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Dynamic Models of Fixed Capital Stocks and Their Application in Industrial Ecology

by

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Dynamic Stocks, Input-Output Modeling, and Technological Change

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Abstract:

The transition to a low-carbon economy requires a radical transformation of energy supply, materials production, fabrication, and manufacturing. This transformation entails substantial investments in new industrial assets that will replace and amend the existing stock of productive fixed capital over the next decades. To model this transition and the associated capital investment flows, resource demand, and environmental impacts, an extended modeling framework that comprises both economic and physical aspects of the transformation is required. We developed a conceptual framework that combines Leontief input-output analysis with dynamic capital and material stock modeling. We identified similarities between economic and physical accounting of capital stocks and developed a demand-driven input output model with dynamic capital stocks that can be connected to both economy wide accounting of capital investment and to life cycle inventories of individual technologies. A central result is a synthesis of the marginal and the attributional matrix of technical coefficients (*A*-matrix) from detailed inventories of productive assets of different vintages and technologies. The framework may facilitate a better understanding of inter-industry material flows and material stocks in industrial assets and we discuss the connection of physical and economic layers in life cycle assessment, input-output analysis, material flow analysis, integrated assessment models, and computable general equilibrium models.

Keywords: Dynamic stock model; Dynamic input-output analysis; Perpetual inventory method; Life cycle inventory; Material flow analysis;

<heading level 1> **1) Motivation and background:**

Climate change mitigation and potential future resource scarcity pose substantial challenges to industrial producers. The transition to a ‘sustainable energy future’ (International Energy Agency 2010) in order to substantially reduce anthropogenic greenhouse gas emissions and to lower dependency on fossil fuels, entails a large-scale transformation not only of the entire energy supply, but also of energy- and material-intensive industries to facilitate more efficient production. This transformation is shaped by many factors, such as the availability and the timing of new and more efficient technologies (International Energy Agency 2010), potential scarcity of mineral resources (Graedel and colleagues 2012), and the speed at which existing assets can be replaced (Davis and colleagues 2010). A central and novel challenge is that a multitude of new or improved technologies, which were developed and tested on a small scale, need to replace existing assets over a long time, in all world regions, and on a large scale. Scenario development represents an important tool to create and test meaningful and realistic story lines of how such an up-scaling could look like. To develop scenarios that depict a substantial transformation of the industrial metabolism one needs to understand the dynamics of *in-use stocks* such as industrial assets, buildings, infrastructure, vehicles, and consumer products (Davis and colleagues 2010). This work focuses on the industrial metabolism.

<heading level 2> **1.1) The role of stocks in the industrial metabolism**

Assets for energy conversion, material production, fabrication and manufacturing of consumer products have different important functions in the transition to a sustainable energy future (Pauliuk and Müller 2013):

i) Low carbon energy technologies are capital and material intensive and the impact of building and maintaining these installations is often much higher that the impact associated with the actual energy transformation during their use phase (Frischknecht and colleagues 2007).

ii) The service lifetime of industrial installations determines how quickly they can be replaced, and thus, how quickly new energy technologies can penetrate, or how quickly one can update to new energy standards or best available technology.

iii) The input-output structure of an industrial sector is determined by the respective ‘recipes’ of all the factories and installations it comprises. The turnover and ageing of the productive capital stock determines how the ‘production recipe’ and thus the coupling between output and input of the sector changes over time.

<heading level 2> **1.2) Previous approaches of dynamic stock modeling and input-output analysis**

Dynamic modeling of capital stocks has a long tradition in economic accounting, and we refer to OECD (2009) for an overview. Many statistical offices apply a dynamic capital stock model called ‘perpetual inventory method’ (PIM), which tracks the different vintages of capital investment over time and determines the retirement of capital assets in different economic sectors according to their service lifetimes OECD (2009). On the physical side, Baccini and Bader (1996), van der Voet and colleagues (2002), and Müller (2006) describe and apply different dynamic models of material stocks in use. Müller (2006) introduces the stock-driven model, where inflows and outflows of products are determined from exogenous time series of total stock size and the service lifetime of the different cohorts. Pauliuk and colleagues (2013a) combine dynamic stock models for end-use and industry by using a demand-driven, multi-regional dynamic stock model of pig iron production capacities in a material flow analysis of the global steel cycle. Both the economic and the physical approach to dynamic stock modeling use very similar concepts, which we will explore in section 2.

An important contribution to representing capital investment and production capacity in dynamic input-output models was made by Duchin and Szyld (1985). Their model includes investments for replacement and expansion of the fixed capital stock in each industrial sector. It represents a generalization of the previous dynamic IO model presented by Leontief (1953) and the model design ensures the existence of a solution with positive output in all sectors. Duchin and Szyld apply exogenous projections on future production capacities and spread the capital investment for new facilities over several years. Data on capital retirement are used to estimate the investments required for replacing existing capacities, and estimates of the total capital stock are used to determine the matrix of capital coefficients per unit of production capacity (Leontief and Duchin 1986).

A first attempt to combine a vintage-lifetime model for the productive capital stock with a dynamic IO model was made by Lennox and colleagues (2005). They specify the lifetime of industrial assets to model the turnover in different sectors and a capacity utilization factor to consider possible under-utilization of capacities in certain sectors and years. The total requirements for installing new production capacities enter a dynamic input-output model similar to the one by Duchin and Szyld (1985). Data on the material intensity of energy supply technologies are used to determine the total material demand from new installations.

The model of Lennox and colleagues (2005) does not relate the turnover of the capital stock to the change of technical coefficients over time, which is crucial when modeling substantial changes of the industrial metabolism. There is no model framework in the IO family that includes both capital stock dynamics *and* material stock dynamics, that includes all life cycle stages of industrial assets, and that consistently distinguishes between average and marginal requirements for capital investment.

<heading level 2> **1.3) Scope and research questions:**

The subsequent work addresses the following specific questions:

(1) What is the connection between dynamic modeling of capital stocks (PIM) and material stocks (dynamic MFA) and what are potential synergies between the two methods?

(2) How does the turnover of the capital stock relate to the change of average and marginal industrial efficiency?

(3) What does the corresponding dynamic IO-model look like and how does this model relate to the model of Duchin and Szyld (1985)?

(4) How does dynamic accounting of capital stocks relate to other models of the industrial metabolism at large scale, i.e., material flow analysis, integrated assessment models, and general equilibrium models?

