. We begin, however, by considering the application of IO analysis to characterize the structure of a nation’s economy.

Rather than describing the structure of a product, Leontief (1951, 1952) developed IO analysis as a technique to characterize the overall structure of the US economy. Instead of items/sub-assemblies, the technique relies on economic sectors, e.g., energy generation, construction, transportation, mining, etc., as fundamental building blocks. The inputs in the analysis correspond to the annual flows between economic sectors. For consistency, the flows are measured in terms of monetary value, and expressed in US dollars. In terms of notation, we consider an economy with  $N$  sectors, and denote the economic IO table  $\mathbb{A}$ , where:

$$\mathbb{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & a_{2N} \\ \vdots & & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} \end{bmatrix} \quad (9)$$

and the coefficients,  $a_{ij}$ , correspond to the inputs (in \$) from sector  $i$  needed to obtain \$1 of output from sector  $j$ . In the USA, the Department of Commerce generates “Benchmark” economic IO tables on a 5 year cycle that capture flows across nearly 600 economic sectors (see [http://www.bea.gov/industry/io\\_benchmark.htm](http://www.bea.gov/industry/io_benchmark.htm)).

Integrating economic IO tables with the bill of materials of a product/process provides a natural approach to calculate the gross, i.e., direct and indirect, economic activity (across all sectors) that is needed to satisfy an exogenous demand. The approach involves expanding the bill of materials to include the direct requirements (in \$) for various economic sectors. Graphically, this expansion can be represented on a product structure tree where the leaves correspond to economic sectors. For illustration, in Fig. 2, we return to the example, and expand Product Structure Tree 1 for end-product A. Only 2 economic sectors, S1 and S2, appear explicitly in the expanded product structure tree. The coefficients,  $a_1$ ,  $b_1$ ,  $c_2$ ,  $d_1$ , and  $d_2$ , correspond to the inputs (in \$) from the economic sectors needed to produce one unit of output.

Even though only sectors S1 and S2, appear explicitly in the expanded product structure tree, it should be noted that these sectors require inputs from the  $N$  sectors that comprise the national economy. These relationships are given in the IO table,  $\mathbb{A}$ , and are repre-

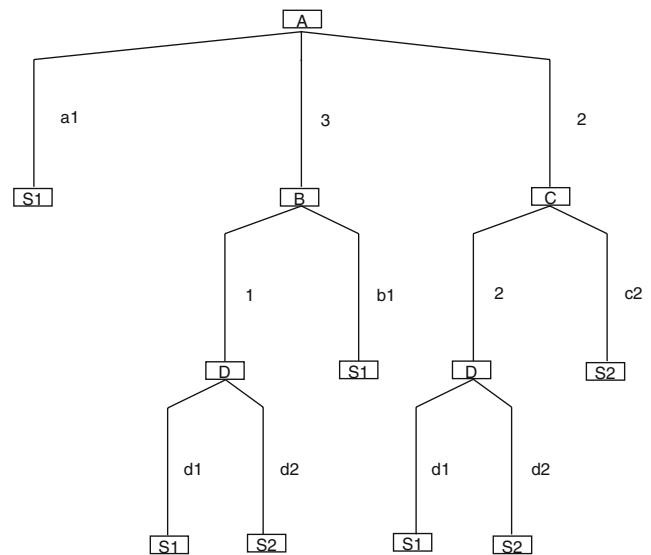


Fig. 2 Expanded product structure tree 1 for product A

sented in the expanded bill of materials,  $\hat{\mathbb{B}}_1$ , presented below:

$$\hat{\mathbb{B}}_1 = \left[ \begin{array}{ccc|cc|c} & \mathbb{B}_1 & & & & \mathbb{O}_{5 \times N} \\ a_1 & b_1 & 0 & d_1 & 0 & \\ 0 & 0 & c_2 & d_2 & 0 & \mathbb{A} \\ \hline & \mathbb{O}_{(N-2) \times 5} & & & & \end{array} \right] \quad (10)$$

where  $\mathbb{O}_{p \times q}$  is a Zero Matrix of dimensions  $p \times q$ .

Again, for an exogenous demand of  $\mathbf{y}$ , the total associated gross requirements,  $\mathbf{x}$ , can be calculated using Eq. (7)—replacing  $\mathbb{B}_r$  with the associated matrix  $\hat{\mathbb{B}}_r$ , which is equivalent in form to the matrix in (10). We also note that the vector  $\mathbf{x}$  can be partitioned as follows:  $\mathbf{x} = [x_1, \dots, x_n | x_{n+1}, \dots, x_{n+N}]'$ , where the first  $n$  components correspond to the gross requirements for the items/sub-assemblies being considered, while the other  $N$  components correspond to the gross requirements for each economic sector represented in the economy.

In the USA, the Department of Energy, among other organizations, has done extensive research to quantify the environmental impact associated with economic activity in various economic sectors. These estimates are presented as a set of coefficients, denoted  $f_{jk}$ , representing the (national average) discharge rate of pollutant  $k$  per dollar of output in economic sector  $j$ . The set of discharge rates can be collected in an environmental impact matrix,  $\mathbb{F} \equiv [f_{jk}]$ . We note that the gross environmental impact to satisfy  $\mathbf{y}$  is given by the vector  $[x_{n+1}, \dots, x_{n+N}] \mathbb{F}$ , where  $\sum_{j=n+1}^{n+N} x_j f_{jk}$  corresponds to the total output of pollutant  $k$ . Single dimensional environmental impact measures, such as global warming potential, can be calculated by constructing weighted

averages of the components of the aforementioned vector, e.g.,  $\sum_{k=1}^M w_k \sum_{j=n+1}^{n+N} x_j f_{jk}$ , where  $M$  pollutants are considered and  $w_k$  is the weight assigned to the repercussions of pollutant  $k$ .

