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Resource effectiveness of the European automotive sector – a statistical entropy analysis over time

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ABSTRACT

The European automotive sector is faced with potentially disruptive challenges. In particular, the projected increase in the share of electric vehicles (EVs) and calls to prepare for the implementation of more circular economy (CE) strategies are increasingly demanding systemic adaptations. Given the goals of the CE, the adaptations should enable a maximal preservation of the function and value of products (e.g. extension of lifetime), components (e.g. reuse of parts) and materials (e.g., material recycling), thus saving on the energy, materials and effort that would be required to restore the lost functionalities. In this context, statistical entropy analysis (SEA) is proposed as a methodology to assess the effort needed for preserving and restoring functionality at different product, component and material life cycle stages. Effort is measured as changes in statistical entropy that are caused by concentration and dilution activities in the production – consumption – End-of-Life (EoL) system. SEA was applied to a generic model of the European automotive system, in combination with a stock-driven model and a material flow analysis (MFA), allowing statistical entropy changes to be projected over time. The paper demonstrates how SEA can facilitate decision making on the transition towards a more circular economy by quantifying the effects of particular CE strategies and their combinations. The results show that without any additional system adaptations, an increasing share of EVs towards the year 2050 will lead to substantially increased effort in production as well as end-of-life vehicle treatment.

1. Introduction

In the European Union (EU), as in other parts of the world, the need for mobility is largely satisfied through the use of personal passenger vehicles, accounting for more than 70% of all journeys (ACEA, 2019). In 2017, a stock of 264 million vehicles was employed for this purpose (EC, 2019). With a global share of 24% of all passenger vehicles produced (16.5 million units), the EU-28 also represents one of the major production regions (ACEA, 2019), making the automotive sector not only one of the most important economic sectors (European Economic and Social Committee, 2016), but a major resource consumer as well.

In the year 2015, 19 million tons of metals were required to maintain and renew the stock of vehicles, while the output of metals from the treatment of end-of-life vehicles (ELVs) was around 8 million tons (Huisman et al., 2017). The difference between the two flows is explained by unregistered exports of vehicles and ELVs, including the 3 to 4 million vehicles of unknown whereabouts (EC, 2018a), which indicates the challenge of closing material loops before considering other limitations such as the fundamental limits of recycling (Ignatenko et al., 2008; Reuter et al., 2006). With EU policy aiming to establish a more circular economy (CE) (EC, 2020, 2018b, 2015), there is a need to better understand the patterns and dynamics of resource use. It is imperative that the most resource-effective measures necessary to meet CE goals of preserving the value of products, components and materials at the highest possible level over time (European Commision, 2015; European Commission, 2018b; Iacovidou et al., 2017a), be clearly identified so as to optimally preserve functionality (Mesa et al., 2020; Proske and Jaeger-Erben, 2019).

In this context, an established method to evaluate the patterns of resource use is Material Flow Analysis (MFA). It is used to quantify flows and stocks of materials in systems of different complexity. The results of a MFA provide a comprehensive and systematic account of a physical

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system, thereby being a valuable tool to support decision making (Brunner and Rechberger, 2016). MFA has been applied to a variety of systems to assess the utilization pattern of single substances (e.g. Saurat and Bringezu, 2009), goods (e.g. Steubing et al., 2010) or mixtures of substances (e.g. Nakajima et al., 2013) for a defined region and time, or for a period of time (e.g. Müller, 2006; Pauliuk et al., 2012). While MFA provides a systematic evaluation of the material flows, often the complexity of the material flow system, the various output flows from different processes as well as possible changes in the composition of the resulting flows make it difficult to directly relate the outcomes of the MFA to the goal of the CE – to preserve functionality. Moreover, derived targets such as recycling rates (e.g. 2000/53/EC) or recycling efficiency, while being most frequently present in CE assessments, underestimate the dimensions of quality (Parchomenko et al., 2019).

Therefore, in order to include the quality dimension into MFA results, the method of Statistical Entropy Analysis (SEA) has been developed (Rechberger, 1999; Rechberger and Brunner, 2002). SEA calculates the changes in the distribution pattern of a material transition in a system, thereby allowing the potential of each process to concentrate or dilute substances to be evaluated and critical stages of dilution and concentration to be identified (Rechberger and Graedel, 2002). Originally developed to assess the distribution pattern of a single substance, flows of higher substance concentration (low entropy) are considered to have a higher potential for utilization. Based on this principle, SEA has proved to be applicable to a variety of systems and scales, such as the European and Chinese copper cycles (Rechberger and Graedel, 2002; Yue et al., 2009), municipal solid waste incinerator technologies (Rechberger and Brunner, 2002), wastewater treatment plants (Sobańtka and Rechberger, 2013), a lead smelting process (Bai et al., 2015), agricultural systems (Sobantka et al., 2012), the Austrian phosphorus cycle (Laner et al., 2017) as well as the combined phosphorus-nitrogen cycle (Tanzer and Rechberger, 2020). Additional developments of the method allowed SEA to be applied to chemical compounds (Sobantka et al., 2012). Further, the method has also been employed to measure the recyclability of e-waste (Zeng and Li, 2016), has been used to assess multiple substances in the process of battery recycling (Velázquez-Martinez et al., 2019a, 2019b), with the latest application representing a case study of bioethanol production in China, where the utilization of phosphorus flows that has been evaluated through SEA (Wang et al., 2021)

Given the variety of systems evaluated and the wide potential of the method's applicability in the context of the CE, SEA has been further developed to a multilevel SEA (which is applied in the following, but for better readability referred to as 'SEA') that can simultaneously assess the material, component, and product levels. Thereby, the method enables combinations of diverse CE strategies applied to end-of-life products that are both destructive (e.g. recycling) and non-destructive (e.g. reuse of components) to be evaluated, while measuring the system performance in reference to a functional product state. Deviations from the functional product state, e.g. through the failure of a component, demand subsequent processes like recycling, remanufacturing or the production of a new component, and are therefore linked to some form of effort (e.g. inputs of energy, human labor). As statistical entropy directly measures the dilution and concentration activities performed in the system, effort is expressed as changes in statistical entropy (Parchomenko et al., 2020). In this context, by analogy with the second law of thermodynamics and the corresponding unidirectional nature of processes, the rationale is that the increases in statistical entropy (e.g. shredding of a vehicle), as well as decreases in statistical entropy (e.g. sorting, heavy media processing), are both related to effort that is required to perform the processes.

In this context, it is important to note that SEA represents only one perspective among a variety of methods that exist and that have been applied for the evaluation of the automotive system. Some of the methods represent mature and sophisticated models. One such example represents the approach of flowsheet simulation that is rooted in process engineering and process optimization. It employs a dynamic model, reflecting not only detailed recycling and metallurgical processes, but also parameters such as the degree of liberation and particle size distribution in the recycling processes, product design, lifetime functions, material interactions, while taking into account economic, legislative and environmental constraints (Reuter, 1998; Van Schaik et al., 2002; Van Schaik and Reuter, 2010, 2006, 2004a, 2004b). Among others, these models have been applied to optimize ELV recycling, deriving recommendations for the EU legislative process (e.g. Ignatenko et al., 2008), for modeling improved recycling yields for a specific metal such as aluminum (e.g. Van Schaik et al., 2003) while considering fundamental limits of recycling based on thermodynamics and interlinkages of resource processing routes that result in specific demands for the recycling and overall processing infrastructure (Castro et al., 2004; Reuter et al., 2013, 2003; Verhoef et al., 2004). Other assessments perspectives target some specific elements of resource management in the automotive system such as the remanufacturing of components (e.g. Smith and Keoleian, 2004), their ease of disassembly (e.g. Igarashi et al., 2016; Vanegas et al., 2018), or the improvement of specific materials concerning their environmental performance (e.g. Luz et al., 2010). Regarding the evaluation of environmental impacts, Life Cycle Assessment (LCA) represents the main method that has also been widely applied in the automotive context (e.g. Bauer et al., 2015; Castro et al., 2003; Gradin et al., 2013; Hao et al., 2017; Notter et al., 2010). Other assessment perspectives include social (e.g. Zanchi et al., 2018) and economic aspects, with the latter being assessed through methods such as Life Cycle Costing (LCC) (e.g. Schau et al., 2011), or Cost-Benefit-Analysis (CBA) (e.g. Farel et al., 2013). Dynamic MFA has been employed to assess future scenarios and system dynamics. It has been used for the planning of ELV treatment infrastructure under the consideration of economic costs and externalities such as CO_2 emissions (e.g. Liu et al., 2020), or has been used to evaluate technological changes such as the transition towards higher shares of EVs and related potential to recover critical materials (e.g. Busch et al., 2014; Ziemann et al., 2018), effects of downsizing of car electronic components (e.g. Restrepo et al., 2020), or the implications of future vehicle stock evolution on supply and demand for specific metals (e.g. Modaresi and Müller, 2012). Another approach represents Exergy analysis. It has been used to assess resource quality, resource consumption and resource savings (e.g. Dewulf et al., 2011; Hannula et al., 2020), being used to assess ELV treatment system performance, including the downcycling of materials during ELV recycling (Ignatenko et al., 2007; Ortego et al., 2018), to select EoL strategies (Almeida and Borsato, 2020), or to identify most valuable components and materials, based on their thermodynamic rarity (Iglesias-Émbil et al., 2020). The impacts of technological changes are reflected by studies that assess effects of technologies such as advanced aluminum scrap sorting (e.g. Hatayama et al., 2012), improvements in the ELV system to reduce the loss of alloying elements (e.g. Løvik et al., 2014; Nakajima et al., 2010; Ohno et al., 2015), or the impacts of light-weighting of vehicles or improved ELV treatment on overall life cycle energy reductions (e.g. Enzo et al., 2021, 2019). Losses of single metals such as steel to other sectors and applications like machinery and buildings are also assessed through dynamic material cycle models (e.g. Nakamura et al., 2014), being further extended for the consideration of material losses to other regions (Pauliuk et al., 2017). Other studies consider the optimization of ELV recycling from a mid-term system-planning perspective, taking into account e.g. the optimal allocation of ELVs to treatment facilities, under uncertainties and changes in regulation such as landfilling costs and price effects for the recycled materials (e.g. Simic, 2020, 2016; Simic and Dimitrijevic, 2013, 2012). Important contributions represent case studies that generate data on material flows, and the performance of different technologies and systems (e.g. Andersson et al., 2017a; Widmer et al., 2015), while comparisons between national systems provide broader insights taking into account additional system characteristics such as legislation (e.g. Sakai et al., 2014; Zhao and Chen, 2011). Here, it is to note that this reflection on the existence of the various sub-fields, methods and perspectives indicates the complexity of resource management in the automotive sector, especially when going beyond ELV treatment alone. Therefore, it does not represents a complete overview, for which dedicated review studies should be taken into account that reflect on the literature of the various sub-fields in the automotive sector (e.g. Cossu et al., 2014; Cossu and Lai, 2015b; Cucchiella et al., 2016; D'Adamo and Rosa, 2019; Karagoz et al., 2019; Mayyas et al., 2012; Vermeulen et al., 2011).

