Is Car-steel's fate in the hands of China's fate?

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Abstract

To understand the change of car-steel's post-recycling fate of China in the last 30 years, this study quantitatively traces the fate of steel recovered from end-of-life (EoL) cars produced in different years by using the Matrace method(Nakamura et al., ES&T 2014) and Chinese IO tables from 1987 to 2007. All the secondary sectors are grouped into 5 categories: cars, buildings, civil engineering, machines, and others, which are of significant importance for ferrous materials. It turns out that most of the car steel are first recycled into machines, and then into buildings. The results of dynamic analysis show that once a unit of steel has been used in car production in 1987, the peak of the in-use stock of the steel recycled from these cars appears in 2000. It implies that the gap between production and reuse peak is 13 years. The corresponding gaps for the new cars produced in the year of 1992, 1997, 2002, and 2007 are 11, 11, 15, and 15 years, respectively. Meanwhile, the peak for the EoL car generated in 1997 is the highest, because the shorter the car-life-span is, the more concentrated car scrappage is. Furthermore, although only small proportions of car steel is reused into cars and machines, both proportions increase over time, indicating the quality improvement of recycling technology in China.

Keywords: Car steel, Dynamic material flow analysis, Input-output analysis, China

1 Introduction

As the iron cycle has already been proved open (Wang, Muller, and Graedel 2007), it seems impossible to recycle metals without losing either material mass or functional quality; the former loss generated during the whole recycling process, while the latter one resulted from mixing of different elements at the (EoL) phase(Gaustad, Olivetti, and Kirchain 2012; Hatayama, Daigo, Matsuno, and Adachi 2009; Nakamura, Kondo, Kagawa, Matsubae, Nakajima, and Nagaska 2014; Reuter, Van Schaik, Ignatenko, and De Haan 2006). To satisfy standards on material, excess presence of impurities would require additional primary material for dilution(Hatayama et al. 2009). Therefore, it is inevitable to minimize the losses and impurities by monitoring every process during open-loop recycling. Imperative to this is tracing the fate of materials quantitatively over time across different stages.

Material Flow Analysis (MFA) has been widely used to trace the fate of materials across different stages in different sectors (Weisz, Krausmann, Amann, Eisenmenger, Erb, Hubacek, and Fischer-Kowalski 2006) while dynamic MFA has expanded its scope of application to estimation of the in-use stock of historical flows of various reproducible materials(Daigo, Hashimoto, Matsuno, and Adachi 2009; Geyer, Davis, Ley, He, Clift, Kwan, Sansom, and Jackson 2007; Müller, Wang, Duval, and Graedel 2006; Wang et al. 2007). Input-Output (IO) based Waste Input-Output (WIO) model was first brought up by Nakamura and Y. Kondo in 2002 which explicitly takes the flow of waste into account, thus it is capable of handling the end-of-life (EoL) phase. Therefore, integration of WIO with MFA would enable one to apply the whole battery of analytical tools of WIO/IOA to MFA and to get the degree of fabrication which is visualized as triangularity of the input coefficients matrix (Nakamura and Nakajima 2005). On the basis of the triangular matrix above, Nakamura, Kondo, Matsubae, Nakajima, and Nagasaka (2010) proposed a new methodology to identify and trace the flow of individual materials associated with the production of a unit of given product, the unit physical input-output by materials (UPIOM). Sankey diagram had been a formal tool for the visualization of MFA(Chancerel, Meskers, Hagelüken, and Rotter 2009; Chancerel et al. 2009) long before UPIOM, while UPIOM was developed from the dilemma in which the Sankey diagram has been too complex for clear visualization as the intersectoral flows of materials get more complicated(Nakamura et al. 2010). Reuter and van Schaik (2012)constructed dynamic simulation-optimization models that accurately describes the recovery of materials from products and residues, and clarifies how process metallurgy affect recycling rates. Most recently, Nakamura et al. (2014) proposed a model used to trace the fate of car steel (initial component of cars) over time and across products in open-loop recycling in Japan, called the MaTrace model. Inspired by the model, I simplified it so that it could fit the data of China.

