Environmental impact of electric car production shifts

TULLIO GREGORI

DISPES, Università di Trieste

1. Introduction

Concerns about the future availability of fossil fuels, increasing greenhouse emissions and air pollution have motivated governments and manufacturers to consider alternative transport energy pathways. Globalization and growth in developing countries such as BRICS pose a threat as, according to the CIA Factbook, US oil consumption is about 61 barrels per day per 1000 people, while in Brazil and China is less than 10 and only 3 in India. Due to rapidly growing countries' car demand, the target of 1.1 billion cars on the road in 2013 and 1.5 in 2050 predicted by Lee and Lovellette (2011) might be achieved sooner. Hence, targeting the private transportation sector as a major emitter of carbon dioxide equivalents is a step in the right direction in regards to reducing emissions. For instance, of all the oil consumed in the U.S., 70% is used for transport and American passenger vehicles use 70% of transportation oil (Todd et al. 2013). It is clear that the current pattern of fuel consumption and pollution is not sustainable. Maybe in an almost near future technical change, subsidies and oil price increases might change the picture and shift consumer demand away from internal combustion engine powered cars (ICE) to battery electric vehicles (BEV) or fuel cell electric vehicle (FCEV). For the time being "*the relative costs of electric vehicles remain elevated for consumers and even more so for society under current conditions and typical use scenarios*" (Crist, 2012, p. 5). Moreover it is important to remember that BEV are displaced emission rather than zero emitters as electricity production can use fossil oil too and generate standard pollution. In the last decade, many papers and reports have examined various scenarios about the introduction of electric vehicles including environmental impacts, employment shifts, impacts on the electrical grid, private and economic costs. They have looked at a vast variety of issues ranging from potential demand of BEV to job creation potential or quality of life (Todd et al. 2013, Massiani, 2015) but a major task is to evaluate the complete life cycle of the vehicle. Well-to-wheel (WTW) assessments are questionable as they only considers the production of the fuel or electricity (Well-to-Tank) and the tailpipe emissions (Tank-to-Wheel). "*This creates a bias towards zero-tailpipe emission vehicles, as the environmental impacts associated with the production of specific components, such as batteries, are not taken into consideration*" (Messagie et al., 2013, p. 1468). Life cycle assessment (LCA) is a better technique to analyse the total impacts of a good or service through the different stages of fabrication, usage, and end-of-life treatment. As shown in Figure 1, this analysis is sometimes termed "cradle-to-grave" as it includes the extraction of raw materials embodied in a product all the way to disposal or recycling.

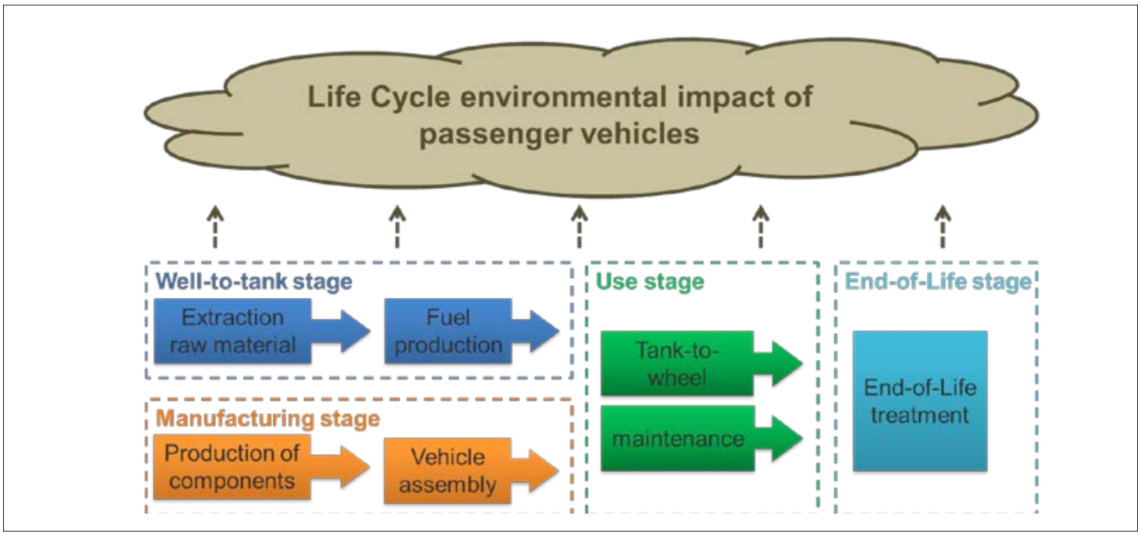

Figure 1 – Schematic representation of the different life cycle stages of a vehicle
Source: Messagie et al. (2013)

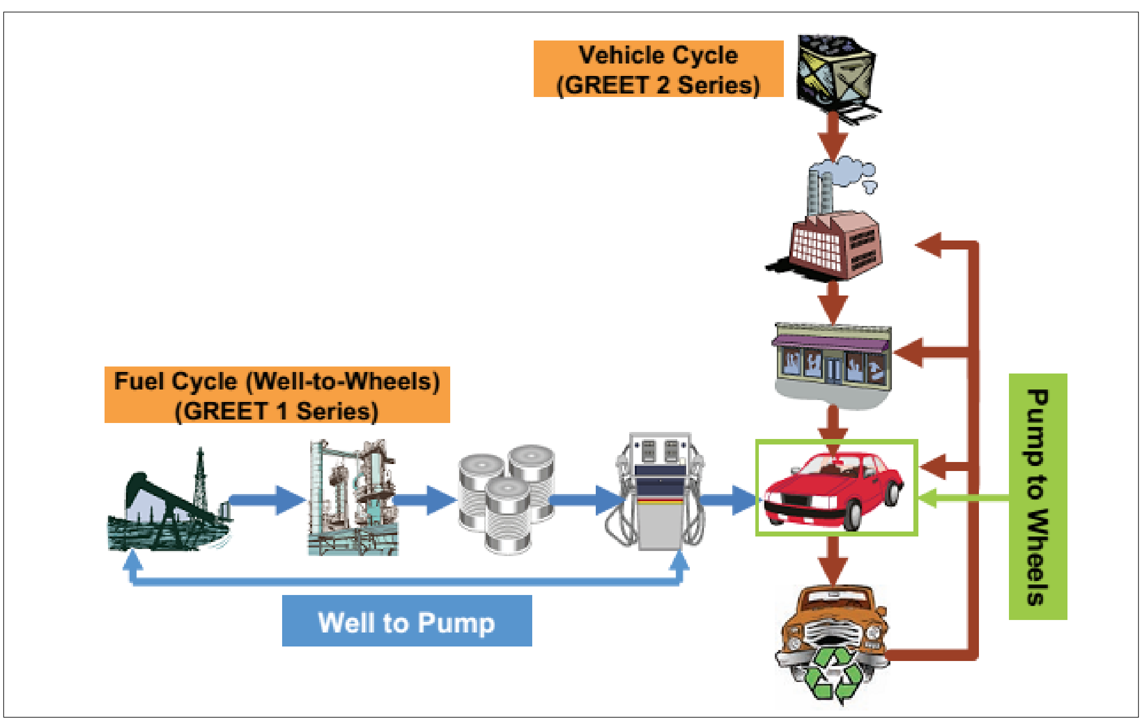

Figure 2 – Total Energy Cycle for Transportation Technologies (Burnham et al., 2006)

LCA is an important tool but capturing all the environmental consequences of fabricating a BEV or FCEV is far from being easy and several reviews stress the uncertainty underlying these analyses (Contestabile et al., 2012, Hawkins et al., 2013, Wilson, 2013). Actually, analysts must draw boundaries as in Figure 1 and it is easy to omit relevant outputs or stages in the supply chains, given the complexity of this product. For instance, the life-cycle model GREET 2.7 by Burnham et al. (2006) combines a *fuel-cycle*, which contains data on fuel cycles and vehicle operations, with a *vehicle-cycle* about the energy and emission effects associated with vehicle material recovery and production, component fabrication, assembly, and disposal/recycling. Figure 2 shows the basic scheme about this lifecycle-based study that has been used to compare the energy use and emissions of conventional and hybrid electric vehicles or fuel cell vehicles. The task is somehow daunting since requires a huge amount of data about energy use and emissions of four major groups: vehicle materials; batteries; fluids; and vehicle assembly, disposal, and recycling (ADR). Each of them can have thousands of parts and for every activity involved within these groups, the energy use and emissions (including emissions from both fuel combustion and specific processes) should be estimated.