#### 4 Case study: print vs. online advertising in the Chicago Metropolitan Area

Historically, newspapers have been the major target of advertising spending. Although more money is spent on newspaper ads than on any other media outlet, recently more people are turning to online sources for news and advertising. Not surprisingly, the proportion of dollars spent by advertisers on online ads is increasing (Pricewaterhouse-Coopers 2009). In this section, we illustrate the flexibility and usefulness of the proposed framework to support decision making applications by considering a Chicago-based company wishing to design/run an environmentally friendly advertising campaign. Our work builds upon the case study presented in Toffel and Horvath (2004), who compare the environmental impact of a consumer in Berkeley, California, reading the print version of the New York Times, versus reading the newspaper online using a PDA device. Both case studies use data from the EIO-LCA tool (Carnegie Mellon University Green Design Institute 2008) and other sources to calculate environmental impacts. In this section, we present a prescriptive model based on the 2004 case study for designing an environmentally friendly advertising strategy.

In particular, we consider an advertiser who is looking to reach a target audience of  $D$  consumers by allocating a budget of  $\$B$  across a set of  $P$  media types. In this context, an advertising campaign specifies the number of ads to be placed in each medium, and is represented by the set of decision variables  $\tau_i$ ,  $i = 1, \dots, P$ , where  $\tau_i$  corresponds to the advertising exposure through medium  $i$ . The environmental impact of the campaign is measured in terms of the discharges of  $M$  greenhouse gas pollutants. These pollutants are then aggregated by their Global Warming Potential (GWP), i.e. the amount that the different gases contribute to global warming. The environmental outcome measure in this research is total GWP, measured in Equivalent Metric Tons (EMTs) of CO<sub>2</sub>. We formulate the problem of designing an advertising campaign that minimizes environmental impact as follows:

Minimize:

$$\sum_{k=1}^M w_k \sum_{j=1}^N f_{jk} x_j \tag{11}$$

Subject to:

$$\sum_{i=1}^P \tau_i \geq D \tag{12}$$

$$\sum_{i=1}^P \kappa_i \tau_i \leq B \tag{13}$$

$$\sum_{i=1}^P c_{ij} \tau_i = y_j, \quad j = 1, \dots, N \tag{14}$$

$$\mathbf{x} = (\mathbb{I} - \mathbb{A})^{-1} \mathbf{y} \tag{15}$$

$$\tau_i \geq 0, \quad i = 1, \dots, P \tag{16}$$

where:

- $f_{jk}$ : Discharge rate of pollutant  $k$  per \$ of production in industry sector  $j$ . Discharge rates are measured in Metric Tons per \$.
- $w_k$ : Conversion factor to obtain GWP associated with discharges of pollutant  $k$ . The coefficients are measured in Metric Tons of CO<sub>2</sub> Equivalent/Metric Tons of pollutant discharges.
- $\kappa_i$ : Cost borne by an advertiser to place an ad in medium  $i$ , adjusted to a per-unit basis.
- $c_{ij}$ : Production requirements per advertisement unit in media type  $i$  implied on economic sector  $j$ . These requirements correspond to the inputs from sector  $j$  needed to produce a unit of  $i$ , are measured in \$/unit, and correspond to the parameters that appear in a product structure tree or Bill of Materials.
- $\mathbb{A}$ : the matrix of requirements of other sectors required to produce each dollar of output to each sector
- $\mathbf{y}$ : Implied demand across all industry sectors associated with an advertising strategy. These demands are measured in \$.
- $\mathbf{x}$ : Production requirements across the  $N$  economic sectors to satisfy the implied demand.

The objective function, Eq. (11), measures the GWP in EMTs of CO<sub>2</sub> of an advertising campaign (represented by the set  $\tau_i$ ,  $i = 1, \dots, P$ ). Equation (12) is a constraint that requires that the total advertising exposures be at least equal to the target population,  $D$ . Constraint (13) limits the advertiser's expenditures to the predetermined budget,  $\$B$ . Equation set (14) is used to estimate the implied demand on the  $N$

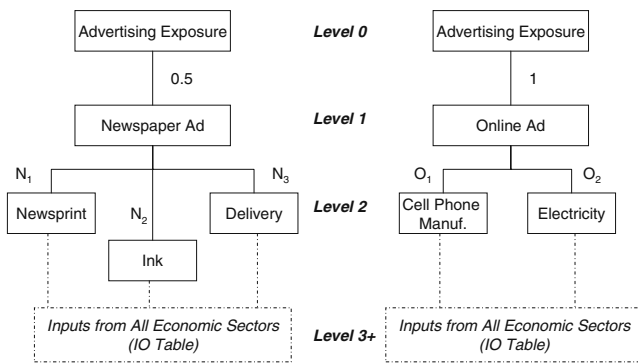


Fig. 3 Dual product structure tree for the advertising case study

economic sectors associated with the advertising campaign, i.e., this set of constraints is used to determine the demand  $y$ . Equation set (15) is used to calculate the gross requirements across the economy associated with satisfying the demand  $y$ . Finally, the nonnegativity constraints, given in equation set (16), constitute logical restrictions on the decision variables in the model.