China ranks $5th$ in iron ore reserves, while the market demand was much higher than it could afford when the reform and opening just happened, due to low productivity. Nowadays, even with the development of technology and economic structure, China still rarely meets its need especially in the situation when many infrastructures are under construction(Li 2005) this century. Based on all the facts, recovery of materials in China from EoL products provokes lots of researchers' interests. This paper is developed to study the influence of changes above on the post-recycling fate of car steel in micro-level by applying MaTrace model to the data of China in the last 30 years. The path of evolution was set in a range of 100 years. The 100-year time span was selected because of the slow release of steel products(Pauliuk, Milford, Muller, and Allwood 2013). Compared with the research Nakamura et al. (2014) did about car steel in Japan, representing the destination of recovered car steel in developed countries, China's fast development makes it more meaningful to study the destination of in-use stock of car steel in continuous rounds on different conditions with different technology, economic structure, policy, etc. Car steel was selected because it occupies the largest use of high-quality steel produced via integrated use of blast furnace (BF) and basic oxygen furnace (BOF) processes(Nakamura et al. 2014; Ohno, Matsubae, and Nakajima 2014). What's more, China modified its policy on retirement life of vehicles from 13 years in $1980s$ to 10 years in $1990s$, and then prolonged it to 15 years in $2000s$; the average life-span of buildings in China also varied in the three periods, 37.9, 45.8 and 56.3 years, respectively. Such changes must influence the trait of car steel significantly and these are also what interest us.

Table 1: *Average life-span of cars and buildings from* 1987 *to* 2007

Year Life-span	1987	1992	1997	2002	2007
Cars	13	10		15	
Buidings	37.9	45.8		56.3	

As the second biggest economies, China's steel use has a great influence on the iron and steel industry. Since recycling steel and primary steel have been two important sources of in-use steel, researches on the post-recycling fate of car steel in China may play as a forecasting of the world's steel demand for iron mine.

2 The Model

2.1 Material Recycled

According to Nakamura et al. (2014), the mass of material in final product j produced at time r is written as $x_j(r)$, and the mass of material occurs in EoL product j generated at time t, $z_j(t)$, is denoted as

$$z_j(t) = \Sigma_{r=0}^{t-1}\varphi_j(t-r)x_j(r), (j = 1, ..., n; t = 1, 2, ...) \tag{2.1}$$

where $\varphi_j(s)$ is the ratio discarded after s years of use, such that $\Sigma_{j=1}^{n}\varphi_j(s) = 1$ and n is the number of final products types, and $x_j(0)$ is given.

Let n_s be the number of scrap types, and γ_{sj} be the recovery yield of scrap s from product j. The amount of scrap s recovered from the EoL products in year t is given by

$$\Sigma_{j=1}^{n}\gamma_{sj}z_j(t), (s = 1, ..., n_s) \tag{2.2}$$

where$\gamma_{sj} \in [0, 1]$.

Denoting Γ as an $n_s \times n$ matrix with $\gamma_(sj)$ as its (s,j)-element, and $z(t)$ as an $n \times 1$ vector of $z_j(t)'s$, the amount of n_s types of scrap recovered in year t is $\Gamma z(t)$ in matrix. Recovered scrap is then put into refining process with yield ratio $\theta \in$ $[0, 1]$. The amount of recovered material obtained from EoL products is given by the scalar:

$$\theta\iota'_{n_s}\Gamma z(t), \tag{2.3}$$

Here we only take one kind of material, car steel, in consideration, the model is also applicable to multiple materials in which (2.3) should be replaced by a $n_s \times n$ matrix, $\hat{\theta}B\Gamma z(t)$, as in

Nakamura's model, where B is a $n_R \times n_s$ matrix representing the share of scrapes allocated to refinery processes.