Then we should provide several production trees, each one shows upstream inputs required for the production of every item included in figure 2. However, each product tree can continue back for a potentially very large number of production layers and loops or cycles will soon appear in these graphs. If an analyst stops after a few levels, he will underestimate environmental effects and reported total emissions will suffer from truncation errors. This is the likely reason why many vehicle-LCA studies provide contradictory results making it difficult to suggest appropriate decisions to policy makers. Moreover, confidential information cannot be easily available to practitioners, as carmakers often do not disclose their production recipes. Finally, double counting is a very likely issue, as it is difficult to impute carbon emissions to specific production trees. Summing up, we can state that LCA methodology is time-consuming, expensive and questionable as often the system boundaries that define the relevant processes are set arbitrarily and private information sometimes does not allow to validate or even compare data and results.

The purpose of this paper has a quite narrow task as I focus on the manufacturing stage in figure 1. The importance of car making pollution is recognized in the literature. Yet "*a few studies consider battery/or EV production explicitly, at varied levels of details and transparency*" (Hawkins et al., 2012, p. 54). This an interesting issue as it has been claimed that manufacturing emissions "*have the potential to be very different between petrol cars and electric vehicles*…(due to) *both energy intensive manufacturing and a lifetime mileage that is expected to be lower for an electric car, due to range restrictions and battery life*" (Wilson, 2013, p.16). The literature shows CO2 emissions resulting from manufacturing should be very significant (Van den Bossch et al., 2006, Matheys et al., 2008, Samaras et al., 2008, Ou et al., 2010, Zackrisson et al., 2010, Kushnier and Sanden, 2011, Majeau-Bettez et al., 2011). Although, "*the high sensitivity of the environmental impacts of battery production to particular manufacturing processes and to the energy mix prevalent in the geographic location of production, coupled with the limited number of studies available, means that it is not possible at this stage to say with any confidence what the range of environmental impacts of battery production are*" (Contestabile et al., 2012, p. 5).

I adopt Environmental Extended Input Output models (EEIO) or IO LCA (Lifset, 2009). EEIO is a powerful tool in supporting information-based environmental and economic policies that result from a particular technological change. This technique is so successful since adopts a comprehensive accounting framework that, in principle, can cover all economic activities and products. Input-output analysis integrate information from energy or material use or pollution into the standard Input-Output model (Miller and Blair, 2009). It has been observed that this approach has limitations as the amount of sectoral/product disaggregation may be insufficient for the desired level of analysis and these models includes sectors that produce homogenous products rather than processes (Hendrickson et al, 1998). Furthermore, the standard symmetric input-output model assumes that each industry sells its characteristic output to all other economic activities and to final consumers at the same price. Practitioners must accept these and other questionable assumptions, which can bias and alter results. Furthermore, IO data are in often in monetary values while environmental analyses need physical units, and their integration is far from being trivial. However, in the following I show how Environmentally Extended Input-Output (EEIO) models are a valuable source of information as they consistently connect consumption, production and environmental impacts into a transparent system of equations, which allow to examine the direct and indirect effects of different economic activities.

The paper is divided into three sections. First, I introduce IO accounting. While symmetric tables are commonly used in EEIO they rely on Make and Use rectangular matrices, which show production of domestic industries and purchases of commodities by firms and final users. Second, I discuss how to assess technical change due a shift from ICE to BEV production. Third, I introduce our dataset and provide a tentative economic and environmental assessment using different scenarios about BEV adoption. Finally, I discuss directions for further research.

2. Input-Output accounting

Input-output transactions can be arranged in several tables, which records flows for a particular period of time in physical or monetary value terms. The standard Leontief system deals with both sides of each market allowing for discretionary consumption and non-produced primary factors. The demand side includes both intermediate and final components, while supply displays production by firms. Let f_i final demand for the i-th commodity and u_{ij} is the quantity of the same commodity bought by j-th industry. Then, the total use of commodities is described by the following system:

$$q_i = \sum_{j=1}^{n} u_{ij} + f_i \quad i = 1,\ldots,m, \tag{1}$$

where m commodities are demanded by n industries and final users. From (1) we can derive the Use matrix **U**, which records the commodities, purchased and used by each industry as intermediate inputs to current production. The Use matrix can be in either physical quantities or monetary values. The latter have to be adopted when its columns show payments for intermediate inputs and primary inputs, that is value added given by compensation of employees, taxes less subsidies on production, depreciation and operating surplus.

Table 1 – Make and Use matrices

	Products	Industries		Final	Demand		Total
Products		**Use Matrix**	Private consumption	Government consumption	Gross capital formation	Exports	Total use of products
Industries	**Make matrix**						Total domestic output
Value Added		Value added					
Imports	Imported products						
Total	Total supply of products	Total domestic output					

Sectoral total output is the sum of its deliveries of any commodity measured at basic prices (net of trade and transport margins and taxes on products):

$$g_i = \sum_{j=1}^{m} v_{ij} \quad i = 1,\ldots,n. \tag{2}$$

This system of equations can be arranged in the Make matrix where rows reveal the value of each commodity produced by each industry. Industries are classified according to the principal product and the value of the primary product is on the main diagonal while other entries along the i-th row present secondary products. Entries in a column represent the value of production by each industry of the commodity named at the head of the column. Adding commodities taxes and subsidies we get domestic supply, while total supply include imported goods at c.i.f. prices.

The complete set of matrices is represented in table 1, where matrix dimensions have been previously defined as $\mathbf{V}$ is the (nxm) Make matrix, $\mathbf{U}$ the (mxn) Use matrix, $\boldsymbol{q}$ is the (mx1) commodity gross output vector as defined by (1), while $\boldsymbol{f}$ has the same dimension and refers to final demand. Vectors $\boldsymbol{g}$ and $\boldsymbol{w'}$ are (nx1) industry output and value added vectors. The former can be diagonalized to get the commodity by industry direct requirement matrix is:

$$\mathbf{B} = \mathbf{U}(\hat{\boldsymbol{g}})^{-1}, \tag{3}$$

whose entry $b_{ij} = u_{ij}/g_j$ shows the amount of the i-th commodity required to produce one unit of the j-th industry. While dividing the Make matrix by sectoral output we see how much of the total production in any industry is attributable to the production of the j-th commodity:

$$\mathbf{C} = \mathbf{V}'(\hat{\boldsymbol{g}})^{-1}. \tag{4}$$

Dividing $\mathbf{V}$ by commodity total production, we get commodity quotas produced by each industry:

$$\mathbf{D} = \mathbf{V}(\hat{\boldsymbol{q}})^{-1}. \tag{5}$$

Commodity output $\boldsymbol{q}$ is equal to intermediate commodity production that is actual commodity by industry direct requirements times total industry output, plus commodity deliveries to final demand:

$$\boldsymbol{q} = \mathbf{B}\boldsymbol{g} + \boldsymbol{f} \tag{6}$$

where $\boldsymbol{q}$ and $\boldsymbol{g}$ span very different spaces. For instance, United Nation's International Standard Industrial Classification (ISIC) contains 17 major sections and 291 classes with four digit coding, while Central Product Classification (CPC) consists of 10 sections (one-digit coding) up to 1,787 sub-classes (five-digit coding) or the Harmonised commodity description of the UN with the Combined Nomenclature has 19.000 classes. However, empirical applications have been criticized as "*even with* 519 *economic sectors represented*[1], *the amount of disaggregation may be insufficient for the desired level of analysis*" (Hendrickson et al, 1998, p. 190).