In section 2 we present our system definition and address question (1). In section 3 we present two methods for determining marginal *A*-matrices (question (2)): one based on the annual capital formation matrix; the other one based on process inventories. We use both approaches to formulate a dynamic input-output model (question (3)). In section 4 we discuss how this model could be applied to better understand inter-industry material flows and the dynamics of material stocks in industrial assets. We discuss how our model relates to the different assessment methods life cycle assessment (LCA), material flow analysis (MFA), input-output analysis (IOA), integrated assessment models (IAM), and computable general equilibrium models (CGE).

<heading level 1> **2) A stock-based model of the industrial metabolism**

<heading level 2> **2.1) System definition of the industrial metabolism**

Table 1 lists all indices or sets and the variables and their respective units. An oriented, bi-partite graph is the common approach to defining the system of the supply and use framework (UN 2008), input output models (Miller and Blair 2009), and integrated assessment models (Loulou and colleagues 2005) (Fig. 1). Industries form one group of nodes, while markets represent the other group. Both groups are mutually exclusive (bi-partite property) and are connected by oriented flows of products. Non-economic inputs and outputs, such as natural resources or emissions, are not considered here. For illustration purposes we assumed that there is a one-to-one correspondence between products and industries. To resolve the issue of where to draw the boundary between stocks and flows the concept of the 'asset boundary' was introduced . It includes a definition of the time interval over which the industrial metabolism is discretized, which is typically *one year* (UN 2008). The asset boundary divides inter-industrial flows into throughput (grey flows in Fig. 1) and investment flows (black flows in Fig. 1) for building new capacity ($B^m \cdot G_{in}$), maintaining existing assets ($R \cdot x$), and demolishing obsolete assets ($D \cdot G_{out}$), where G_{in} and G_{out} denote the new and retiring capacity, respectively, and the matrices B^m, R, and D contain the per-unit capital requirements for building up, maintaining, and disposing of a certain capacity or output unit.

Table 1: Overview of the variables used in the system, their symbols, and respective units. Dollars ($) represent the monetary unit, but any other currency can be used as well. All monetary values are in constant prices.

Index name and description	**Symbol**	**Domain**
Time	t	Case-specific
Cohort or vintage	t'	Same as model time
Industrial sector	j	$1\ldots N_{ind}$
Material (good or substance)	m	$1\ldots N_{mat}$
Sub-sector or specific technology within a certain industrial sector	s	$1\ldots N_{tech}$
Variable name and description	**Symbol and dependency**	**Unit**
Time horizon for asset boundary and discrete model increment: 1 year	τ	yr
Industry output	x(t)	$/yr
Final demand	y(t)	$/yr
Final demand minus investments in industrial assets	$\tilde{y}(t)$	$/yr
Capital stock (year, cohort, industry)	C(t,t’,j)	$
Capital service (year, cohort, industry), equals production capacity	G(t,t’,j)	$/yr
Flow of new production capacity	$G_{in}(t,t’,j)$	($/yr)/yr
Flow of retiring production capacity	$G_{out}(t,t’,j)$	($/yr)/yr
Gross fixed capital formation	GFCF(t)	$/yr
Investment matrix (GFCF broken down by target sector)	K(t)	$/yr
Investment matrix for building up new capacity	$K_B(t)$	$/yr
Investment matrix for maintaining existing capacity	$K_R(t)$	$/yr
Investment matrix for disposing of retiring capacity	$K_D(t)$	$/yr
Lifetime distribution (probability distribution of discard)	λ(t-t’,j)	1
Age-efficiency (factor that relates capital service to capital stock)	$\eta_1(t,t’,j)$	1
Utilization rate (factor that denotes the fraction of the assets that is utilized in a given year)	$\eta_2(t,t’,j)$	1
Material intensity of industrial output	μ(t’,j,m)	kg/$
Material stock in the gross fixed capital stock	M(t’,j,m)	kg
Matrix of technical coefficients, average	A(t), $A^a(t)$	$/$
Matrix of technical coefficients, marginal	$A^m(t)$	$/$
Matrix of requirements for building up new capacity, attributional	B(t), $B^a(t)$	$/($/yr)
Matrix of requirements for building up new capacity, marginal	$B^m(t)$	$/($/yr)
Matrix of requirements for maintaining existing capacity	R(t)	$/$
Matrix of requirements for disposing of retiring capacity	D(t)	$/($/yr)
Unit process inventory of specific technology s in sector j	u(i,j,t’,s)	$/$
Share of technology s in new capacity for a certain industry j	T(t’,j,s)	1

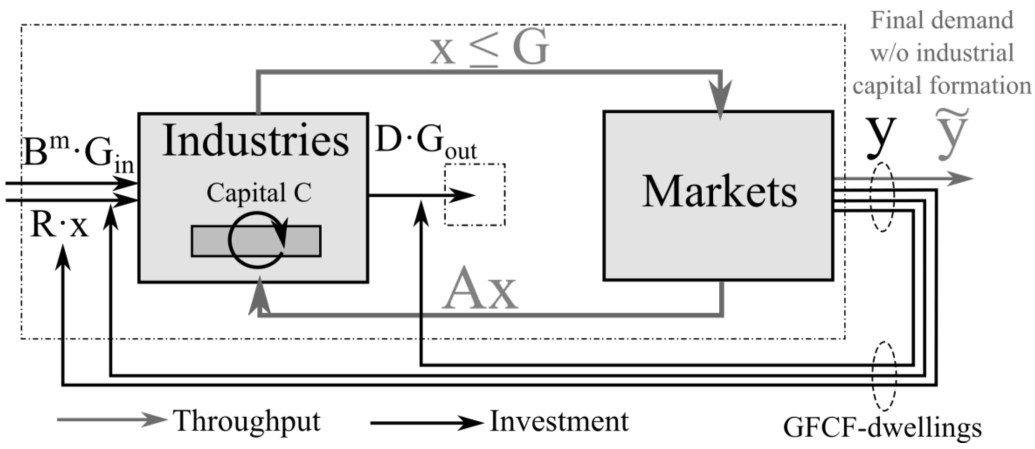

Figure 1: Definition of the IO system. The drawing contains the most central system variables listed in Table 1.