Given the large variety of existing methods and evaluation perspectives, in the following, SEA is applied to a case study of a generic European automotive system which serves as the demonstration and extension of the SEA method by an additional temporal perspective. SEA is applied to combinations of diverse CE strategies, that focus on the level of materials (e.g. recycling), components (reuse), products and overall vehicle stock (lifetime extension, reduction of the vehicle stock). Thereby, the aim is to assess the resource utilization and related losses of product, component and material functionality over time, while identifying the most effective CE strategy combinations that preserve functionality at the highest level with minimal effort (measured in terms of statistical entropy changes). The method is applied to a set of future scenarios of the automotive system in order to provide insights into system changes that result from commonly applied CE strategies.

Based on that the article is structured as follows: The method is introduced following a three-step procedure, (1) employing a stock-driven model to calculate the flows of vehicles per year, (2) which serve as inputs into a generic MFA that translates the flows of vehicles into more detailed material flows, (3) to which the SEA method is applied. After elaboration on the vehicle components and material composition as well as the resulting Relative Statistical Entropy (RSE) values, a single vehicle's lifecycle is discussed, with attention being drawn to the changes in RSE, leading to a system evaluation and a discussion of the scenarios involved. For the evaluation of possible future transitions, several scenarios are employed that combine different sets of CE strategies, allowing for an evaluation of the effects of each CE strategy in the context of the electrification of the vehicle stock until the year 2050. Finally, in the results and discussion part, the scenarios and the model outcomes are interpreted, followed by the conclusion.

2. Materials and methods

For the evaluation of the resource effectiveness of possible future transition paths of the EU automotive system, a sequence of steps is followed (see Fig. 1). Depending on the parameters that characterize each of the scenarios employed (see Section 2.4), a stock-driven model is used to calculate the flows of vehicles between the production, the use, and the ELV treatment phases. The outputs from the stock-driven model are used as inputs for the generic MFA, thereby translating the overall vehicle flows into a more detailed set of material flows for each system phase within a certain period of time. By employing additional parameters such as reuse and recycling rates, a further scenario differentiation is achieved. Finally, SEA is applied to the MFA results.

2.1. Stock-driven vehicle model

Stock-driven models have been employed in different contexts, e.g. to estimate the evolution of housing stock and related material flows in the Netherlands (Müller, 2006), Norway (Bergsdal et al., 2007), and China (Hu et al., 2010), as well as for evaluating more specific material flows, e.g. steel (Pauliuk et al., 2012; Yan et al., 2013). Besides the stock-driven model approach that calculates the material flows based on historical or extrapolated stock data, with the in-use stock being the main driver for the material cycle, another model type is the input-driven model, which uses input and output flow data to calculate the stock (Müller et al., 2014). In the following, the stock-driven model is employed, which is based on the model provided by Pauliuk (2020). The model serves two purposes: (1) to quantify the inflows of vehicles to the use-phase and (2) to quantify the outflows of vehicles from the use-phase to the ELV-phase for each year. The model distinguishes between inflows and outflows of electric vehicles (EV) and internal combustion engine vehicles (ICEV). The structure of the model and the parameters employed are summarized in Fig. 2.

For the time period 2010 – 2017, the inflows of vehicles are based on reported data for the EU-28 (European Commission, 2019), with the 2018–2019 values being extrapolated based on the German vehicle stock evolution (Statista, 2020). For the projection of future vehicle stock for the time period 2020 – 2050, the data is extrapolated based on the projected population by EEA (EEA, 2020) and a constant vehicle ownership rate (in the base scenario) employing the base year 2019.

The vehicle stock is used to derive the outflows and inflows of vehicles per year. Based on an average vehicle lifetime of 16 years

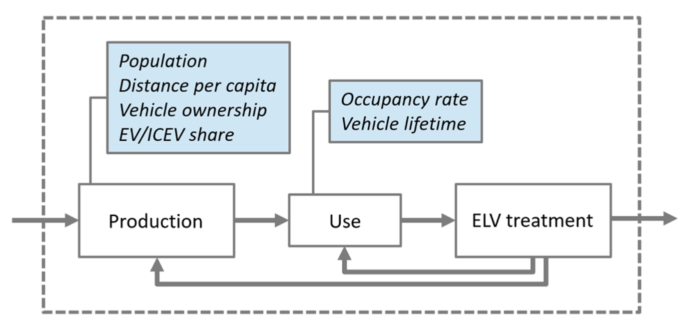

Fig. 2. Overview of the stock-driven model and parameters with an influence on overall flows of vehicles.

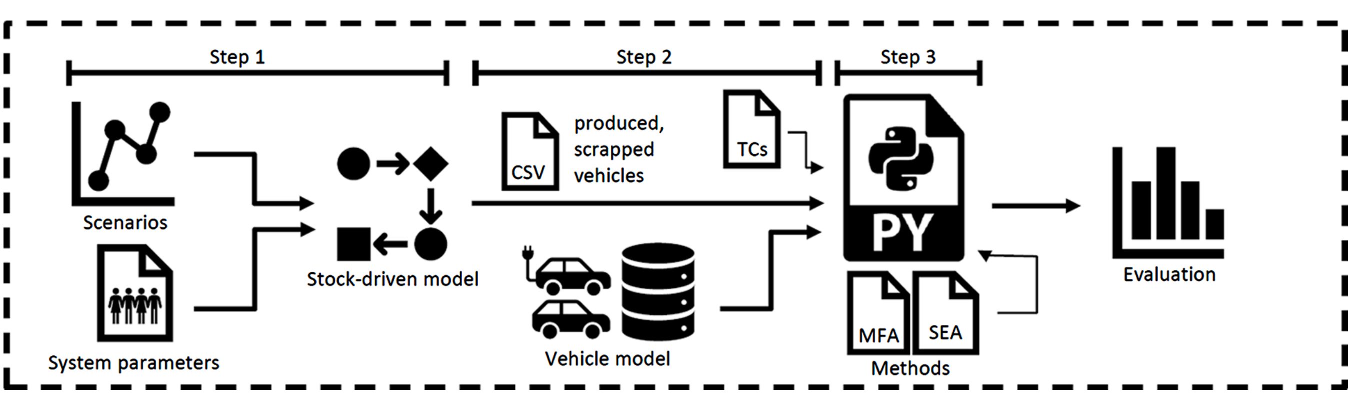

Fig. 1. Sequence of methodological steps followed to calculate the Relative Statistical Entropy, (abbreviations: CSV = 'comma separated values' data set, TC = 'transfer-coefficients' file, PY = 'Python' program, MFA = Material flow analysis, SEA = Statistical Entropy Analysis).

(scrapping age of vehicles) with a standard deviation of 5 years (Modaresi et al., 2014b), the renewal rate expresses that in each year an average of $\frac{1}{16}$ of the vehicle stock is replaced with newly produced vehicles. The number of new vehicles that enter the vehicle stock can be multiplied by the EV/ICEV ratio of each scenario (see Section 2.4).

The outflows of vehicles are derived based on the inflows of vehicles to the use system per year. The parameters that influence the outflows of vehicles include the size of the vehicle stock, the share of EVs/ICEVs in each age cohort (holding vehicles of the same age), and the lifetime function employed. Even though different lifetime distribution functions exist, the example of Müller (2006) is followed, using a normal distribution applied to each vehicle age cohort. In this case, the use of the normal distribution is applicable as vehicles are (1) considered a mature product with low initial failure rates, while (2) the average vehicle lifetime of 16 years with a standard deviation of 5 years locates the distribution far away from negative lifetime values. Otherwise, both aspects, the higher initial failure rates, e.g. such as in the case of electric and electronic equipment, as well as a lifetime distribution that is located closer to negative lifetime values, make the employment of a Weibull distribution advisable (e.g. Bakker et al., 2014; Geyer, 2020; Zeng et al., 2018). Further, the example of Modaresi et al. (2014b) is followed, employing the identical lifetime function for EVs and ICEVs, with more information, including the overall model provided in the supplementary information (see SIA1, vehicle model).

Based on the scenarios employed that, among others, model a demand reduction and an extension of the vehicle lifetime, additional system parameters are required (see Fig. 2, dashed boxes). In order to keep the functional unit constant, the average distance driven per person is set to 12,000 km/capita/year, representing a rounded average value for the EU-28 (Enerdata, 2016). The intensified use of the vehicle stock is modeled through a higher occupancy rate per vehicle so that the average distance driven per vehicle (15,000 km/vehicle/year), and the average vehicle lifetime remain constant. Based on the known vehicle stock, the population size and the distance driven per person, the occupancy rate of 1.52 (capita/vehicle) is derived for the year 2019, using the MS Excel® solver method. The derived occupancy rate is in the range of the reported value of 1.4 and 2.7 capita/vehicle for the EU-28 countries (Fiorello et al., 2016). For scenarios that model a reduction in the vehicle stock, the occupancy rate increases over time, reaching the value of 2.14 (capita/vehicle) in the year 2050. Another set of scenarios increases the vehicle lifetime, which reduces the renewal rate and leads to a demand reduction for new vehicles as well as to a time delay in the vehicle outflows from stock to End-of-Life treatment.

In addition to the changes in the flows of vehicles, two components, here identified as the *EV battery* (for EVs) and *other powertrain components* (for ICEVs), are employed to quantify the component flows that are replaced during the use phase of a vehicle. The lifetime of the EV battery is modeled with 9 years and a standard deviation of 3 years (Bobba et al., 2020), with the same lifetime distribution being applied to *other powertrain components*. Together with the component flows, the derived flows of vehicles are employed as inputs to the MFA. Thereby, the flows of EVs and ICEVs and related components are translated to more detailed materials flows, which are introduced in the next section.

2.2. Material flow analysis of the automotive sector

In the automotive sector, MFA has been applied to analyze the use pattern of materials like aluminum, steel, polybrominated diphenyl ethers (Cheah et al., 2009; Choi et al., 2017; Hatayama et al., 2014; Niero and Kalbar, 2019), scarce and critical metals (Andersson et al., 2017a; Restrepo et al., 2017), as well as the flows and stocks of components (e.g. Bobba et al., 2019, Diener and Tillman, 2015). The MFA model employed consists of three main sub-systems (1) production, (2) use, and (3) ELV treatment (Fig. 3), with each of them comprising more detailed processes and flows. For better readability, the production sub-system, the use sub-system and the ELV sub-system are referred to as 'production system', 'use system' and 'ELV (treatment) system' in the following.

For the conversion of the vehicle flows from the stock-driven model described further above (Section 2.1), the component composition for each vehicle type is based on the characterization by Hawkins et al. (2012). Overall, 16 materials categories (iron, steel, plastic, copper, glass, aluminum, cast aluminum, paint, rubber, carbon black, lead, graphite, neodymium, ethylene carbonate, lithium manganese oxide ($LiMnO_4$), Lithium hexafluorophosphate ($LiPF_6$) (further referred to as materials) and 11 groups of car parts, assemblies and sub-assemblies (further referred to as components) are employed. The components and materials considered represent a mass fraction of 95% for EVs and 96% for ICEVs of the original vehicle compositions (Table 1) (see SIA2–1 EV-ICEV composition).