2.2 Material Destination

The secondary material refined from above process is then processed into new final products with some inevitable loss during the process. The amount of refined material destined to a final product is proportional to C and y, where C is the material-composition matrix of product (Nakamura and Nakajima 2005) and y is the $n \times 1$ vector of final demand. Writing D for the allocation of refined material to the final products , it is then given by:

$$D = \hat{y}Cdiag(y'C)^{-1} \tag{2.4}$$

where the elements of D are range from 0 to 1. Thus we calculate D through IO similar to Duchin and Levine (2010). Multiply D and (2.3) together, we can get a $n \times 1$ vector, indicating the amount of n kinds of final products made up of secondary material recovered from EoL products. There are also losses incurred during the production of the final products, the overall equation of the evolution of material becomes

$$x(t) = \hat{\lambda}(I - D\hat{\theta}\Xi(I - \hat{\lambda}))^{-1}D\hat{\theta}\Gamma z(t) \tag{2.5}$$

where $\lambda_i \in [0, 1]$ refers to the yield ratio of final product i and Ξ is an $n_s \times n$ matrix with ε_{ij} as its element referring to the recovery rate of scrap s in the production process of production j. For simplicity, here in this paper, we only tackle with the case of a singular scrape, $n_s = 1$.

So far, the model developed in this paper is mostly based on a simplified MaTrace model of Nakamura et al. (2014). The model is applicable to materials of China because it can accommodate differences of technology innovation between different markets by changes in matrix A, total demand in vector y and such that C and D, and other parameters reflecting international difference such as Γ, the recovery yield of scrap from EOL, and θ, yield of refining process, which vary from country to country due to the technology gap between developed and developing countries.

3 Data and Results

Data. The model is applied to ferrous material initially embedded in cars, car steel, and traces the fate of it over a time-span of $100 - year$. For simplicity, the initial value is given as $x_j(0) = 100$ for $j = vehicals$, and $x_j(0) = 0$ for all other products, and the choice of $100 - year - life - span$ is motivated by the long life time of some special final products such as building and civil engineering.

Taking a series of Chinese Input-Output Table of year 1987, 1992, 1997, 2002, 2007 as data source, all the 23 sectors with physical output are grouped into 5 final product sectors (shown in **Table** 2), cars, buildings, civil engineering, machines, and others. The lifetime density function $\varphi(s)$ is specified by the two-parameter Weibull density whose value of shape parameter is preset to 5 according to Geyer et al. (2007), and the scale parameter is derived by equating the mean lifetime to the average lifetime. For refining process, due to the scarcity of statistic data, we consider only one kind of refining technology with one kind of material output of yield ratio 0.94. From 1987 to 2007, changes in Chinese retirement life of vehicles and of buildings are implemented by varying the scale parameter of the Weibull density. As to other parameters, such as the recovery rate of product Γ and recovery rate of process waste Ξ, we refer to those of Japan in **Table** 3 and keep them constant.

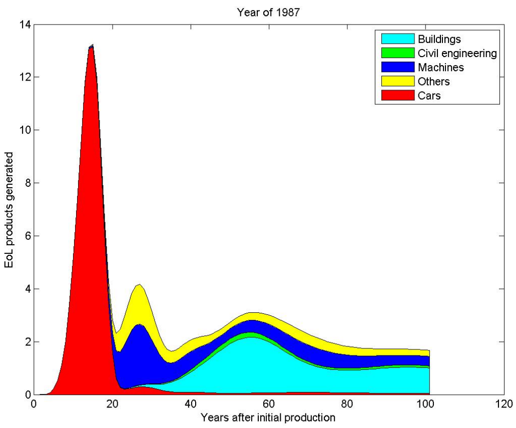
Results. Fig 1 shows the main feature of each pattern is the appearance of three decreasing peaks, meaning the amount of EoL products generated is decreasing over time due to the losses during cycles of the recovery and refining processes every time it repeats. The first peak is both the highest and sharpest in every pattern, and almost all of them are composed of EoL vehicles. Through the composition of the three peaks in each pattern, we can conclude that most of the car steels are first recycled into machines, and then into buildings. Extracting the amount of car steel generated from vehicles, and displaying it in **Fig** 2(a), which shows car steel tendency in three years(year of 1987, 1997, and 2007) with different average life-span of cars, we can see that the positions where they peak are 13, 11, and 15 on the time line, respectively, exactly corresponding to the average life of cars under different policies on retirement life of vehicles, representing the first generation of EoL products discarded. Thus we assert that polices on average life-span of cars have significant influence on the recycle of car steel: the longer the compulsory car life-span is, the later will the peak of car steel recovered from EoL cars emerges.