For the system in Fig. 1, a general market balance equation between the total industry output *x* and the different end uses holds for each year (equation 1), cf. also Duchin and Szyld (1985).

$$x = Ax + \underbrace{Rx + B^m G_{in} + DG_{out}}_{GFCF-dwellings} + \tilde{y} \qquad (1)$$

Here, $\tilde{y}$ denotes the final demand vector without investment for construction (B^m), maintenance (R), and demolition (D) of industrial assets. B^m stands for the capital intensity of *new* production facilities, it is thus a marginal capital coefficients matrix. The market balance equation (1) is the starting point for the Leontief primary model, as equation (1) can be resolved for *x*, provided that all other variables are known.

<heading level 2> **2.2) The relation between economic and physical accounting of capital stocks**

Industrial sectors are complex structures with complicated internal dynamics. The vintage structure and vintage-specific technological properties of fixed assets determine the system-wide efficiency at a given time. We now compare the two main methods of modeling capital and material stocks of productive assets.

Each year, a certain fraction of the final demand is invested into industrial assets. This flow, together with investments into dwellings, is termed *gross fixed capital formation* (GFCF) (European Commission 2008). By breaking down the GFCF into target sectors, one obtains the investment matrix K, that maps the GFCF from source to target industry (Figure 2), (European Commission 2008). In economics, two types of capital stocks are distinguished (Figure 2). The *gross capital stock C* is the sum of all past investments minus the assets that already have retired, measured in historic investments costs converted to constant prices (OECD 2001). The *net capital stock* comprises the same assets but determines their value based on the future capital services that are expected to be provided over the remaining technical asset life, discounted into the current year (OECD 2001).

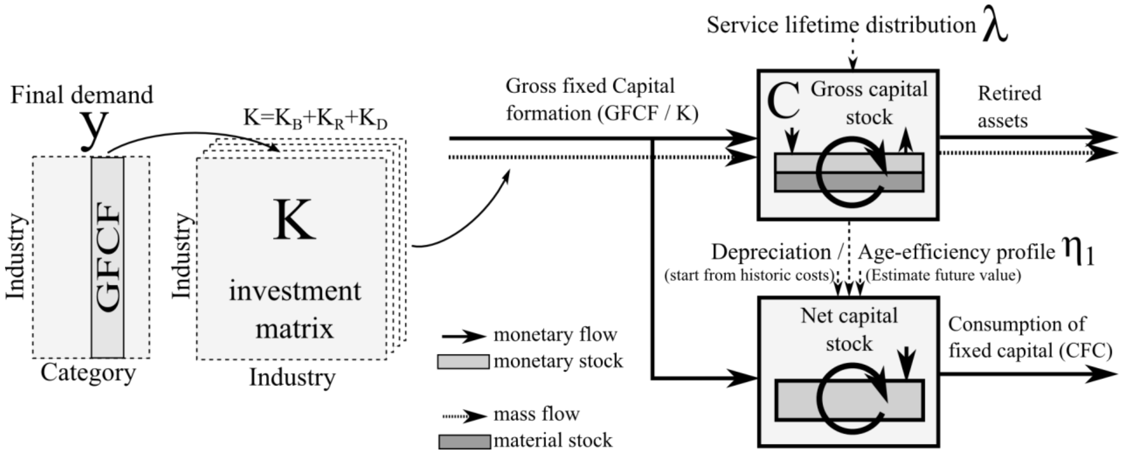

Figure 2: Left: Gross fixed capital formation and its disaggregation into the investment matrix *K*. Right: Schematic drawing of the perpetual inventory method ‘PIM’.

<heading level 3> **2.2.1) The relation between capital stock modeling and material stock modeling**

To estimate the assets leaving the productive phase, a cohort-lifetime model is applied as part of the so-called *perpetual inventory method* (PIM) (European Commission 2008). Let $\lambda(t\text{-}t')$ be the discrete distribution of the probability that the asset acquired in year *t’* leaves the stock at age *t-t’* in year *t*. Then the gross capital stock *C(t,j)* in the industrial sector *j* in a given year can be calculated in terms of past investments and the service lifetime distribution of the different vintages (equation (2)):

$$C(t,j)=\sum_{t'\le t} GFCF(t',j)\cdot\left(1-\sum_{t'\le t''\le t}\lambda(t'',j)\right)\cdot\tau \quad (2)$$

The estimation of asset lifetime and the shape of the lifetime distribution has a long tradition (OECD 2001; Lennox and colleagues 2005); it reaches back to the 1930ies (Winfrey 1935). Moreover, this method of capital stock accounting has a parallel in dynamic material flow analysis: the cohort-based dynamic stock model (Van der Voet and colleagues 2002; Müller and colleagues 2007; Baccini and Bader 1996; Müller 2006). The perpetual inventory method for determining the gross capital stock and the dynamic material stock model with a cohort-lifetime approach are technically identical; one represents the monetary flow and the other the material flow associated with a certain capital investment. By defining the material concentration array $\mu(t',j,m)$ of material *m* per dollar of output from sector *j* in year t' and multiplying it by *GFCF*, one can determine the material *M* contained in the capital stock:

$$M(t,j,m)=\sum_{t'\le t}\mu(t',j,m)\cdot GFCF(t',j)\cdot\left(1-\sum_{t'\le t''\le t}\lambda(t'',j)\right)\cdot\tau \quad (3)$$

Equation (3) establishes a formal identity between the perpetual inventory method and the cohort-lifetime model in dynamic material flow analysis. This equation allows us to track materials through industrial assets and estimate the potential for material recycling when industrial assets retire.

The technical efficiency of an asset may change during its operational life; it may require more maintenance and have therefore more idle days as it gets older, or it may be upgraded by installing new process control equipment. To model these effects the perpetual inventory method assigns an *age-efficiency* η_1 to each asset in stock, which represents a relative measure of the capital service provided by the asset at a certain time. It has the initial value 1 for a new asset. The net capital stock is determined by multiplying the age efficiency factor to all assets in stock, and to discount and sum up the expected revenues that the asset will generate in the years until retirement (OECD 2001, 2009). The consumption of fixed capital, *CFC*, is the diminishment of the net capital stock of existing assets between two consecutive years. As assumptions on future revenue and a discount rate are involved in its calculation, the consumption of fixed capital does not have a physical counterpart.