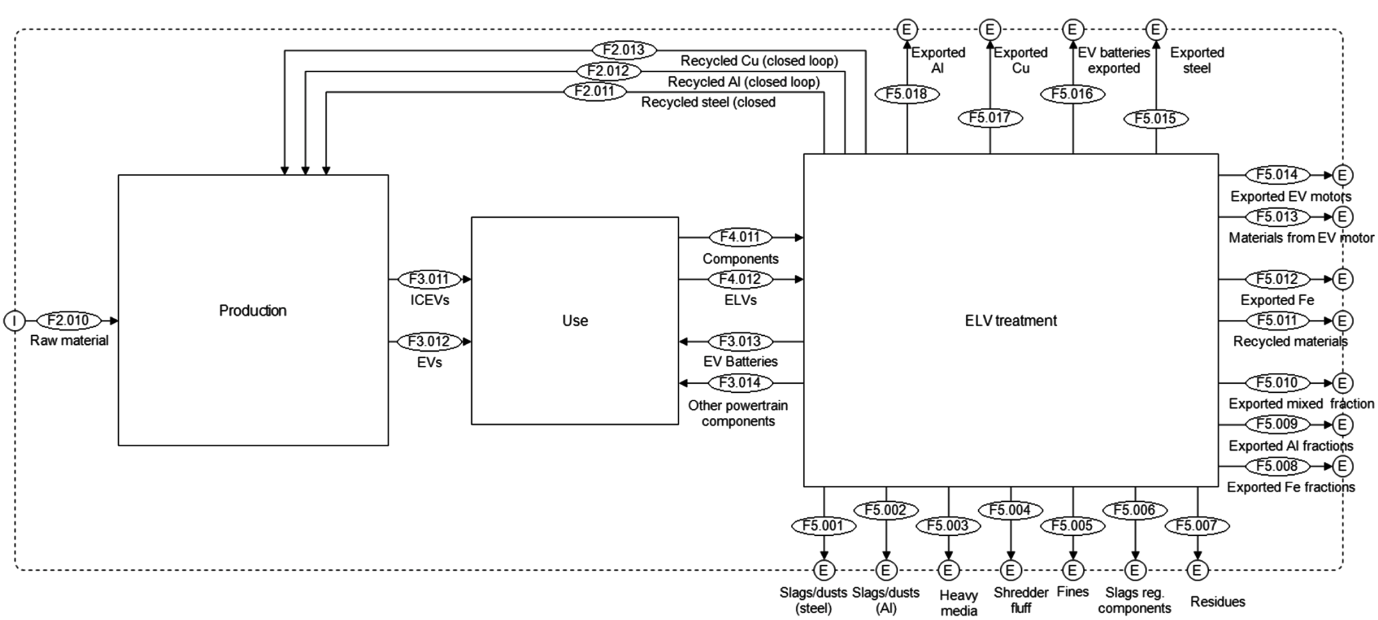

Fig. 3. Car metabolic system, with its three sub-systems referred to as the (1) production system, (2) use system, and (3) ELV (treatment) system.

Table 1
Composition of EV and ICEVs (values in kg), distinguishing between common EV and ICEV components and distinct EV and ICEV components, including the representation of the overall EV and ICEV mass for the materials employed.

Generic component composition	Components	Iron	Steel	Plastic	Copper	Glass	Aluminum	Cast aluminum	Paint	Rubber	Carbon black	Lead	Ethylen carbonate	Graphite	Nd	LiMn04	LiPF6	Total mass
Common EV and ICEV components	Interior and exterior	-	70.6	118.8	11.5	-	18.5	-	11.8	5.3	-	-	-	-	-	-	-	236.4
	Tires and wheels	-	46.9	-	-	-	-	-	-	18.1	8.3	-	-	-	-	-	-	73.4
	Brakes	18.2	10.6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	28.8
	Chassis	-	172.5	5.9	4.1	-	-	-	-	-	-	-	-	-	-	-	-	182.4
	Body and doors	-	389.0	25.0	-	28.8	-	-	-	-	-	-	-	-	-	-	-	442.8
	Lead battery	-	-	0.7	-	-	-	-	-	-	-	11.2	-	-	-	-	-	11.9
EV components	EV battery	-	-	21.3	57.9	-	35.8	-	-	-	-	-	46.4	54.6	-	56.7	5.5	278.2
	EV motor and transmission	4.5	35.9	8.1	109.5	-	184.4	-	-	3.7	-	-	-	-	1.7	-	-	347.9
ICEV components	Engine	89.3	29.0	-	-	-	-	29.8	-	-	-	-	-	-	-	-	-	148.1
	Transmission	-	26.6	4.0	-	-	12.1	-	-	-	-	-	-	-	-	-	-	42.7
	Other powertrain	-	53.1	29.7	6.5	-	-	-	-	-	-	-	-	-	-	-	-	89.3
EV		22.7	725.4	179.7	183.1	28.8	238.7	-	11.8	27.1	8.3	11.2	46.4	54.6	1.7	56.7	5.5	1601.8
ICEV		107.4	798.3	184.0	22.1	28.8	30.6	29.8	11.8	23.4	8.3	11.2	-	-	-	-	-	1255.9

The production system and the ELV treatment system are linked by the use system, which is represented by the stock-driven model introduced further above (Section 2.1). The number of vehicles produced as well as the relative fraction of EVs and ICEVs determine the flows in the production system. Similarly, the outflows of vehicles from the use system result in the ELVs to be treated in the ELV system.

2.2.1. Vehicle production and use systems

The vehicle production system reflects the production of the individual components and the vehicle assembly. Three component categories are distinguished: components produced for (1) EVs, (2) ICEVs and (3) the so-called glider that represents a vehicle without the power train and that is employed in the EV as well as in the ICEV (see Table 1). The material flows are determined by the composition of each component and by the demand for vehicles in a specific year, including the distribution of EVs/ICEVs (Fig. 4). Raw material inputs into the production system are modeled as pure material flows, with additional flows of recycled materials returning from the ELV system (steel, cast aluminum, copper). Other materials are recycled in an open-loop recycling process and are therefore directed to other sectors. The degree to which the recycled materials can be reused in the car production process is limited by the corresponding absorption capacity of the vehicle numbers produced. An example is the utilization of recycled cast aluminum (cast-Al) that is primarily utilized in the ICEV engine block and transmission components, representing the main sinks for recycled cast-Al (Modaresi et al., 2014a). In the following, the recycled cast-Al uptake potential is limited by the cast-Al fraction of the *engine*, the steel uptake potential is limited by the vehicle's *body and doors*, and the copper uptake is limited by the *EV motor and transmission*. In the case that, in one or more years, the production system cannot take up the recycled materials, a surplus of recycled material can occur that is not utilized in the vehicle system and instead is exported to other sectors (Buchner et al., 2017).

Besides the recycling of materials, a reuse of two components, the *EV battery* (for EVs) and *other powertrain components* (for ICEVs), is implemented. Even though in practice a larger number of components could be reused and remanufactured, consideration of the two selected components allows the effect of functionality maintenance to be assessed at the level of the component. Component reuse avoids the need for production of new components for repair activities during the vehicle lifetime. Even though the simplification of the model is apparent, the proposed component selection allows scenarios in which a large proportion of car components are exchanged, scrapped, or reused to be modelled, thereby establishing a more comprehensive flow diversion as compared to one in which minor components (e.g. brake calipers) are reused.

2.2.2. ELV treatment system

The implementation of the ELV directive (Directive 2000/53/EC) resulted in an intensified study of ELV system assessments in terms of specific material fractions, e.g. automotive shredder residue (ASR) (Cossu and Lai, 2015a), treatment processes (e.g. Ciacci et al., 2010), and ELV systems of EU member states (e.g. Andersson et al., 2017, Restrepo et al., 2017). Despite compliance among a large majority of EU-member states with the ELV directive's (2000/53/EC) targets to recycle and reuse 85% and recover 95% of the vehicle mass (Eurostat, 2020), few studies take an overarching EU perspective (e.g. Mathieux and Brissaud, 2010). The reasons for this could be the diversity of ELV treatment systems and/or the uncertainty and variability regarding the input and output material flows and their composition, especially when translating the available information to the European level (see SIA2–2 Uncertainties ELV). In this context, it must be stressed that the MFA derived here is meant to serve as a generic model.

The structure of the ELV treatment system is based on the study by Andersson et al. (2017a), which provides one of the most detailed MFA studies concerning the processes and mass flows for the EU member state

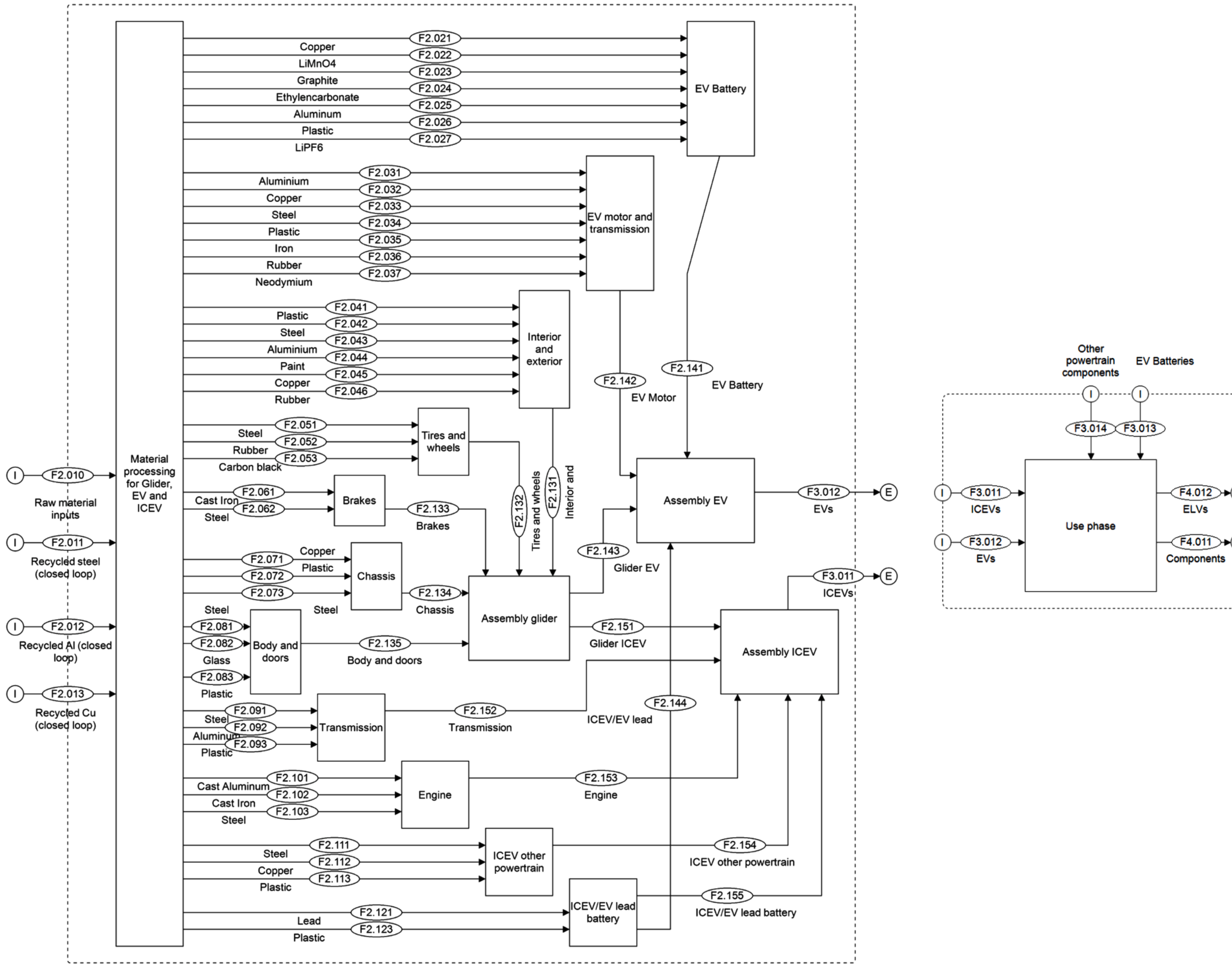

Fig. 4. Vehicle production and use systems.