Table 2: *Sector classification*

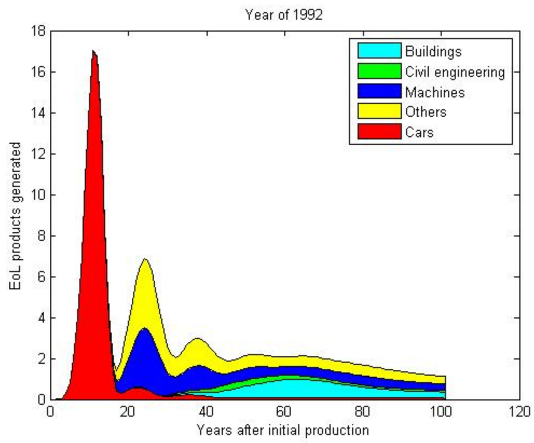
Original sector	***Aggregated sector***
Manufacture of Transport Equipment	Cars
Manufacture of Building Materials	Buidings
Construction Industry	Buidings
Farming	Civil Engineering
Electricity and Steam, Hot Water Production and Supply Industry	Civil Engineering
Freight Transport and Post	Civil Engineering
Mechanical Industry	Machines
Manufacture of Electrical Machinery and Equipment	Machines
Manufacture of electronics and Communication Equipment	Machines
Manufacture of Measuring Instruments	Machines
Maintenance of Machines	Machines
Processing of Foods	Others
Spinning and Weaving	Others
Manufacture of Textile Products, Leather, Fur, Feather and Its Products	Others
Processing of Timbers and Manufacture of Furniture	Others
Manufacture of Paper and Articles for Culture, Education and Sports	Others
Processing of Petroleum	Others
Coking	Others
Chemical Industry	Others
Manufacture of Metal Products	Others
Other Industries	Others
Business Services	Others
Catering Services	Others

Table 3: *Recovery rate of EoL products, Process waste*

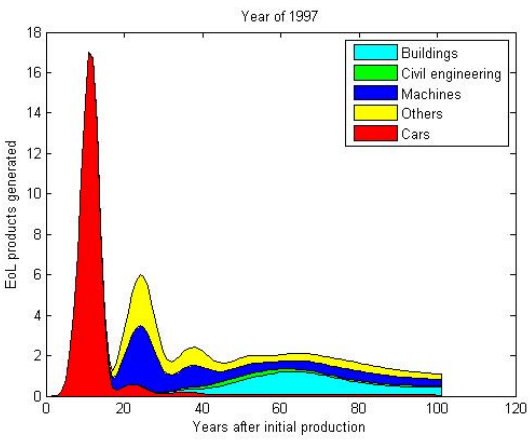
	Recovery rate of EoL products	Recovery rate of process waste
Cars	0.989	0.8
Buildings	0.95	0.8
Civil engineering	0.466	0.6
Machines	0.95	0.9
Others	0.50	0.7