As case study parameters, we consider an advertiser with a budget of \$120,000 targeting a population of ten million customers in the Chicago Metropolitan Area. For simplicity, and to allow for a graphical representation of the model, we restrict the advertiser’s choices to two media types: a widely distributed printed newspaper, or a high-traffic newspaper website. In our example, we replace the PDA from the 2004 case study with a modern cellular phone, e.g., the iPhone, designed for extended internet use. A product structure tree depicting the alternatives in this problem is presented in Fig. 3 with the corresponding Bill of Materials in matrix form below.

$$B_{np} = \begin{bmatrix} 0 & 0 & 0 \\ 0.5 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}; \quad B_{ol} = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (17)$$

where the rows and columns of  $B_{np}$  and  $B_{ol}$  correspond to the Level 0 and Level 1 products in Fig. 3.

$$\hat{B}_{np} = \left[ \begin{array}{ccc|c} & B_{np} & & O_{3 \times N} \\ 0 & N_1 & 0 & \\ 0 & N_2 & 0 & \\ 0 & N_3 & 0 & \\ 0 & 0 & 0 & \\ 0 & 0 & 0 & \\ \hline & O_{(N-5) \times 3} & & \end{array} \right] A;$$

$$\hat{B}_{ol} = \left[ \begin{array}{ccc|c} & B_{ol} & & O_{3 \times N} \\ 0 & 0 & 0 & \\ 0 & 0 & 0 & \\ 0 & 0 & 0 & \\ 0 & 0 & O_1 & \\ 0 & 0 & O_2 & \\ \hline & O_{(N-5) \times 3} & & \end{array} \right] A \quad (18)$$

The level 1 products correspond to the decision variables of the linear program,  $\tau_{np}$  and  $\tau_{ol}$ . Level 2 inputs are specified, while Level 3 and beyond are modeled using the IO tables of the US economy. Further details about the construction of the Bill of Materials and various level inputs can be found in Appendix A.

Among the parameters we note that:

- For the Level 1 inputs, one unit of Newspaper Advertising gives us twice the exposure as one unit of online advertising. Therefore, we can satisfy demand with 1/2 the number of newspaper ad units as online ad units.
- The relative costs of placing ads is calculated as  $(2 \times \kappa_{np})/\kappa_{ol} = 1.71$ ; that is, each newspaper ad (which satisfies two units of demand) is slightly less than twice the cost of an online ad; and
- The ratio between the environmental impact of the two media  $E_{np}/E_{ol} = 1.91$  where  $E_i$  is the measure of environmental impact (GWP) associated with medium  $i$ .

#### 4.1 Results and discussion

We begin to analyze the problem of designing an environmentally friendly advertising campaign by comparing the optimal advertising campaign to two benchmarks utilizing an exclusive media outlet. We then analyze the structure of the linear program, and in particular the tradeoffs between conflicting objectives and constraints. We also highlight the capability of this framework to conduct sensitivity analysis. We illustrate this feature by considering how the optimal strategy and ensuing emissions change in response to perturbations in the budget,  $B$ , the demand,  $D$ , the cost of placing ads,  $\kappa_i$ , and in the bill of materials,  $c_{ij}$ .

In Table 1, we compare the optimal advertising campaign obtained by solving the above linear program, to two benchmark strategies where a single medium is used. The first column of Table 1 corresponds to the baseline strategy where the demand is satisfied using newspaper advertising.<sup>4</sup> The second baseline is for the

<sup>4</sup> $\tau_{np} = 0.5$  units of Newspaper Advertising, hence only  $D/2$  units of advertising are required to satisfy  $D$  units of demand



**Table 1** Advertiser expenditure and environmental impact of advertising strategies

	Advertising strategies		
	Newspaper only	Online only	Optimal
$\tau_{np}$	10,000,000	0	$\tau_{np}^* = 4.3M$
$\tau_{ol}$	0	10,000,000	$\tau_{ol}^* = 5.7M$
Newspaper ad expenditure	\$109,500	\$0	\$47,351
Online ad expenditure	\$0	\$128,000	\$72,649
Total	\$109,500	\$128,000	\$120,000
GWP ( $E$ )	29,842 EMT	15,588 EMT	21,752 EMT
Campaign cost per consumer	\$0.011	\$0.013	\$0.012
$E$ per consumer	2.98 kg	1.56 kg	2.17 kg

strategy utilizing exclusively online advertising.<sup>5</sup> The two campaigns illustrate the tradeoffs between environmental impact and monetary costs, i.e., the second campaign results in reduced emissions and increased advertising expenses. Indeed, the advertising expenditures exceed the predetermined budget of \$120,000 by 6.7%. Finally, the third strategy, as found by solving the linear program, corresponds to the optimal advertising campaign. We note that the optimal solution, denoted  $\tau_{np}^*$ ,  $\tau_{ol}^*$  is for the advertiser to reach 43% of customers with newspaper ads, and the remaining 57% with online ads. The associated, minimum GWP is 21,752 EMTs of CO<sub>2</sub>. We also observe that the optimal strategy has a campaign cost per individual (\$0.012) that is 8% less than the online-only strategy,<sup>6</sup> and 8% higher than newspaper only strategy. Importantly, we note that the optimal strategy yields a 37% reduction in the environmental impact ( $E$ ) per individual (from 2.98 to 2.17 kg), and that the online only strategy provides an additional reduction of 28% (from 2.17 to 1.56 kg).

**Greenhouse gas emissions and energy use** To illustrate the versatility of the IO approach, we proceed to analyze the environmental impact of the three strategies considered above. In particular, we first break down the environmental impact into component greenhouse gases. We then analyze the energy consumption associated with each of the strategies and disaggregate the results by energy sources. We note that the results presented herein are consistent with other similar studies of print and online media (Toffel and Horvath 2004; Moberg et al. 2007).