<heading level 3> **2.2.2) The relation between capital stock and capital service**

Depending on its age-efficiency, a certain amount of gross fixed capital provides an annual flow of capital service to the sector it belongs to. Throughout this work, we measured the capital service by industrial assets in terms of their production capacity G, and inspired by Lennox and colleagues (2005), we introduced the capacity utilization rate $\eta_2(t,t',j)$, that relates industrial output and production capacity:

$$x(t,j) = \sum_{t'} G(t,t',j) \cdot \eta_2(t,t',j) \quad (4)$$

There are two ways of determining the capital intensity matrix of new production capacity from aggregated data. First, the average or attributional capital matrix is determined as amount of capital stock needed to produce a unit of output (Miller and Blair 2009)[1]:

$$B^a = C \cdot \hat{X}^{-1} \qquad (5)$$

In the marginal approach (Fleissner and colleagues 1993), the capital intensity is determined by the recent investment to build new assets, K_B, divided by the capacity addition G_{in},

$$B^m = K_B \cdot \hat{G}_{in}^{-1}, \qquad (6)$$

[1] Miller and Blair (2009) denote the capital stock by *K*, whereas here, we use *C* for the stock of gross fixed capital and *K* for the flows into fixed capital.

where K_B denotes the part of the investment matrix K associated with building up new capacity. Provided that both K and C are determined by national statistical offices, both attributional and marginal capital requirements matrixes can be calculated. Here we applied a vintage-lifetime capital model and therefore, we used the marginal B matrix as it contains information on the capital intensity of the latest assets.

<heading level 2> **2.3) Modeling the resources needed to build up, dismantle, and maintain fixed capital**

We now embed the dynamic capital and material stock model shown in Figure 2 into the general system of the industrial metabolism shown in Figure 1. To illustrate the connection between stock dynamics and technical coefficients, we first present a model of the life cycle input requirements of a capital good (Figure 3) in a given sector. The life cycle consists of three stages, and each of them is characterized by a specific capital requirements vector: construction (B), maintenance (R), as well as demolition (D)[2] (Figure 3). The throughput properties are characterized by the technical coefficients (A).

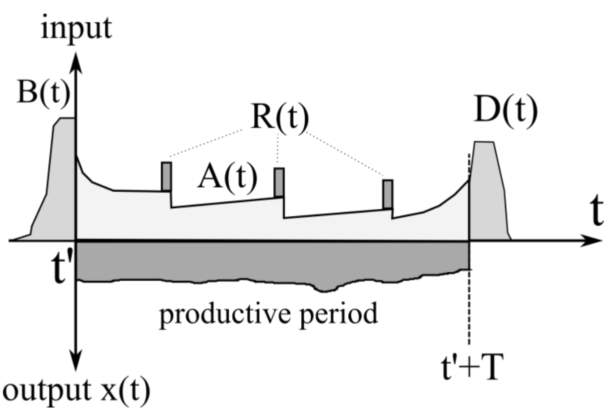

Figure 3: The life cycle of a single factory as part of an industrial sector.

To treat all industrial sectors simultaneously, these requirements can be written in matrix form, where the row indicates the sector that supplies the requirement and the column

[2] Note that the elements of D can be negative, which represents the salvage value of the asset.

indicates which sector the capacity belongs to. There are two ways of obtaining these matrices. One uses top-down data on gross fixed capital formation *GFCF* or the capital flow matrix *K* from the system of national accounts. The second approach is to use life cycle inventories (LCI) of existing and future technologies, to convert them to monetary units by applying appropriate price information, and to scale them up to the sectoral level. The latter approach may contain much detail about physical inputs, especially for different materials, but usually overlooks ancillary inputs such as planning, insurance, parts of facility operation, etc. We first discuss the 'top-down'-method and show that the previous approaches of modeling investment can be related to a common 'investment equation'. Then we introduce the life-cycle inventory-based 'bottom-up'-approach and establish a further connection to the perpetual inventory method.

<heading level 3> **2.3.1) Capacity expansion and gross fixed capital formation in the literature**

The previous approaches to include capital stock formation in static and dynamic IO modeling can all be derived or at least understood from the general equation (7), where only requirements for maintenance/replacement *R* and new construction *B* are considered:

$$GFCF = R \cdot x + B \cdot \dot{x} \qquad (7)$$

A first special case are static models, where $\dot{x}$ and B are not defined and where all capital investment is attributed to the existing stock (equation (8)).

$$R = K \cdot \hat{x}^{-1} \qquad (8)$$

Examples include Lenzen (2001) and Peters and Hertwich (2006). This approach leads to a systematic over-estimation of the impacts of current production, as between 15% and 40% of economic output is invested in new industry assets or residential buildings (World Bank

2013), which is not related to the throughput or historic investments required to satisfy current final demand.

Alternatively, one can attribute all investment to the expansion of production capacity, as was proposed by Leontief (1951), (equation (9)). The *B*-matrix contains many sectors that do not contribute to capital formation and hence, *B* is in general not invertible, but the system can be re-arranged into a form that only inverts a part of the system that does produce capital goods (Fleissner and colleagues 1993). Duchin and Szyld (1985) point out that the model requires full production capacity utilization at any time, which means that in periods of falling output (negative $\dot{x}$), the term $B\dot{x}$ turns negative and the industry 'eats itself'.

$$\begin{cases} R = 0, \\ x = Ax + \tilde{y} + B\dot{x} \end{cases} \qquad (9)$$

Duchin and Szyld (1985) therefore propose a modified model (equations (10)) with exogenously determined capacity estimates c^* and a set of investment matrices B^θ that refer to investments made several years before a new facility is eventually taken into operation.

$$\begin{cases} o(t+\tau) = \max\left(0, c^*(t+\tau) - c(t+\tau-1)\right) \\ c(t+\tau) = c(t+\tau-1) + o(t+\tau) \\ x(t) = Ax(t) + Rx(t) + \tilde{y}(t) + \sum_{\theta=1}^{\tau} B^\theta(t) \cdot o(t+\theta) \end{cases} \qquad (10)$$

The first of the equations (10) ensures that the capacity change *o* is not negative. In expanding sectors the capacity change is the difference between expected capacity c^* and actual capacity *c* in the previous year. The second equation adds the capacity addition *o* to the existing capacity *c*. The last equation is the market balance with an investment term $B \cdot o$ with a time lag. This approach was applied to forecast changes in capital investments in the US economy as consequence of increasing automation (Duchin and Szyld 1985; Leontief and Duchin

1986). Scenarios for the *A*-matrix for 1990 and 2000 were built by Leontief and Duchin (1986), but the changes in the *A*-matrices were not derived from a combination of dynamic stock models of existing assets with the deployment of new, marginal technologies. Their approach neglects dismantling and demolishing, which are crucial when modeling a metabolic transition, as certain production technologies are to be phased out over time. The distinction between maintenance (applied to existing facilities) and replacement (new assets that replace old ones) is not made. This distinction is important in a cohort-based model where the *A*-matrix changes from one year to the next due to both maintenance and replacement.

