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Supporting Information

Modeling demand for critical materials through a technology-specific stocks and flows model.

Jonathan Busch, Julia K. Steinberger, David A. Dawson, Phil Purnell and Katy E. Roelich

December 11, 2013

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Part I.
Mathematical Model Detail

1. Modeling Background

There is already a long history to the study of the material demands of human activity. Motivated by a variety of factors - e.g. investment planning in mining, government land and environmental planning, build-up of strategic stockpiles, waste management infrastructure planning - a variety of academic disciplines has developed approaches to project future material demand. Projections have been based on demand functions (e.g. [1]), production functions (e.g. [2]), input-output analysis (e.g. [3, 4]), the intensity of use technique (e.g. [5]) and stock dynamics (e.g. [6]). The approach this work is based on is the stock dynamics technique which has its conceptual foundations in the fields of Social Metabolism and Industrial Ecology.

Social Metabolism aims to understand societies interrelation with the environment in analogy to an organisms metabolism, i.e. the processes to convert raw inputs (food) into energy and the building blocks for useful products (cells and tissues), the processes to produce useful products and the processes that regulate this system ([7]). The hypothesis underlying social metabolism is that the functioning and evolution of societies can be understood in terms of these metabolic processes. In further analogy, understanding metabolic processes requires an understanding of the energy and material inputs, accumulations and outputs of the system. Material Flow Analysis (MFA) provides a framework for quantifying these stocks (accumulations) and flows (inputs and outputs) ([8, 9]). The stock dynamics methodology (also known as dynamic MFA or just stocks and flows modeling) ([10, 11, 12, 13, 14, 6, 15]) is based on the combination of MFA, which defines the links between stocks and flows in a material cycle, and system dynamics, which calculates projections of those stocks and flows ([16, 17]). As a modeling technique, stock dynamics aims to provide scenarios for future material demand, in-use stocks and outflows based on historical MFA statistics, in-use dynamics of materials and projections of future socio-economic activity.

Stock dynamics is distinct from the other four material demand projection techniques mentioned above in two key ways:

- **Stock driven** - this technique recognises that the dynamics of in-use stocks are a driver of long term future demand and waste flows. From a record of in-use stocks and an estimation of their lifetime distributions ([18]), waste flows ([10, 19, 20, 12, 21, 14, 22, 23]) and future demands ([24]) may be calculated.

- **Service based** - the difficulty of estimating future in-use stocks for a stock driven calculation is diminished by introducing services provided by materials as a determinant. Although the determination of in-use stocks of materials dates back to at least the 1930s ([25]), this linkage to service is first seen in the United States President's Materials Policy Commission of 1952 ([26]) but was scarcely used again

([27, 28]) until the work of Baccini, Bader, Real and Müller ([10, 11, 6, 15]). Service provision can also be linked to macro-economic models as, for example, in the MARKAL-MATTER project [29].

The justification for these methodological choices is described in detail by Müller ([6]), who also provides a clear description of stock dynamics as a modeling framework. Recent extensions to dynamic material flow modeling include the addition of GIS for the geo-location of stocks and flows by Tanikawa and Hashimoto [30] and the addition of layers of energy use and carbon emissions to quantify the climate change implications of material stocks and flows by Pauliuk et al. [31]

The extension of the stock dynamics model we have developed aims to go beyond a 'one-dimensional' description of in-use materials. Previous examples have used an in-use system definition of three layers ([6, 32, 33, 34]). The service provided sits at the top driving the in-use stock of technologies that provide this service. The dynamic calculation of stocks and flows occurs at this level of technologies that have a lifetime function. From the determination of the inflows and outflows of technologies, the stocks and flows of materials embedded in the technologies are then calculated. Mathematically, there is only a single dynamic calculation of stocks and flows at the technology level and the other variables are derived linearly from this - hence we term this 'one-dimensional'. Our model expands the technology layer, allowing a technology structure, such as a vehicle or building, to have components, such as a battery or heating system. These components each can have their own lifetime functions and the dynamic calculation must thus be carried out at each technology layer. As components may be nested in the model to any depth, this could be described as an 'n-dimesnional' model.

2. Model Scope and Structure

The model developed here describes the stocks and flows of technology objects as well as the materials contained in those objects. It is, however, restricted to the stocks and flows of technologies and materials only in a limited part of their complete lifecycles. Only the in-use stocks and treatment of outflows into waste and secondary stocks is included. The full mining, processing and manufacturing phases of the lifecycle are not included. A high level, graphical representation of the stocks and flows for a single infrastructure, technology structure, component and material is shown in Figure S1. At the infrastructure level, the only variable is the in-use stock. For technology structures, components and materials, the in-use stock is joined by a waste stock and a secondary stock as well as flows between these and a virgin inflow.

It should be noted that the purpose of this model is not to precisely model the lifecycle of materials, including all the processing and waste management they undergo, but to identify the connections between technology attributes and material flow dynamics and to identify opportunities for reuse and recycling to improve material efficiency. The hierarchical model structure and focus on in-use stocks reflects this purpose.

In the remainder of this document, the details of how the model is implemented is described. Section 3 describes the general structure of the model in words, briefly describing the different types of stocks that are used and how they are connected. Section 4

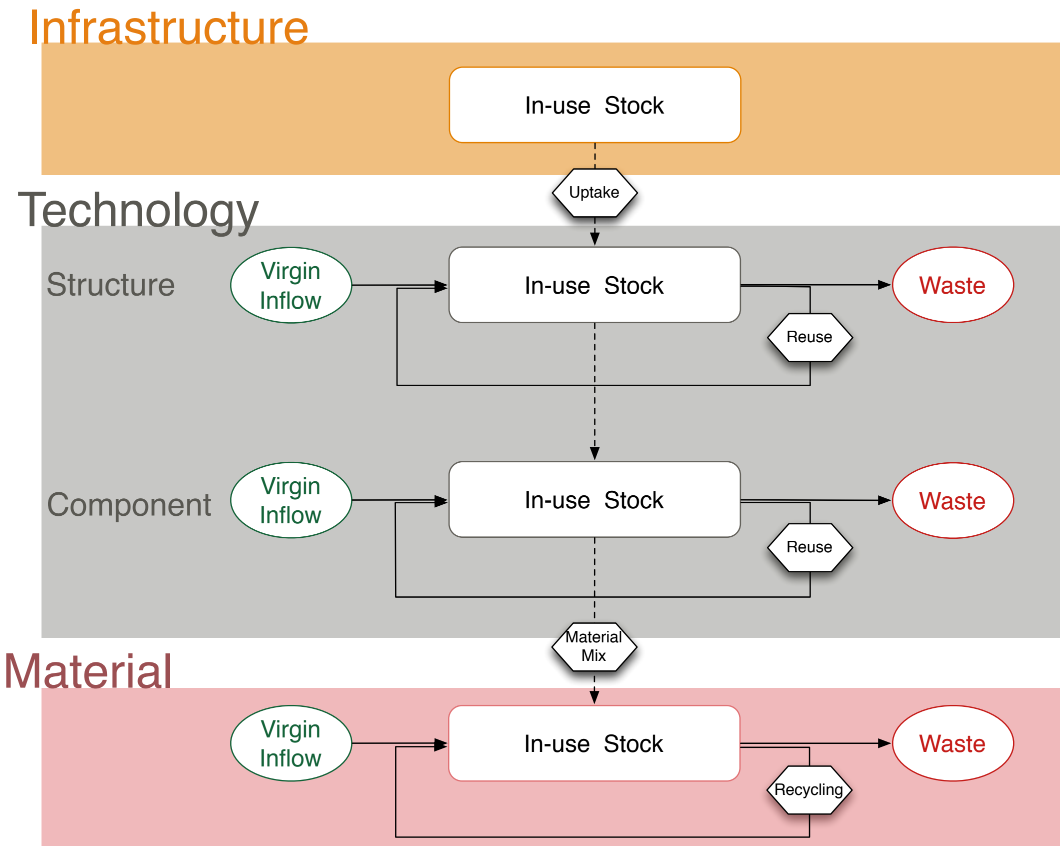

Figure S1: A schematic of the model indicating the different types of stocks and flows in the model and relationships between them.

describes the basic differential equations that describe the time evolution of stocks and flows.

3. Model structure - types of stocks and flows

The model is split into three basic types of stocks: infrastructure, technology and material. Infrastructure stocks are determined by a deployment scenario and represent a service level; they do not represent any physical stocks. The technology objects that make up real world infrastructure are further split into structures and their components. Structures are those things that directly provide a service. Components may be nested such that a structure contains many components, each of which may contain more components and so on. Finally, both structures and components are made up of materials represented in the material stocks. Figure S1 shows a diagrammatic representation of the types of stocks, their associated inflows and outflows, and the connections between them.

The infrastructure stocks are determined by a deployment scenario that defines what level of service the infrastructure will provide over the period of time being simulated (from time t_0 to t_f). The infrastructure stock represents only a service level, not any physical stock that exists in the real world, hence it does not really make sense to speak of inflows or outflows of infrastructure.

Structure stocks are derived from infrastructure stocks via a technology mix that describes how much of the infrastructure service will be provided by each of a set of structure types. Structures are a representation of physical objects with real inflows (deployment of new structures) and outflows (decommissioning of structures). The inflows and outflows are determined by the required stock level and the lifetime of a structure.

Component stocks are derived from their parent stocks which can be either a structure or another component. The inflows and outflows of a component stock are determined by the stock level required, the lifetime of the component, and potentially the lifetime of the parent stock that it is a component of.

Finally, material stocks are derived from the structures and components in which they are contained via a material intensity.

3.1. End-of-life recovery

The treatment of end-of-life stock is intended to quantify the level of stock availability for recovery, recycling, re-manufacturing or reuse; not to provide a realistic representation of these processes. For this purpose, end-of-life stock outflow is sorted in the model into three different outflows: reuse/recycling, embedded and waste. Reuse/recycling has different names depending on the type of stocks involved. Technology structures and components may be 'reused', where this term includes the possibility of direct reuse of the structure or component for the same or a different purpose, or it may involve a re-manufacturing step which is not included in the model. In the case of materials, this process is called 'recycling' - materials are recovered from end-of-life to be recycled for either the same, or a different purpose. The reuse/recycling outflow in the model is hence defined as occurring at a single level; structures and components are reused, and materials are recycled at the same system level. Embedded flows are present in the model for accounting purposes and represent components or materials that are contained in a parent structure of component that is being reused. These components or materials are hence not available themselves for reuse or recycling, nor do they go to waste. The final possible outflow is structures, components and materials that are not embedded in a reused parent and cannot be reused or recycled themselves. These make up the 'waste' outflow. Waste outflows represent end-of-life stocks that go to end-of-life disposal to landfill (or incineration), or end-of-life structures or components that can be disassembled such that their constituent components and materials are available for reuse or recycling. Disassembly, in this context, could include simply removing the battery from a car or more complex processes like shredding the car and extracting the steel and aluminium.

The split into the three possible end-of-life flows is determined by a recovery fraction time-series that is supplied to the model for each structure, component and material. The fraction determines the how much of the end-of-life outflow at any time can be reused or recycled. This is performed top-down, such that a structure will be reused preferentially to its components and materials. The details of how this is applied in the model is given in the equations in the following section. The recovery fraction represents the total rate of reuse or recycling from end-of-life that is possible for a given structure, component or material. As such, it includes both the recovery efficiency, i.e. how much of the end-of-life stock is collected, and the process efficiency, i.e. how much is lost in disassembly, extraction, sorting or re-manufacturing.