Figures 4 and 5 present the environmental effects—greenhouse gas emissions and energy use, associated with the three strategies described earlier. In both cases, the first two bars correspond to the baseline scenarios. The third bar corresponds to the optimal

scenarios found using the LP model. In particular, Fig. 4 breaks down the GWP reported in Table 1 into component greenhouse gases, CO<sub>2</sub>, CH<sub>4</sub>, N<sub>2</sub>O, CFCs, released under each strategy. The total amount of greenhouse gases from energy generation is also present. We observe that the strategy to advertise online exclusively minimizes emissions of each of the component greenhouse gases. When broken down into component gases, the newspaper only strategy results in emissions that are between 29% (N<sub>2</sub>O) and 44% (CFCs) above those associated with the optimal strategy. Conversely, emissions under the online-only strategy are 22–34% below those of the optimal strategy. A very high proportion of the greenhouse gases are due to the generation of electricity, a breakdown of which is presented in Fig. 5.

Figure 5 shows that the largest energy source required for the campaigns is coal, which varies 15–20% between strategies. This variation is smaller than those of other fuels, due to the high usage of coal in utilities and other mining/power generation sectors, which are main contributors of the energy use in both newspaper and electronics production. Other fuels vary about 35–55% between strategies. Distillate Fuel has one of the highest variations (43–56%), largely due the heavy fuel requirements of transporting and delivering newspapers. Electricity use, measured in million kilowatt hours, equivalent to Giga-watt hours also varies about 40% between strategies.

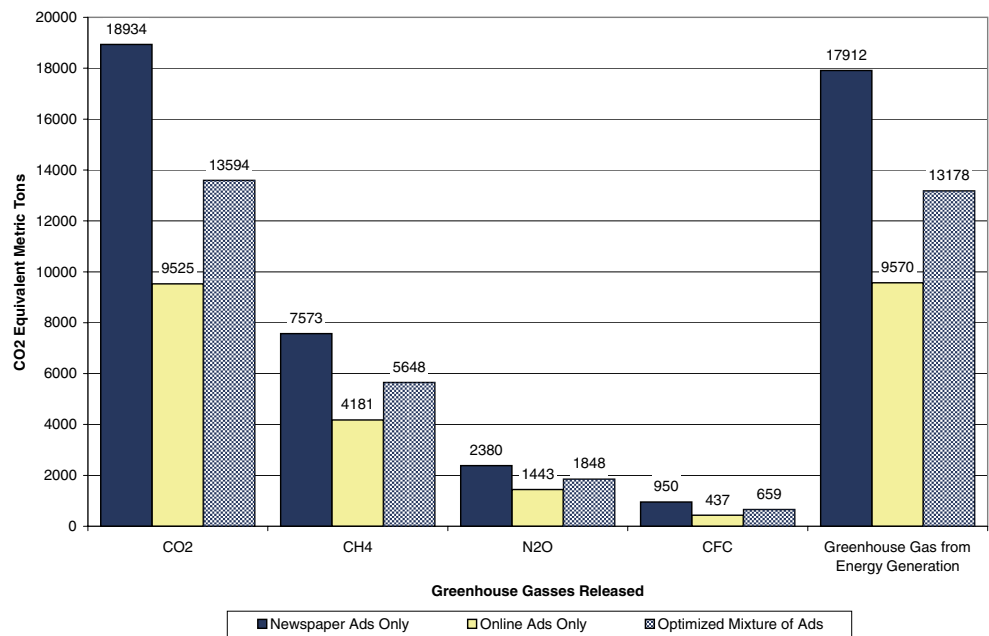
**Structural analysis** In the remainder of this section, we analyze the structure of the linear program and how the model trades off conflicting objectives or constraints. We also emphasize one of the most attractive features of the approach from a managerial perspective: the ability to conduct sensitivity analysis.

Figure 6 displays the relationships between the objective function and constraints in the above linear program. In particular, we map the two decision variables  $\tau_{np}$  and  $\tau_{ol}$  on to the space of the percentages of the target population reached through the two available media types. The horizontal axis is used to measure the percentage reached through online ads, whereas the

<sup>5</sup> $\tau_{np} = 1$  unit of Online Advertising

<sup>6</sup>Percentages are calculated with respect to the optimal strategy levels.

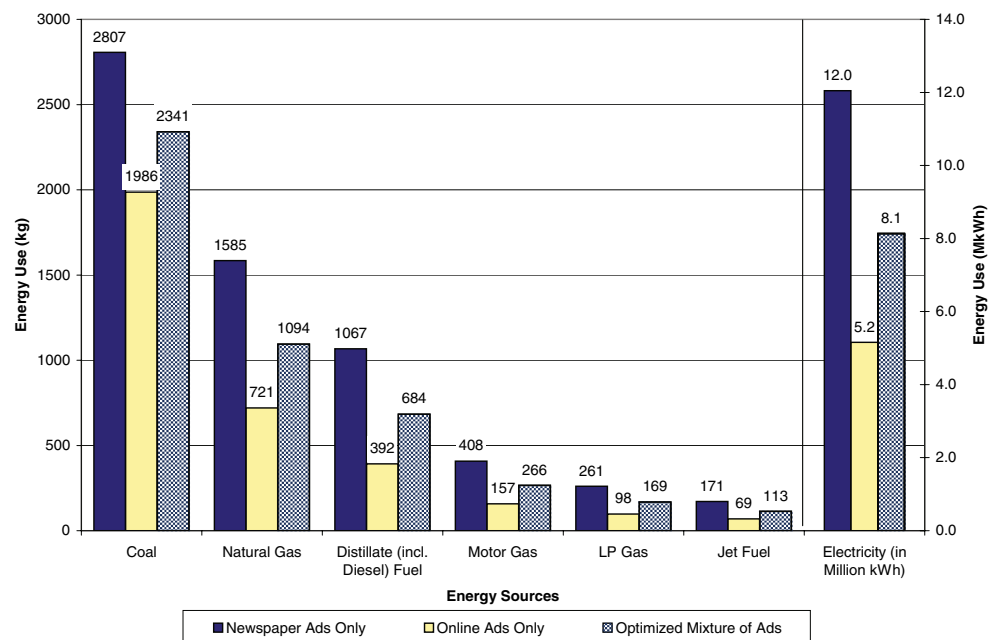
**Fig. 4** Greenhouse gas emissions of benchmark and optimal strategies