Sweden. As the system structure varies between individual ELV treatment plants and between countries, the complexity of the system structure is reduced to represent the main processes (see SIA2–3 Generic MFA), thereby allowing for a larger number of literature sources to be considered, especially when deriving the compositions of the material flows (see SIA2–4 Derived transfer-coefficients).

The ELV treatment process starts with the dismantling of vehicle components. Some components, like batteries, represent regulated components and require separate recycling processes. Depending on the vehicle age and condition, most valuable components are dismantled to serve as spare parts for reuse, ultimately resulting in around 90% of the vehicle being directed to the shredder (Cossu and Lai, 2015b; Despeisse et al., 2015). In the ELV model employed, the reuse of components is modeled through the partial reuse of *Other powertrain components, EV batteries,* and *EV motor and transmission*. In addition to components that enter the system as part of the vehicle (integrated in the ELV), component flows generated during the vehicle lifetime (*Other powertrain components* and *EV batteries and transmission*) are also included.

After dismantling and the diversion of some components to specialized processes, like battery recycling, the remaining ELV hulks enter the shredder, where the vehicle is compacted and cut by a hammer mill (Vermeulen et al., 2011). Air separation partitions the shredded fraction into a light and a heavy fraction, which enter two different treatment processes. The heavy fraction largely consists of metals, which are further segregated by magnetic separation into ferrous and non-ferrous scrap that eventually enter a specialized metal recycling process. The light fraction is divided into different fractions of automotive shredder residue (ASR), further referred to as shredder fluff. Shredder fluff consists of light combustible materials in varying proportions, e.g. rubber, plastic, and textiles (Gradin et al., 2013; Mancini et al., 2012; Ruffino et al., 2014; Santini et al., 2011). The non-ferrous fraction typically undergoes an eddy-current separation, where metals such as aluminum and copper are separated (Despeisse et al., 2015), with the rest of the material sent on for heavy media processing. Based on the density of the materials, additional material fractions of different density groups are produced, which are exported to be treated in more specialized processes, are landfilled, or enter the energy recovery process (Cossu and Lai, 2015a; Mancini et al., 2014).

Based on the processes and material flows shown in Fig. 5, additional literature sources are employed to derive transfer-coefficients (TCs) that describe the partitioning of the material input flow to the output flows of each process, thereby allowing the material flows in the ELV system to be modelled (SIA2–3 Generic MFA). Based on the vehicle flows and the shares of EVs/ICEVs, the material flows can be calculated for each year, while allowing the introduction of system improvements based on the scenarios employed. Each of the scenarios can then be evaluated for its ability to produce functional components and materials, while quantifying the effort that is expressed in terms of statistical entropy changes

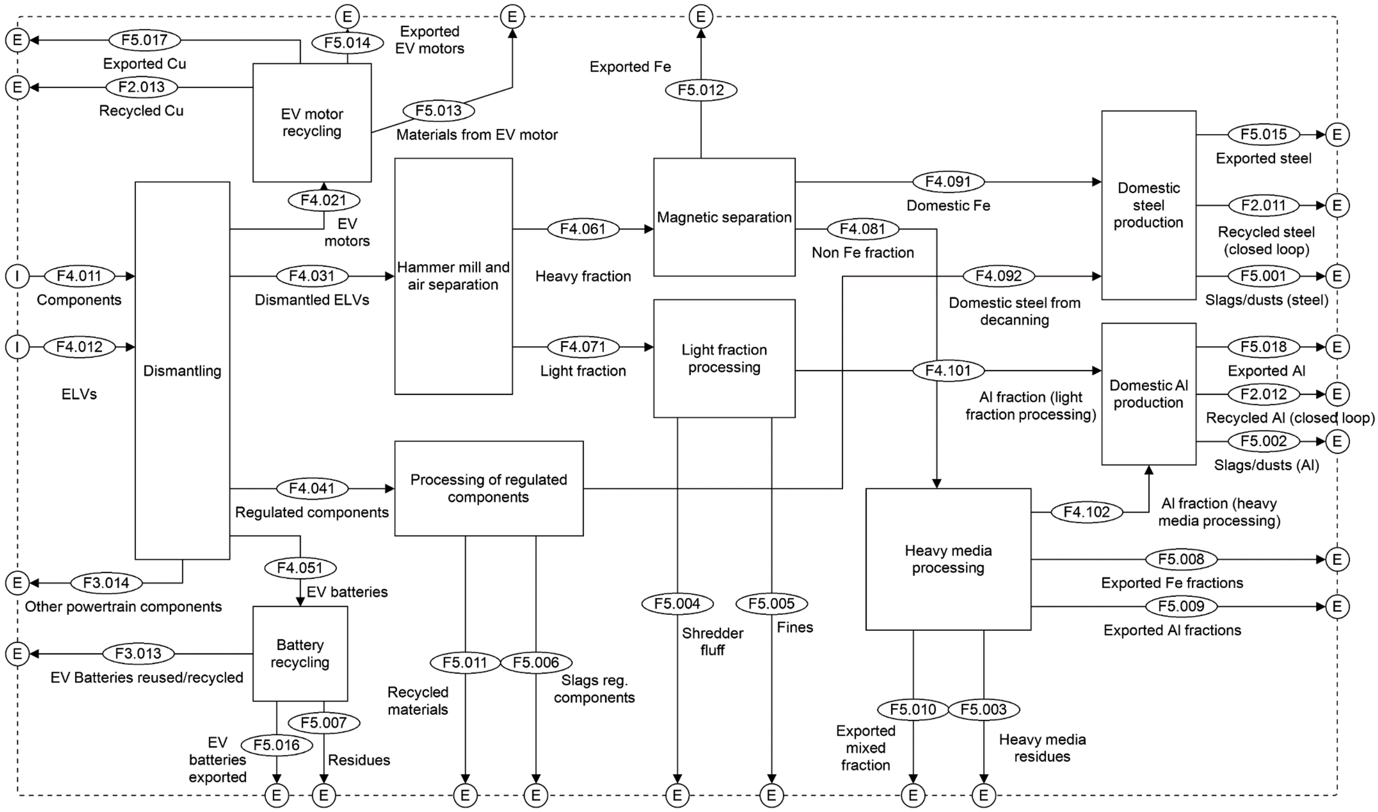

Fig. 5. ELV treatment system.

over time.

2.3. Statistical entropy analysis

Statistical Entropy Analysis (SEA) is a method that has its origins in information theory and has been developed to further analyze the outcomes of an MFA by assessing the distribution patterns of substances. Originally applied to a single substance, SEA quantifies to what degree the distribution pattern of a substance is altered throughout the system by concentration or dilution processes (Rechberger, 1999; Rechberger and Brunner, 2002). The basic principle is that processes such as recycling, sorting and refining concentrate substances, resulting in a decrease in statistical entropy, while processes that mix and dilute substances, e.g. by directing a substance to a waste flow or an environmental compartment, increase statistical entropy. SEA results are expressed in terms of Relative Statistical Entropy (RSE), a normalized value in the interval [0, 1], with the value of one representing the highest possible state of dilution and the value of zero indicating a state of full concentration or purity of each substance present in the system.

The recently proposed extension of the method (multilevel SEA) takes additional hierarchical levels of components and products into consideration, allowing the assessment of (combinations of) different CE strategies such as reuse, remanufacturing and recycling (Parchomenko et al., 2020). Further, it has been demonstrated that RSE results can be related to an ideal CE state that preserves functionality at the highest possible level over time. In a product production – use – end-of-life system, the preferred state is the state of the functional material or component embedded in a functional product. Once this functional product state is reached, the functionality should be preserved for a maximum period of time. From that point on, any increase in RSE indicates a functionality loss that can only be restored by employing additional processes that reverse the RSE increase (e.g. a worn-out component is discarded, processed as waste and substituted by a working one, or is repaired). The rationale is therefore that any changes in RSE should be avoided as long as possible once a functional product state is reached to avoid the effort required for returning it to the initial functional state. In order to demonstrate the rationale behind the method, in the following the calculation of RSE values is described for the material level.

Statistical entropy values are calculated for each stage in a system that consists of a set of material flows between processes, imports to and exports from the system. An illustration of the transformation of a material flow diagram into a stage flow diagram is provided in Fig. 6. More

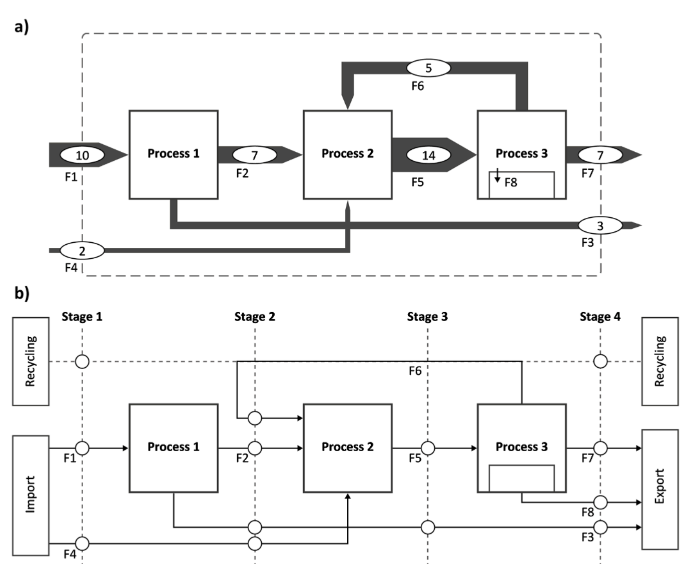

Fig. 6. Illustration of the transformation of flows in a material flow diagram (a) to a stage flow diagram (b) (from Laner et al., 2017).

detailed descriptions on the transformation procedure are provided by Rechberger and Graedel (2002) and Laner et al. (2017).