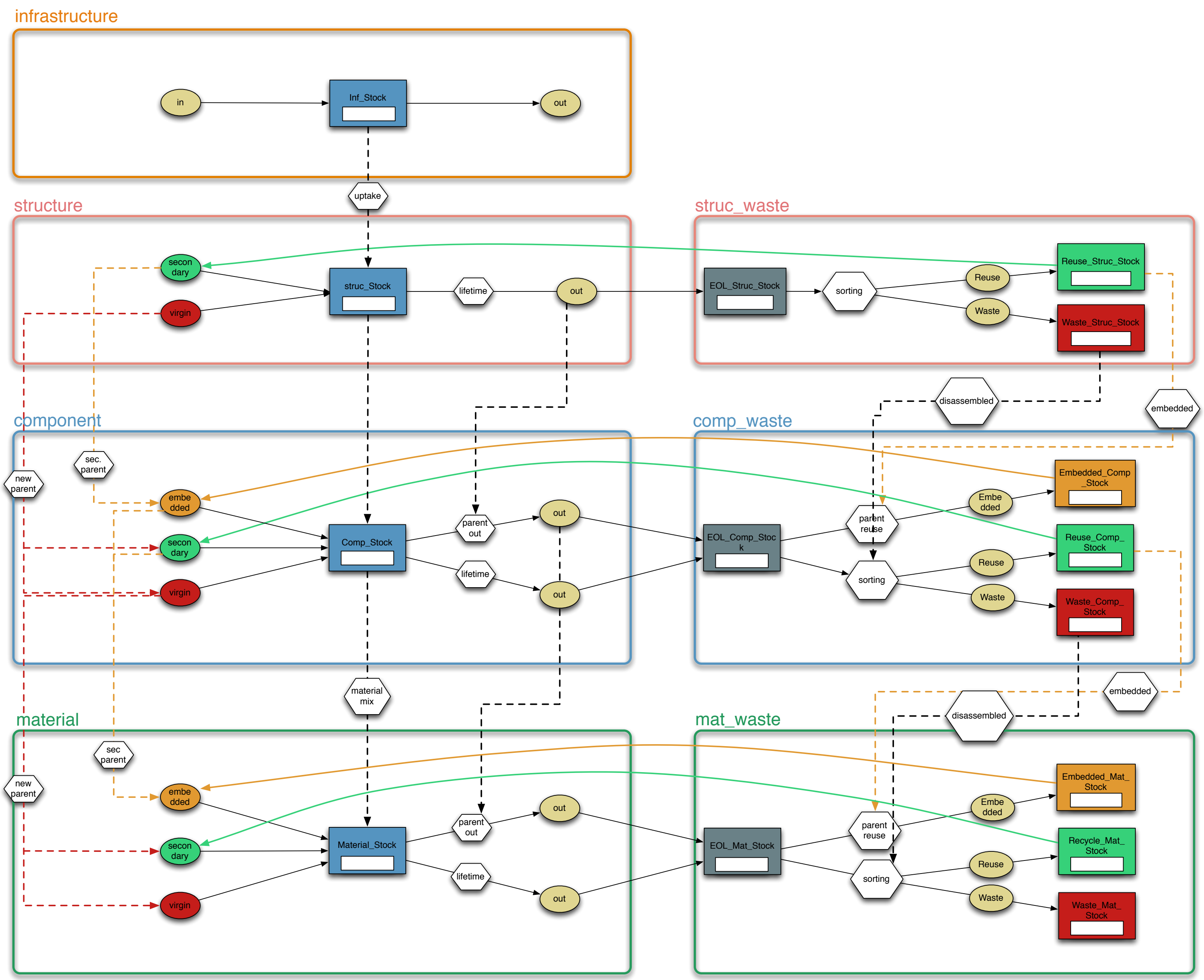

Figure S2: A schematic of the entire model showing in-use stocks as well as end-of-life stocks and all flows between them.

4. Differential equations for stocks and flows

The model is built, much like all material flow models, out of individual stocks with inflows and outflows. central to this description is the balance equation

$$\frac{\mathrm{d}}{\mathrm{d}t}K^{(i)}_m(t) = I_m(t) - O_m(t), \tag{1}$$

where $K^{(i)}_m(t)$ is the stock amount of object m at time t and $I_m(t)$ and $O_m(t)$ are the corresponding inflow and outflow respectively. This relation applies to every stock in the model.

Infrastructure stocks are determined by either the historical stock level or the scenario. As these stocks represent a service level, the inflow and outflow variables really have no physical meaning and are excluded from the model. For the remaining levels of the model hierarchy, the calculations for stocks and flows are described in the following sections and visually represented in Figure S2.

4.1. Structure stocks

The structure stocks are treated not as a single one-dimensional time-series but as a two-dimensional time-series where the install time of the structure provides the second dimension. A discretisation of this leads to the description of cohorts of the structure stock that evolve over time. The structure stock obeys the relation

$$K^{(s)}_m(t) = \int_{t_0}^{t} \mathrm{d}\kappa K^{(s)}_m(\kappa, t) = M^{(s)}_m(t) K^{(i)}(t) \tag{2}$$

where $K^{(s)}_m(\kappa, t)$ is the stock of structure m, installed at time κ, at time t (i.e. the cohort stock), $K^{(s)}_m(t)$ is the total stock at time t and $M^{(s)}_m(t)$ is the technology mix giving the number of structures of type m that make up the parent infrastructure.

The time evolution of the stocks and flows is derived from the following set of equations. The central relation describes the balance between inflows, outflows and the change in stock level

$$\frac{\mathrm{d}}{\mathrm{d}t}K^{(s)}_m(t) = I^{(s)}_m(t) - O^{(s)}_m(t)\,, \tag{3}$$

where $I^{(s)}_m(t)$ is the inflow and $O^{(s)}_m(t)$ is the total outflow at time t for all cohorts. The outflow can also be disaggregated into cohorts, denoted by $O^{(s)}_m(\kappa, t)$. The inflow, by the definition of a cohort, only happens once for each cohort and is hence completely defined by the variable $I^{(s)}_m(t)$. The balance equation can hence be written

$$\frac{\mathrm{d}}{\mathrm{d}t}K^{(s)}_m(\kappa, t) = I^{(s)}_m(t)\delta(t-\kappa) - O^{(s)}_m(\kappa, t)\,, \tag{4}$$

where $\delta(t-\kappa)$ is the Dirac delta function.

As well as the above balance equation, it is useful to define a 'conservation' equation for cohort stocks:

$$\int_{\kappa}^{\infty} \mathrm{d}t\, O^{(s)}_m(\kappa, t) = K^{(s)}_m(\kappa, \kappa)\,. \tag{5}$$

This equation is a consequence of the balance requirements and the assumption that all the stocks in a cohort will eventually be decommissioned.

4.1.1. Outflows

To use the balance equation to calculate the time evolution of the structure stocks, the next step is to determine the outflows of structures. Outflows of structures can be driven by two processes:

1. The structure reaches the end of its serviceable life and must be decommissioned. This process is represented by $O^{(l)}_m(\kappa, t)$.

2. The infrastructure stock decreases, reducing the required number of structures. This would be the case, for example, with a car scrappage scheme where internal combustion engine vehicles are replaced by low-carbon alternatives before they have reached the end of their serviceable life. As this outflow is caused by a reduced parent requirement, it is not obvious how it applies across the cohorts of the structure stock. This process is denoted by $O^{(r)}_m(\kappa, t)$.

The total outflow of structure stock is a combination of the outflows described above. In any case, the first reasonable step is to remove the stock that have reached the end of their serviceable life. This outflow is labelled $O^{(l)}_m(\kappa, t)$, and is calculated using a lifetime function, $L^{(s)}_m(\kappa, t)$ which obeys the relation

$$\int_\kappa^\infty \mathrm{d}t\, L^{(s)}_m(\kappa, t') = 1\,. \tag{6}$$

The lifetime function returns the fraction of stock added at time κ that reaches end-of-life at time t. If this was the only factors causing the decommissioning of structures, the outflow would be calculated simply using

$$O^{(l)}_m(\kappa, t) = L^{(s)}_m(\kappa, t) K^{(s)}_m(\kappa, \kappa)\,. \tag{7}$$

However, as outflows may also be caused by a reduction in infrastructure demand, applying this equation effects a double-counting of outflowing structures eventually leading to a negative stock level. To remedy this, the lifetime outflow must be adjusted such that the final stock level reaches zero, i.e.

$$K^{(s)}_m(\kappa, t) - \int_\kappa^\infty \mathrm{d}t \left[O^{(l)}_m(\kappa, t') + O^{(r)}_m(\kappa, t')\right] = 0\,, \tag{8}$$

in accordance with the conservation rule. To achieve this, we define the lifetime outflow with an additional scaling factor to account for stock previously decommissioned by the $O^{(r)}_m(\kappa, t)$ process,

$$O^{(l)}_m(\kappa, t) = A_m(\kappa, t) L^{(s)}_m(\kappa, t) K^{(s)}_m(\kappa, \kappa)\,. \tag{9}$$

We define the scaling factor, $A_m(\kappa, t)$, such that, should the lifetime be the only determinant of outflow from the current time forward and the factor remain constant, the stock level would eventually drop to zero and no lower, i.e.

$$K^{(s)}_m(\kappa, \hat{t}) - \int_{\hat{t}}^\infty \mathrm{d}t A_m(\kappa, \hat{t}) L^{(s)}_m(\kappa, t) K^{(s)}_m(\kappa, \kappa) = 0\,. \tag{10}$$

From this, it is straightforward to derive that the lifetime outflow is given by

$$O_m^{(l)}(\kappa, t) = K_m^{(s)}(\kappa, t) L_m^{(s)}(\kappa, t) \left[1 - \int_\kappa^t \mathrm{d}t' L_m^{(s)}(\kappa, t')\right]^{-1} . \tag{11}$$

We can now turn to the infrastructure demand driven outflows $O_m^{(r)}(\kappa, t)$. This outflow only occurs when there is a reduction in the demand for infrastructure, when the demand for infrastructure rises, an inflow is required instead. The additional outflow or inflow required to meet the required structure stock level can be calculated with

$$F_m^{(s)}(t) = \frac{\mathrm{d}}{\mathrm{d}t} K^{(i)}(t) + \int_{t_0}^t \mathrm{d}\kappa \, \frac{O_m^{(l)}(\kappa, t)}{M_m^{(s)}(\kappa)} . \tag{12}$$

If this is negative, then an additional outflow occurs, i.e.

$$\tilde{O}_m^{(r)}(t) = \min\left(0, F_m^{(s)}(t)\right) , \tag{13}$$

where $\tilde{O}_m^{(r)}(t)$ is the outflow not accounting for the structure intensity (i.e. in the infrastructure units **not** the structure units). This outflow needs to be evenly distributed over the cohorts of the structure stock, i.e.

$$O_m^{(r)}(\kappa, t) = \tilde{O}_m^{(r)}(t) M_m^{(s)}(\kappa) \frac{K_m^{(s)}(\kappa, t)}{K_m^{(s)}(t)} . \tag{14}$$

The total stock outflow is simply

$$O_m^{(s)}(\kappa, t) = O_m^{(l)}(\kappa, t) + O_m^{(p)}(\kappa, t) \tag{15}$$

The method of modeling outflows from structure stocks outlined above contains a couple of implicit assumptions. Firstly, it is assumed that old stock is always removed first before further redundant stock is removed. Secondly, the outflow of redundant stock is evenly distributed according to age - implying that no account is taken of the age of structures when redundant structures are removed.

4.1.2. End-of-life Stocks

The end-of-life stocks, unlike in-use stocks do not accumulate. The model processes these directly into stocks that may be reused and waste stocks that are destined for final disposal to landfill. The end-of-life stocks are thus directly determined by the outflow calculated above. The split of end-of-life stocks into reuse stocks and waste is carried out by a *recovery* process which is driven by a recovery scenario that determines the fraction of end-of-life stock that can be reused at any time. Reuse stocks and waste stocks both accumulate with reuse stocks being available for substitution of virgin inflows.

4.1.3. Inflow

If the stock change in Eq. 12 is positive, then an inflow into the new cohort is required, i.e.

$$I_m^{(s)}(t) = \max\left(0, M_m^{(s)}(t) F_m^{(s)}(t)\right) . \tag{16}$$

In the case where reuse of structure outflows takes place, this inflow is reduced. If we denote the reuse stocks $R_m^{(s)}(t)$, then the required virgin inflow can be calculated from the required total inflow, minus the available reuse inflow, i.e.

$$V_m^{(s)}(t) = I_m^{(s)}(t) - R_m^{(s)}(t)/\mathrm{d}t \, . \tag{17}$$

4.2. Component stocks

Component stocks are similar to structures, they are also derived from a parent stock and their time evolution is determined by factors that include a lifetime function. The outflow of components is again driven by the two possibilities of end-of-life decommissioning and reduced stock requirement. In the case of components, the second of these is a very different process. The reduction in parent stock for a component is caused by the decommissioning of a parent object. This is fundamentally different to the argument for reduced requirement of infrastructure. In the infrastructure case, it is fair to assume that old structures would be removed first before balancing the stocks. In the case of components, the reduction of parent stock will be due to the parent dynamics, usually regardless of the age of the components. The combination of these two outflows is thus different for the component dynamics.