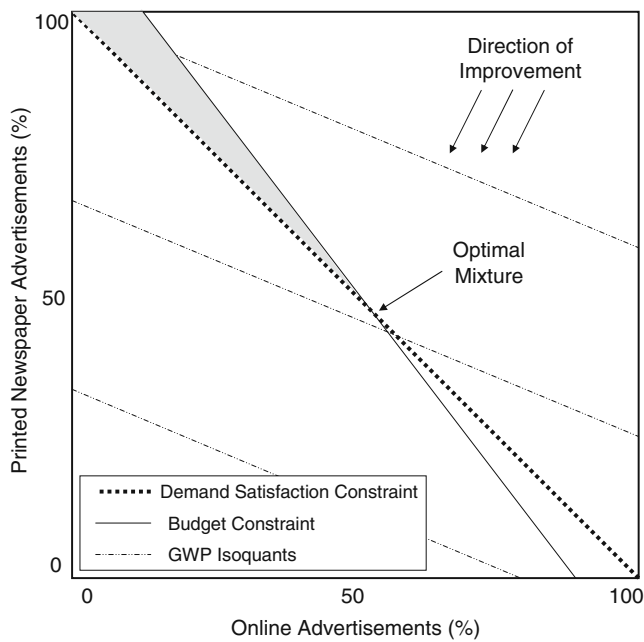


vertical axis measures the percentage reached through newspaper ads. The problem’s feasible region, i.e., the advertising campaigns that satisfy the (demand satisfaction and budget) constraints, is given by the intersection of the constraints/inequalities (12–16), and corresponds to the shaded region that is bounded by the vertical axis, the demand constraint (12), and the budget constraint (13). The slope of the budget constraint reflects the ratio between the costs to reach the target population with online vs. newspaper ads.

Figure 6 also includes four lines labeled “GWP Isoquants” obtained by setting the objective function (11) to various levels, i.e., they are *level curves* that yield the same GWP. The slope of these lines is the rate at which the media types can be substituted for each other to produce the same GWP. From Table 1, newspaper ads are associated with 2.98 kg per person, while online ads are associated with 1.56 kg per person. The substitution rate,  $\tau_{np}/\tau_{ol}$  is therefore 1.91. The arrow labeled “Direction of Improvement” is in the direction

**Fig. 5** Energy requirements of benchmark and optimal strategies





**Fig. 6** Graphical representation of the optimal advertising strategy

of the negative gradient and defines the direction of steepest descent of the objective function. We observe that the “Optimal Mixture” corresponds to the corner-point of the feasible region given by the intersection of the demand and budget constraints. The optimal advertising campaign,  $\tau_{np}^*$  and  $\tau_{ol}^*$ , specifies that 43% of the target population be reached via newspaper ads, and the remainder via online ads. When evaluated at  $\tau_{np}^*$  and  $\tau_{ol}^*$ , constraints (12) and (13) are satisfied with equalities, and referred to as *binding*. The other constraints that define the feasible region, i.e., the nonnegativity constraints (16), are *non-binding*. We note that the point labeled “Optimal Mixture” corresponds to the feasible advertising campaign that falls on the most desirable isoquant, i.e., no feasible ad campaigns can be reached from the “Optimal Mixture” in the direction of improvement.<sup>7</sup>

**Managerial insights/implications** In the next few paragraphs, we discuss the managerial insights and implications of the advertising case study. First, we interpret the *shadow prices* or *dual variables* in terms of describing the sensitivity of the optimal level of emissions to changes in the resources or requirements imposed by

the constraints (see Hillier and Lieberman 2010, page 217). We then consider the sensitivity of the results to changes in the relative costs to place ads in the two media types. Finally, we consider the effect of changes to the underlying bills of materials for the two media types.

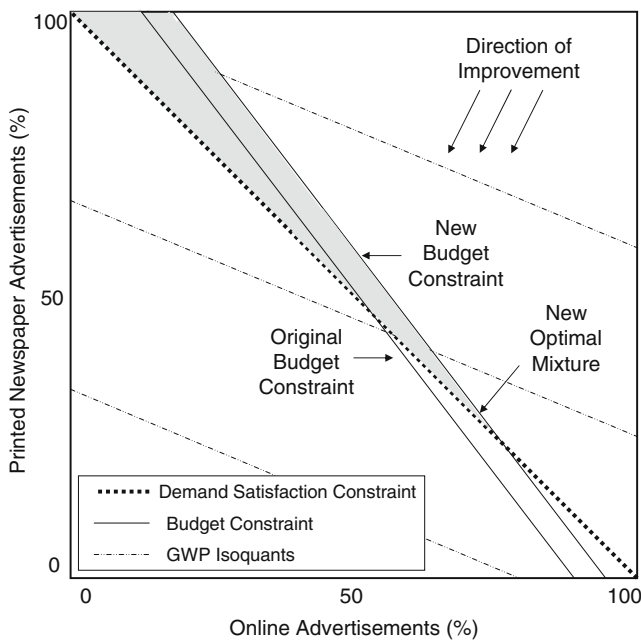
Shadow prices reveal the sensitivity of the optimal objective function value to changes in the parameters representing the available resources or the requirements imposed by the binding constraints. In the example, the binding constraints, (12) and (13), require that the target population,  $D$ , be reached without exceeding the predetermined budget,  $B$ . The shadow prices associated with these constraints are 0.0114 and  $-0.7705$ , respectively. The shadow price of constraint (12) implies that the marginal environmental impact of changing the size of the target population of ten million is 0.0114 EMTs of CO<sub>2</sub> per customer. Similarly, the shadow price of constraint (13), 0.7705 EMTs of CO<sub>2</sub>, is the rate at which the GWP of the optimal campaign is reduced for every dollar added to the budget of \$120,000.