Given a set of I material flows, the first step in the description of a material flow requires its mass that is expressed as M_i (in mass per time[1]). By calculating the substance concentration c_{ij} of substance j in material flow i, the substance flow rate is obtained by the product of M_i and c_{ij} ($X_{ij} = M_i c_{ij}$). Each material flow is described by its substance composition, reflected in terms of substance concentrations (substance mass divided by the total mass of the material flow [-]), so that the concentrations $\sum c_{ij}$ of all substances j in material flow i always equal to one. Therefore, M_i also represents the sum of substances $j = 1,\ldots J$, with J number of substances in the material flow i, so that $M_i = \sum X_{ij}$ (in mass per time). Further, each material flow is normalized through Eq. (1) (mass per time divided by mass per time, [-]), setting each material flow in relation to the total material turnover in a system. For the comparison of a set of different systems the normalization is performed in relation to the system with the largest material turnover.

$$m_i = \frac{M_i}{\sum_{i=1}^{I}\sum_{j=1}^{J} X_{ij}} \tag{1}$$

After the calculation of the substance concentration c_{ij} and the normalized mass m_i ([-]) for each material flow, they enter the statistical entropy function through Eq. (2).[2]

$$H_i(c_{ij},\ m_i) = -\sum_{j=1}^{J} m_i \cdot c_{ij} \cdot ld(c_{ij}) \tag{2}$$

After the calculation of statistical entropy values they are translated to relative statistical entropy values ($H_{i,\ rel}$) by dividing each value by the maximum statistical entropy value that is possible in a set of systems ([-]). In the following, the maximum statistical entropy value is derived based on the largest possible dilution within the system. By employing a set of scenarios that are modelled over time, a system with the largest material turnover is identified, and its state of highest possible dilution is chosen, e.g. representing a shredded and mixed waste flow, that is calculated by Eq. (3)

$$H_{max}(c_{ij}) = -\sum_{j=1}^{J} c_{ij} \cdot ld(c_{ij}) \tag{3}$$

In this case, the largest material turnover is set to 17.46 million vehicles that enter the vehicle stock (based on scenario S70 introduced in Section 2.2). The maximum vehicle mass is chosen by employing MS Excel® solver, for identifying the EV and ICEV proportions that lead to the identification of the H_{max} (see SIA2–5 H_{max} & M_{max}).[3]

By dividing each entropy value by the maximum possible entropy value leads to the relative statistical entropy $H_{i,\ rel}$, for each material flow, Eq. (4).

$$H_{i,\ rel} = \frac{H_i}{H_{max}} \tag{4}$$

Thereby, Statistical Entropy is always expressed as a dimensionless RSE value, ranging between [0,1]. For the calculation of the statistical entropy value of components and products, an analogues approach is employed, with the difference that components represents entities with a more differentiated structure. Product entropies are calculated as the sum of component entropies, with a more detailed introduction to the method, please see Parchomenko et al. (2020). The changes in RSE (ΔRSE) between system stages (e.g. stage a-e) are calculated according to Eq. (5).

$$\Delta RSE_{a-e} = |RSE_e - RSE_d| + |RSE_d - RSE_c| + \ldots + |RSE_b - RSE_a| \tag{5}$$

The calculation of the material flows and the ΔRSE values is performed in a combined MFA-SEA model (*SI: MFA_SEA_model_supplementary_python*).

2.4. Future transition scenarios

The scenarios that are employed in the following serve to evaluate possible future states of the EU automotive system through SEA and are explicitly stated as hypothetical, being subject to various limitations that are discussed by Vergragt and Brown (2007). The scenarios are summarized in Table 2, followed by a more detailed description.

2.4.1. Scenario I – II: (S70 and S100)

In the first two scenarios the only transition driver is the increased market share of EVs. In the year 2050 the share of EVs sold is 70% (*S70*) and 100% (*S100*). Other parameters, like lifetime and ELV recycling system performance, are left unchanged. The first two scenarios thus focus only on the different speed and magnitude of EV uptake.

2.4.2. Scenario III – increased component reuse (S70-REU)

The third scenario builds upon the *S70* scenario with the addition that higher reuse of vehicle components is implemented. The reuse of components is modeled through the flows of *EV batteries*, and *EV motors* for EVs and *Other powertrain components* for the ICEVs. The components are sourced from two routes: (1) from ELVs that enter the dismantling process and (2) from components that broke down and were removed during the lifetime of a vehicle (see Fig. 5). EV motors enter the recycling system only as part of an ELV.

The increase in reuse is modeled as an increase in the diversion rate away from the process of hammer mill and air separation, directing the components to specialized processes like *EV motor* recycling, battery recycling, or to the reuse flow of *other powertrain components* (see Fig. 5). For component flows that enter the recycling system as part of an ELV, the diversion rate of the components to specialized processes (EV battery recycling and EV motor recycling) increases for *EV batteries* from 0.45 to 0.95 and from 0.3 to 0.5 for *other powertrain components*. For components that do not enter the recycling system as part of an ELV, the diversion rates are set to 0.95 for *EV motors* and *batteries* and 0.5 for *other powertrain components*. The uptake of components is limited by the number of components produced for spare parts for one year, reflecting the situation that used components are only employed as spare parts for repair and not employed in the production of new vehicles.

2.4.3. Scenario IV – increased component reuse and recycling (S70-REU-REC)

In addition to the increased reuse of components, the *S70-REU-REC* scenario includes an improvement in the ELV recycling system. As the ELV recycling system is modeled via TCs, system improvements are also translated to TCs that are employed from the year 2030 onwards. Even though it is unlikely that system improvements occur during a time period of one year, the rapid transition allows to the effects of recycling and reuse to be clearly distinguished. The changes implemented in the ELV system from the year 2030 onwards are summarized in Table 3.

2.4.4. Scenario V - VII – demand change (S70D, S70D-REU, S70D-REU-REC)

Scenarios *V-VII* build upon the scenarios *I, II* and *IV,* with the only difference being that a demand reduction for new vehicles is implemented. The demand reduction is modeled through a higher occupancy rate per vehicle, which increases steadily from 1.52 persons/vehicle in the year 2020 to 2.14 persons/vehicle in the year 2050. The modeled

[1] Any material flow system expresses the flows of materials over a defined time period. Therefore, formally each component and product represents a component flow and product flow over time, which for better readability is simply referred to a/the component or product.

[2] ld() stands for "logarithm dualis", the logarithm to the base 2

[3] twice the mass of the EV model employed, thereby ensuring that normalization values always represent the maximum mass, even if considering additional flows from the vehicle stock such as components that reached EoL.

Table 2
Scenarios employed in the analysis with their corresponding key parameters, indicated by the color codes (S = 'scenario', D = demand reduction, REU = reuse, REC = recycling, LFT = lifetime, EV= electric vehicles, ICEV = internal combustion engine vehicles).

	S70	S100	S70-REU	S70-REU-REC	S70D	S70D-REU	S70D-REU-REC	S70D-LFT	S70D-REU-REC-LFT	S100-REU-REC-LFT
Share of EVs in 2050 (sales) 70%	■		■	■	■	■	■	■	■	
Share of EVs in 2050 (sales) 100%		■								■
Demand reduction (from year 2025)					■	■	■	■	■	■
Higher reuse of components			■	■		■	■		■	■
Improved ELV recycling (from year 2030)				■			■		■	■
Lifetime increase								■	■	■

Table 3
Improvements in the ELV recycling system from the year 2030 onwards, based on reported sources and assumptions to be found in the supplementary information (SIA2–4.2 TCs improved).

Process	Improvement
EV motor recycling	*10% improvement in the reuse of the metal fraction that is present in EV motors (iron, steel, copper, aluminum)*
Battery recycling	*Recycling of battery materials doubled, (compensated by reductions of batteries exported)*
Hammermill and air separation	*Diversion of iron and steel increased from 96.7% to 97.0%, and of plastic from 86.7% to 90.0%*
Magnetic separation	*Domestic recycling of ferrous metals increased by 10%, as well as diversion of copper from ferrous fraction*
Heavy media processing	*Diversion of copper from 14.5% to 60.0%, and glass from 50.0% to 80.0%*
Domestic steel production	*Closed-loop recycling of ferrous metals increased by 20% (potential uptake limited by the demand created by the component body and doors in a specific year)*
Domestic Al production	*Closed-loop recycling of cast aluminum increased by 70% (potential uptake limited by engine cast aluminum demand in a specific year)*

increase in the occupancy rate per year results in a vehicle stock reduction of 74 million vehicles in 2050 if compared to the 272 million vehicles in the year 2020. The increase in the occupancy rate is based on the assumption that an increasing use of various car-sharing strategies will be employed, representing one element of the updated Circular Economy Action Plan of the EU (European Commission, 2020).

2.4.5. Scenario VIII to X – lifetime increase (S70D-LFT, S70D-REU-REC-LFT, S100D-REU-REC-LFT)

The scenarios *VIII* to *X* model the effect of a lifetime increase in the vehicle stock from the year 2020 onwards. The lifetime increases from 16 to 18 years for the scenarios *S70D-LFT, S70D-REU-REC-LFT and S100D-REU-REC-LFT*. The last two scenarios are included as they combine the implementation of all CE strategies that have been employed in previous scenarios with EVs, representing 70% and 100% of all vehicles entering the stock in 2050.

3. Results and discussion

3.1. Flows of produced vehicles and ELVs

The flows of newly produced vehicles that enter the use system (Fig. 7A) and the outflows of ELVs from the use system entering the ELV system (Fig. 7B) are projected over time (in millions of vehicles per year). A distinction is made between the total flow of vehicles, EVs and ICEVs. The projections are shown only for the *S70, S100, S70D*, the *S70D-LFT and the S100D-LFT* scenarios, as all other scenarios build on one of these projections (e.g. *S70D-REU* employs the flows of vehicles from the scenario *S70D*, with additional improvements in the reuse *'REU'*). The increase or decrease in the uptake of EVs and ICEVs is shown by the slopes for each scenario graph, e.g. the inflows of ICEVs being directly related to the number of EVs entering the vehicle stock in a specific year. Aggregation of the inflows of ICEVs and EVs results in the total inflows of vehicles for each scenario. The total inflows and outflows of vehicles decrease for the scenarios with a demand reduction (*S70D*), while the increase in the vehicle lifetime leads to a further reduction of total vehicle flows (*S70D-LFT*). Besides the overall number of vehicles that enter the use system per year, Fig. 7A also shows the intersection of EV and ICEV graphs, indicating when EV and ICEV inflows are equal.

The outflows of vehicles from the use system to the ELV system are shown in Fig. 7B. The outflows of vehicles react with a delay that results from the vehicle lifetime. For this reason, the outflows of vehicles start changing only towards the year 2030. The changes of outflows between the different scenarios accelerate towards the year 2035, from then on following a similar pattern as the inflows in the year 2020, with the difference that the curves are smoothed due to the lifetime function applied.

The inflows and outflows of vehicles are used as inputs to the MFA-SEA model. Before presenting the results of the MFA-SEA model over time, a single vehicle's RSE values, distinguished by its materials and components, are presented, followed by a discussion of a vehicle's lifecycle.

3.2. Relative statistical entropy and its evolution over a single vehicle's lifecycle

The direct comparison between the material composition of each component in terms of its mass (Fig. 8A), the resulting RSE values (Fig. 8B) and the RSE per kg of material employed (Fig. 8C) allows to illustrate how each component and its materials contribute to the overall RSE of the vehicle. According to the vehicle's composition presented further above (Table 1), the same three main component groups are distinguished.