The added complication of a component outflow being driven directly by it's parent dynamics, requires a component to know what parent cohort it belongs to. The component stock variable is thus a function not only of time, t, and deployment time, κ, but also the parent deployment time, κ'. We hence denote the component stock function as $K_{m,n}^{(c)}(\kappa', \kappa, t)$ where n labels the component type and m the parent.

The derivation of component stocks from a parent stock is defined similarly to the structure stocks as

$$K_{m,n}^{(c)}(t) = \int_{t_0}^{t} \mathrm{d}\kappa \, K_{m,n}^{(c)}(\kappa', \kappa, t) = M_{m,n}^{(c)}(\kappa', t) K_m^{(p)}(\kappa', t) \, , \tag{18}$$

where the technology mix is dependent on both the current time and the age of the parent stock. The parent stock may be either a structure, in which case

$$K_m^{(p)}(\kappa', t) = K_m^{(s)}(\kappa', t) \, , \tag{19}$$

or another component, in which case

$$K_m^{(p)}(\kappa', t) = \sum_n \int_{t_0}^{t} \mathrm{d}\kappa \, K_{n,m}^{(c)}(\kappa, \kappa', t) \, , \tag{20}$$

i.e. the sum of all components of the same type, regardless of their parents, and integrated over all the stock of the components at time t regardless of when their parents where deployed.

4.2.1. Outflows

As for structure stocks, the component stock outflow can be split into two separate parts: outflow due to parent decommissioning, $O^{(p)}_{m,n}(\kappa', t)$, and outflow due to components reaching end-of-life, $O^{(l)}_{m,n}(\kappa', \kappa, t)$. The parent outflow is simply

$$O^{(p)}_{m,n}(\kappa', t) = \max\left(0, -\frac{\mathrm{d}}{\mathrm{d}t} K^{(p)}_{m}(\kappa', t)\right) , \tag{21}$$

where the parent stock is as defined in Eq's (19) or (20) and in the units of the parent stock. When $t = \kappa'$, the parent cohort is new and no outflow occurs at this time - only inflows.

This parental outflow must be somehow shared amongst all the child cohorts. How this sharing is managed represents an assumption on how the age of a component impacts the preferential decommissioning of a parent. We assume that there is no impact - hence the parent outflow is distributed as an equal fraction of all child cohorts. This results in a parent induced outflow of

$$O^{(p)}_{m,n}(\kappa', \kappa, t) = \frac{K^{(c)}_{m,n}(\kappa', \kappa, t)}{K^{(p)}_{m}(\kappa', t)} O^{(p)}_{m,n}(\kappa', t) . \tag{22}$$

The end-of-life outflow of components is determined by the components lifetime function applied to the remaining stock. As for structures, this lifetime outflow must take account of outflows due to other processes so as to not result in negative stocks. The resulting lifetime outflow is

$$O^{(l)}_{m,n}(\kappa', \kappa, t) = K^{(c)}_{m,n}(\kappa', \kappa, t) L_{m,n}(\kappa, t) \left(1 - \int_{\kappa}^{t} \mathrm{d}t' L_{m,n}(\kappa, t')\right) \tag{23}$$

Implicit in this equation is the assumption that the lifetime applies only to the stock that is left after the components decommissioned with parents are removed.

The total component outflow is now given by

$$O^{(c)}_{m,n}(\kappa', \kappa, t) = O^{(p)}_{m,n}(\kappa', \kappa, t) + O^{(l)}_{m,n}(\kappa', \kappa, t) . \tag{24}$$

4.2.2. End-of-life stocks

The parent-child relationship between structures and components also complicates the treatment of end-of-life stocks. To begin with, it is now possible for a component to have reached end-of-life but be contained in a structure (or parent component) that has been processed into reuse stock. The first step to the component recovery process is thus the sorting of these component stocks into an embedded stock variable, i.e.

$$E^{(c)}_{m,n}(t) = R^{(p)}_{m}(t) + E^{(p)}_{m}(t) , \tag{25}$$

where $E^{(c)}_{m,n}(t)$ is the embedded stock and $R^{(p)}_{m}(t)$ is the parent reuse stock and $E^{(p)}_{m}(t)$ is the parent embedded stock. The remaining end-of-life stock, $\bar{K}^{(c)}_{m}(t)$ is then separated into reuse stock and waste stock according to a recovery scenario that determines the fractional split between these two - this is the same as the handling of reuse for structures.

4.2.3. Inflow

The equation describing inflow of components consists of two parts. The first is the inflow required to the new component cohort of each parent cohort to replace the components of remaining parents that have reached end of life. This is simply calculated directly from the lifetime outflows of cohorts adjusted for the change in component intensity, i.e.

$$I^{(c)}_{m,n}(\kappa', t) = \int_{\kappa'}^{t} \mathrm{d}\kappa \frac{O^{(l)}_{m,n}(\kappa', \kappa, t)}{M_{m,n}(\kappa', \kappa)} M_{m,n}(\kappa', t) \tag{26}$$

This equation holds for all $\kappa' < t$.

For the new parent cohort, the inflow replaces the outflows due to parent decommissioning. The inflow here is thus directly derived from the inflow of parent stock, i.e.

$$I^{(c)}_{m,n}(t) = M_{m,n}(\kappa', t) I^{(p)}_{m,n}(\kappa', t) \,. \tag{27}$$

In the case where reuse of the old stock is possible, the virgin inflow is calculated as for structures using

$$V^{(c)}_{m,n}(t) = I^{(c)}_{m,n}(\kappa', t) - R^{(c)}_{m,n}(t) \,. \tag{28}$$

4.3. Material stocks

The final step in the model calculations is the determination of material stocks derived from structures and components. Material stocks are treated almost exactly the same as component stocks – all the equations describing how the stocks and flows evolve over time are identical. The only difference is that materials currently cannot be nested like components.

4.4. Lifetime functions

The lifetime functions used to calculate the outflow of a stock resulting from a previous inflow have not been discussed until now. The functions used must obey the relation

$$\int_{\kappa}^{\infty} \mathrm{d}t \, L(\kappa, t) = 1 \,, \tag{29}$$

for both the structure lifetime, $L^{(s)}_{m}(\kappa, t)$, and the component lifetime, $L^{(c)}_{m,n}(\kappa, t)$, functions. This guarantees that all deployed stock will eventually be decommissioned. The current version of the model assumes a Gaussian lifetime function

$$L(\kappa, t) = \frac{1}{\sqrt{2\pi\sigma^2}} \mathrm{e}^{-\frac{(\tau - (t-\kappa))^2}{2\sigma^2}} \tag{30}$$

where τ is the mean lifetime and σ is the standard deviation. This function obeys the above required relation to a very good approximation as long as the mean is large enough and the standard deviation small enough. For stocks where the mean is small and the standard deviation large, a Weibull distribution would be more appropriate.

Part II.
Electric Vehicle Case Study

5 System Definition and Variables

5.1 System Scope and Structure

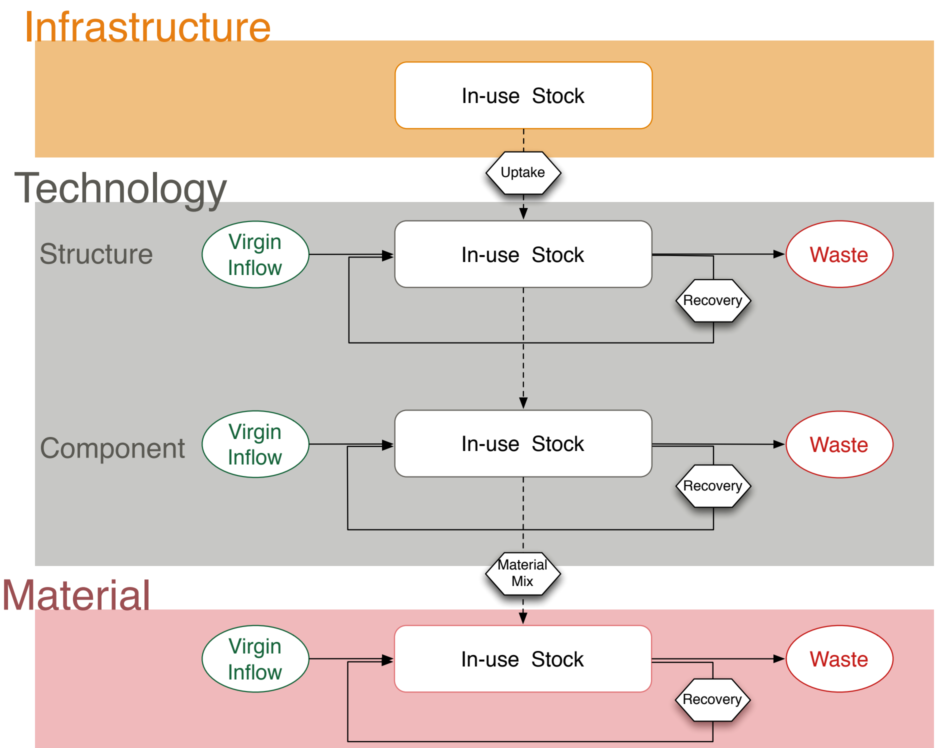

Figure S3: High level schematic of the hierarchical model structure including only single instances of infrastructure, technology structure, technology component and material stocks.

The model developed here describes the stocks and flows of technology objects as well as the materials contained in those objects. It is, however, restricted to the stocks and flows of technologies and materials only in a limited part of their complete lifecycles. Only the in-use stocks and treatment of outflows into waste and secondary stocks is included. The full mining, processing and manufacturing phases of the lifecycle are not included. A high level, graphical representation of the stocks and flows for a single infrastructure, technology structure, component and material is shown in Figure S3. At the infrastructure level, the only variable is the in-use stock. For technology structures, components and materials, the in-use stock is joined by a waste stock and a secondary stock as well as flows between these and a virgin inflow.

It should be reiterated that the purpose of this model is not to precisely model the lifecycle of materials, including all the processing and waste management they undergo, but to identify the connections between technology attributes and material flow dynamics and to identify opportunities for reuse and recycling to improve material efficiency. The hierarchical model structure and focus on in-use stocks reflects this purpose.

5.2 Infrastructure, technologies and materials

The model outlined in Figure S3 consists of four distinct types of stocks: infrastructure, technology structures, technology components and materials. This segmenting is used as the simplest set of possible classifications of objects that make up infrastructure. The infrastructure stock represents a level of service provided by the technologies and hence has no flows, as these are not physical. The physical infrastructure is described as being made up of technology structures that directly provide an infrastructure service (vehicles provide mobility, wind turbines provide electric power, etc.). Technology structures in turn are made up of functional components including batteries, motors, magnets, catalytic converters etc… Technology components in the model can be nested to any depth, thus a wind turbine structure could contain a nacelle, which contains a generator, which contains a permanent magnet. Any technology object (structure or component) can also contain materials, care must be taken not to double-count materials in nested components!

Type	Name	ID	Components		Material	Distinct Lifetime
			Name	ID		
Structure	ICE Vehicle	ICE	Catalytic Converter	Cat_Conv		Yes
Structure	Hybrid Electric Vehicle	HEV	Catalytic Converter	Cat_Conv		Yes
			NdFeB Motor	NdFeB_Motor		
			NiMH Battery	NiMH_Battery		
Structure	Plug-in Hybrid Electric Vehicle	PHEV	Catalytic Converter	Cat_Conv		Yes
			NdFeB Motor	NdFeB_Motor		
			Li-ion Battery	PHEV_Li-ion_Battery		
Structure	Electric Vehicle	EV	NdFeB Motor	NdFeB_Motor		Yes
			Li-ion Battery	EV_Li-ion_Battery		
Component	Catalytic Converter	Cat_Conv			Pt	
Component	NdFeB Motor	NdFeB_Motor			Nd	
Component	NiMH Battery	NiMH_Battery			Nd	
Component	Li-ion Battery	PHEV_Li-ion_Battery			Li	Yes
					Co	
Component	Li-ion Battery	EV_Li-ion_Battery			Li	Yes
					Co	

Table S1: The technology structures and components included in the case study of electric personal transportation in the UK.