The model is simplified further as most of empirical analyses deals with Symmetric Input Output (SIO) table where the same classification is used in both rows and columns. Either an industry-by-industry or a commodity-by-commodity table can be derived. In the former, product technologies are depi-

1 As in the US IO tables.

cted in columns of the SIO matrix, while rows represent the distribution of products to intermediate and final uses. The latter considers industries as groups of establishments or enterprises. In the commodity or product SIO matrix secondary products must be transferred and inputs associated with secondary outputs must be removed from the industry in which that secondary output actually takes place to the activity to which characteristically belong. Questionable assumptions must be made (Miller and Blair, 2009, Gregori, 2009) and nowadays national and international statistical agencies publish both symmetric transaction flows and rectangular ones, i.e. the Make and Use matrices. In the former, we can distinguish between two distinct forms of equilibrium. If $\mathbf{T}$ is the symmetric interindustry transaction flow matrix then total output by industry $\boldsymbol{x}$ is the sum of final ($\boldsymbol{y}$) and interindustry demands:

$$\boldsymbol{x} = \mathbf{T}\boldsymbol{i} + \boldsymbol{y} \tag{7}$$

and supply of primary (i.e. value added $\boldsymbol{v}$) and interindustry inputs from all sectors forming the national economy:

$$\boldsymbol{x}' = \boldsymbol{v} + \boldsymbol{i}'\mathbf{T}. \tag{8}$$

As for the Use matrix, (7) can be either in physical or in value terms while (8) makes sense in monetary flows only. This system provides the analytical framework for most of EEIO models that assume the following input or technical matrix:

$$\mathbf{A} = \mathbf{X}(\hat{\boldsymbol{x}})^{-1}, \tag{9}$$

where $\mathbf{X}$ is the physical flow matrix. From the value table $\mathbf{T}$ we get:

$$\mathbf{S} = \mathbf{T}(\hat{\boldsymbol{p}}\hat{\boldsymbol{x}})^{-1}, \tag{10}$$

where $\boldsymbol{p}$ is the price vector. With homogeneous prices, it is easy to see that the following relationship holds:

$$\mathbf{S} = \hat{\boldsymbol{p}}\mathbf{A}(\hat{\boldsymbol{p}})^{-1}. \tag{11}$$

Standard micro theory shows that profit-maximizing industries endowed with Leontief production functions will choose outputs and prices according to:

$$\boldsymbol{x} = (\mathbf{I} - \mathbf{A})^{-1}\boldsymbol{y}, \tag{12}$$

$$\boldsymbol{p} = (\mathbf{I} - \mathbf{A}')^{-1}\boldsymbol{v}. \tag{13}$$

System (12) is an equilibrium material balance with exogenous final demand, while industries are price setting due to constant returns to scale implied by Leontief production functions (Varian, 1992). We must stress that technological structural relationships are in physical units while most of compiled tables report flows in value. We can derive the input matrix if sectors are compared in a point in time (or period) or the Leontief model is true and the law of unique price holds. However, we must be careful when we assess the impact of a new product with a different price as in the ICV vs BEV comparison. Matrix inverses $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}, \mathbf{K} = (\mathbf{I} - \mathbf{A}')^{-1}$ are useful as their entries depict multipliers. Standard applications concern impact analysis, where a new final demand and/or valued added or their respective projections show by how much output and prices will change. Nonetheless, technical change can modify equilibria too. A new input matrix, due to a modification in production technologies, can change output too. This is our setting, as I assume a new production function to manufacture electric cars. I discuss this issue and environmental extensions in the next section.

3 – Environmental extensions and technical change in IO

The IO framework has been extended to include environmental issues since the late ‘60s. Within this huge literature, we can distinguish three strands (Miller and Blair, 2009). The first one augments the basic IO table adding new sectors usually linked with specific spending programs such as pollution abatement. These programs usually require a comprehensive examination of a wide variety of effects ranging from employment to capital provision. A suitable procedure is to introduce new sectors in either the technical coefficient matrix, as suggested by Leontief (1970), or in the Supply-Use tables (Quyum, 1991, Luptacik and Böhm, 1999). With a SIO, in the case of pollution abatement, the added column is the technology needed in such a program while row coefficients depict the amount of this new product needed per each euro’s worth of every industry output. Alternatively, we can deem pollution generation where existing sectors produce a given amount of waste that is included in the new technical matrix. In the latter these “negative inputs” and their associated “pollution multipliers” can require more stringent requirements than the standard Hawkins-Simon conditions, to provide meaningful solutions (Luptacik and Böhm, 1994). However, it can be shown that a non-negative solution exists if the amount of pollution generated by the pollution-abatement sector is less than the amount it eliminates. “*The Hawkins-Simon conditions are satisfied for the extended model when the amount of pollution generated in the economy is greater than the amount desired. More generally, this indicates that in polluted areas where pollution generally exceeds the tolerated or desired levels, the augmented model satisfy the Hawkins-Simon conditions. If this is not the case, this augmented model is not necessary*” (Miller and Blair, 2009, p. 481).

A more comprehensive approach is the so-called Economic–Ecologic model that adds an ecosystem matrix rather than appending one sector only. This extension is similar to interregional IO models where several economies are linked together in a unique framework. Taking advantage of the assumption of linear relationships, the Economic–Ecologic model deems flow matrices within and between both industries and environmental processes, where off diagonal submatrices show links between standard economic activities and the ecosystem. Daly (1968) adopts a highly aggregated industry-by-industry framework while Isard et al. (1972) opt for the commodity-by-commodity accounting scheme with multiple outputs and pollutants. Both approaches are very data demanding. Therefore, Victor (1972) suggests a smaller model with a limited scope that is shown in Table 2. This accounts only for flows of ecological commodities from the environment into the economy and waste products from the economic system into nature. **R** is the matrix of economic commodity by ecological commodity outputs, that is the amount of each ecologic commodity discharged as a result of production, while **B** depict ecologic commodity-by-industry inputs, i.e. the amount of ecological commodities utilized by each sector.

Table 2 – Limited Commodity-by-Industry Economic–Ecologic model

	Economic system			Ecological system	
	Products	**Industries**	**Final demand**	**Total output**	**Ecological Commodities**
Products		**U**	**y**	**q**	**R**
Industries	**V**			**x**	
Value Added		**v**			
Total output	**q**	**x’**			
Ecological commodities		**B**			

Our approach is simplified as we consider SIO monetary tables extended with environmental information for every sector. These external effects can be measured in physical or monetary terms and are apt to express the impact of a quantitative change in the economy due to a larger BEV demand.