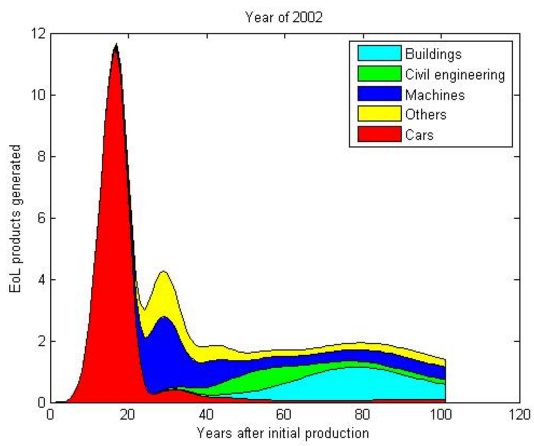
(a) EoL products generated in 1987



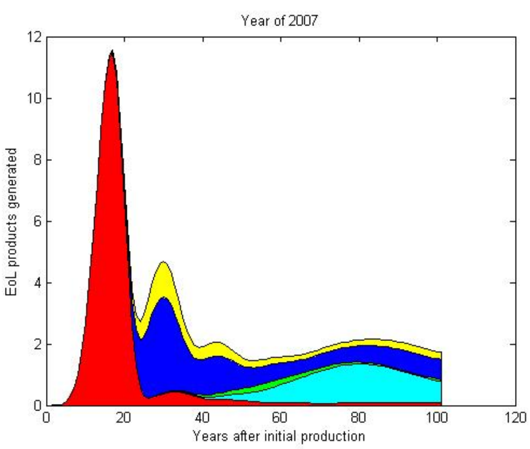
(b) EoL products generated in 1992



(c) EoL products generated in 1997

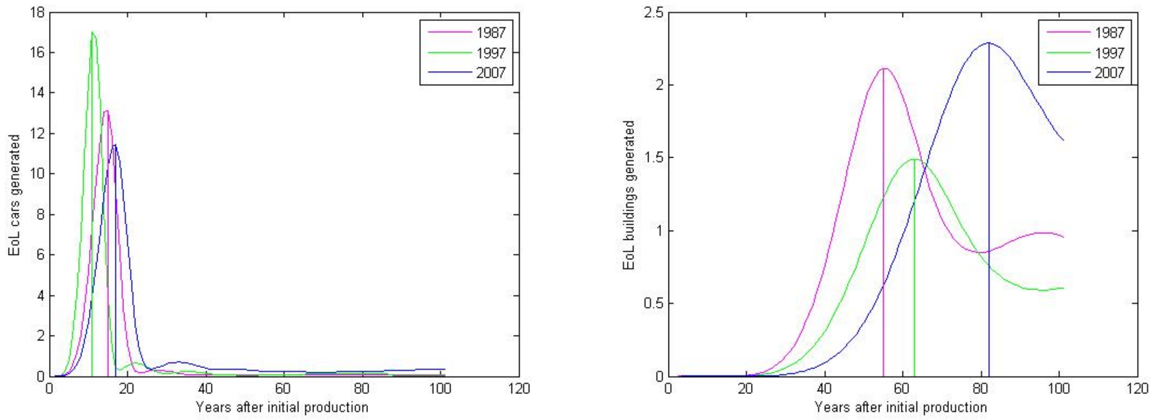


(d) EoL products generated in 2002



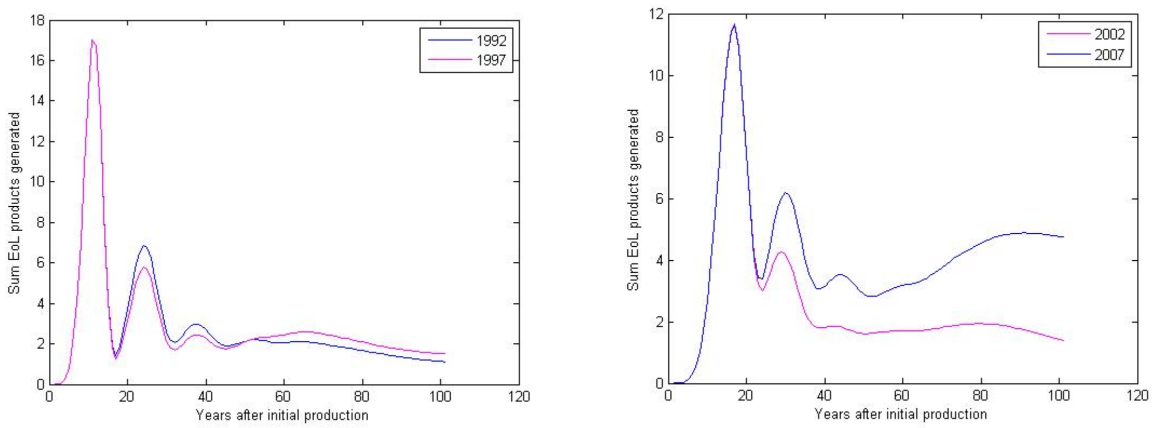
(e) EoL products generated in 2007

Figure 1: EoL products generated in various periods