The stock types described in this abstract form allow the model to be applied to a wide variety of infrastructure systems. In this paper, the example of personal transportation in the UK was used as a transition to low-carbon technologies. The full list of technology structures, components and materials included in this case studies are given in Table S1, along with the substructure of each object and whether it has a distinct lifetime from the object within which it is contained.

There are four different types of vehicles making up the four distinct structures. Each of these structures has components, some of which are common to more than one structure, e.g. all vehicles except full electric vehicles have catalytic converters. All three types of electric vehicles have the same type of NdFeB motor but the lithium-ion batteries in plug-in hybrid electric vehicles are different to those in electric vehicles. This is reflected in the material intensities of these components. All the vehicles also have a lifetime attribute, as do the lithium-ion batteries in electric and plug-in hybrid electric vehicles. Catalytic converters, NdFeB motors and NiMH batteries are assumed to last for the full lifetime of the vehicles in which they are contained. Hence, they do not have a separate lifetime.

5.2.1 A Note on Units

An important consideration in defining the objects that will exist in the model as shown in Table S1 is the choice of units that will be used. In an LCA study, or a material flow analysis without technological detail, a suitable unit for the material intensity of lithium in a battery, for example, would be kg/kWh. The reason this is a good measure in these cases is that it links the mass of material to the functional units that provide a desirable service. In the case of the model developed here, this approach is complicated by the presence of batteries as objects in the model that can be recovered and reused. There are thus several layers of 'functional service' within the model: transportation service (vehicle km) provided by the vehicles and energy storage (kWh) provided by the batteries. The relation between these is complicated and depends on a number of intrinsic and extrinsic factors, including the weight and air resistance of the car and the driving conditions of the average journey. In future work, the battery lifecycle could be elaborated to account for degradation in the storage capacity of the battery, which would then have to be described as an increase in the material intensity of lithium in a battery (kg are constant but kWh are less). A simpler solution is to combine the material intensity in kg/kWh with the kWh capacity of batteries required for a car outside the model and use units of kg/battery (or kg/unit) in the model. Because of this, all material intensities in the paper are given in kg/unit.

6 Data Sources and Manipulation

In this section, the technology details required for the model are listed along with their source. This includes the details of the material intensity of technologies, their lifetimes and recycling rates, and the details of scenarios that determine the roll-out of infrastructure.

6.1 Scenarios

6.1.1 Historical Stocks

Data on the historical stock levels of all types of vehicles are taken from Department for Transport (DfT) statistics. As the sales of electric vehicles where negligible up to 2010 and the sales of PHEVs non-existent, the historical stocks are only really relevant for ICE vehicles. We use the DfT statistics from 2001-2009 for sales of vehicles in the model (the future scenarios we use begin in 2010). Combined with the vehicle lifetime of 13 +/- 3 years, this means the results for end-of-life platinum stocks will be accurate by about 2020.

6.1.2 Future Projections

The scenarios used in the model come from the Department for Energy and Climate Change (DECC) 2050 Pathways Calculator[1]. This calculator relates possible infrastructure transition scenarios to the carbon emissions reductions they would achieve. There are a core set of four scenarios developed by DECC that aim to meet the government targets for carbon emissions reduction. These scenarios are:

MARKAL - a cost-optimised model of technology adoption.
Renewables - increased adoption of renewable energy generation.
CCS - rapid development and adoption of carbon capture and storage technologies in energy generation.
Nuclear - increased adoption of Nuclear power for electricity generation.

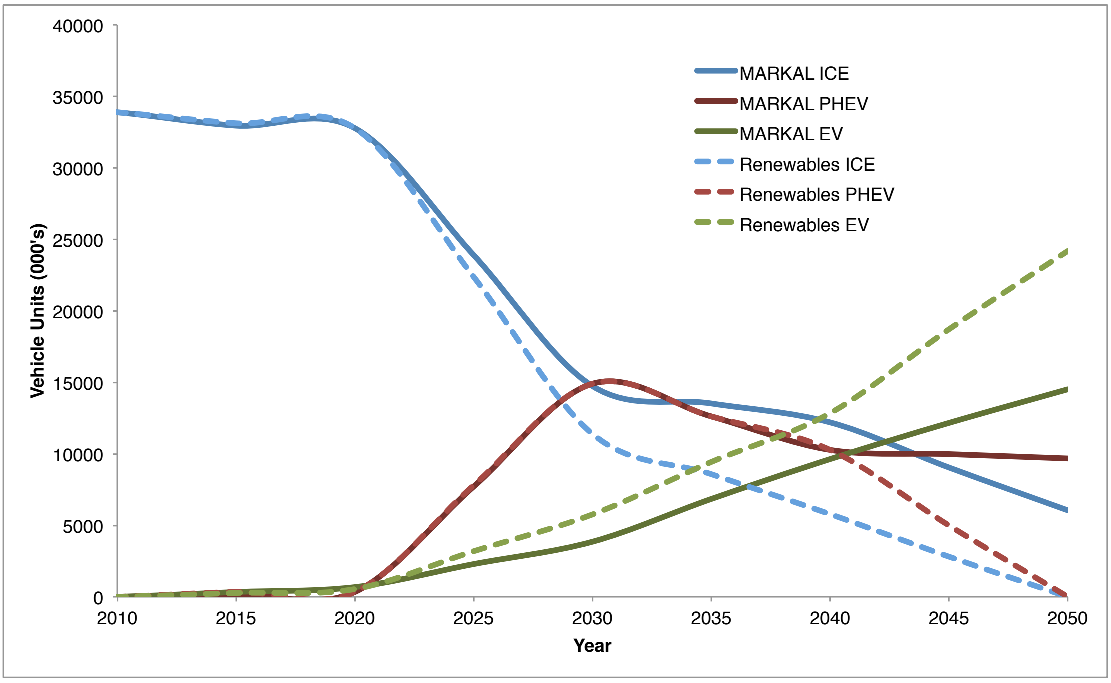

Figure S4: In-use vehicle stocks of ICE, PHEV and EV under the MARKAL and Renewables scenarios. DECC provides the scenario in 5 year increments, we apply a cubic interpolation for a continuous timeseries.

Of these, we use the **MARKAL** and **Renewables** scenarios for the analysis. Because of their slight differences, only the Renewables scenario results are shown in the paper and the MARKAL scenario is used like a sensitivity variation in the supporting information. The roll-out of electric vehicles in these scenarios is shown in Figure S4.

6.2 Technology details

6.2.1 Technology lifetimes

To model the lifetime of technologies, we use a normal distribution. The vehicle lifetime that we are interested in is, as defined by Murakami et al. [18], the total lifespan, which for vehicles is not drastically different to the domestic service lifespan.

For the vehicle lifetimes, statistics only exist for ICE vehicles, PHEVs and EVs have not been on the market for long enough for an accurate assessment of their lifetime. It is possible that the change in drive technology will have an impact on the potential lifetimes of vehicles, assuming for example that the relative simplicity of electric motors extends their service life over that of internal combustion engines and that this is a significant factor in the decision to scrap a car. However, without any data to support this, the safest assumption to make is that the lifetimes for all three types of vehicles in this study will be equal.

For data on the average vehicle lifetimes in the UK, we looked to the Department for Transport (DfT) statistics on licensed cars. By fitting a normal distribution to the scrappage rates between 1994 and 2011 of vehicle first registered between 1991 and 2000, we find the mean of the distribution to be 11.4 years and the variance 7.7 years. For more recent vintages, there are not enough data points for a reasonable estimate of lifetimes. This figure does not tally very well with a recent BCA report that shows recent trends of lengthening lifetimes, probably due to the impact of the recession – in 2011, 75.3% of cars ran until the 12 year mark, 36.1% at the 15 year point down from 40% 10 years earlier [35].

Other studies on material flows in vehicles and LCAs of electric vehicles and Li-ion batteries use vehicle lifetimes that range between about 12 and 18 years – although these are used as global averages (see, for example, Alonso et al., Modaresi and Muller, Hawkins et al., Notter et al., Gruber et al. [36,34,37,38,39] and references therein). As the UK vehicle fleet is likely to remain younger that the global average, we use a standard lifetime of 13 years for cars with a standard deviation of 3 years and sensitivity analysis values of 11 and 15.

The lifetime of most other components is inherited from the vehicles they are a part of. Catalytic converters, NiMH batteries and NdFeB motors are very rarely replaced, when they reach end of life the whole car will be scrapped. The only exception to this is the Li-ion batteries contained in plug-in hybrid and electric vehicles, which are expected to last for around 8 years (taken from the Tesla Model S, Vauxhall Ampera and Toyota Prius Plug-in battery warranties) with a standard deviation of 2 years. For sensitivity analysis, we vary this lifetime to 6 and 10 years (10 years being the assumption in the LCA study of Li-ion batteries of Hawkins et al. [37]).

6.2.2 Material Intensities

Although in general the model allows any technology structure or component to have a material intensity, in the case study of electric vehicle roll-out we are only interested in the Cobalt, Lithium, Neodymium and Platinum contained in catalytic converters, Li-ion batteries and NdFeB motors. The material intensities of these components are given in Table S2 below.

Table S2: Material Intensities and sources.

Name	Material	Intensity (kg/unit)	Source
NdFeB Motor	Neodymium	0.31 – 0.60	USDOE[4]
Li-ion Battery EV	Lithium	3.38 – 12.68	USDOE[4]
	Cobalt	0 – 9.41	
Li-ion Battery PHEV	Lithium	1.35 – 5.07	USDOE[4]
	Cobalt	0 – 3.77	
Catalytic Converter	Platinum	0.0015 – 0.0025	Ravindra[25]

Although we base our data primarily on the USDOE Critical Materials Strategy report, these numbers are supported by a growing body of other studies, see for example [41,42,43,44,39,36,45].

The range of material intensities is particularly wide for Lithium-ion batteries. This is because there are a variety of possible battery chemistries that could be used for electric vehicles in the future. Each of these has specific advantages and drawbacks and all are still subject to active research. The best we can do with the data available is run the model for the highest and lowest material intensities to establish a likely range for lithium and cobalt demand. We choose to keep the material intensity per battery constant despite likely improvements in battery capacity with fixed weight. This is done to reflect a likely rebound where improvements in capacity per weight would likely result in the use of higher capacity batteries (and thus longer driving range) rather than a reduction of the material weight used per vehicle.

6.2.3 End-of-life recovery

As described in Part 1 of the supporting information, the end-of-life recovery process of the model is a very abstract division of stocks into different flows. The purpose is to quantify stocks available for reuse or recycling, not provide an accurate description of the process. As such, an explanation of the relation between the 'recovery rate' used in the model and real world recycling rates is required. In the case of recycling, which is the term we use to describe end-of-life materials being recovered and used to substitute primary inflow, the recovery rate describes the efficiency of this full process, what the UNEP report on recycling rate of metals defines as the end-of-life recycling rate [46]. That includes recovery of the material at end-of-life, including collection efficiency, processing of recovered material so that it is appropriate for secondary input and the efficiency of the manufacturing process (which is otherwise not included in the model!). To put this into context, recycling rates for lead from end-of-life lead-acid batteries in the US are currently 98% [47], including collection and processing efficiencies. For aluminum recycling, more than 95% of vehicles in the U.S. enter a comprehensive recycling system at end-of-life [48], and in Europe, recovery of aluminum from shredder plants can be around 89 – 95% [49]. A combination of these two numbers would lead to an end-of-life recycling rate for aluminum from vehicles of 85 – 90%.