Let's introduce the direct impact matrix $\mathbf{D} = [\boldsymbol{d}_{ij}]$ that shows the amount of the i-th pollutant, say CO_2, generated per euro's worth of j's output. $\mathbf{D}$ is sometimes called the intervention matrix. Hence the overall level of pollution associated with a given vector of total output is:

$$\boldsymbol{x}^{\boldsymbol{P}} = \mathbf{D}\boldsymbol{x} = \mathbf{D}(\mathbf{I} - \mathbf{A})^{-1}\boldsymbol{y} \tag{14}$$

where $\boldsymbol{x}^{\boldsymbol{P}}$ is the total direct and indirect vector of environmental burdens. If we are interested in the contribution to the total burdens from different final demand categories we can turn to Sraffian vertically integrated sector or subsystems (Pasinetti, 1973). This is performed diagonalizing the final demand vector in order to obtain a matrix $\bar{\mathbf{X}}^{\boldsymbol{P}}$ in which each column gives the burdens attributed to the corresponding category of final demand.

If the intervention matrix is also in monetary values, we can figure out the overall burden in each sector adding up items in a given column: $\boldsymbol{d}' = \boldsymbol{i}'\,\mathbf{D}$, where $\boldsymbol{i}$ is the usual column summation vector. Hence, we can derive the value per unit of sectoral output simply dividing by actual production: $\lambda_i = d_i/x_i$ $i = 1,\dots, n$ and get the subsystem representation of the EEIO in money value:

$$\bar{\mathbf{X}}^{\boldsymbol{M}} = \hat{\boldsymbol{\lambda}}(\mathbf{I} - \mathbf{A})^{-1}\hat{\boldsymbol{y}}, \tag{15}$$

where final demand and direct pollution coefficients have been diagonalised. Gregori e Schachter (2001) show that (15) can be represented by a concatenation of König digraphs that is helpful to stress the role of the Leontief inverse since $\bar{x}_{ij}^{M} = \lambda_i l_{ij} y_j$. Within this framework, the topological structure of the model, in terms of strategic links between sectors, is still condensed in the multiplier matrix $\mathbf{L}$. Therefore, we have to open such a black box, as suggested by Gregori e Schachter (2001), to get a better understanding about the multilayer mechanism described in Kitzes (2013).

These models can be written in the so called "*impact analysis form*":

$$\breve{\boldsymbol{x}} = \mathbf{H}\boldsymbol{y} \text{ where } \boldsymbol{H} = \begin{bmatrix}\mathbf{D}\\ \mathbf{L}\end{bmatrix}, \breve{\boldsymbol{x}} = \begin{bmatrix}\boldsymbol{x}^{\mathbf{P}}\\ \mathbf{x}\end{bmatrix},\ \mathbf{D}^{*} = \mathbf{DL} \tag{16}$$

or in "*planning form*":

$$\tilde{\boldsymbol{x}} = \mathbf{G}\boldsymbol{x},\ \text{where } \mathbf{G} = \begin{bmatrix}\mathbf{D}\\ (\mathbf{I} - \mathbf{A})\end{bmatrix}, \tilde{\boldsymbol{x}} = \begin{bmatrix}\boldsymbol{x}^{\mathbf{P}}\\ \boldsymbol{y}\end{bmatrix}. \tag{17}$$

Impact analysis is the most common framework in the literature that investigates the relationship between industry outputs and other elements items associated with them, ranging from employment and pollution to environmental and energy use (Ardent et al., 2009, Miller and Blair, 2009, Nathani, 2009). Final demand is still driving these processes and we can cast even an optimizing model so that public consumption or investment is controlled in order to maximize a social welfare function or multiple objectives (Cohen, 1978, Nijkamp e Rietveld, 1976, Tanino et al., 2003).

This paper's task is different. I would like to analyse the effect of a gradual switch from ICE to BEV in production and consumption. This calls for structural decomposition analysis. Changes in gross output can be decomposed in several ways. However, according to Dietzenbacher and Los (1998), a suitable one is the following:

$$\Delta \boldsymbol{x}^{\boldsymbol{P}} = \frac{1}{2}\Delta\mathbf{D}(\mathbf{L}^1 + \mathbf{L}^0)(\boldsymbol{y}^1 + \boldsymbol{y}^0) + \frac{1}{2}(\mathbf{D}^1 + \mathbf{D}^0)\Delta\mathbf{L}(\boldsymbol{y}^1 + \boldsymbol{y}^0) + \frac{1}{2}(\mathbf{D}^1 + \mathbf{D}^0)(\mathbf{L}^1 + \mathbf{L}^0)\Delta\boldsymbol{y}$$

where superscript 0 refers to the actual car provision, i.e. ICE, while superscript 1 is the new car industry with larger BEV penetration. In the present setting, we do not allow for changes in $\boldsymbol{y}$ as we assume an identical car demand by families and public agencies. This is a quite strong hypothesis what will be relaxed in a following paper but, for time being, it allows to consider a straightforward impact model:

$$\Delta \boldsymbol{x}^{\boldsymbol{P}} = \frac{1}{2}[\Delta\mathbf{D}(\mathbf{L}^1 + \mathbf{L}^0) + (\mathbf{D}^1 + \mathbf{D}^0)\Delta\mathbf{L}]\boldsymbol{y}\,, \tag{18}$$

that can be simplified further if we tackles production technical change only:

$$\Delta \mathbf{x}^{\boldsymbol{P}} = \mathbf{D}\,\Delta\mathbf{L}\,\boldsymbol{y}\,. \tag{19}$$

The latter can be addressed using fields of influence (Sonis and Hewings, 1992) that is an extension of the well know Morris- Sherman formula that states how changes in entries in a non-singular matrix is transmitted to changes in elements of its inverse. For a modification in just one entry, say $|\Delta a_{ij}| > 0$, the new inverse $\mathbf{L}^{\mathrm{N}ij} = [l_{rs}^{N}(\Delta a_{ij})]$ is given by:

$$l_{rs}^{N}(\Delta a_{ij}) = l_{rs} + \frac{l_{ri}\, l_{js}\Delta a_{ij}}{1 - l_{ji}\Delta a_{ij}}, \tag{20}$$

and technical change is:

$$\Delta l_{rs}^{N}(\Delta a_{ij}) = l_{rs}^{N}(\Delta a_{ij}) - l_{rs} = l_{ri}\, l_{js} k_{ij}^{1}, \tag{21}$$

with $k_{ij}^{1} = \Delta a_{ij}/(1 - l_{ji}\Delta a_{ij})$. It is obvious that Δa_{ij} will produce the largest impact on l_{rs} when $i = r$ and $j = s$ since both elements multiplying k_{ij}^{1} are larger than unity. Moreover, next-largest influences will be found in row i and column j of $\mathbf{L}$ since, in virtually all other entries, both elements in the product $l_{ri}\, l_{js}$ are less than one. The new inverse is given in compact form by:

$$\mathbf{L}(\Delta a_{ij}) = \mathbf{L} + \frac{1}{1 - l_{ji}\Delta a_{ij}} \mathbf{F}\binom{j}{i} \Delta a_{ij}\,, \tag{22}$$

where the field of influence is

$$\mathbf{F}\binom{j}{i} = \begin{pmatrix} l_{1i} \\ \vdots \\ l_{ni} \end{pmatrix} (l_{j1} \quad \cdots \quad l_{jn})\,. \tag{23}$$

It has been stated that if matrix inverse $\mathbf{L}$ reflects the economic landscape of interdependence between industries, then equation (23) "*provides a comparable landscape generated by change in one or more elements of the direct coefficients matrix,* **A**. *The field of influence provides an assessment of the degree to which the change is concentrated in the sector of origin, diffused only to a small set of linked industries or spread through the economy*" (Van der Linden et al., 2000, p. 1290). Yet, the real issue is how to compare these matrices as several matrix norms are available (Sonis and Hewings, 1992).

