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# Sensitivity analysis of environmentally extended input–output models as a tool for building scenarios of sustainable development

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ABSTRACT

There is an urgent need to develop scenarios and roadmaps for a more sustainable future than where business-as-usual is heading. This paper addresses the use of sensitivity analysis for analyzing environmentally extended input–output (EEIO) models in order to develop cost-effective and comprehensive scenario building. Main components of resource use, emission intensity and final demand are extracted from the complete network of interactions contained in the input–output tables of the national accounts. The method is demonstrated using a detailed Finnish EEIO-model (ENVIMAT). Based on the results, only 0.3% of the 23 103 interactions were found to have a significant effect on Finnish greenhouse gas emissions. The same parameters were also relevant for waste generation and land use, but not for gross domestic product. The identified main components were tested by structural decomposition. Actual development of greenhouse gas emissions from 2002 to 2005 was compared to that predicted by updating only the identified components. Based on the results, the development of greenhouse gas emissions could be predicted with high accuracy using only the identified main components. Generalizing the results, sensitivity analysis can assist in identifying the main components to be included in future scenarios for sustainable development.


## 1. Introduction

The global environmental crisis is becoming more and more evident. Several planetary thresholds have been exceeded (Rockström et al., 2009) and the growth rate of global greenhouse gas emissions is faster than ever before (Peters et al., 2011a). Comparing the actual emissions to the IPCC scenarios (Nakicenovic et al., 2000), the annual emissions have reached the “worst case” scenario (“A1FI”), predicting a 4 °C global surface warming by the end of the century (IPCC, 2007). Looking at other aspects of environmental sustainability, the development through the last 30 years has been found to follow closely the “standard run” of the Limits to Growth simulations (Turner, 2008). The standard run predicts an overshoot of resource use in the 1990s and a collapse of society around the middle of the 21st century (Meadows et al., 1972). Therefore there is a growing body of scientific evidence that the current trend of global development needs to be changed rapidly. Following the current patterns of behavior would result in a very undesirable and possibly unlivable future environment.

At the same time the world has become highly interconnected. The production structure within individual countries is a complex network of interactions (Lenzen, 2003). In addition global supply chains connect the consumption of one country to the production of another (Peters and Hertwich, 2008). Attempts to control emissions with national and regional measures have even resulted in emission increases globally through international trade (Peters et al., 2011b; Wiedmann et al., 2010). Because of the high level of global interconnection, it is difficult to change the system by focusing on individual industries, emission sources or even countries. This makes emission reduction a typical “wicked problem”, where improvements in one part of the system result in new problems in other parts (Jackson, 2003). Solving wicked problems calls for a thorough systems analysis of the current situation, its trends and (most importantly) identifying possible futures, which avoid the problems of continuing current development (Ackoff, 1974, 1999).

Various sustainability scenarios have been built with different methodologies (Ahlroth and Höjer, 2007; Mander et al., 2008; NIES, 2008; Rijkee and van Essen, 2010). Forecasting from the business as usual as well as backcasting from a potential future state has been applied (Rijkee and van Essen, 2010). The widely referenced IPCC scenarios represent both of these options (Nakicenovic et al., 2000). Delphi expert panels and system dynamics have also been applied. The most known examples of these are the Limits to Growth simulations (Meadows et al., 1972) as well as several general equilibrium models (such as GTAP (Hertel and Hertel, 1999)). In addition several industries have applied foresight (Salo and Cuhls, 2003; UNIDO, 2005) to create their own sets of future scenarios, for example transport (Helmreich and Keller, 2011), energy (IEA, 2008) and food production (Beddington, 2011).

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There are in general two approaches for scenario building: forecasting and backcasting. Forecasting builds a dynamic model of historical development and with the aid of assumptions projects future development across the economy. Backcasting starts from the future and asks, what the system should look like to provide the desired characteristics (i.e. dramatically less resource consumption and greenhouse gas emissions). A roadmap is then later built towards that desired configuration. However a considerable problem in backcasting is that the desired state can be achieved with many combinations of system changes. And detailed representations of economic systems are complex, for example the single country EIOLCA EEIO-model has 129 976 inter-industry connections (Hendrickson et al., 2005). How can one identify all the relevant potentials for change with such an amount of potential variables? Consequently most scenarios oversimplify the problem, looking at single sectors or single regions (Warren, 2011). Without a full supply chain view, the approaches may miss important linkages which influence the system in focus. For example the emissions of food and fuel production are both very strongly interlinked and connected to the extent of climate change. Yet assessments of the combined effects of biofuels, food and climate change are rare (Haberl et al., 2011). Even in very comprehensive studies on agriculture, the energy scenarios of the background economy are rarely considered and the extent of climate change is limited to scenarios well below the possible 4 °C temperature rise (Haberl et al., 2011).

Economic input–output (IO) analysis seems like the ideal tool for backcasting studies (Duchin and Lange, 1995). It was originally developed to analyze the interlinkages between industries of a country and to identify the amount of production needed to satisfy increased consumption (Leontief, 1936). Today it forms the basis of the collection of national accounts and the calculation of gross domestic product (GDP) (Ten Raa, 2006). Especially when the input–output tables of multiple regions are connected (so-called MRIO-tables), the tool can capture the entire supply chain (Tukker et al., 2009). Therefore the interactions between countries and industries can be quantified and analyzed. The economic input–output tables can readily be coupled with satellite accounts of emissions and resource extraction (Leontief, 1970). Environmentally extended input–output (EEIO) analysis has become a key tool for sustainability assessment (Murray and Wood, 2010; Suh, 2009). The ability to follow global supply chains has allowed the consideration of local emissions as consumer, producer or shared responsibility problems (Lenzen et al., 2007). Applied to backcasting, once a sustainability goal is defined, various economy wide scenarios can be set up to see which would meet the goal. The comprehensiveness and detail of EEIO forces the analyst to consider the economy as a whole, thus avoiding the problems of partial analysis.