The glider components are common to both vehicle types (EV and ICEV) and represent a large fraction in terms of their mass as well as in terms of RSE. The comparison between the material composition and the resulting RSE values shows that components with a less complex material mix like the *body and doors* or the *chassis* (see Fig. 8A) have lower RSE values if compared to their mass fraction in the vehicle (see Fig. 8B). The reason is that both components are composed of only a few materials, with one material, in this case steel, being the dominant constituent. The contribution of steel to the components' RSE values is small, and if expressed in terms of RSE/kg (Fig. 8C), steel becomes even less important, while other materials such as copper, glass and plastic have a

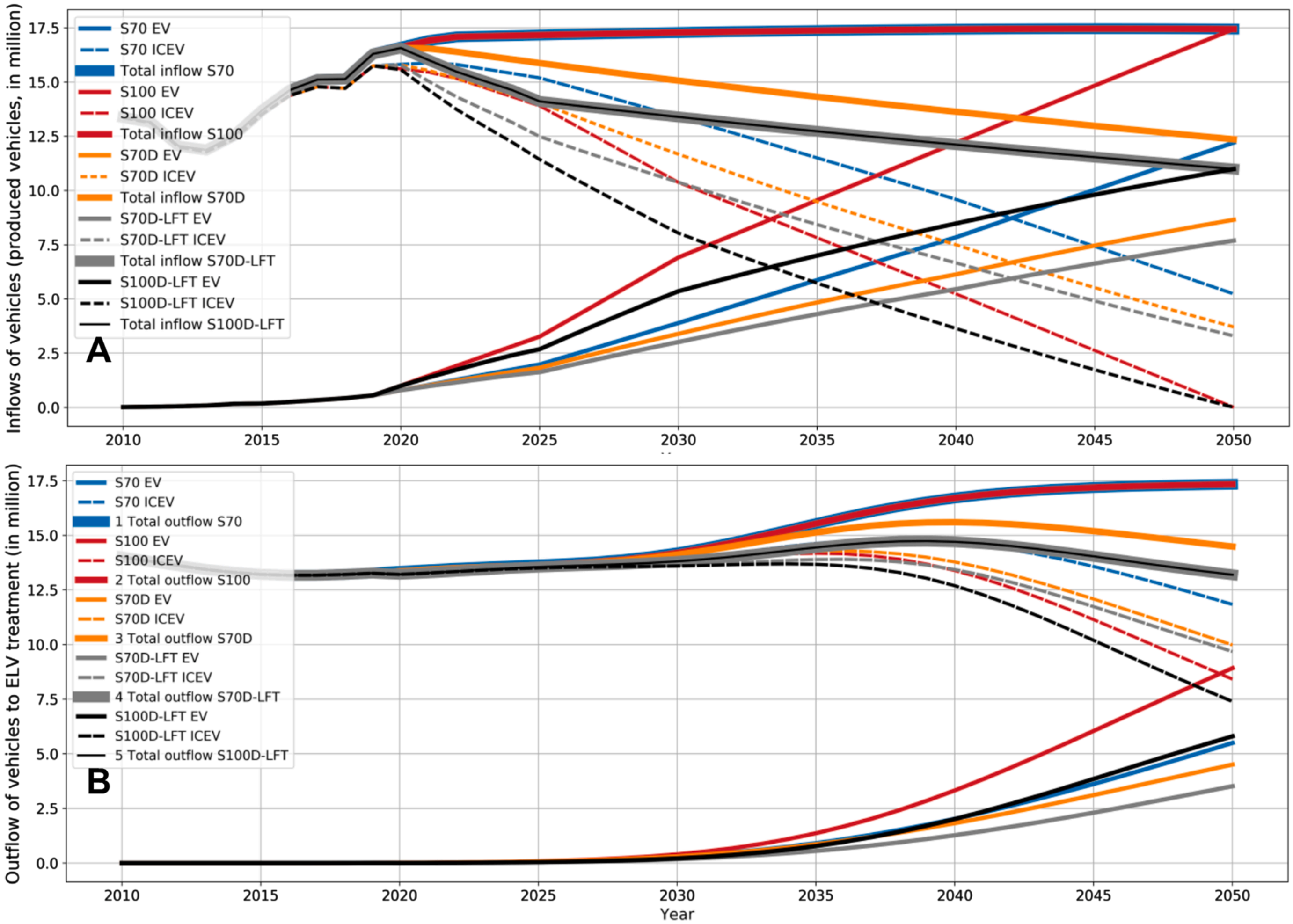

Fig. 7. (A) Inflows of vehicles from the production system to the use system, and (B) outflows of vehicles from the use system to the end-of-life treatment system as end-of-life vehicles (ELVs).

larger influence on the components' RSE (Fig. 8B).

Employing another component example of the *interior and exterior* shows that the presence of a larger diversity of materials and their higher dilution is reflected in higher RSE values. In this case, rubber, paint, aluminum and copper represent 20% of the component's mass (Fig. 8A) but contribute 45% to the component's RSE (Fig. 8B). Expressed in RSE/kg, Fig. 8C shows that rubber, paint, aluminum and copper are present in a highly diluted form. Given that larger component complexity and higher material dilution (here expressed in higher RSE values) has an implication for subsequent end-of-life treatment processes, e.g. having a negative influence on their recyclability (Gutowski et al., 2011; Iacovidou et al., 2017b; Tam et al., 2019), RSE values can be employed to identify material and component hot-spots that make recycling more challenging, while triggering further considerations, e.g. regarding product design. Nevertheless, it is not the main function of SEA to guide design choices, and RSE values have always to be viewed in the inherent systemic perspective of the method, with the changes in RSE always resulting from the underlying MFA system.

The comparison between EV and ICEV specific components shows how component composition and component mass contributes to their different RSE values. Both EV components, the *EV battery* as well as the *EV motor and transmission,* have a large mass (Fig. 8A) that together with their more complex material composition and higher material dilution (Fig. 8B) results in their high RSE values. In contrast, the ICEV related *engine, transmission* and *other powertrain* components exert relatively low influence on the overall RSE of the vehicle. Besides copper and plastic, which are diluted to a higher degree, the base metals steel, iron, aluminum and cast-Al add little to the RSE of ICEV specific components (Fig. 8B). The higher RSE values of the EV components and their materials (Fig. 8B, 8C) draw attention to the challenges that are related to their recycling and the effort involved (e.g. Oliveira et al., 2015; Yun et al., 2018; Zeng et al., 2014). As an example, Nd that is present in a highly diluted form (Fig. 8C) requires more targeted recycling processes and therefore remains a challenge for the recycling sector due to related effort and costs, despite the potentially high-value recovery (e.g. Bandara et al., 2014).

3.2.1. Evolution of relative statistical entropy over a single vehicle's lifecycle

The lifecycle of a vehicle starts with the production phase, representing a dilution and/or mixing process of the very pure and refined raw materials, which is shown by an increase in RSE for both the ICEV and EV and is expressed as ΔRSE (see Fig. 9). The RSE increase is larger for the EV, being the result of the higher material dilution within the *EV battery* and the *EV motor and transmission* components. Both components have a high mass, while representing a higher complexity in their material composition, resulting in overall higher ΔRSE values. For the ICEV, the *engine, transmission* and *other powertrain components* represent the ICEV specific components, which lead to a smaller RSE increase as they have a less complex composition, consist of less diverse raw materials and have an overall lower mass.

The higher dilution of materials that is related to the EV specific

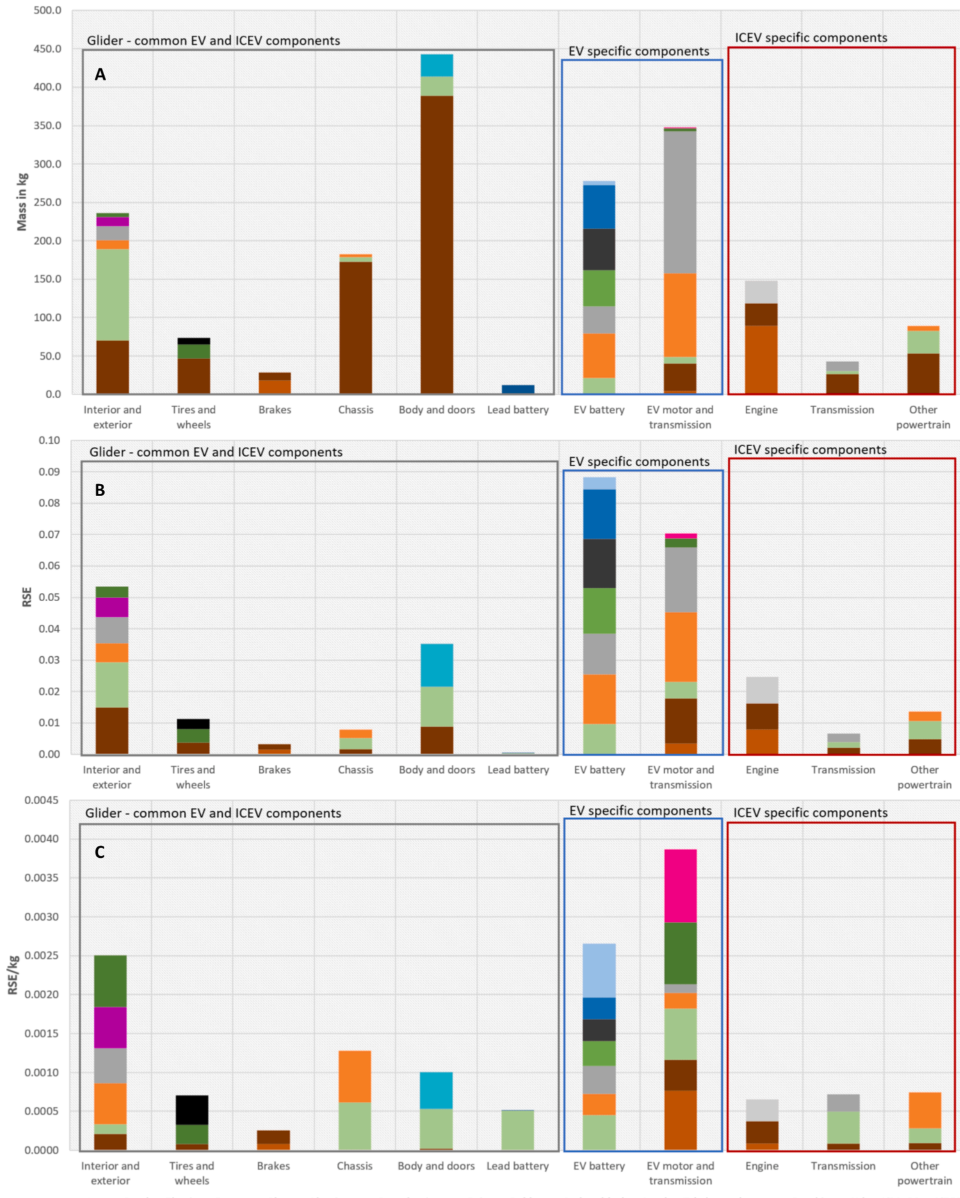

Fig. 8. Component material composition (in kg) (A), Relative Statistical Entropy (RSE) for components and materials (B), and RSE per kg of material (EV = electric vehicle, ICEV = internal combustion engine vehicle).

components also has a strong influence on the ΔRSE in the use-phase of the vehicle. With an average battery lifetime of 9 years, the replacement of the battery during the use-phase of the EV by a newly produced battery means that additional ΔRSE are produced to prolong the lifetime of the vehicle. The here assumed high degree of EV battery reuse in other, non-automotive applications leads to a small fraction of 7% of the ΔRSE being attributed to the end-of-life handling of the battery. Nevertheless, the overall increase in RSE that is related to the replacement of the EV battery is substantial, representing 34% of ΔRSE of the initial EV production. Therefore, the high fraction of the ΔRSE that is attributed to the battery, also in light of the overall lifecycle, as is shown by the cumulated ΔRSE-values over all system stages ($\Delta RSE_{cum,\ EV}$) (Fig. 9), highlights the importance of preserving the battery and extending its lifetime.