In EEIO, the main task is to measure environmental impacts of economic activities generated by final demand. If we measure these effects in monetary terms or just using a single dimensions, say CO_2, then we can focus on $\Delta\breve{x}$ where:

$$\Delta x_r(\Delta a_{ij}) = \frac{l_{ri}\, x_j \Delta a_{ij}}{1 - l_{ji}\Delta a_{ij}} = l_{ri} k_{ij}^2, \tag{24}$$

and

$$\Delta x_r^P(\Delta a_{ij}) = \lambda_r \frac{l_{ri}\, x_j \Delta a_{ij}}{1 - l_{ji}\Delta a_{ij}} = \lambda_r l_{ri} k_{ij}^2. \tag{25}$$

Here we are mostly interested in analysing the sensitivity of the Leontief inverse and environmental impacts by a technical change such a switch to BEV production. Let's assume a set of changes in car production technology: $|\Delta a_{hC}| > 0$, $h = 1,\dots, n$. In this case, the extension of (20) is (Sherman and Morrison, 1949):

$$l_{rs}^{\mathrm{N},C} = l_{rs} + \frac{l_{Cs}\ \sum_h l_{rh}\ \Delta a_{hC}}{1 - \sum_h l_{Ch}\ \Delta a_{hC}}. \tag{26}$$

and

$$\Delta l_{rs}^N(\Delta a_{ij}) = l_{rs}^N(\Delta a_{ij}) - l_{rs} = l_{Cs} k_{rC}^3, \tag{27}$$

with

$$k_{rC}^3 = \frac{\sum_h l_{rh}\ \Delta a_{hC}}{1 - \sum_h l_{Ch}\ \Delta a_{hC}}. \tag{28}$$

This approach implicitly takes for granted that there is no substitution effects between primary inputs and intermediate ones. Alternatively, we can impose some specific pattern as in Van der Linden et al. (2000). In the next section, I will discuss this issue at length.

3. Analysis of EV production enhancement

In this explorative analysis I embrace the short version of well know EXIOBASE-1 database year 2000. EXIOBASE is a global, detailed Multi-regional Environmentally Extended Supply and Use / Input Output (MR EE SUT/IOT) dataset. Supply and Use tables of individual countries are transformed into an international input-output table that can be used for the analysis of environmental impacts associated with final consumption. The actual dataset is quite large since it deems 44 countries with 129 products and can be managed with dedicated applications and graphical user interface only (Tukker et al., 2013, Wood et al., 2015). Therefore, I prefer to work with the simplified IO table aggregated into 3 regions. The three regions are roughly the EU27 + Norway and Switzerland, the OECD countries outside the Europe and finally the non OECD countries. The industry by industry input-output tables are based on fixed industry sales structure assumption (Gregori, 2009). The number of industry sectors is only 60. IO data are supplemented with environmental and economic extensions. Table 3 shows the list about 28 air emissions.

Table 3 – Air emissions: Car manufacturing place in selected rankings

	In the world (180 Sectors)			Within the area (60 sectors)		
	Europe	Other OECD	Rest of the world	Europe	Other OECD	Rest of the world
CO_2	112	77	126	25	28	48
CH_4	121	68	110	29	32	43
N_2O	132	78	130	38	32	48
SOx	98	55	54	22	18	26
NOx	128	88	96	32	31	42
NH_3	99	31	115	24	23	34
CO	140	83	63	32	28	39
Benzo(a)pyrene	100	62	58	23	16	31
Benzo(b)fluoranthene	95	63	59	23	16	32
Benzo(k)fluoranthene	105	69	68	25	19	35
Indeno(1,2,3-cd)pyrene	105	66	62	25	17	34
PAH	155	98	41	35	35	35
PCBs	70	55	46	16	13	24
Dioxins	89	64	61	21	18	32
HCB	114	85	75	34	21	37
NMVOC	31	30	6	6	9	5
PM 10	124	90	96	27	29	41
PM 2.5	121	90	93	27	29	40
TSP	125	91	96	29	31	41
As	112	70	80	26	21	36
Cd	97	57	106	25	21	40
Cr	124	81	117	31	31	44
Cu	118	63	94	24	27	38
Hg	74	56	53	19	16	27
Ni	121	79	145	34	33	46
Pb	108	71	72	23	25	32
Se	107	70	68	24	23	32
Zn	108	74	90	24	27	38

Source: Exiobase _1

Combustion-related air emission accounts are computed directly based on the energy accounts provided by The International Energy Agency. For the non-combustion air emission accounts, emissions are calculated in a similar way by combining various activity statistics such as industrial production and use of products (Wood et al., 2015). Presenting raw data is messy and almost useless as overall values range from million tons for CO2 to some kilos for dioxins. Hence, as I prefer to show car production place in the industry rankings in order to check if it is one of the most important emitters. In table 3, I provide worldwide place (first three columns) of the Manufacturing of motor vehicles, trailers and semi-trailers in Europe, other OECD countries and the Rest of the World. The last three columns show the position within these areas. As table 3 shows, car manufacturing stands in the up-middle range where most of the factories are located, i.e. OECD nations, as European and other OECD countries productions account for, respectively, 32% and 62% of the overall output. Its impact is important for Non-methane volatile organic compounds (NMVOC) indeed and, to a lower extent, for benzos in other OECD countries. As we can see from table 3, we cannot expect a big change in global CO2 pollution if European carmakers switch to BEV production, as they hold the 112-th place as worldwide emitters. However, they have the 25-th place within Europe and the local impact might be relevant.

We can wonder how a different technology can improve such a situation. First, we must change the technology that can be used to produce both BEVs and ICVs and not only the latter, as done in the Exiobase dataset. We rely on the study by Leurent and Windisch (2015), who treat the vehicle body and the battery as separate entities[2]. They assume a vehicle composition, as set out in Table 4, with main input supplied by: Automobile construction itself (30%), Metallurgy and metal processing (12%), Automotive equipment manufacturing (9%), Chemicals, rubber, plastics (7%) and Financial, real estate and rental activities (7%). These are total coefficients, i.e. without separating inputs from different origins, while value added accounts for only 10% of gross output. In the same table other important coefficients are also included and the (almost) comparable ones in European countries (a_{iC}^{EC}) and other OECS economies (a_{iC}^{OO}) technologies from the Exiobase dataset. The last two columns in table 4 refer to total coefficients too. The former resembles the ICV technology provided by Leurent and Windisch for several inputs but value added that is much more relevant in Exiobase.

Table 4 – Intermediate inputs: CV vs EV

	ICV	a_{iC}^{ICV}	BEV	a_{iC}^{BEV}	a_{iC}^{EC}	a_{iC}^{OO}
Electric vehicle construction			3350			
Manufacture of IC vehicle	4350					
Car manufacturing	4350	29.79%	3350	14.19%	26.72%	36.06%
Electrical and electronic equip.	321	2.20%	10321	43.73%	3.17%	2.20%
Metals and metalworking	1742	11.93%	1742	7.38%	10.70%	8.78%
Automotive equipment	1341	9.18%	1341	5.68%	6.98%	5.14%
Financial, real estate, rental	1105	7.57%	1105	4.68%	1.37%	1.92%
Chemicals, rubber, plastics	1084	7.42%	1084	4.59%	6.88%	5.70%
Services to companies	823	5.64%	823	3.49%	5.88%	4.49%
Machinery	770	5.27%	770	3.26%	3.22%	2.25%
Consumer goods	433	2.97%	433	1.83%		
Electrical and electronic comp.	271	1.86%	271	1.15%	1.37%	1.92%
Other items	879	6.02%	879	3.72%		
Value added	1481	10.14%	1481	6.28%	22.63%	24.46%
Total	14600		23600			

Source: Leurent and Windisch, 2015, Exiobase _1

2 The very detailed description provided by Hawkins et al. (2013) will be used in forthcoming paper.

Leurent and Windisch devise component values per a hypothetical electric car too. They assign BEV values taken from their ICV counterparts for most fittings of the body, but reduced by €1000 for self-provision since an electric motor is easier to assembly. For the battery, using data from Renault and Nissan, they have counted €10.000 under "Electrical and electronic equipment". Having assumed the same added value for an EV as for a CV, Leurent and Windisch obtained a total production cost per BEV (before tax) that is €9000 larger than comparable ICV. Finally, they devise technical coefficients for the new activity "BEV manufacturing" simply dividing the cost of each material supplied by BEV production cost, as shown in table 4.