For technology structure and component recovery, the definition of reuse is very similar to the definition we use for material recycling. Reuse is defined as the recovery of end-of-life technology objects that are possibly re-manufactured for subsequent inflow to substitute for primary inputs. The recovery fraction for this process is very dependent on the technology and use in question. For example, for lithium-ion batteries to be reused in electric vehicles would require a re-manufacturing procedure that restores the batteries to full capacity. This would likely result in the loss of some lithium and cobalt, reducing the recovery rate. In contrast, reusing NdFeB magnets in electric motors could, in principal, have a very high efficiency as the magnets do not significantly lose magnetism and so very little re-manufacturing would be required so long as the motor design has not changed too much.

Lithium and Cobalt

The recycling of lithium-ion batteries has not only been studied academically but also found some commercial application with companies such as Toxco and Umicore. An example of recent research initiatives is the EU VALIBAT program [EU project ID G1RD-CT-2000-00232] which achieved recycling rates of 95% for magnetic metallic compounds, 90% for lithium from the electrode material, 90% for metal oxides and 70% for lithium salt. Xu et al.[50] report Cobalt recovery upwards of 93%. These rates are high for current commercial procedures [51,52] but reasonable targets for the longer term. We assume process efficiencies of 75% for lithium recycling and 95% for Cobalt recycling based on the numbers compiled by Kushnir and Sanden [41], with purities high enough for reuse in batteries. Combined with the 95% collection efficiency of end-of-life vehicles seen in the U.S. (with the EU end-of-life vehicle directive likely to lead to similar rates in the UK), we hence use values of 70% and 90% for the recovery fraction of lithium and cobalt from electric vehicle batteries respectively.

Platinum

Global end-of-life recycling rates for platinum in vehicles are currently around 50-55% [46]. 50% is also what Alonso et al. [36] use in their assessment of platinum availability for future vehicles. In contrast, a 2003 report by TIAX llc for the U.S Department of Energy assumed a recycling rate of 90% for catalytic converters. Gordon et al. [53] similarly assume a 90% recycling rate.

Recycling rates of platinum are limited not only by the collection rates of vehicles at end-of-life, but also by the dissipation of platinum from catalytic converters in use. The recycling processes commercially used for catalytic converters are less limiting, with Umicore being able to recover 95% of platinum at high enough purity to substitute for primary demand.

Neodymium

Current recycling rates of Neodymium are very low (~1% in 2011). This has been limited most significantly by a lack of incentives [54]. The largest technological barrier to magnet recycling is the separation of magnetic material from other metallic scrap –

once this is achieved, the magnetic material can be re-sintered into a new magnet without much loss of material. The recovery of magnets from end-of-life vehicles is likely to be much less problematic than other electronics because of the large size of the magnets. This makes it both easier and more economic to remove the magnets by disassembly. This points to much higher potential recycling rates for neodymium from end-of-life vehicles into new electric vehicles. Based on the recovery rates being comparable to battery collection rates, and a recycling process efficiency of around 90% [54], we assume a recycling rate for Neodymium of 80%.

6.2.4 Reuse

Lithium-ion batteries

Very little evidence exists to suggest any progress on remanufacturing and reuse of Li-ion batteires – although a TSB funded project on battery remanufacturing at the Centre for Remanufacturing & Reuse [55] indicates that there is some interest and potential. The rationale behind such a process is that, with EU directives on end-of-life vehicle recycling, the collection of electric vehicle batteries will be a highly regulated process, allowing the collection and processing of a homogeneous waste stream. This should serve to simplify the remanufacturing process when compared to other batteries at end-of-life (disassembly of an inhomogeneous mix of small batteries is cost prohibitive). With collection efficiency around 95%, the only significant losses in material would be from the remanufacturing process. Lithium-ion batteries lose capacity primarily due to lithium deposition and the formation of passive films on electrodes. A remanufacturing process would likely involve the removal of these deposits and hence some loss of both electrolyte and electrode material [56,57,58]. As a conservative estimate, we assume that the process would still retain 95% of the cobalt and lithium in the battery – effectively giving a reuse rate of 90% of batteries.

NdFeB Motors

Evidence for recovery and reuse of rare-earth magnets from motors is also hard to come by. Honda and Siemens have expressed interest in pursuing this approach and a project funded by the German Federal Ministry of Education and Research (BMBF) [59] is investigating the possibility. Binnemans et al. [54] suggest this would be a reasonable approach for large magnets such as those used in wind turbines and electric vehicles, as their size makes them both easy to extract at end-of-life and provides an economic incentive for doing so. As these types of magnets can theoretically maintain their magnetization for up to 300 years, this process would be limited only by the recovery rate of magnets from end-of-life vehicles, which we can assume to be around 95% (c.f. battery recovery).

7 Model Results

7.1 Scenarios

The analysis for this paper is based on two core scenarios taken from the DECC Pathways Analysis [citation!!!]. The two we use are the “MARKAL” scenario, based on a cost optimization analysis, and the “Renewables” scenario, which boosts the use of renewable energy and associated technologies such as electric vehicles. These scenarios provide time series for the breakdown of UK vehicle stocks into conventional ICE vehicles, PHEVs and EVs. These time series were presented in Figure S4 above.

7.2 Technology Lifetime Modeling

One of the innovations of the model presented here is the hierarchical representation of technology objects, their components and materials. Any object at each of these levels may have distinct lifetimes. The importance of distinguishing the lifetime of technology objects in this hierarchy and modeling them separately is highlighted by the graph below showing lithium demand due to EV and PHEV lithium-ion batteries in the ‘Renewables’ scenario. Including the 8 year lifetime of the batteries significantly changes the shape of the demand curve after 2025 and raises the peak in demand in 2044 by almost 80% above what it would be for batteries that last the full 11.4 year lifetime of a car.

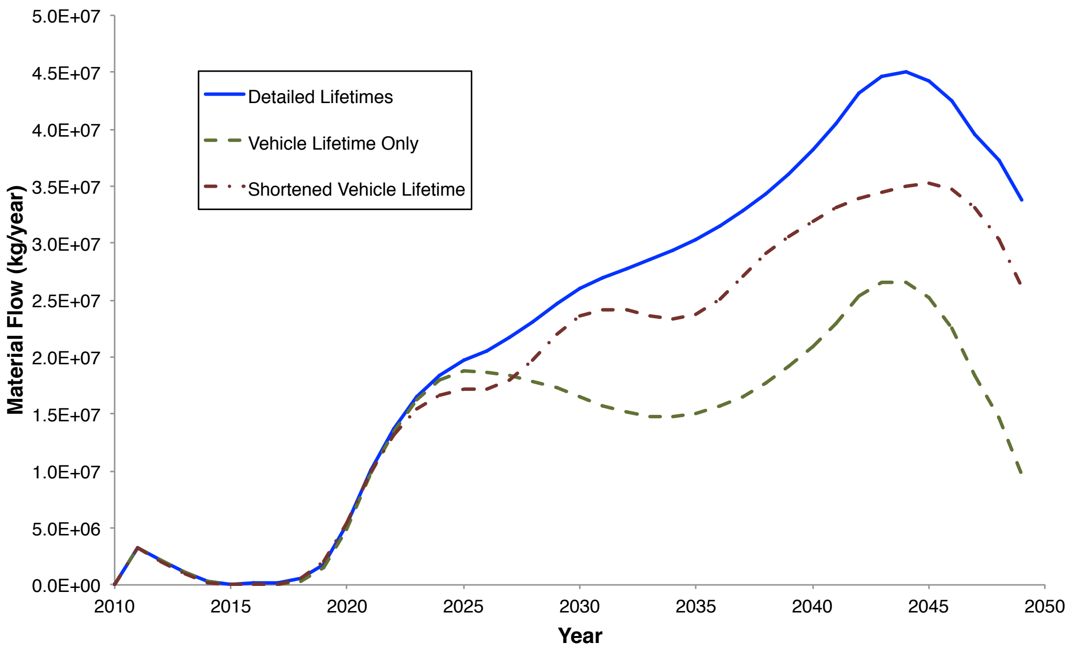

Figure S5: Total inflow of lithium required for the 'Renewables' scenario with the high material content limit using three different technology lifetime configurations. ‘Detailed Lifetimes’ assign a 11.4 year lifetime to the EVs and PHEVs and an 8 year lifetime for their batteries. ‘Vehicle Lifetime Only’ eliminates the battery lifetime so they are scrapped only when the vehicle is and ‘Shortened Vehicle Lifetime’ also shortens the vehicle lifetime to 8 years.

7.3 No Recovery Scenarios

The first result we calculate using the stocks and flows model is the outflows resulting from technologies reaching end-of-life and the inflows required to maintain the service stock level. The model provides these stocks and flows for every object type in the system: infrastructure objects such as electric vehicles, technology components such as Li-ion batteries and materials such as lithium.

7.3.1 Scenario Sensitivity

To illustrate the difference in stocks and flows of components and materials that can arise from different infrastructure roll-out scenarios, we show the stocks and flows of structures, components and materials for two different scenarios below: the MARKAL scenario and the Renewables scenario.

Figure S6 below shows the stocks and flows of the technology structures: ICE, PHEV and EV vehicles. The primary differences are in the scale of adoption of EV technology and the more steep decline in ICE technology.

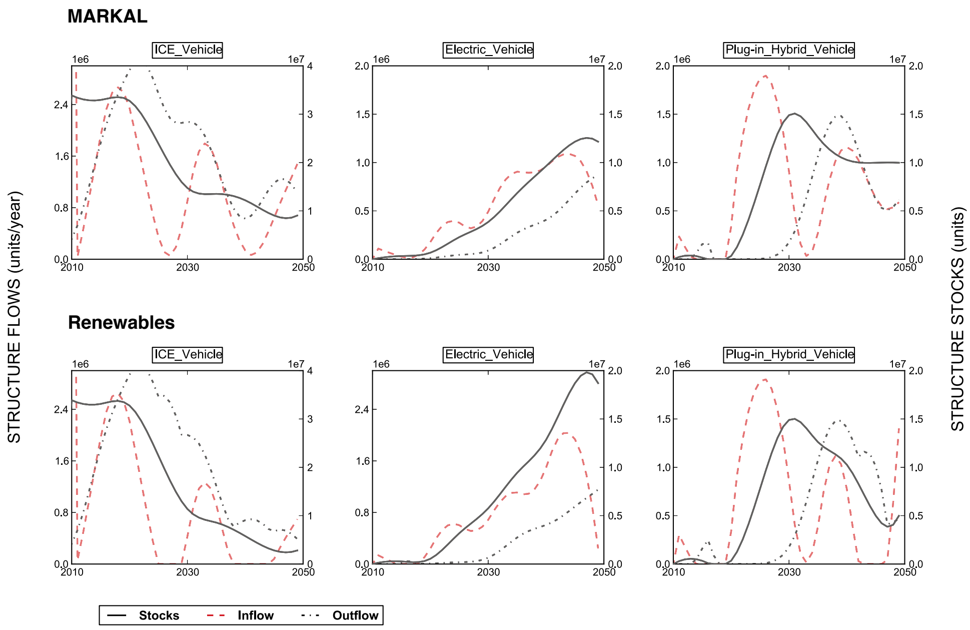

Figure S6: Technology structure stocks and flows for the MARKAL and Renewables scenarios.

Figure S7 shows the stock and flows of the technology components embedded in the technology structures of the graphs above.