For the ICEV, the components replaced during the vehicle lifetime are modeled through *other powertrain components* as it is assumed that the *engine* and *transmission* have the same lifetime as the vehicle. If compared to the EV, the ΔRSE are smaller for the ICEV use-phase, with a higher share of 43% of ΔRSE being related to RSE reductions performed during ELV recycling. Comparing the two cases of vehicle maintenance and component replacement that are performed during the use-phase, and in light of their relative weight regarding the overall ΔRSE_{cum}-values of the entire vehicle lifecycle, the magnitude of the ΔRSE related to replacing the EV battery must be highlighted.

After the use-phase the vehicle reaches its end-of-life and enters the ELV system. The disassembly and diversion of components for further reuse and specialized recycling processes play not only an important role in preserving components but also influences the downstream material recycling processes. The level of disassembly of the components and their diversion from shredding affect the ΔRSE at the *reuse and shredding stage*. The degree to which RSE increases can be avoided depends on the type of components that are diverted and on their respective component mass.

Following the vehicle through the ELV system, the reuse and shredding stage is succeeded by material recycling processes. The here modeled ELV recycling processes are described in more detail further

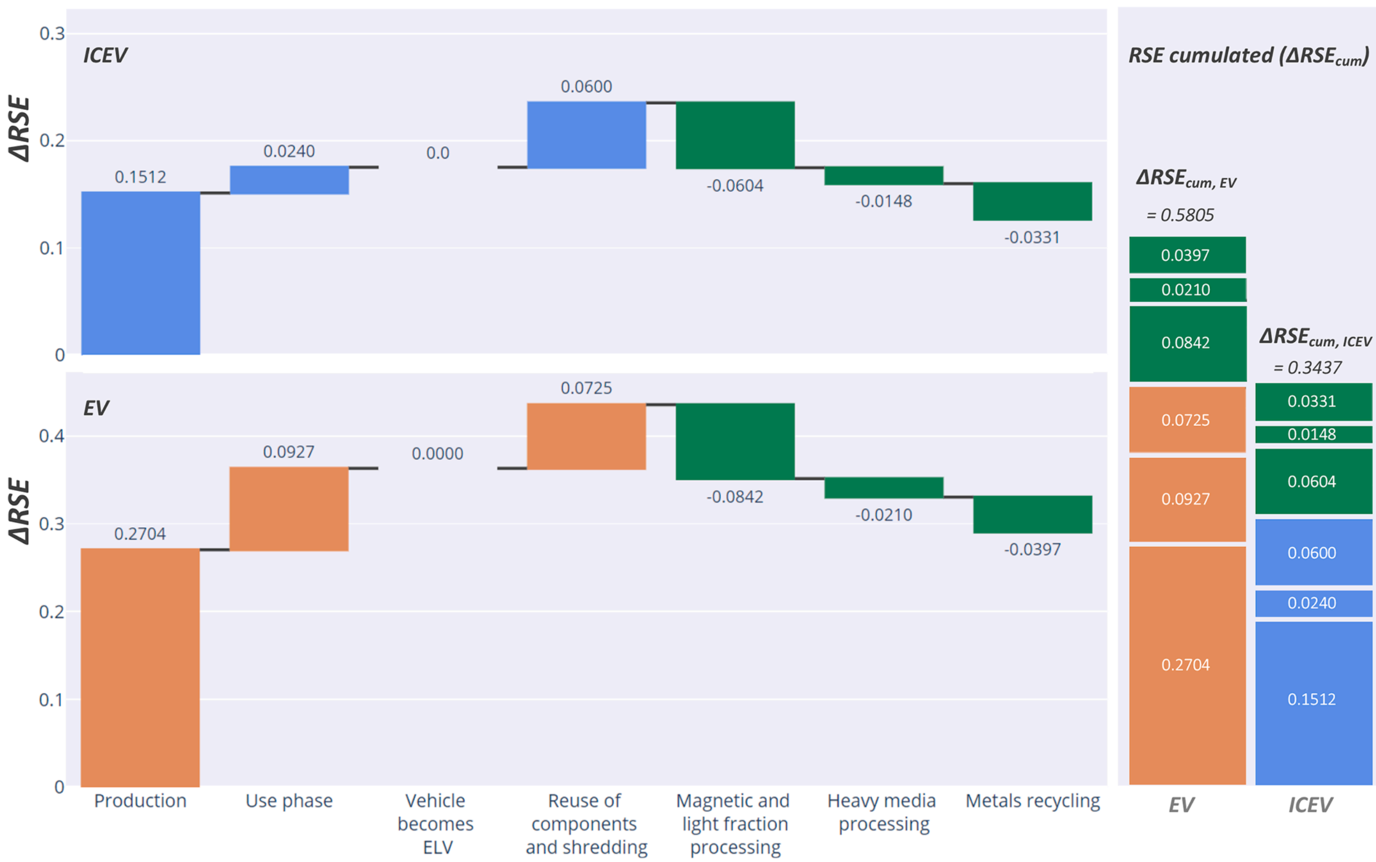

Fig. 9. Changes in Relative Statistical Entropy (ΔRSE) for a single vehicle (ICEV and EV) during its lifecycle, additionally shown as cumulated values (ΔRSE_{cum}).

above (Fig. 5) and are represented by three stages of (1) *magnetic and light fraction processing*, (2) *heavy media processing*, and (3) *metals recycling*. The three stages have in common that each of them reduces RSE values and recovers functionality by sorting, separating and concentrating target materials in specialized flows. The reduction of material dilution in the flows leads to reduced RSE values. Here it should be noted that ELV system performance can be improved by optimizing the recycling processes in terms of material yields and purities or by installing additional processes that extend the number of recovered materials.

Besides the adaptation of the ELV system, it should be stressed that improvement in the ELV system is not limited to the ELV treatment processes alone but can also be achieved by adapting any preceding stage. Starting with the design of the product that determines the choice of materials and their initial level of mixing, the lifetime, the degree of disassembly and reusability of the components as well as the relative fraction of EVs and ICEVs that enter the ELV system will all influence the ΔRSE in the automotive system under consideration. Therefore, the ΔRSE for a single vehicle lifecycle indicate how processes such as production, replacement of components, component reuse as well as the ELV recycling processes are interconnected and might only be effectively evaluated from a systems perspective.

Further, the case example demonstrates which processes increase, maintain, or reduce RSE values. It is shown that the preservation of functionality at the component and product level is reflected by the absence of ΔRSE, with production and ELV treatment processes being able to either increase or decrease RSE values. While aiming to preserve the initially achieved state of the functional product, any subsequent increase in the RSE value represents a loss of functionality. The lost functionality has to be restored through recycling and similar processes (e.g. remanufacturing) as well as production processes that are also quantified in terms of ΔRSE. Therefore, besides employing a single vehicle lifecycle perspective, as demonstrated in Fig. 8, in the following ΔRSE are cumulated (ΔRSE_{cum}) for the entire system for each single year for the time period 2010 - 2050, thereby enabling evaluation of the scenarios introduced in Section 2.4.

3.3. Evolution of relative statistical entropy changes over time

Following the introduction of the results of the single vehicle lifecycle (Section 3.2), the transition scenarios are evaluated until the year 2050. With the functional unit remaining constant for all scenarios over time, the resulting ΔRSE_{cum}-values are directly comparable. The results are presented for the production system (Fig. 10A), the ELV treatment system (Fig. 10B) and for both systems combined (Fig. 10C). The substitution of components replaced, reused and recycled are included in the overall ΔRSE_{cum}-values for each year.

3.3.1. Production system

For the vehicle production system, the ΔRSE_{cum}-values show four distinguishable trajectories (Fig. 10A). The largest RSE changes result for the *S100*-scenario, followed by the second group of scenarios (*S70, S70-REU, S70-REU-REC*) with lower ΔRSE_{cum}-values. The next two sets of scenarios are related to a demand reduction (*S70D, S70D-REU, S70D-REU-REC)* and an additional lifetime increase (*S70D-LFT, S70D-REU-REC-LFT, S100D-REU-REC-LFT*). The *S100D-REU-REC-LFT* scenario bridges the gap between the two latter sets of scenarios due to its continuous increase in ΔRSE_{cum}-values, a result of the more rapid increase in the share of EVs produced.

The accelerated uptake of EVs in the *S100* scenario shows the largest ΔRSE_{cum}-values in the production system. One reason is the higher mass of EVs (~350 kg) when compared to ICEVs, which outweighs the effect of the less complex EV product structure assumed here, leading to a net effect of higher ΔRSE_{cum}-values (see Fig. 10). The second group of scenarios (*S70, S70-REU, S70-REU-REC)* shows a slower increase in

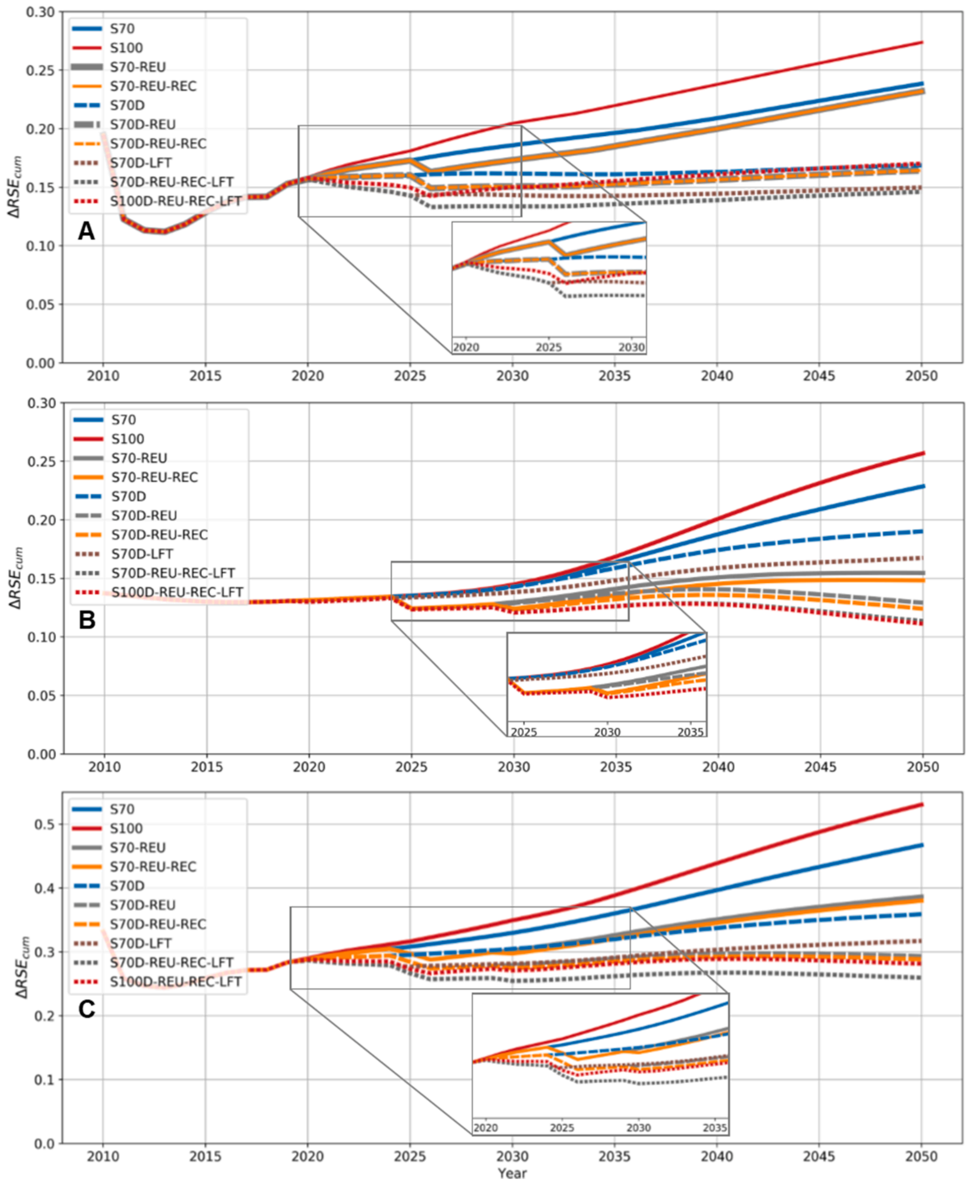

Fig. 10. Changes of Relative Statistical Entropy per year for (A) production of new vehicles, (B) ELV treatment, (C) production and ELV treatment combined.