In both cases, the shadow prices apply in ranges where both of the aforementioned constraints remain binding. In the example, these ranges correspond to cases where the budget is sufficiently large to reach the target population with newspaper ads, but not large enough to reach the target population exclusively with online ads. The *allowable increase* is \$8,000, and the *allowable decrease* is \$10,500. To illustrate, consider a 5% increase in the advertiser’s budget to \$126,000. The budgetary increase leads to a change of  $-0.7705 \times 6,000 = -4,623$  EMTs of CO<sub>2</sub>, a 21.25% reduction from the emissions in the original optimal strategy. The optimal ad campaign with the increased budget is such that 89% of the target population is reached via online ads, whereas 11% is reached via newspaper ads. This change is represented in Fig. 7 by shifting the budget line to the Northeast.

Next, we consider the effect of changes in the (relative) prices to place ads in each of the media outlets. To make the discussion tangible, consider a 5% reduction  $\kappa_{ol}$ , the cost of online ads. This increase the ratio  $\kappa_{np}/\kappa_{ol}$ , and decreases the slope of the budget line, as shown in Fig. 8. This change, in turn, allows a higher fraction of the demand to be served by the online ads, and thus decreases GWP by 4,279 EMTs (19.7%).

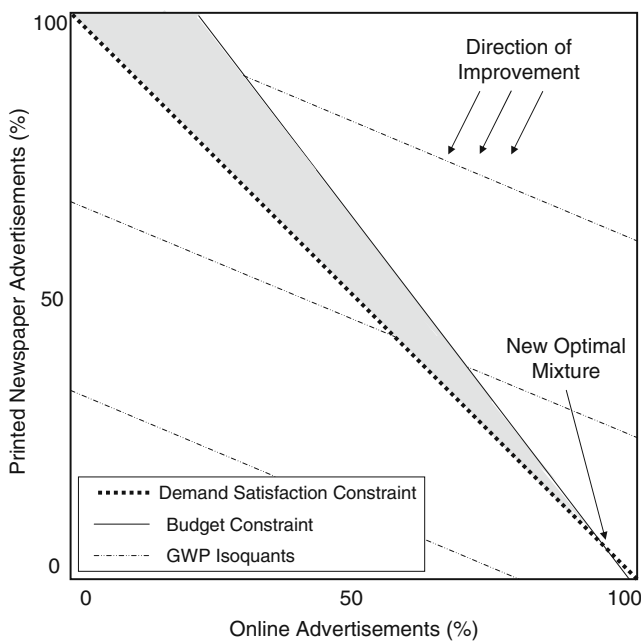
We now examine the effect of changing the underlying bill of materials of the media. Initially, the ratio of environmental impact,  $E_{np}/E_{ol} = 1.91$ , implying that newspaper ads contribute to the optimal GWP at about twice the rate online ads. Now, consider a technological advancement that decreases the production cost and

<sup>7</sup>In technical terms, we note that, at  $\tau_{np}^*$  and  $\tau_{ol}^*$ , the negative gradient of the objective function is in the span of the gradients of the *binding* constraints.



**Fig. 7** Shift in budget constraint due to increase in  $B$

energy consumption of a cell phone by 5%. Noticing that online ads result in 41% of the environmental impact, we expect on the order of 2.1% change in the optimal level of emissions. Indeed, the environmental impacts decrease by 1.9–2.2%, as shown in Table 2, and the environmental impact ratio,  $E_{np}/E_{ol}$  increases, indicating a higher marginal cost (in terms of GWP) between the two ad media.



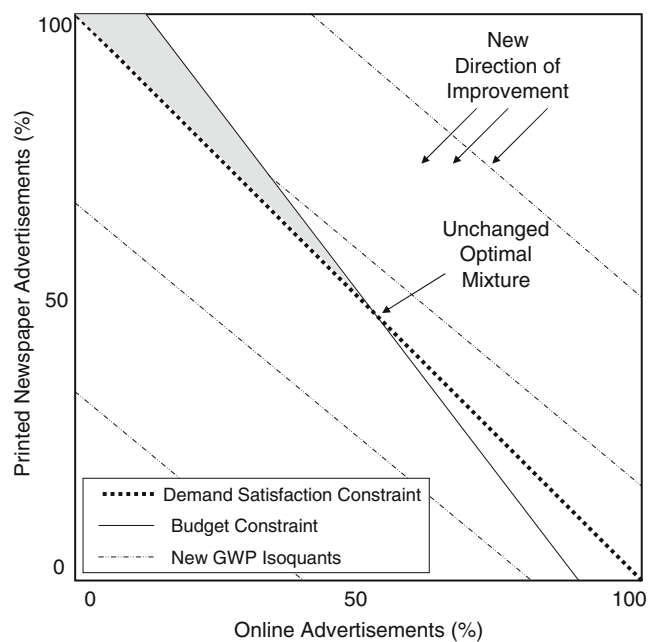
**Fig. 8** Shift in budget constraint due to decrease in  $\kappa_{np}/\kappa_{ol}$