<heading level 3> **2.3.2) Obtaining capacity expansion and gross fixed capital formation from national statistics**

In section 3 we will develop a dynamic model that computes the total industry output x *and* the inter-industry requirements A for a given future demand level and industrial technology mix, as given by the BLUE MAP scenario, for example (International Energy Agency 2010).

To obtain the required model parameters, we need to divide the investment matrix *K* into one part K_B associated with building new assets, one for maintenance (K_R), and one for dismantling (K_D) (Fig. 2).

$$K = K_B + K_R + K_D \quad (11)$$

This divide allows us to determine the B, R, and D-matrices from top-down data, provided that total output, new capacity, and retiring capacity are known:

$$\begin{cases} B^m = K_B \cdot \hat{G}_{in}^{-1} \\ R = K_R \cdot \hat{x}^{-1} = K_R \cdot \left(\underset{i}{diag} \left(\sum_{t'} G \odot \eta_2 \right) \right)^{-1} \\ D = K_D \cdot \hat{G}_{out}^{-1} \end{cases} \quad (12)$$

Figure 4 provides a graphical representation of the relationships between the different system variables.

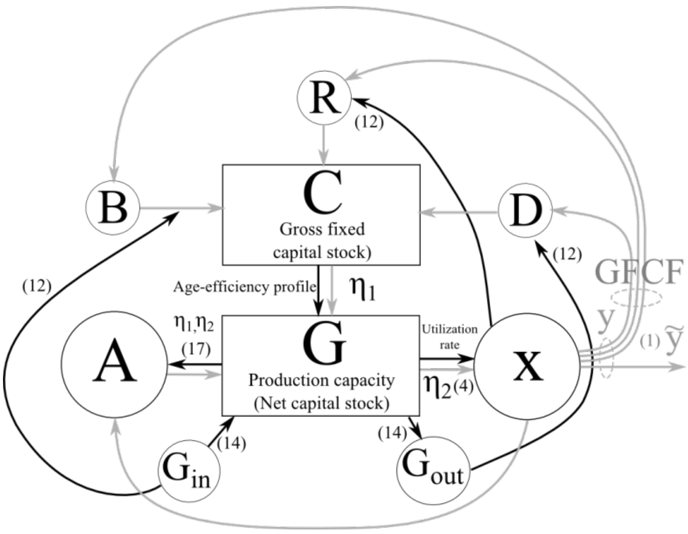

Figure 4: Overview of the relationship between the stocks of gross fixed capital and production capacity (boxes) and the variables representing or describing throughput (circles). Model relationships are drawn black and monetary flows are drawn grey.

<heading level 3> **2.3.3) Capacity expansion and life cycle inventories**

A comprehensive set of life cycle inventories covering construction, operation, and the end-of-life phase of different assets would allow us to determine the matrices B, R, and D by converting the physical inventories to monetary flows by using appropriate price information. Moreover, life cycle inventories can be connected to input-output models to estimate additional service inputs that are not commonly tracked in physical inventories. This type of hybridization has some tradition in the research community (Suh and colleagues 2004; Stromman and colleagues 2009; de Haes and colleagues 2004). Including life cycle inventories of very specific or even future technologies may help to increase the resolution of different industrial sectors and may amend the predictive capacity of the model. For example, the electricity generation sector may be split into established (coal-, nuclear-, or hydropower), or new energy technologies (concentrated solar power or coal combustion with carbon capture and storage) (Hertwich and colleagues 2013). A compilation of commensurable LCIs for cutting-edge or future energy technologies, together with exogenous assumptions on their future market shares, enables us to synthesize the marginal *A*-matrix of a given year. The inventories would also allow us to obtain the matrices B^m, R, and D for a specific technology or an entire sector. Life cycle inventories can thus be used to determine the technical coefficients $u(i, j, t', s)$ of the unit process of industry j using technology s produced in vintage t', and they provide a physical basis for determining the age-efficiency profiles $\eta_1(t, t', j, s)$ that are required to estimate the net capital stock and the consumption of fixed capital (section 2.2).

<heading level 1> **3) A capacity-driven dynamic input-output model**

The model of productive capital stock tracks the capacity of each industrial sector *j* over different vintages *t'* and technologies *s*. To distinguish capacity from capital, we denote the former by *G* and the latter by C (cf. Table 1).

$$G(t, j) = \sum_{t',s} G(t, t', j, s) \qquad (13)$$

New capacity $G_{in}(t = t', j, s)$ of technology *s* in industry *j* and retiring capacity $G_{out}(t, t', j, s)$ are connected via a dynamic capacity model, as in the perpetual inventory method (OECD 2001) or in cohort-based dynamic stock modeling (Müller 2006) (cf. section 2.2):

$$\begin{aligned} G_{out}(t, t', j, s) &= G_{in}(t', j, s) \cdot \lambda(t - t', j, s) \\ G(t, t', j, s) &= G_{in}(t', j, s)\left(1 - \sum_{t' \le t'' \le t} \lambda(t'', j, s)\right) \cdot \tau \end{aligned} \qquad (14)$$

By using the technical coefficients of a unit of production $u(i,j,t',s)$ as defined in section 2.3.3, we can synthesize the inter-industry flow matrix from

$$Z_{ij}(t) = \frac{u(i,j,t)}{\eta_1(t,j)} \cdot x(j,t) = \sum_{t',s} u(i,j,t',s) \cdot \eta(t,t',j,s) \cdot G(t,t',j,s) \qquad (15)$$

Where $\eta(t,t',j,s)$ is defined as the ratio of capacity utilization and age-efficiency:

$$\eta(t,t',j,s) = \frac{\eta_2(t,t',j,s)}{\eta_1(t,t',j,s)} \qquad (16)$$

In equation (15) the inter-industry flow between sectors *i* and *j* is the product of the unit process requirements *u* corrected for the age-efficiency η_1, multiplied with the total output of sector *j*, which is the product of capacity *G* and utilization rate η_2.