Their analysis is interesting but flawed because they misunderstand the Leontief technology, that is the input quantity needed to produce a unit of output. Since most items are the same these coefficient are not changing. The only ones affected by the new car manufacturing technology refer to "Electrical and electronic equipment" and "Car manufacturing" itself. The latter is reduced while the former is increased a lot. If they are not offsetting each other, value added is decreased too. Such a change is deeper as BEV production is enhanced. For BEV production, Leurent and Windisch state valued added is 6% only, while Electrical and electronic components make about 44% of the car value. The latter coefficient is questionable, as the very little primary input usage. Hence, I assume the following scenarios with variations in Electrical inputs and car production self-provision in European countries alone:

$$a_{CC}^{EC} = \theta a_{CC}, \quad a_{EC}^{EC} = \delta a_{EC} \tag{29}$$

where parameters θ and δ drive technical change. These are set in steps so that, at the edge, car production entails mostly electric vehicles. However, such changes must be linked together in order to satisfy the Bauer-Solow conditions (Takayama, 1985) and cannot have the magnitude suggested by Leurent and Windisch anyway. First of all, I change domestic coefficients alone to simplify algebra. Then, at most, I halve the intra industry coefficient a_{CC} and increase δ up to 12. Hence, the maximum coefficient of Electrical and electronic equipment is about 33% that is somehow away from the figure devised by Leurent and Windisch (44%). Value added is reduced from 22.6% to 5.3%. Any further reduction appears to be unsound.

Table 5 shows changes in air emissions with respect to baseline, i.e. Exiobase data with ICV production only. We expect a reduction in pollution, but this is not always true. Actually, our application has sometimes an unappealing outcome. The BEV technology implies larger Electrical and electronic equipment inputs and lower value added. This enhances multiplicative processes in the economy and generates "negative" impacts. In the first and last columns in table 5 total emissions are larger than in the baseline and switching to BEV production is increasing pollution.

However, due to fixed final demand and emission coefficients, overall variations are rather small and never larger than 1% even in the last scenario where BEV production dominates. Polycyclic Aromatic Compounds (PAH) and Polychlorinated biphenyls (PCBs) are adversely affected in this case as the battery production impact is utmost and value added reaches its lowest level. Quite interestingly, where car production is the greatest polluter, i.e. NMVOC, the change is quite whimsical as for CH_4 and N_2O, while it is even lower for NH_3. As expected, there is a noticeable impact on Pb whose increase ranges from 0.06% to 0.65%.

Table 5 – Increase in air emissions due to BEV production in European countries

	θ = 0.9 δ = 2.5	θ = 0.65 δ = 4	θ = 0.2 δ = 8	θ = 0.6 δ = 10	θ = 0.5 δ = 12
CO_2	0.02%	-0.02%	-0.03%	0.19%	0.22%
CH_4	0.01%	-0.01%	-0.01%	0.06%	0.07%
N_2O	0.01%	-0.01%	-0.01%	0.05%	0.06%
SOx	0.01%	-0.01%	-0.02%	0.13%	0.15%
NOx	0.01%	-0.02%	-0.03%	0.12%	0.14%
NH_3	0.00%	0.00%	0.00%	0.02%	0.02%
CO	0.01%	-0.01%	-0.01%	0.10%	0.12%
Benzo(a)pyrene	0.02%	-0.01%	-0.02%	0.17%	0.20%
Benzo(b)fluoranthene	0.02%	-0.01%	-0.02%	0.18%	0.21%
Benzo(k)fluoranthene	0.02%	-0.01%	-0.02%	0.21%	0.24%
Indeno(1,2,3-cd)pyrene	0.02%	-0.01%	-0.02%	0.15%	0.18%
PAH	0.08%	-0.06%	-0.11%	0.71%	0.83%
PCBs	0.08%	-0.07%	-0.12%	0.74%	0.87%
Dioxins	0.01%	-0.02%	-0.03%	0.10%	0.11%
HCB	0.01%	-0.02%	-0.03%	0.11%	0.13%
NMVOC	0%	-0.07%	-0.13%	0.09%	0.10%
PM 10	0.01%	-0.01%	-0.02%	0.13%	0.15%
PM 2.5	0.02%	-0.01%	-0.02%	0.14%	0.16%
TSP	0.02%	-0.02%	-0.03%	0.16%	0.19%
As	0%	-0.07%	-0.14%	0.10%	0.11%
Cd	0.03%	-0.06%	-0.11%	0.28%	0.33%
Cr	0.06%	-0.04%	-0.07%	0.53%	0.62%
Cu	0.01%	-0.06%	-0.11%	0.12%	0.14%
Hg	0.01%	-0.04%	-0.08%	0.15%	0.17%
Ni	0.02%	-0.02%	-0.03%	0.16%	0.19%
Pb	0.06%	-0.05%	-0.08%	0.56%	0.65%
Se	0.02%	-0.01%	-0.02%	0.13%	0.16%
Zn	0.03%	-0.03%	-0.05%	0.31%	0.36%

Finally, in table 6 a new ranking is introduced. It refers again to the output mix with the largest BEV share, i.e. $\theta = 0.5$, $\delta = 12$. We can focus on the first and fourth columns as other figures are almost identical to the ones presented in table 3. In contrast, there are some significant changes in pollution by European manufacturers. On average, this sector improves its relative position by almost six position in the overall ranking (first column) and some improvements are noticeable as for CO_2, SO_x, Cd and Pb. This result is as expected, as technical change is reducing intra flows and increasing outsourcing of battery production to the Electrical and electronic equipment industry.

Table 6 – Position of car prod. air emissions with large BEV output ($\theta = 0.5$, $\delta = 12$)

	in the world (180 Sectors)			*within the area (60 sectors)*		
	Europe	**Other OECD**	**Rest of the world**	**Europe**	**Other OECD**	**Rest of the world**
CO_2	126	77	127	32	28	48
CH_4	127	68	110	31	32	43
N_2O	134	78	132	39	32	48
SOx	111	55	54	29	18	26
NOx	135	88	96	34	31	42
NH_3	102	31	116	25	23	34
CO	143	83	64	35	28	39
Benzo(a)pyrene	107	62	58	27	16	31
Benzo(b)fluoranthene	103	63	59	25	16	32
Benzo(k)fluoranthene	112	69	68	29	19	35
Indeno(1,2,3-cd)pyrene	109	67	63	27	17	34
PAH	155	98	41	35	35	35
PCBs	72	55	46	17	13	24
Dioxins	95	65	61	25	18	32
HCB	116	85	75	36	21	37
NMVOC	37	30	6	6	9	5
PM 10	131	90	96	32	29	41
PM 2.5	130	91	93	32	29	40
TSP	130	91	96	33	31	41
As	115	70	80	29	21	36
Cd	107	57	106	28	21	40
Cr	128	81	118	34	31	44
Cu	122	63	94	25	27	38
Hg	81	56	53	22	16	27
Ni	124	80	145	36	33	46
Pb	118	71	72	27	25	32
Se	110	70	68	26	23	32
Zn	114	74	90	26	27	38

In order to understand why sometimes we get a larger pollution and sometimes a smaller one we must turn to the Sherman-Morrison formula with perfect substitution between car/battery inputs. Let's assume that the increase in Electrical and electronic equipment input is equal to the Car self-provision reduction:

$$\Delta a_{CC} = -\Delta a_{EC} \, . \tag{30}$$

Using (28) we get:

$$\Delta l_{rs}^{N}(\Delta a_{EC}) = l_{Cs} \frac{(l_{rE} - l_{rC}) \ \Delta a_{EC}}{1 - (l_{CE} - l_{CC}) \ \Delta a_{EC}}, \tag{31}$$

whose denominator is always positive as $l_{CC} > l_{CE}$. Hence multiplier changes depend on the numerator only. In our case, most of the times $l_{rC} > l_{rE}$ and $\sum_r l_{rE} - l_{rC} = -\,0.422$. Hence with a symmetric change there is an air pollution reduction, while with an asymmetric shock, as proposed by Leurent and Windisch, the opposite holds.