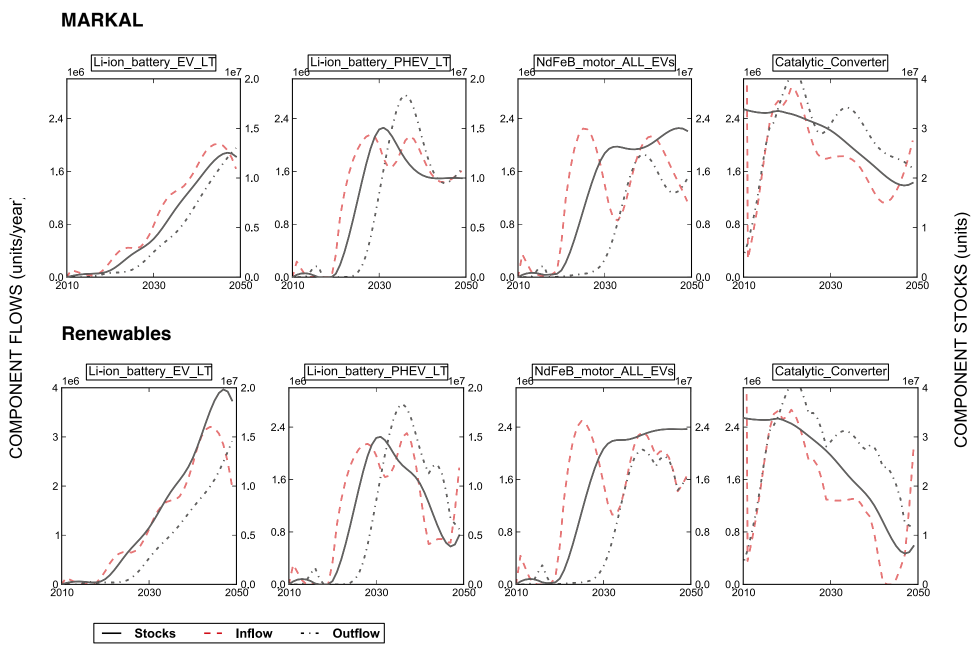

Figure S7: Component stocks and flows for MARKAL and Renewables scenarios.

Finally, Figure S8 shows the stocks and flows of materials that are contained in the components in the graphs above including both the high and low estimates for material intensity.

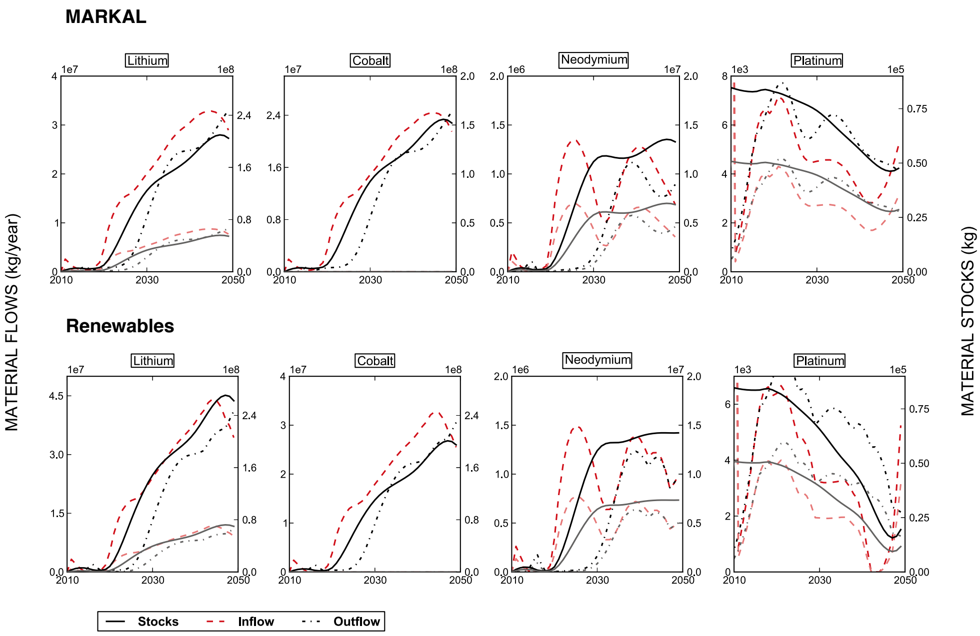

Figure S8: Material stocks and flows for the MARKAL and Renewables scenarios including both high and low estimates for the material intensity.

The implications of these material demands are discussed in the paper with reference to current global demand for each material. The comparison between the two scenarios that is given here and not in the paper serves to highlight that the relationship between vehicle roll-out and material demand is linear, so long as all other factors are kept equal. The difference in material demand for the two scenarios can hence be fairly easily interpolated from the differences in vehicle and component roll-out. Similarly, the difference between low and high material intensities is simply one of scale. For the sake of brevity, we hence limit the results from here on to an analysis of the Renewables scenario with high material intensity only.

7.3.2 Lifetime Sensitivity

A more complex variable dependence exists for variations in lifetime of technology structures and components in the model. For our base results, we assumed vehicle lifetimes of 13 years and battery lifetimes of 8 years. As a sensitivity analysis, we vary first the vehicle lifetime between 11, 13 and 15 years; and then the battery lifetime between 6, 8 and 10 years. Figure S9 below shows the inflow of vehicle structures for the three lifetimes.

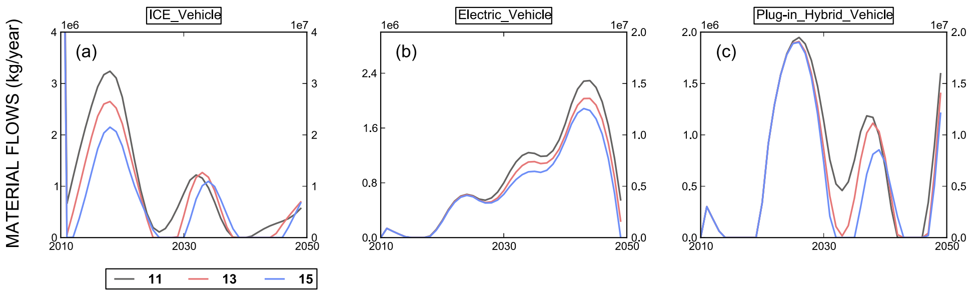

Figure S9: The effect of varying vehicle lifetimes between 11, 13 and 15 years on the inflow of new vehicles for each of the vehicle structures in the model.

The effect of an increase or decrease in vehicle lifetime can result in a significant difference in the demand for new vehicles to maintain the same stock. It also shifts the peaks in that demand slightly. The result of this on the material demands is shown in Figure S10 below.

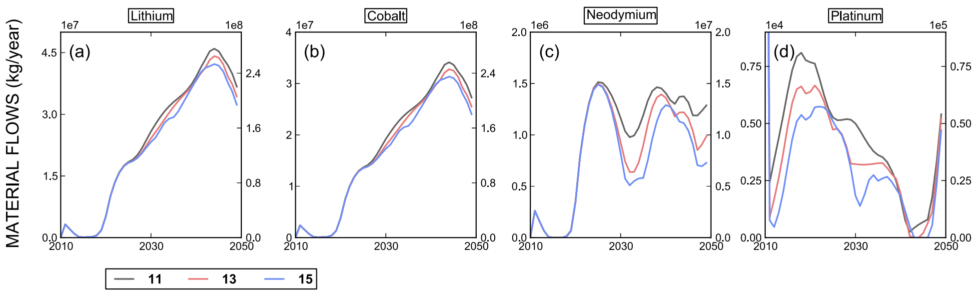

Figure S10: The effect of varying vehicle lifetimes between 11, 13 and 15 years on the material inflows to vehicle stock.

While the results of varying lifetime on vehicle demand is fairly predictable, the same cannot be said for the material demand shown in Figure S10. In the case of Lithium and Cobalt, both of which are contained in Li-ion batteries that have their own distinct lifetimes (of 8 years), there is not much difference in material demand between a vehicle lifetime of 11 and 15 years. The difference is much more marked for neodymium and platinum where demand at times can be almost 50% less if the vehicle lifetime is 15 years compared to 11 years.

Figure S11 below shows the impact on Li-ion battery demand of varying the battery lifetime between 6, 8 and 10 years. The effect is the same as seen for a varying vehicle lifetime; there is a significant difference in the scale of demand and a smaller shifting in the occurrence of peak demand.

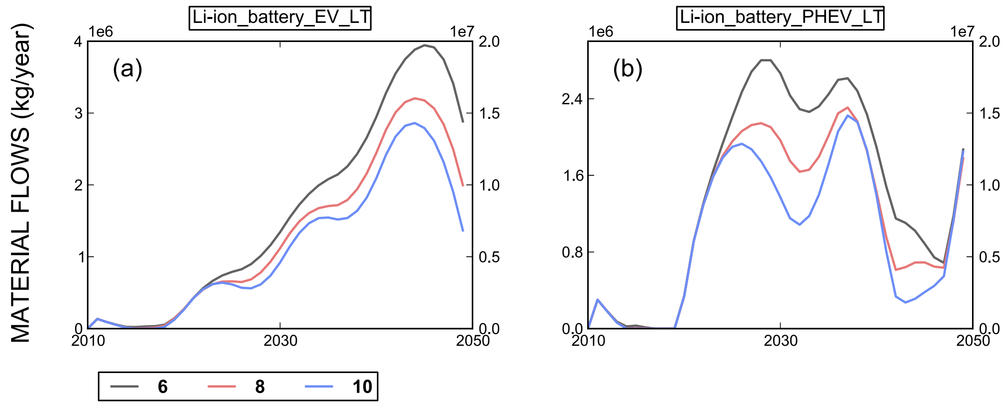

Figure S11: Effect of varying the lifetime of Li-ion batteries between 6, 8 and 10 years. The inflow of batteries is shown for the two types in the model.

The implications of this for the lithium and cobalt demand for these Li-ion batteries is shown in Figure S12. The difference between the lifetime choices is now much more marked than was the case for varying vehicle lifetime. This can be explained by realizing that the battery lifetime is shorter than the vehicle lifetime and hence dominates the material flow dynamics.

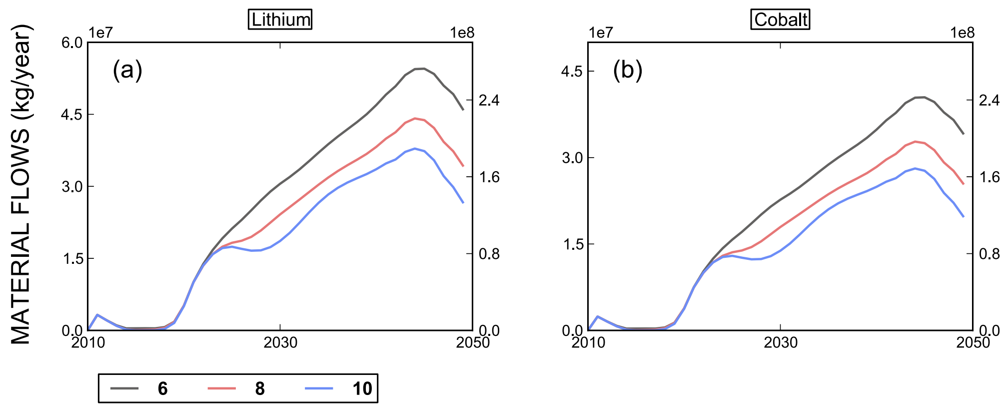

Figure S12: Effect on material inflows of varying the lifetime of the Li-ion batteries in which they are contained between 6, 8 and 10 years.

Given the large and unpredictable impact of lifetime on material demands, the same consideration will be given in the case of reuse and recycling of components and materials that will be presented in the next section.

7.4 Recovery and Reuse/Recycling

The model also supplies a number of time-series characterizing the flow of waste out of the system. This allows a more thorough treatment of recovery of materials and technologies. More detailed results of simulations of this are presented in the following two subsections.

End-of-life stock that flows out of the in-use phase follows one of three possible routes:

1. It is embedded in a parent object that is recovered and may be reused. In this case the stock is not available for any other processing and may re-enter the in-use phase along with it's parent.
2. The stock cannot be recovered and it goes to waste.
3. The stock itself may be recovered, is added to reusable/recyclable stock and may re-enter the in-use phase.

There is a set of stock and flow variables in the model representing these possibilities – embedded, waste and reuse (which also represents material recycling). The total inflow of structures, components or materials are then also disaggregated into virgin inflow and reuse/recycling inflow.

The split of end-of-life outflow into reuse/recycling and waste is determined by a recovery time-series. In the following two subsections, the potential effect for recovery and reuse is modeled first at the material level – as in conventional recycling – and then at the component level. To illustrate the potential impact of recycling and reuse, we model a set of scenarios for each material and for Li-ion batteries and NdFeB motors. There are three scenarios for each, defined by the recycling/reuse process starting in 2015, 2025, and 2035, with a ten year linear increase to the maximum recycling/reuse rate discussed in section 6. The 2015 scenario marks an ambitious scenario, assuming a very rapid implementation of recycling policy with ambitious targets for bringing recycling infrastructure online. A 2025 start represents a realistic timeline, should policy be put into place in the very short term, whereas a 2035 start represents late action.