The total *attributional A-matrix* can be synthesized from the inventories of the individual units as follows:

$$A^a{}_{ij}(t) = \frac{Z_{ij}(t)}{x_j(t)} = \frac{\sum_{t',s} u(i,j,t',s) \cdot \eta(t,t',j,s) \cdot G(t,t',j,s)}{\sum_{t',s} \eta_2(t,t',j,s) \cdot G(t,t',j,s)} \qquad (17)$$

Equation (17) combines life-cycle inventory data with dynamic stock modeling and represents a synthesis of the average A-matrix of technical coefficients from bottom-up inventories. The possibility of such a synthesis was pointed out by Lennox and colleagues (2005). The *marginal A-matrix* comprises the latest technology only *(t'=t)*, and reads

$$A^m{}_{ij}(t) = \frac{\sum_{s} u(i,j,t,s) \cdot \eta(t,t,j,s) \cdot G_{in}(t,t,j,s)}{\sum_{s} \eta_2(t,t,j,s) \cdot G_{in}(t,t,j,s)} \qquad (18)$$

We can now formulate a demand- and capacity-driven dynamic input output model. Assume that for each year of the modeling period we were given an exogenous net final demand $\tilde{y}$

that does not contain requirements for build-up, maintenance, or disposal of fixed capital. We assume the capital intensity matrices B^m, R, and D to be known from prospective studies on future technologies, and we assume lifetimes $\lambda(t-t', j, s)$, age-efficiencies $\eta_1(t, t', j, s)$, load factors $\eta_2(t, t', j, s)$, and the type split of new investments, $T(t, j, s)$, and the age structure of the capital stock at a starting year, $G(t=t_0, t', j, s)$, to be given:

Given: $\tilde{y}, R, B^m, D, \lambda, \eta_1, \eta_2, T, u, G(t=t_0, t', j, s)$

To be obtained: x, A, G_{in}, G_{out}

The following equations are to be performed as year-by-year calculation, starting in the first model year t_0+1. The scheme of calculations is illustrated in Figure 5.

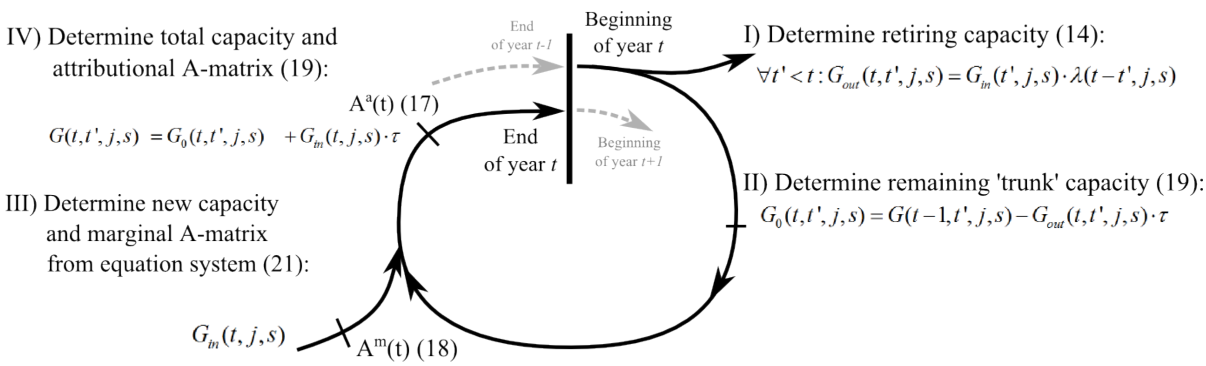

Figure 5: Scheme of calculations for the year-by-year loop.

First, we determine $G_{out}(t, t', j, s)$ according to equation (14) and subtract the dismantled capacity from the existing stock, which was transferred from the previous year, and denote the so-obtained intermediate capacity by $G_0(t, t', j, s)$:

$$\begin{aligned} G_0(t,t',j,s) &= G(t-1,t',j,s) - G_{out}(t,t',j,s)\cdot\tau \\ G(t,t',j,s) &= G_0(t,t',j,s) \quad + G_{in}(t,j,s)\cdot\tau \end{aligned} \qquad (19)$$

By substituting $x(t,j)$ with $\sum_{t',s}\eta_2(t,t',j,s)\cdot G(t,t',j,s)$ according to equation (4), we can reformulate the market balance (equation (1)) as shown in equation (20). Here, the type split *T(t,j,s)*, that denotes the share of different technologies within a sector, e.g. the share of wind power in electricity generation, was introduced.

$$\begin{aligned} &\sum_{t',s}\left(\eta_2(t,t',j,s)\cdot G_0(t,t',j,s) + \eta_2(t,t,j,s)\cdot T(t,j,s)\cdot G_{in}(t,j)\cdot\tau\right) = \\ &\tilde{y}(t) + \left(A(t)+R(t)\right)\cdot\left(\sum_{t',s}\left(\eta_2(t,t',j,s)\cdot G_0(t,t',j,s) + \eta_2(t,t,j,s)\cdot T(t,j,s)\cdot G_{in}(t,j)\cdot\tau\right)\right) \\ &+\sum_{s} B^m(t,s)\cdot T(t,j,s)\cdot G_{in}(t,j) + \sum_{t',s} D(t',s)G_{out}(t,t',j,s) \end{aligned}$$

$$(20)$$

We solve equation (20) for $G_{in}(t,j)$ and combine the so-obtained equation with equation (17) for the A-matrix and (19) for the capacity balance. This leads us to equation system (21), which comprises equations (17), (19), and (20), and which has to be solved for each model year.

$$\begin{cases} G_{in}(t,j) = \left(\left(1-A(t)-R(t)\right)\cdot\sum_{t',s}\eta_2(t,t,j,s)\cdot T(t,s)\cdot\tau - \sum_{s}B^m(t,s)\cdot T(t,s)\right)^{-1}\cdot \\ \qquad\qquad \left(\tilde{y} - \left(1-A(t)-R(t)\right)\sum_{t',s}\eta_2(t,t',j,s)G_0(t,t',s) + \sum_{t',s}D(t',s)G_{out}(t,t',j,s)\right) \\ \\ A^a{}_{ij}(t) \quad = \dfrac{Z_{ij}(t)}{x_j(t)} = \dfrac{\sum_{t',s}u(i,j,t',s)\cdot\eta(t,t',j,s)\cdot G(t,t',j,s)}{\sum_{t',s}\eta_2(t,t',j,s)\cdot G(t,t',j,s)} \\ \\ G(t,t',j,s) \;= G_0(t,t',j,s) + G_{in}(t,j,s)\cdot\tau \end{cases} \qquad (21)$$

Given that a unique solution for $G_{in}(t, j)$ and $A(t)$ could be obtained using an iterative approach similar to the one designed by Lennox and colleagues (2005), $x(t)$ can be determined by solving equation (1) for the total required industry output *x*:

$$x(t) = \left(\mathrm{I} - A(t) - R(t)\right)^{-1} \cdot \left(B^{m}(t) \cdot G_{in}(t) + D(t) \cdot G_{out}(t) + \tilde{y}(t)\right) \quad (22)$$

Performing these calculations for all model years from t_0+1 to the time horizon of the model yields a time series of *A*-matrices and industry output *x*, which can be further analyzed using standard techniques of input-output modeling.