**Table 2** Effect of technological advancement on greenhouse gas emissions

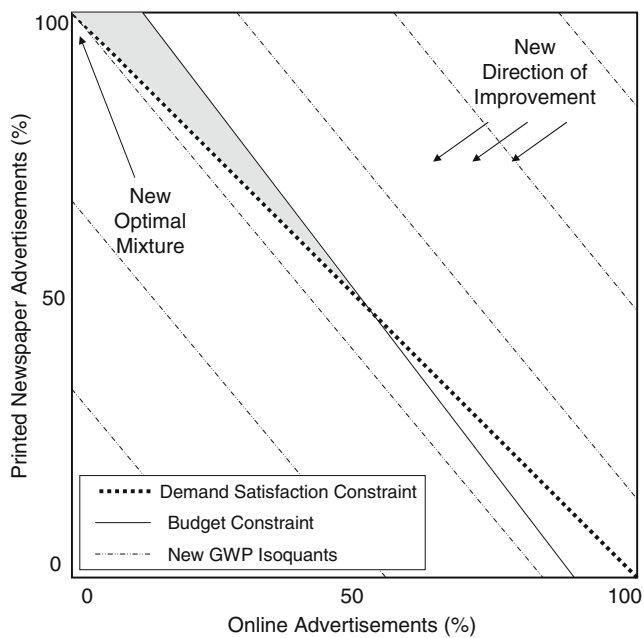
Environmental distress	Percentage change in $E$
Global warming potential	-2.0%
CO2	-2.0%
CH4	-2.1%
N20	-2.2%
CFC	-1.9%
Total GH gas from energy generation	-2.1%

The change in relative environmental impact is indicated by a change in the slope of the GWP isoquants to the southeast, as shown in Fig. 9. The optimal advertising strategy does not change as long as the direction of steepest descent is in the span of the gradients of the active constraints. Thus a change in  $E_{np}/E_{ol}$  will not result in a strategy change, even though the total  $E$  may change.

Finally, we consider an example where the optimal solution changes. In a situation where newspapers decrease the raw materials used in production and delivery significantly, so that they become more environmentally friendly than online ads ( $E_{np}/E_{ol} < 1$ ) the slope of the objective changes to favor newspaper ads as the environmentally friendly component. As shown in Fig. 10, the direction of improvement changes to the northwest, and the optimal strategy shifts to a newspaper only mixture.



**Fig. 9** Shift in GWP isoquants with increase in  $E_{np}/E_{ol}$  (optimal mixture remains stable)



**Fig. 10** Shift in GWP isoquants with decrease in  $E_{np}/E_{ol}$  (optimal mixture changes)

## 5 Conclusions

We present a practical, prescriptive framework to support problems associated with the design and production of sustainable products, processes and services. The proposed framework relies on the use of IO analysis as a tool to quantify the life cycle and supply chain environmental impact associated with meeting a given, exogenous demand. The framework also builds on literature in production economics, where numerous IO models with substitution have appeared to support product/process design, as well as production planning and scheduling problems. In the latter, models are often analyzed and solved as linear programs, which provides an appealing computational approach to solve the ensuing problems, as well as an established theory to conduct subsequent sensitivity analysis. One of the important contributions of our work is to bridge these two streams of literature.

In addition to describing the proposed framework in detail, we present an example inspired by Toffel and Horvath (2004). In particular, we consider a hypothetical, “environmentally conscious” advertiser, in the Chicago Metropolitan Area, wishing to allocate a budget to place ads in either the print or the online versions of a local newspaper. We formulate the problem of finding an advertising strategy that minimizes global warming potential, subject to reaching a target population, as a linear program. We then solve the problem

and compare the optimal strategy to two benchmarks, in terms of discharges of component greenhouse gases, and in terms of requirements imposed on various energy sources. The results illustrate how the model captures and balances economic and environmental measures/concerns. In particular, the optimal policy trades off the reduced environmental repercussions of online advertising with the increased effectiveness per dollar of print advertisements to reach the target population. To showcase the versatility of IO analysis, we also present the energy requirements by source that are imposed by the advertising strategies that we consider.

We analyze the sensitivity of the optimal advertising strategy (and associated global warming potential) to perturbations in the budget, the size of the target population, the relative costs to place ads, and in the relative environmental impact associated with each medium. Among the interesting observations, we interpret the *shadow prices* or *dual variables* in the linear programming formulation as the marginal environmental impact associated with changing the size of the target population or the budget. Thus, shadow prices provide a measure of the value of flexibility associated with changing the resources or requirements. In particular, the shadow price associated with the budget constraint provides a conversion factor between environmental impact and direct costs to the advertiser, and thus would be useful, for example, in the context of trading pollution credits (in financial markets).

With the current popular focus on sustainability and the potential for stricter environmental regulation in the future, we confidently predict that LCA will be a focus for research for many years. Future research directions of interest include the integration of uncertainty analysis and multi-objective modeling into life cycle models. Furthermore, the integration of environmental impacts and indicators with monetary markets and policy will require advancement and refinement of current modeling techniques.

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## Appendix A: Parameters for the case study

In this section, we discuss the assumptions and approach used to generate the parameters in the linear program presented in Section 4. Much of the cost and other technical information was obtained from the Chicago Tribune Media Group (2008).