7.4.1 Material Recycling

In the material recycling case, the stocks and flows of structures and components is unchanged. The relevant material flows – virgin inflow, reuse inflow (recycled material) and waste flows are shown in Figure S13 for the Renewables scenario with high material intensity for all four of the materials studied. The results for lithium and cobalt have the same shape but differ in scale. Lithium, with recycling rate limited to 70%, has the potential to reduce virgin inflow from a peak of about 40 kilo-tonnes in 2045 to just over 10 kilo-tonnes. In the nearer future, the 2030 peak of 25 kilo-tonnes can be reduced to just over 10 kilo-tonnes if recycling policy is implemented in the very short term. For cobalt the reduction in 2045 could be from over 30 kilo-tonnes to less than 10 kilo-tonnes.

The demand curve for neodymium is dominated by a peak in 2025 that is unavoidable by any of the recycling strategies investigated. There is simply not sufficient secondary stock available from electric vehicles at end-of-life to substitute for virgin demand. The second peak of 1.3 kilo-tonnes in 2040 is almost completely avoidable. Even the 'realistic' recycling scenario of a 80% recycling rate by 2035 reduces this peak to nearer 0.4 kilo-tonnes, a reduction of almost 70%.

Platinum recycling shows the simplest result of the four materials. Because the end-of-life outflow of platinum is greater than the demand from about 2020 onwards, instituting recycling at any time after this, even with a 70% recycling rate, immediately reduces the demand for virgin platinum to zero.

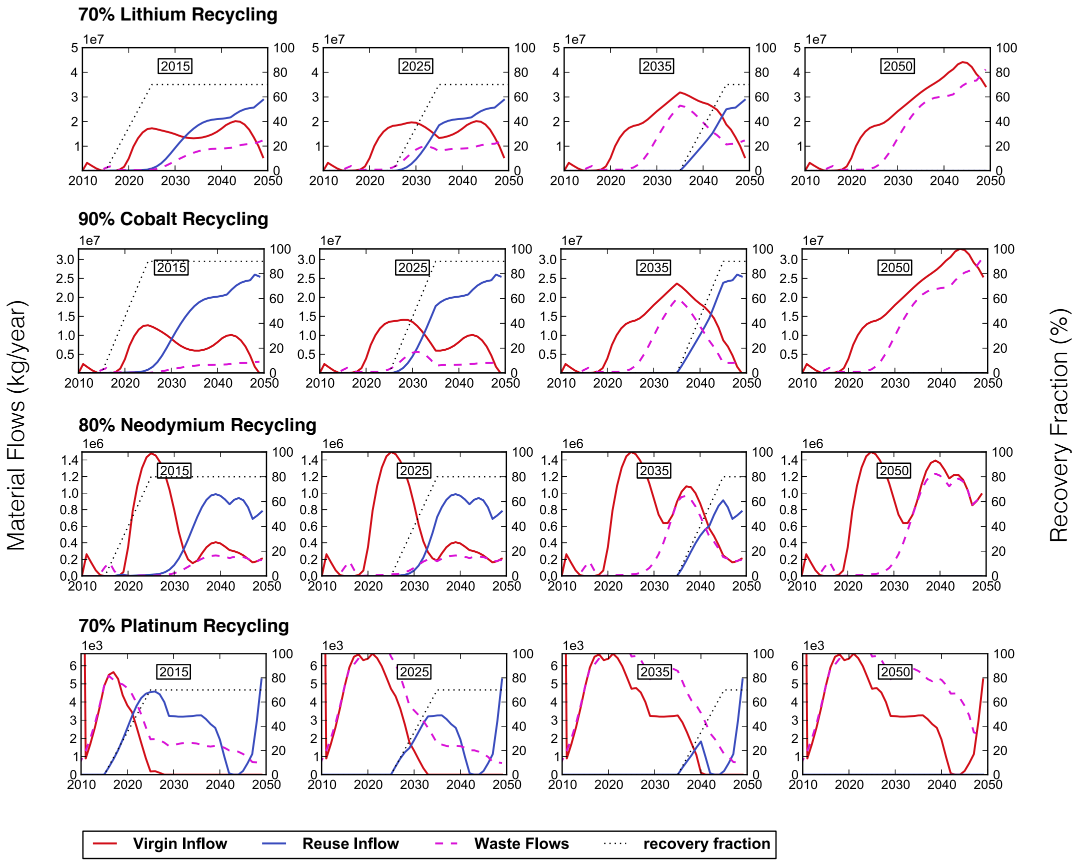

Figure S13: Material flows with material recovery scenarios for the Renewables scenario assuming the high limit for material intensity.

Figure S14 shows the results of varying the recycling rate for each of the material between 50%, 70%, 90% and 95%. The impact of varying recycling rates has the expected effect with large potential differences for lithium and cobalt in virgin material demand, and less effect on neodymium and platinum demand. This is because there is greater availability of end-of-life lithium and cobalt than neodymium because of the longer lifetime of electric vehicle motors than batteries, and platinum demand is, in most cases, already outstripped by secondary supply.

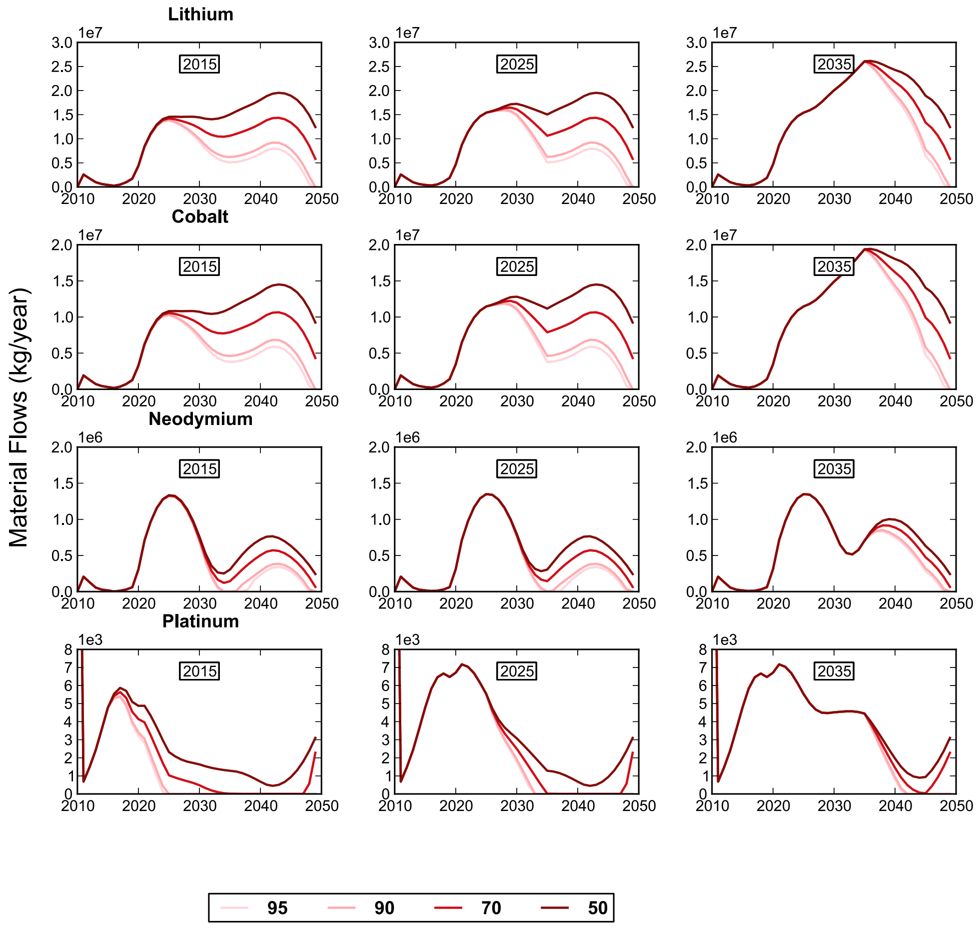

Figure S14: Variations in recycling rate between 50%, 70%, 90% and 95% for all four of the materials and three different time horizons for recycling.

As we noted earlier, variations in the lifetime of vehicles can have a significant and unpredictable impact on the demand for virgin material. To determine the impact of lifetime variations when material recycling is also performed, we show in Figure S15 the results of varying vehicle lifetimes between 11, 13 and 15 years when 90% of material is recycled. The results are consistent with what was found in Figure S10; where there was no effect on material demand caused by different lifetimes, the addition of recycling also makes no difference. Otherwise, a longer lifetime reduces material demand and shifts it to the right.

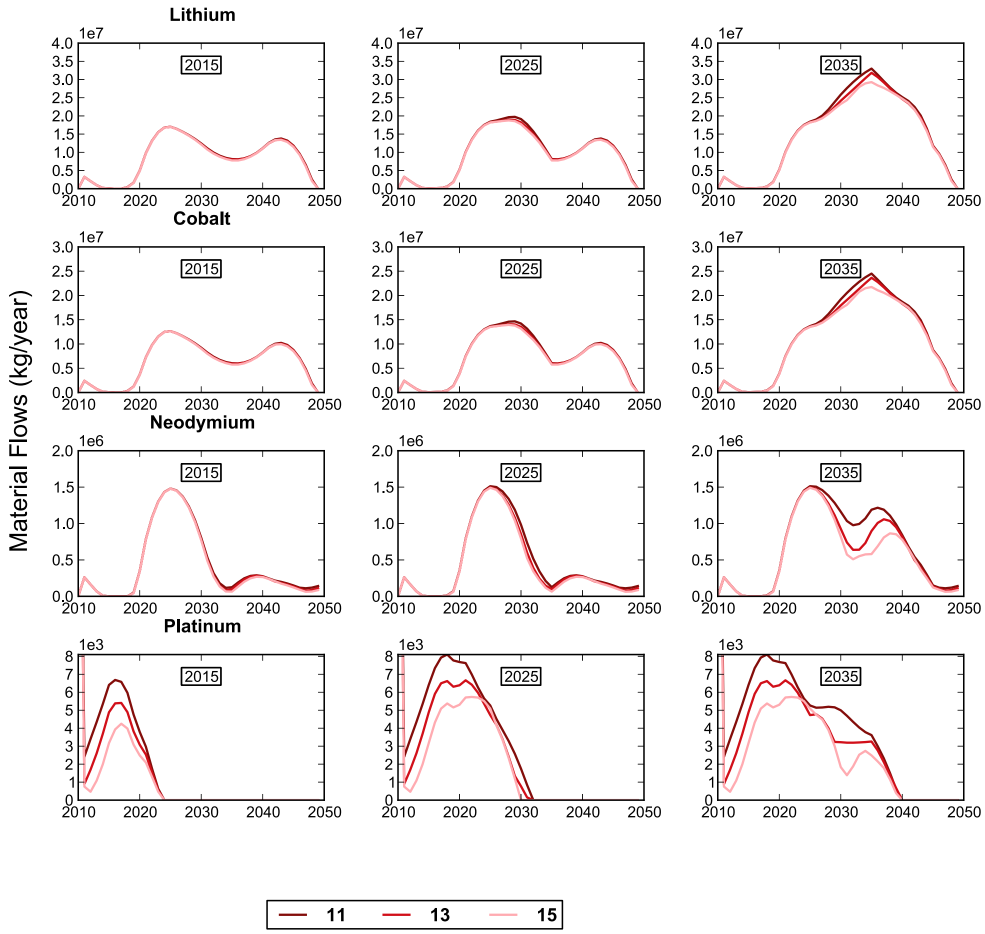

Figure S15: Virgin inflow of all materials in the Renewables scenario with high material intensity and a 90% recycling rate where the vehicle lifetime is varied between 11, 13 and 15.

7.4.2 Component Reuse

As a contrast to the above, the effect of recovery on the component level is also examined using the same recovery scenarios. In this case, the stocks and flows of technology structures are unchanged but both the component stocks and flows and material stocks and flows are changed. The component inflows and waste flows for the Renewables scenario are shown in Figure S16 below. The corresponding material flows (including virgin inflow, embedded inflow and waste flows) are shown in Figure S17 for high material intensity.