<heading level 1> **4) Discussion**

We discuss to what extent the concepts and the model developed answer the research questions formulated, how they could be applied in future work, and how they could be linked to other models of the social metabolism.

The connection between dynamic modeling of capital stocks and material stocks was identified in section 2.2., and in sections 4.1 and 4.2 we discuss potential synergies between the two methods. In section 3 we showed how ageing and turnover of the capital stock determine the change of industrial efficiency and marginal inventories over time, and in sections 4.3 and 4.4 we discuss the consequences of this approach. Section 3 also contains a dynamic IO model based on a vintage approach for the productive capital stock, and in section 4.5 we discuss and compare this model to the one by Duchin and Szyld (1985). Finally, section 4.6 addresses research question 4 about the relation between our framework and dynamic material flow analysis, integrated assessment models, and general equilibrium models.

<heading level 2> **4.1) Physical and economic accounting of capital stocks: The connection between dynamic MFA and IOA**

The similarities between measuring the gross capital stock with the perpetual inventory method and dynamic modeling of material stocks with a cohort-lifetime approach open up the opportunity to cover both physical and monetary aspects of industrial assets by a common modeling framework. A profound understanding of the material demand for building up these assets and the material stocks stored within them would allow us to indentify the contribution of industrial assets to overall material demand, potential resource scarcity, and the future potential for material recycling. Including both physical and monetary aspects in the dynamic stock model may increase resolution and validity of the assessment: Using detailed industry classification codes would allow a more detailed tracking of material flows associated with industrial assets as it is possible today, and statistics on scrap recovery could amend the monetary statistics on capital retirement and vice versa. Data reconciliation between different pieces of information on the physical and the monetary layer could lead to a mutual refinement of the quantification of both aspects. Finally, both models share the same data and assumptions on asset lifetime and its distribution. Compiling statistics on asset lifetimes has an 80 year old tradition in econometrics (Winfrey 1935; OECD 2001), whereas MFA has focused on service lifetimes of products in final use (Müller and colleagues 2007). Comprehensive data on asset and product lifetime that covers both industry and final use exist. However, these data need to be reviewed regarding how they were obtained and what sectors and cohorts they represent, and harmonized before being used in a common model framework. Modeling the turnover of industrial assets is a delicate task, as different parts or materials of an asset may have different lifetimes, or some parts may be replaced more frequently than others. An oil refinery, for example, consists of infrastructure such as roads or pipes, different reactors, and catalysts, which all have their specific material content and turnover. Our approach is not consistent regarding how these dynamics are treated. The investment model (equations (11) and (12)) distinguishes between investment K_B, maintenance K_R, and demolition K_D, but the lifetime model (equation (14)) only applies to the historic investments and does not cover the capital flowing into maintenance and demolition. This problem could be solved by considering that the lifetime of capital goods depends not only on the sector where it is deployed but also on the type of product. One could therefore distribute the different capital goods within one sector onto the K_B, K_R, and K_D matrices and assign product and sector-specific lifetimes, as it is shown in the appendix of OECD (2009).

In a world constrained by resource scarcity and emissions caps, material stocks should be tracked as carefully as capital stocks to facilitate the estimation of future mineral resource use related to industrial assets and the potential for material recovery and recycling from obsolete productive capital.

<heading level 2> **4.2) Tracking materials through inter-industry flows and stocks**

The model presented here does not respect the mass balance for industries. The use of natural resources, waste generation and use, and emissions to air and water are not covered by monetary supply and use tables (SUT). Recent developments in accounting and modeling allow for establishing a mass balance not only for product markets but also for industries (Schmidt and colleagues 2010; Nakamura and colleagues 2007). When constructing an IO model from an SUT one has to consider that different constructs affect the production balance and the process-wise mass balance in different ways, and routines to include the accounts for resources, waste, and emissions, in the construction of IO tables have yet to be developed (Majeau-Bettez and colleagues 2013). The introduction of the material concentration array $\mu(t',j,m)$ may be a first step to quantify the material content of industrial outputs. Since the output of industrial sectors is aggregated from many individual products and factories, the array $\mu(t',j,m)$ is actually not a single value, but a distribution of many different values. If one knew the specific product composition of all subsectors s of a given industry *j*, one could obtain the probability distribution of material concentration $\mu(t',j,m)$ from aggregating the material concentration of individual outputs $\mu(t',j,s,m)$ by weighting the latter with the output of each technology $\eta_2(t,t',j,s)\cdot G(t,t',j,s)$. Using material content distributions rather than only their mean values would not only increase the scientific value of these estimates; it would also allow us to perform data reconciliation to obtain mass-balanced industrial processes and to determine missing flows from the mass balance equation. By considering distributions rather than mean values only, one can quantify how well the product studied is represented by the sectoral average. This would help us to decide whether to use material concentrations of monetary flows or genuine material flow statistics for each specific case.

<heading level 2> **4.3) Modeling marginal inventories and dynamics of change, replacement rates, and technology learning**

By separating accounting from modeling, the validity of the data gathered and the flexibility of their application can be improved significantly (Majeau-Bettez and colleagues 2013). A vintage model that tracks capital stocks over time is such an example. Combined with a model for asset service lifetime, it can be used to determine the gross capital stock and the associated material stock and their respective turnover, the average and marginal capital intensity of productive assets, the investment flows required to maintain the stock, and the distribution of technical coefficients of that particular industry and the change of these coefficients over time. The principle calculations to obtain this information from a bottom-up inventory were derived in sections 2 and 3. As outlined in the introduction, it is the turnover speed of the existing assets that determines how quickly new technologies can replace old ones, and the model presented here shows how technological change expressed in terms of process inventories can be used together with a cohort-lifetime model to determine both attributional (retrospective) and marginal (prospective) matrices of technical coefficients of inter-industry flows. The practical implementation of such a model is challenging due to data limitations and uncertainties. Still, the modeling and accounting framework we presented can serve as a guideline for future modeling efforts. The framework brings together different aspects of the social metabolism, which at present are covered by the different sub-disciplines LCA, IOA, and national accounting, but which were shown to have substantial overlap.