5 – Conclusions

Environmental Extended Input Output tables provide detailed information on production, resource utilization and pollution by recording all economic transactions and environmental flows between producers and consumers. Make, Use, SIO, Ecological commodity discharge/usage, intervention matrices provide a framework to analyse the uses of produced goods and available natural resources. The literature on this issue is growing as concurrent concerns about gas availability and greenhouse gas emissions, but most of it focuses on private and social cost comparisons between ICVs and BEVs and adopts Life-Cycle Assessments. Nonetheless, the "analysis of lifecycle GHG emissions of EVs in the peer-reviewed scientific literature is rather incomplete and affected by significant uncertainty" (Contestabile et al., 2012, p. 11). It has been noted that "*LCA obviously encompasses the emissions arising from the assembly of the car, from manufacture of steel used in the car – including the emissions from the energy used to power the factory making the steel – but does not necessarily include the energy used to mine the coal used in the power plant at the steel factory ... it is not the just releases from individual processes that may be overlooked, but also the aggregate of the all of the releases from the processes outside modeled system that may change the results of the LCA*" (Lifset, 2009, p. 9). EEIO or IO LCA models resolve these issues. In the present study, EEIO has been applied to evaluate emission impact by Battery Electric Car manufacturing as "the production phase of EVs proved substantially more environmentally intensive" (Hawkins et al., 2012, p. 61). Actually, IO is the very first step in applying Computable General Equilibrium theory and, despite, its limitations, it continues to grow in popularity (Suh, 2009). Technological change is another key theme in this literature and industrial ecology too. We tackle this issue trying to assess the impact of a gradual shift from ICV to BEV manufacturing. We embrace the small version of the Exiobase dataset with only 60 sectors and 3 macro regions (European countries, other OECD countries, the rest of the world). We could assess land use and energy use but we focus on air emission considering 28 pollutants. Rather than providing an astonishing quantity of data about the absolute amount of pollution due to car manufacturing, we simply discuss the relative position of this industry in term of pollution worldwide and within the 3 macro regions. Car manufacturing contributes very little to some emissions, such as CO_2 and N_2O, while it has an impact on Non-methane volatile organic compounds (NMVOC) pollution and, to a lower extent, for benzos (respectively 6th and 23rd position in Europe, 9th and 16th in other OECD countries). Hence, even if it is not one of the worst emitters, it is reasonable to check the impact of a production shift from ICVs to BEVs.

We rely on the recent work by Leurent and Windisch (2015) to gauge the most important ingredient in this analysis, i.e. input changes. It is quite well known that BEVs require expensive batteries and need a simplified engine, but it is far from being easy to calculate these production costs and associate coefficients. Leurent and Windisch suggest a decrease by 50% in self-provided inputs and a huge share (about 43%) in Electrical and electronic equipment inputs. These values can vary according to different engines and cars so that we suggest a simple procedure that allows to alter them gradually as BEV production substitutes ICV manufacturing. We get some interesting results.

First, pollution changes are not very relevant. In the worst scenario, the increase in CO_2 emissions, with respect to actual production, is 0.22% alone. Benzofluoranthene and Benzopyrene expand by nearly the same amount (respectively 0.21% and 0.2%). The most noticeable increases are still lower than 1%, i.e. PAH with 0.83% and PCBs with 0.87%. On the contrary, in some different scenarios, there are some pollution reductions, but still with the very same or even lower magnitudes. Most of the impacts are in the range from -0.01% to -0.13%.We can claim that shifting production to BEVs has little impacts on pollution issues.

Second, the relative position of the industry improves by some positions in the overall pollution ranking, when changes are positive yet. For instance, it slips to the 25th position from the 32nd in European CO_2 emissions or from 25th to 29th in Benzo(k)fluoranthene emissions in the same area. Nonetheless, BEV manufacturing emits more. The reason why there is an increase in pollution is due the greater roundness of the input matrix, which produces larger multipliers. When value added is reduced, a given change in final demand pushes production and pollution further. However, this outcome is not always true. Sometimes, when we have an offsetting change between the battery input and intra flows emissions are smaller. To understand this result we have to turn to the Sherman-Morrison formula. It is easy to see that, in our setting without changes in value added, this offsetting input switch reduces multipliers.

Finally, the latter remark calls for a better understanding of these interindustry links in a more complex specification, such as a SAM. An overall decomposition is required, with assessments about consumption changes, i.e. if more cars are demanded and the value of the total expenditure, and pollution per unit of output changes, i.e. modifications in the impact matrix. Further research is still needed in this field.

References

ARDENT, F., BECCALI, M., CELLURA, M. (2009) "Application of the IO Methodology to the Energy and Environmental Analysis of a Regional Context", In SUH, S. (ed) *Handbook of Input-Output Economics in Industrial Ecology*, Springer, New York.

BURNHAM, A., WANG, M., WU Y. (2006) "Development and Applications of GREET 2.7 – The Transportation Vehicle-Cycle Model", ANL/ESD/06. Argonne, IL, USA: Argonne National Laboratory, University of Chicago, U.S. Department of Energy.

COHEN, J. L. (1978) *Multiobjective Programming and Planning*, Elsevier, New York.

CONTESTABILE, M., OFFER, G., NORTH, R. (2012) "Electric Vehicles: A Synthesis of the Current Literature with a Focus on Economic and Environmental Viability", LCA Works, Technical Paper.

CRIST, P. (2012) "Electric Vehicles Revisited-Costs, Subsidies and Prospects", Discussion Paper No. 2012-03, International Transport Forum, OECD, Paris, France.

DALY, H. (1968) "On Economics as a Life Science", *Journal of Political Economy*, 76(3), pp. 392–406.

DIETZENBACHER, E., LOS, B. (1998) "Structural Decomposition Techniques: Sense and Sensitivity", *Economic Systems Research*, 10(4) pp. 307-324.

GREGORI, T. (2009) "Input-Output techniques applied to construction" in Les Ruddock (ed) *Economics for the Modern Built Environment*, Taylor & Francis, Oxford.

GREGORI, T., SCHACHTER, G. (1999) "Assessing Aggregate Structural Change", *Economic Systems Research*, 11(1), pp. 67-82.

HAWKINS, T. R., GAUSEN, O. M., STRØMMAN. A. H. (2012) "Environmental impacts of hybrid and electric vehicles – a review", *International Journal of Life Cycle Assessment*, 17(8), pp. 997–1014.

HAWKINS, T. R., SINGH, B., MAJEAU-BETTEZ, G., STRØMMAN, A. H. (2012) "Comparative Environment Life Cycle Assessment of Conventional and Electric Vehicles", *Journal of Industrial Ecology*, 17(1), pp. 53-64.