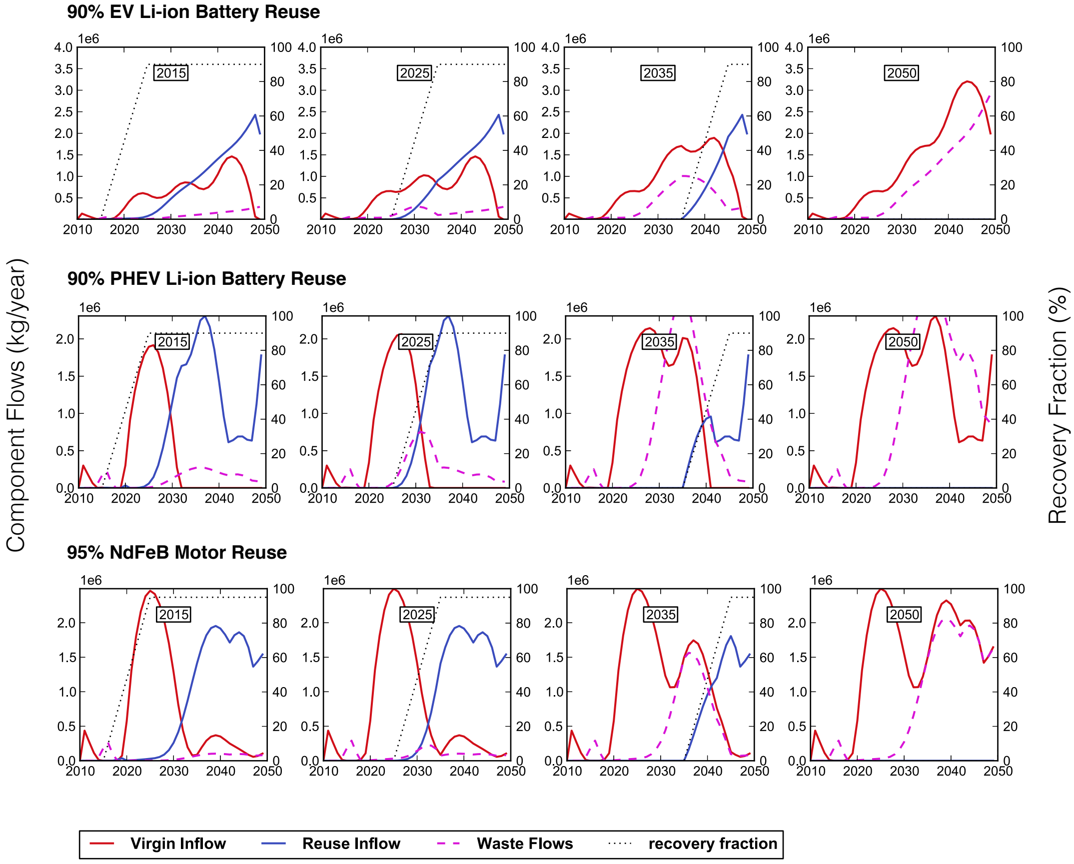

Figure S16: Component flows in the Renewables scenario under varying component recovery scenarios.

The results clearly indicate that component recovery and reuse can greatly reduce the requirement for new component inflow. This is discussed in detail in the paper. The effect of this on material demand (Figure S17) is also as expected, although the incompatibility between PHEV and EV Li-ion batteries makes their reuse less effective than recycling their constituent materials.

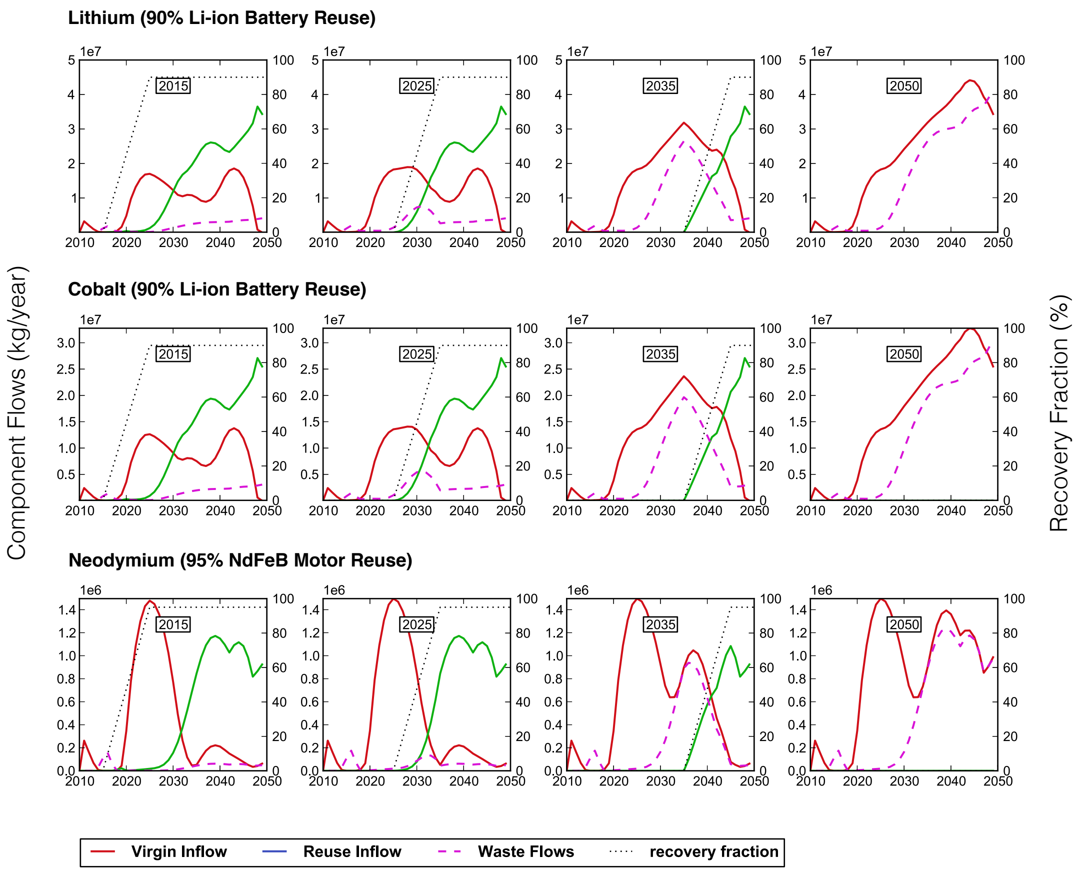

Figure S17: Material flows in the Renewables scenario under varying component recovery scenarios assuming high material intensity.

Figure S18 further shows the effect of varying recycling rates between 50%, 70%, 90% and 95%, displaying much the same effect as the equivalent material recycling rate variations in Figure S14. Similarly, the effect of varying Li-ion battery lifetimes on virgin material demand, shown in Figure S19, is what would be expected from taking the results in Figure S12 and reducing them by applying the reuse as in Figure S17.

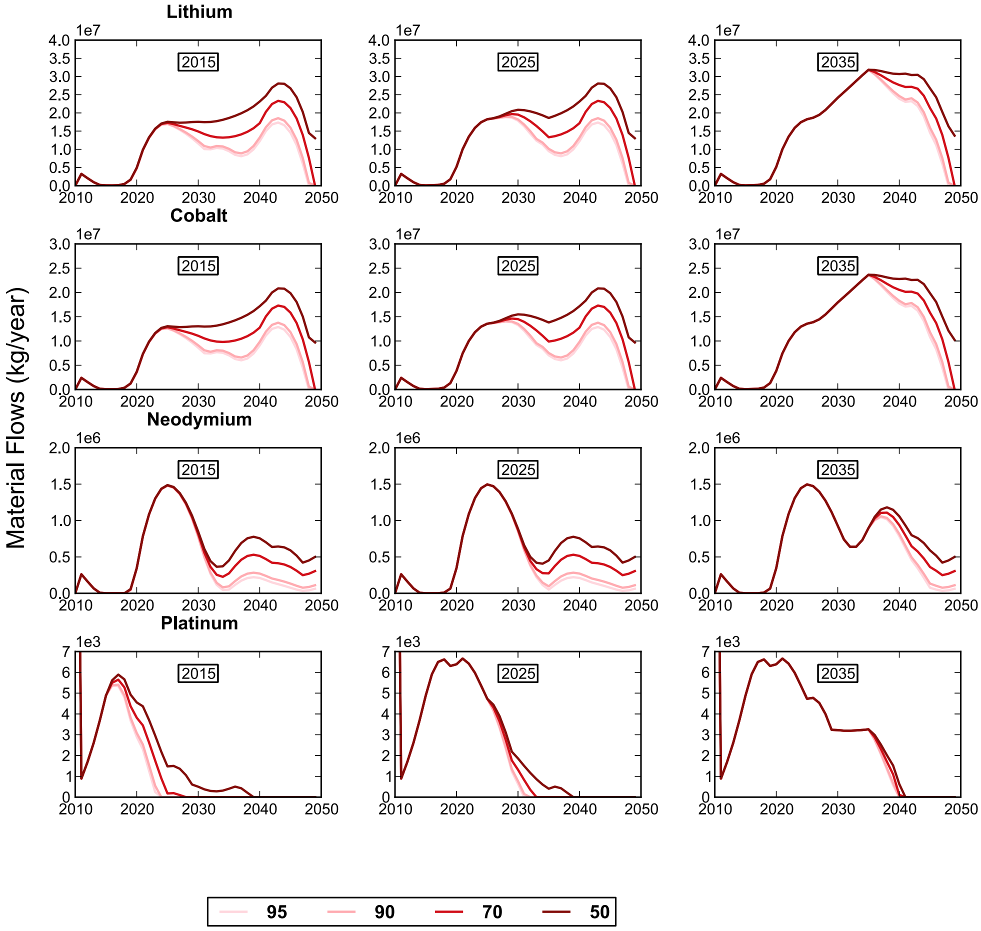

Figure S18: The effect of varying component reuse rates between 50%, 70%, 90% and 95% on the demand for virgin material in the Renewables scenario with high material intensity.

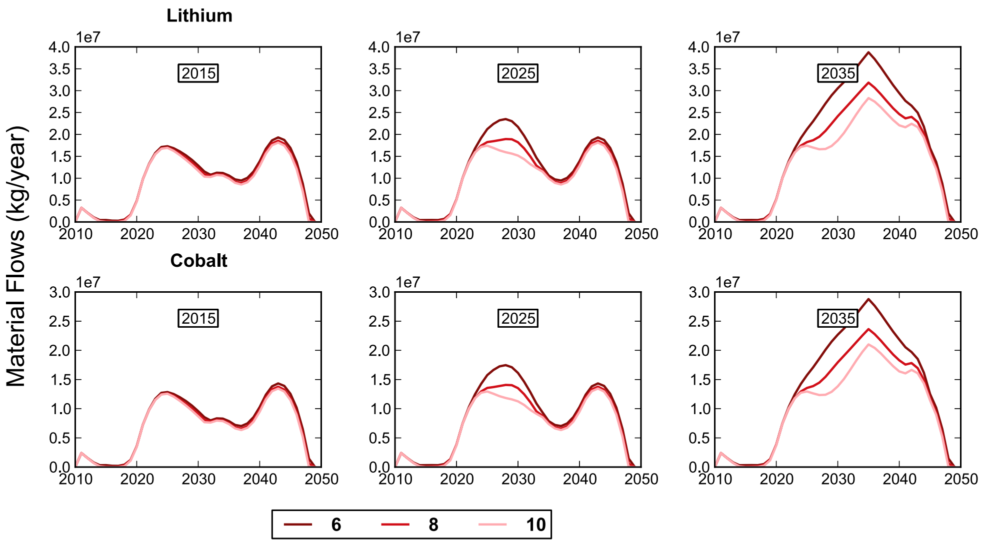

Figure S19: Effect of varying Li-ion battery lifetime between 6, 8 and 10 years on demand for virgin material in the Renewables scenario with high material intensity.

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