The comprehensiveness and detail of EEIO models is also their main weakness. When involving stakeholders in scenario work, the sheer complexity (amount of parts and connections) present in input–output tables makes it mentally difficult to capture the whole system. Several analytical tools have been developed to identify the main components from the network of an EEIO model. For example structural decomposition analysis (SDA) describes, which parts of the system explain most of the change between years (Dietzenbacher and Los, 1998; Peters et al., 2007). Conversely structural path analysis (SPA; (Lenzen, 2003)) data mines the environmentally most relevant production chains from the EEIO-system for a given year. The methods have also been combined to yield structural path decomposition (SPD) (Wood and Lenzen, 2009), which explains the main supply chains where emission change manifests. The problem in analyzing single supply chains is that network nodes, which belong to several supply chains are not identified (i.e. the emissions of business services are allocated between almost all industries). Sensitivity analysis on the other hand identifies important nodes in the model, without regard to the supply chains where they belong. It is commonly used in life cycle assessment (Heijungs, 2010) and recently also in EEIO (Mattila, 2012; Wilting, 2012).

A general result in complex models is that usually only a small fraction of all the variables are relevant for a given decision situation (Saltelli et al., 2008). This has also been observed in the case of EEIO models for single indicators such as the ecological and carbon footprints (Mattila, 2012; Wilting, 2012). The aim of this study was to identify relevant parts of the economy to be included in backcasting scenarios. It was also analyzed, whether the same parts of the economy could explain the impacts in several impact categories (global warming, land use, waste generation and gross domestic product). The process was checked by predicting the observed development in greenhouse gas emissions between 2002 and 2005, using only the components, which were identified as important. Finally a generalization of the results to a more general case of backcasting is presented.

## 2. Materials and Methods

### 2.1. Sensitivity Analysis of the EEIO Model and Testing of Its Results

Sensitivity analysis attempts to answers the question: "what, if changed, can affect the outcome of a model?" Applied to sustainability scenarios, sensitivity analysis can identify the main components from an EEIO model. Several methods have been developed for sensitivity analysis (Saltelli et al., 2008), but we chose one of the simplest, a perturbation analysis based on partial derivatives (Heijungs, 2010; Heijungs and Suh, 2002). The perturbation analysis yields the sensitivity of the model output to relative changes in the input (i.e. $(\Delta f/f)/(\Delta x/x)$).

The EEIO model can be described with a single equation (Leontief, 1970):

$$\mathbf{g} = \mathbf{B}(\mathbf{I}-\mathbf{A})^{-1}\mathbf{y} = \mathbf{My} = \mathbf{Bx}, \tag{1}$$

where $\mathbf{g}$ is the vector of indicator results (categories of GDP, employment, environmental impacts, resource use), $\mathbf{B}$ is the intensity of production matrix (impact/production amount; impact-by-industry), $(\mathbf{I}-\mathbf{A})^{-1}$ is the Leontief inverse matrix, $\mathbf{B}$ is a diagonal matrix, $\mathbf{A}$ is the input-coefficient matrix (industry-by-industry or product-by-product) and $\mathbf{y}$ is the vector of final demand by product (or industry). The $\mathbf{M}$ is the intensity multiplier matrix, which contains the life cycle emission intensities for all products or industries and $\mathbf{x}$ is the amount of total production needed to produce the entire consumption $\mathbf{y}$.

Applying partial derivatives for Eq. (1), the following sensitivity indices are obtained (Heijungs, 2010):

$$S_{y,ki} = \frac{\delta g_k/g_k}{\delta y_i/y_i} = M_{ki}\frac{y_i}{g_k} \tag{2}$$

$$S_{a,kij} = \frac{\delta g_k/g_k}{\delta a_{ij}/a_{ij}} = M_{ki}x_j\frac{a_{ij}}{g_k} \tag{3}$$

$$S_{b,kj} = \frac{\delta g_k/g_k}{\delta B_{kj}/B_{kj}} = x_j\frac{B_{kj}}{g_k}, \tag{4}$$

where the subscripts refer to the corresponding element of the matrix. Since the Eq. (3) gives the sensitivity in regard to changes in the $(\mathbf{I}-\mathbf{A})$ matrix (technology matrix, in Heijungs, 2010), the $S_a$ of diagonal elements $(1-a_{ii})$ were scaled with the ratio of $a_{ii}/(1-a_{ii})$ to give the sensitivity of the original input coefficient.

$S_y$ describes the sensitivity to final demand, $S_a$ to inter-industry input-coefficients and $S_b$ to emission and extraction intensities. A subjective limit value of 0.01 was chosen for the sensitivity indices to separate the main components from less important parameters. With a sensitivity index of 0.01, a change of 100% in the component would influence the overall criteria by only 1%. Components which had a smaller potential for changing the overall criteria were not considered important. (Final demand was not disaggregated to overall demand scale and demand structure as in structural decomposition.