HENDRICKSON, C., HORVATH, A., JOSHI, S., LAVE, L. (1998) "Economic Input-Output Models for Environmental Life-Cycle Assessment", Environmental Science & Technology, 32(7), pp. 184A-191A.

ISARD, W. (1968) "On the Linkage of Socio-Economic and Ecological Systems," *Papers of the Regional Science Association*, 21(1), pp. 79-99.

KITZES, J. (2013) "An Introduction to Environmentally-Extended Input-Output Analysis", *Resources*, 2(4), pp. 489-503.

KUSHNIR, D., SANDEN, B.A. (2011) "Multi-level energy analysis of emerging technologies: a case study in new materials for lithium ion batteries", *Journal of Cleaner Production*, 19(13), pp. 1405-1416.

LEE, H., LOVELETTE, G. (2011) "Will Electric Cars Transform the U.S. Vehicle Market? An Analysis of The Key Determinants", Discussion Paper #2011-08, Energy Technology Innovation Policy Discussion Paper Series, Harvard Kennedy School, Cambridge, Mass.

LEONTIEF, W. (1970) "Environmental Repercussions and the Economic Structure: An Input-Output Approach", *Review of Economics and Statistics*, 52(3), pp. 262-271.

LEURENT, F.,WINDISCH, E. (2015) "Benefits and costs of electric vehicles for the public finances: An integrated valuation model based on input e output analysis, with application to France", *Research in Transportation Economics*, http://dx.doi.org/10.1016/j.retrec.2015.06.006.

LIFSET, R. (2009) "Industrial Ecology in the Age of Input-Output Analysis", In Suh, S. (ed) Handbook of Input-Output Economics in Industrial Ecology, Springer, Heidelberg.

LUPTACIK, M., BÖHM, B. (1994) "Reconsideration of Non-negative Solutions for the Augmented Leontief Model", *Economic Systems Research*, 6(2), pp. 167-170.

LUPTACIK, M., BÖHM, B. (1999) "A Consistent Formulation of the Leontief Pollution Model", *Economic Systems Research*, 11(3), pp. 263-275.

MAJEAU-BETTEZ, G., HAWKINS, T. R., STRØMMAN, A. H. (2011) "Lifecycle environmental assessment of lithium-ion and nickel metal hydride batteries for plug-in hybrid and battery electric vehicles", *Environmental Science & Technology*, 45(10), pp. 4548-4554.

MASSIANI, JÉRÔME (2015), *Cost-Benefit Analysis of policies for the development of electric vehicles in Germany: Methods and results*, *Transport Policy*, vol. 38, pp. 19-26

MATHEYS, J., MIERLO, J. V., TIMMERMANS, J. M., VAN DEN BOSSCHE, P. (2008) "Life-cycle assessment of batteries in the context of the EU directive on end-of-life vehicles", *International Journal of Vehicle Design*, 46(2), pp. 189-203.

MESSAGIE, M. BOUREIMA, F. S., COOSEMANS, T., MACHARIS, C., VAN MIERLO, J. (2013) "A Range-Based Vehicle Life Cycle Assessment Incorporating Variability in the Environmental Assessment of Different Vehicle Technologies and Fuels", *Energies*, 7(3), pp. 1467-1482.

MILLER, R., BLAIR, P. (2009) *Input-Output Analysis: Foundations and Extensions*, 2nd ed., Cambridge University Press, Cambridge, UK.

NATHANI, C. (2009) "Analysing the Economic Impacts of a Material Efficiency Strategy", In Suh, S. (ed) Handbook of Input-Output Economics in Industrial Ecology, Springer, New York.

NIJKAMP, P., RIETVELD, P. (1976) "Multiobjective Programming Models: New Ways in Regional Decision Making", *Regional Science and Urban Economics*, 6(3), pp. 253-274.

PASINETTI, L.L. (1973), "The notion of vertically integration in economic analysis", *Metroeconomica*, 25(1), pp. 1-29.

QAYUM, A. (1991) "A Reformulation of the Leontief Pollution Model", *Economic Systems Research*, 3(4), pp. 428-430.

SAMARAS, C., MEISTERLING, K. (2008) "Life cycle assessment of greenhouse gas emissions from plug-in hybrid vehicles: Implications for policy", *Environmental Science & Technology*, 42(9), pp. 3170-3176.

SHERMAN, J., MORRISON, W. J. (1949) "Adjustment of an Inverse Matrix Corresponding to Changes in the Elements of a Given Column or a Given Row of the Original Matrix", Annals of Mathematical Statistics, 20, p. 621.

SHERMAN, J., MORRISON, W. J. (1950) ""Adjustment of an Inverse Matrix Corresponding to a Change in One Element of a Given Matrix," Annals of Mathematical Statistics, 21(1), pp. 124-127.

SONIS, M., HEWINGS, G. J. D. (1992) "Coefficient Change in Input-Output Models: Theory and Applications", *Economic Systems Research*, 4(2), pp. 143-157.

SUH, S. (ed) *Handbook of Input-Output Economics in Industrial Ecology*, Springer, Heidelberg.

TAKAYAMA, A. (1985) *Mathematical Economics*, Cambridge Univ. Press, Cambridge, UK.

TANINO, T., TANAKA, T., INUIGUCHI, M. (eds.) (2003) "Multi-Objective Programming and Goal Programming: Theory and Applications", Springer: Heidelberg.

TODD, J. ET AL. (2013) "Creating the Clean Energy Economy. Analysis of the Electric Vehicle Industry", International Economic Development Council, Washington, DC.

TUKKER, A., DE KONING, A., WOOD, R., HAWKINS, T., LUTTER, S., ACOSTA, J. RUEDA CANTUCHE, J.M., BOUWMEESTER, M., OOSTERHAVEN, J., DROSDOWSKI, T., KUENEN, J. (2013) "EXIOPOL—Development and illustrative analyses of a detailed global MR EE SUT/IOT", *Economic Systems Research*, 25(1), pp. 50-70.

VAN DEN BOSSCHE, P., VERGELS, F., VAN MIERLO, J., MATHEYS, J., VAN AUTENBOER, W. (2006) "SUBAT: An assessment of sustainable battery technology", *Journal of Power Sources*, 162(2), pp. 913-919.

VAN DER LINDEN, J. A., OOSTERHAVEN, J., CUELLO, F. A., HEWINGS, G. J. D., SONIS, M. (2000) "Fields of influence of productivity change in EU intercountry input – output tables, 1970-80", *Environment and Planning A*, 32(7), pp. 1287-1305.

VARIAN, H. (1992) *Microeconomic Analysis*, 3rd ed., Norton & co., New York.

VICTOR, P. A. (1972) *Pollution: Economy and Environment*, George Allen and Unwin Ltd., London: UK.

WILSON, L. (2013) "Shades of Green. Electric Cars' Carbon Emissions around the Globe", Shrink that footprint, mimeo.

WOOD, R., STADLER, K., BULAVSKAYA, T., LUTTER, S., GILJUM, S., DE KONING, A., KUENEN, J., SCHÜTZ, H., ACOSTA-FERNÁNDEZ, J., USUBIAGA, A., SIMAS, M., IVANOVA, O., WEINZETTEL, J., SCHMIDT, J.H., MERCIAI, S., TUKKER, A. (2015) "Global sustainability accounting-developing EXIOBASE for multi-regional footprint analysis", *Sustainability*, 7(1), pp. 138-163.

ZACKRISSON, M., AVELLAN, L., ORLENIUS, J. (2010) "Life cycle assessment of lithium-ion batteries for plug-in hybrid electric vehicles – Critical issues", *Journal of Cleaner Production*, 18(15), pp. 1519-1529.