<heading level 2> 4.4) The connection between LCA and IOA: The issue of scale and representation.

Calculating the average *A*-matrix from equation (17) discards all information about the sub-structure of the different industries; only the average technical coefficients are kept. In reality the different technical coefficients of the assets within the sector form a distribution of input requirements with cohort- and technology-specific values $u(i, j, t', s)$ and weighting factors $\eta(t, t', j, s) \cdot G(t, t', j, s)$. The break-down of the input structure of a sector into different vintages *t'* and technologies *s* allows us to determine how well a given technology is represented by the distribution of the sectoral input structure. It also allows for removing specific technologies and vintages from the calculation of the sectoral average, which may facilitate the compilation of hybrid life cycle inventories of larger systems (Arvesen and colleagues 2013).

<heading level 2> 4.5) Comparison of our dynamic model with the one of Duchin and Szyld (1985):

The IO model based on a vintage-lifetime model of the productive capital stock represents an extension of the model developed by Duchin and Szyld (1985), as tracking different vintages of capital through their lifetime allows us to endogenously determine both the demand for new capacity and the flow of retiring capacity. Most importantly however, our model connects the *A*-matrix of technical coefficients to the composition and the turnover of the productive capital stock, which makes it suitable for modeling substantial changes in the industrial metabolism that occur over many years, such as the transition to a low-carbon economy. Duchin and Szyld use exogenous values for capacity estimates and final demand, whereas we assume exogenous utilization rates and final demand. Duchin and Szyld introduce a time lag between investment and commissioning of plants to reflect that large construction projects take some years to be completed. Our model is based on a year-by-year calculation of the turnover of the capital stock and cannot handle such a time lag; however, it could be modified to include an optimization routine that minimizes overcapacity between different years and that at the same time accounts for the time-lag between investment and commissioning of new assets.

<heading level 2> **4.6) Application and the connection to technology-rich IAMs:**

Cohort-lifetime-based models are already state-of-the-art for certain end-use sectors, especially the vehicle fleet (Van Schaik and colleagues 2002; Cheah and colleagues 2009; Pauliuk and colleagues 2012) and the building stock (Sandberg and Brattebø 2012; Pauliuk and colleagues 2013b). Applying equation 17 to the passenger vehicle fleet illustrates the meaning of the computation of the *A*-matrix from bottom-up inventories: in this case it represents the fleet average fuel consumption calculated from cohort-age-specific data on the number of passenger cars (here: G), the annual distance travelled (here: η), and the age-dependent fuel efficiency (here: u). As industrial energy consumption and the materials contained in industrial assets receive more attention, the need for a cohort-age-specific treatment of these assets arises. Vintage-based accounting has a long tradition in capital stock measurement and a coordinated effort may enable researchers and accountants to synchronize and harmonize their inventories to provide a more detailed and reliable understanding of the dynamics of industrial efficiency and the related capital and material requirements.

One can 'rank' the different model families of the social metabolism regarding their physical and neo-classical economic stringency (Figure 6). While MFA systems are always mass balanced, no economic layer is contained in these models. An LCA only respects the mass balance for some inputs, and through hybrid LCA, there is a continuum of models between physical and process-based LCA and economic IOA. The Leontief IO-model is a specific formulation of the monetary balance for markets, and the Leontief dual model can be derived from the monetary balance of the industries. An IO-model is considered to follow the classic tradition in economics, as prices and quantities can vary independently of each other and are not interlinked by the concept of marginalism.

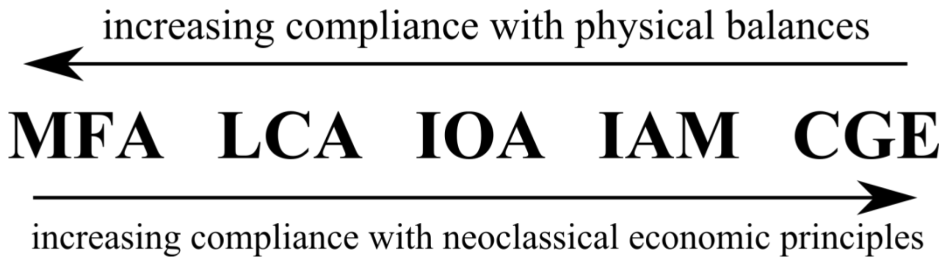

Figure 6: Major assessment methods in the framework of socio-economic metabolism, ranked by the extent to what they respect physical and economic principles.

Several integrated assessment models (IAM), e.g., the TIMES-model (Loulou and colleagues 2005), contain detailed descriptions of capital stocks including vintages and different types, similar to the concepts outlined here. Moreover, since these models minimize costs, the technical coefficients do not need to be fixed, but can vary over a certain range. This provides more flexibility in modeling, e.g. of recycling or by-product generation, but poses new challenges regarding the physical balances of the processes in these models, as material stocks in productive assets are not consistently covered. Computable general equilibrium models, finally, represent global, perfectly competitive product and labor markets; they represent an ultimate implementation of neo-classical principles. They typically use nested production functions, which assume some substitutability between different production factors, but no substitutability between intermediate requirements (Burfisher 2011). This model class is ‘time-less’ as it only computes equilibrium states. The capital stock is modeled on an abstract and aggregate level only, no vintages or even materials are tracked.

For long-term scenario modeling of resource use, emissions, and waste flows, a physically balanced model is indispensable. No matter how products and production factors are distributed between end users and producers (economic layer), physical balances should always be respected by the models, as they represent an insurmountable constraint to a transition to a low carbon society. Especially when modeling on the large scale this leads to challenges, when, for example, the extent of material recycling assumed needs to fit the actual amount of available recyclable material. The simultaneous cohort-lifetime based accounting of capital and material stocks can be combined with assessment methods other than dynamic input-output analysis. It well reflects the inertia that capital stocks represent in the system of the industrial metabolism and the constraints that result for the turnover of industrial assets on the large scale. In a world that is subject to resource and emissions constraints, the deliberate management of stocks over long time intervals is essential to create sufficient human well-being (Boulding 1966).

About the authors

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