ΔRSE_{cum}-values, with a delay in the increase of ΔRSE_{cum}-values due to the slower uptake of EVs. It must be noted that besides the reuse of components, which can partly substitute for the production of components required during the lifetime of a vehicle, the recycling strategies employed have only a limited effect on the ΔRSE_{cum} reduction in the production system. The reasons are related to the limited closed-loop recycling in the automotive system. Another reason is related to the system boundary conditions since upstream processes such as mining and raw material processing were not included in the production system proposed. The intensified reuse of components from the year 2025 that is implemented in the reuse scenarios shows the effectiveness of component preservation in reducing ΔRSE_{cum}-values.

The next set of scenarios includes the effect of a vehicle demand reduction, which could be achieved through an increasing occupancy rate per vehicle. The increase in the occupancy rate and, in addition to that, the increase in the vehicle lifetime both lead to an absolute reduction of vehicle flows, which is shown by the two different downward shifts in the curves between the years 2020 and 2025. The last two scenarios show that a similar effect could also be achieved through an increase in the vehicle lifetime. The lifetime effect leads to a parallel shift in the curves towards lower ΔRSE_{cum}-values since it also translates to an additional demand reduction for new vehicles. From the year 2025, the additional implementation of the reuse strategy demonstrates how a combination of CE strategies can lead to an additional decrease in ΔRSE_{cum}-values, while showing the overall effectiveness of a demand reduction strategy.

3.3.2. *ELV system*

Compared to the production system, the overall increase in the ΔRSE_{cum}-values is delayed for all scenarios due to the lifetime of vehicles. Further, based on the CE strategies applied, a high differentiation between the scenarios is present.

First, it can be observed that the proposed increase in the component reuse rate in the year 2025 reduces the changes in RSE in the ELV system (see Fig. 10B). The reason for this is the prolonged preservation of functionality at the component level, diverting the components from the destructive material recycling processes, and thereby avoiding the correspondingly high RSE increases.

Second, in addition to a higher component reuse rate, further improvements related to material recycling are proposed to be implemented in the year 2030. These improvements are reflected by a downward shift in the ΔRSE_{cum}-curves (see Fig. 10B). It should be noted that improvements can lead to both increases and decreases in ΔRSE_{cum}-values. Increases in ΔRSE_{cum}-values will occur when proposed system changes do not reduce initial material mixing upstream and are instead implemented only in the later stages in the system (e.g. heavy media processing). Such end-of-pipe improvement would imply undertaking greater effort to separate the more diluted material flows into fractions of the required purity. On the other hand, optimizations of upstream processes (e.g. higher dismantling) will prevent mixing and dilution later on so that processes further downstream will receive a less diluted material flow. Such a system will produce comparatively lower ΔRSE_{cum}-values as the dilution of material flows is avoided to a larger degree, consequently saving effort for separation and concentration at later stages. In the scenarios proposed here, improvements in the ELV system are implemented both in upstream processes and in the processes further downstream (see Table 3). The overall effect is a reduction in ΔRSE_{cum}-values that need to be undertaken to produce material fractions of high purity.

Third, the reduction in the vehicle stock in those scenarios with a demand reduction from the year 2020 onwards leads to an additional reduction in the slope of the ELV scenario curves. The slopes of the scenarios with a demand reduction flatten and become negative towards the year 2050, with the decreasing demand reinforcing the decline in the future number of ELVs to be processed. The delay of ELV outflows that is the result of the vehicle lifetime is also present here so that the number of ELVs entering ELV treatment is reduced, showing increasing effects from the year 2030 onwards. Further, the continuous increase in the occupancy rate that is implemented in the year 2020 leads to a reduction in ELV flows with a delay in time.

Analogous to a demand reduction, an increase in the vehicle lifetime will result in an additional decrease in ΔRSE_{cum}-values. The lifetime increase reduces the demand for new vehicles and delays the outflows of ELVs to ELV treatment, which reduces the slope of the scenario curves even further. Combined with other strategies, such as demand reduction (*S70D-LFT*), increasing the vehicles' lifetime by two years is clearly very effective in reducing effort in the ELV system. Putting in place additional CE strategies beyond the strategy of lifetime extension, such as increasing the reuse of components, improved recycling and demand reduction, will further decrease future recycling effort to a minimum. The scenario with an accelerated EV uptake that is accompanied by the full implementation of the CE strategies employed (*S100D-REU-REC-LFT*) shows that an accelerated transition to electric mobility can be undertaken with decreased effort, but requires an intensified implementation of CE strategies. The low ΔRSE_{cum}-values after the year 2040 can be explained not only by the higher reuse of EV batteries, but also by a higher potential for their uptake in the increasing EV vehicle stock.

The results for the ELV system show that with the CE strategies employed, a combination of multiple CE strategies is required to preserve functionality and thereby keep overall effort that is related to the processing of components and materials low. Further it is shown that electrification of the vehicle fleet alone not only leads to increased effort in the production system but also, although delayed in time, to greater effort in the ELV system. The results also indicate that a demand reduction and/or lifetime increase are effective measures in decreasing recycling effort, especially if combined with additional CE strategies.

3.3.3. *Production and ELV system*

The combined effect of the production and the ELV system represents the aggregated ΔRSE_{cum}-values of both systems for each year. Consequently, the patterns that have been described for the production and ELV systems based on Fig. 10A and B can also be recognized. The effect of an accelerated electrification of the vehicle stock without any further system changes is indicated by the steep increase in the ΔRSE_{cum}-values towards the year 2050. It is also shown that each of the CE strategies proposed here will reduce the ΔRSE_{cum}-values, e.g. an increased reuse of components in the year 2025 or an improved ELV recycling system in the year 2030, both clearly represented by the ΔRSE_{cum}-value reductions in these years. Fig. 10C also shows the effectiveness of a demand reduction and/or lifetime increase in reducing overall effort in the aggregated production and ELV systems. Both strategies show immediate as well as long term effects by minimizing the increases in ΔRSE_{cum}-values that are related to an increased share of EVs making up vehicle demand. Moreover, the effectiveness of non-technological CE strategies, such as the increase in the occupancy rate per vehicle and an increase in the vehicle lifetime (being partially governed by so-called soft factors such as the 'want' to drive a new vehicle), need to be taken into consideration in conjunction with CE strategies that target materials management.

4. Conclusion

In the present study, Statistical Entropy Analysis (SEA) has been applied in combination with a stock-driven model and a material flow analysis (MFA) in order to assess a set of possible future transition scenarios related to the EU automotive system with regard to resource effectiveness until the year 2050. By providing an evaluative perspective that considers the effort required to preserve functionality (expressed as aggregated changes in Relative Statistical Entropy (ΔRSE_{cum}) per year), different transition scenarios are evaluated in the circular economy context over a 40-year period. It has been demonstrated how SEA can be used to assess production-consumption systems and the effects of system changes over time, allowing for the identification of effective measures to maximally preserve functionality and, in doing so, avoiding the effort that would be required to restore functionality losses. Further, it has been shown how SEA can be employed to identify material and component hot-spots that, depending on the CE strategy employed, could increase efforts to restore functionality. As the model is run on parameters such as recycling rates, reuse rates of components and transfer-coefficients for materials, it can be adapted to available data and allows for alternative transition scenarios and different production – consumption – End-of-Life systems.

Applying the method to transition scenarios with a higher share of electric vehicles in combination with different CE strategies, the results show that the largest effort for preserving and restoring the functionality of mobility provided by a fleet of passenger cars are required in the case of rapid electrification of the vehicle stock without further system adaptations. However, slowing the electrification down is not a solution but delays the problem to a later time period. Therefore, the transition to a higher share of electric vehicles necessitates additional system changes if preservation of functionality is targeted. In order to keep the effort required to meet this target low, a combination of different CE strategies must be implemented. An effective measure is a reduction in demand, either through increased intensity of vehicle use (increasing occupancy rate per vehicle, which leads to a stock reduction) or through an increase in the vehicles' lifetime. When additional demand reduction strategies are combined with CE strategies that aim to preserve functionalities at the level of the product (lifetime extension), components (reuse), and materials (recycling), more effort could be saved. Therefore, an accelerated CE transition will require a combination of technological system improvements (e.g. reuse, recycling, lifetime increase) and less technology-focused system adaptations that will directly impact the routines of people, e.g. a higher fraction of ride-sharing trips.

When interpreting the results, it is important to be aware of some limitations of the study that provide direction for further research. The results are subject to the uncertainty that is inherent in the transfer-coefficients derived for the MFA. Further, it is to consider that SEA represents an additional evaluation step of the underlying MFA. Moreover, aspects such as the degree of liberation, the influence of material associations, that are also influenced by the type of connections between materials and components, are important elements consider, including the material linkages that are rarely considers in MFA studies (Reuter and Van Schaik, 2006; Watari et al., 2020), also providing an important research direction that should be taken into account if further developing the SEA method. The case study employed vehicles with a simplified vehicle composition and only proposed basic CE strategies. Therefore, future research should be concerned with targeting the lack of robust data, a shortcoming that should be resolved based on a sensitivity analysis, as has been previously proposed in a similar context (e.g. Bobba et al., 2019). Further, when elaborating on the detail of the scenarios employed, the focus could shift from showing the impact of CE measures (that are implemented at a discrete point in time) to finding the optimal intensity of the CE measures employed. In this context, the effort required to achieve a change in RSE is likely to be different depending on the direction of the change (increases in RSE vs. decreases in RSE) and the location of the RSE change (an identical change in RSE located closer to an RSE value of zero is likely to involve greater effort). Here, it is to note that SEA allows assessing metabolic resources systems regarding their ability to preserve functionality over time, including the evaluation on the material, component and product level strategies. In this regard, it has been demonstrated how the method can quantify the preservation of functionality over time that is considered valuable and complementary to commonly applied methods for evaluating resource systems, so that the subsequent evaluation of SEA results from an LCA perspective could provide additional insights. Extending the system boundaries to include imports and exports of vehicles and components, as well as mining and raw material processing, would add another important perspective, enabling a more detailed evaluation of the effort required along the value chain.

Despite the stated limitations and the need for further research, the SEA results presented add a novel dimension to the evaluation of production and consumption systems over time. With the goal of preserving functionality and thus saving effort, SEA can be employed to guide system adaptations towards improved resource effectiveness and a more circular economy.

Declaration of Competing Interest

The author declares that he has no relevant or material financial interests that relate to the research described in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2021.105558.

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