### A.1 Advertising costs, $\kappa_{np}$ and $\kappa_{ol}$

In terms of advertising products, we consider a newspaper ad consisting of a 1/8-page ad placed on the front page vs. an online ad consisting of a static, highlighted, homepage based “Cube Ad” appearing on the first displayed page to the right of the text.

A 1/8-page ad measures  $5 \times 2.875$  inches, which translates to 14.375 column inches. At a posted rate of \$1,135 per column inch (plus \$7,100 for a front page space) on Sunday and a rate of \$455 per column inch (plus \$4,700 for a front page space) on a weekday or Saturday, this sums to a weekly running cost \$90,859.38. The Chicago Tribune reports a distribution 4,148,681 papers on a weekly basis, which translates into a per-paper cost of  $2 \times \kappa_{np} = \$0.0219$ . A conservative readership assumption for a major newspaper is two readers per paper, and so we assume that the total readership is double the circulation.

A static, highlighted, “Cube Ad” appearing on the Tribune’s homepage costs \$50,000 per week. The Tribune reports 16,943,601 monthly visitors to their website, which translates into 3,899,349 visitors per week, and a cost per visitor of  $\kappa_{ol} = \$0.0128$ .

### A.2 Bill of materials, $c_{ij}$

In the example, newspapers are modeled as having direct inputs from three economic sectors: newsprint, ink and printing, and transportation delivery. Online ads, on the other hand, are assumed to consist of inputs from two sectors: electronics manufacturing, and energy production. The assumptions used to estimate the inputs that appear in Fig. 3 are presented below:

- Newsprint
  - Newsprint is a commodity that varies in cost each year because of price variations. Toffel and Horvath (2004) estimated the cost for newsprint at \$540 per metric ton. Newsprint varied from \$580 to US \$660 per metric ton between 2006–2008 (Newfoundland Labrador Department of Finance, Economic Research and Analysis Division 2008). Newsprint costs are expected to increase 15% in 2009, as commodity prices continue to rise. We used a price of \$580 per ton to align the costs for newsprint with those estimated in previous research, and to minimize the bias that inflated prices would have on the analysis.
  - The weight of the Chicago Tribune was measured to be 4.05 g per numbered page. From a small sample, we estimate the weekly average number of pages at 108 (not including separate

circular advertisement sections). Thus, the estimated weight per paper is  $4.05 \cdot 108 = 437.4$  g per paper. Thus, the estimated weight per paper is 437 g per paper, and a single newspaper requires \$0.2537 in inputs from the newsprint sector.

- Ink and printing
  - Data are not available on ink usage in printing the Chicago Tribune. From Toffel and Horvath (2004), we estimate inputs of \$0.1249 per kilogram (converted to 2007 dollars) for ink and printing costs. The corresponding cost for the Chicago Tribune is calculated to be  $\$0.1249 \cdot 437.4 = \$0.0546$  per paper.
- Delivery
  - Delivery costs were calculated using the cost in diesel fuel to deliver the newspapers, plus a yearly maintenance allowance for each vehicle. The average diesel fuel price for 2007 was reported from the US Department of Energy as \$2.94 per gallon. An estimate of 5 mpg with a carrying capacity of 1,000 newspapers was used. The Chicago Tribune is printed at 777 West Chicago Avenue, Chicago IL. The average population-weighted distance for Cook County and the six surrounding counties, the area comprising the majority of the Chicago Tribune subscribers, is 15.99 statute miles. For a round trip, the cost per truck in diesel fuel is calculated to be \$9.40, and the cost per paper is \$0.0188. A maintenance allowance is given as \$1,000 per year per truck, i.e., \$0.01923 per paper. This totals \$0.038 per paper in delivery costs.

The components of Online Ads used in this paper are from two sectors: electronic and cell phone manufacturing, and energy generation.

- Electronic and cell phone manufacturing
  - We considered a popular, small size, multi-function, internet ready cellular phone. The 2007 production cost of this phone is estimated by iSuppli Corporation to be \$245. Assuming a cell phone life of 3 years, the cost per week is \$1.57. Users were estimated to spend 5% of their time on news sites, resulting in a per user cost of \$0.0785.<sup>8</sup>

<sup>8</sup>For reference, see: <http://www.energy.gov/2008/08/how-much-energy-does-apple-iphone-use.html>, [http://www.eia.doe.gov/cneaf/electricity/epm/table5\\_3.html](http://www.eia.doe.gov/cneaf/electricity/epm/table5_3.html), and <http://www.eia.doe.gov/emeu/steo/pub/gifs/Fig21.gif>

## – Energy generation

- The energy use was estimated to be the energy required to regularly charge the cellular phone. The phone in question was estimated to consume 4–6 W while recharging daily, plus 0.5 W of use when left in the charger. At an average cost of 10.4 cents per kWh this translates to \$0.47 in electricity usage per week, and a cost of \$0.024 (5% of total cost) allocated to the Online ad.

### A.3 Economic input-output tables and environmental impact coefficients

The economic IO Tables were obtained from US Department of Commerce Bureau of Economic Analysis Benchmark Input-Output Tables for 2002. The emissions and energy use coefficients are derived from the US 1997 Industry Benchmark Economic Input-Output Life Cycle Assessment (EIO-LCA) models, <http://www.eiolca.net> (Carnegie Mellon University Green Design Institute 2008).

Global Warming Potential (GWP) is defined as “the ratio of the time-integrated radiative forcing from the instantaneous release of 1 kg of a trace substance relative to that of 1 kg of a reference gas” (Houghton et al. 2001). In practice, GWP values represent the amount to which gases add to the greenhouse effect in the atmosphere with reference to the impact of CO<sub>2</sub>. Thus, GWP can be used as a measure of the total impact of greenhouse gases associated with a product or process.

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