(a) Cars (b) Buildings

Figure 2: EoL products generated under different policies

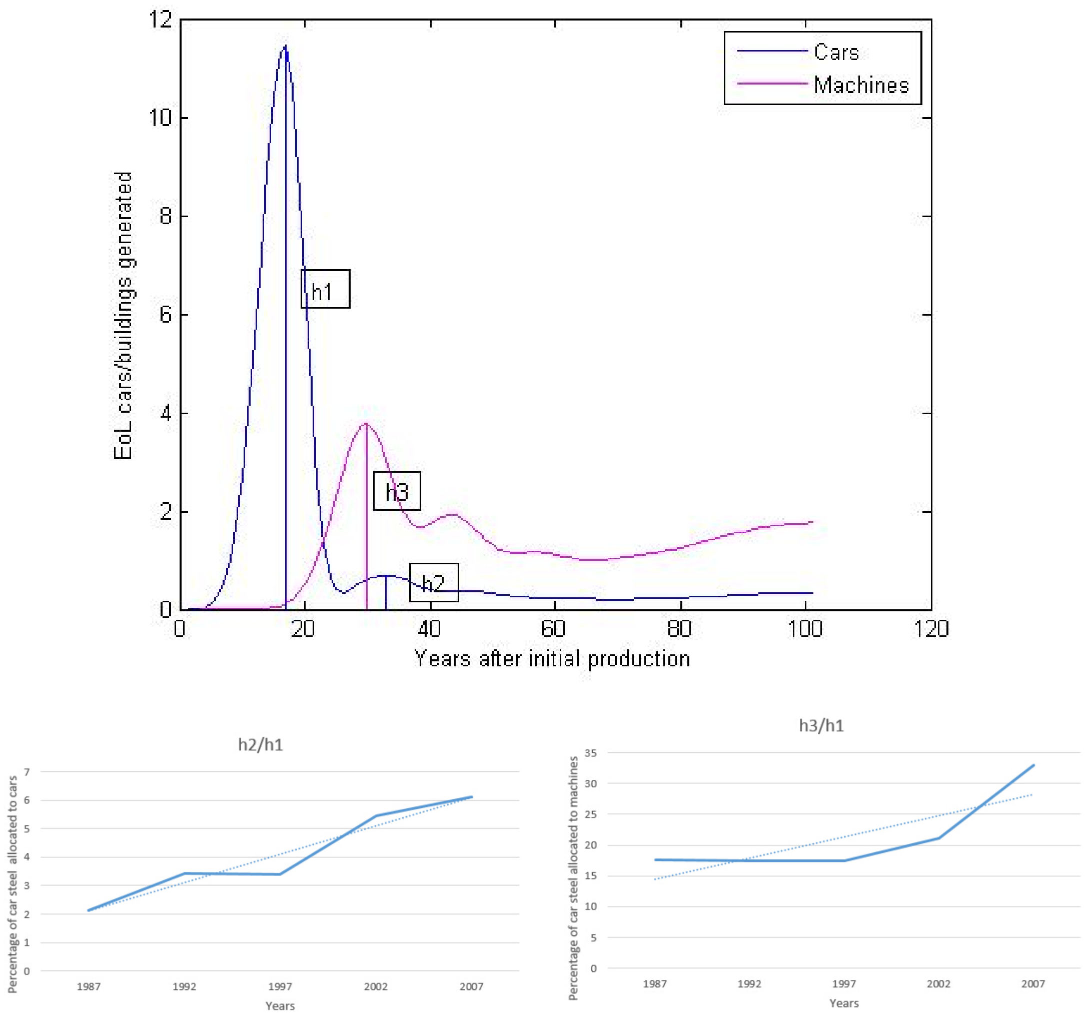


(a) (b)

Figure 3: EoL products generated in different years without policy changes

What's more, the the peaks for the EoL car generated in 1992 and 1997 are both the sharpest, because the shorter the car-life-span is, the more concentrated car scrappage is. The similar conclusion can be reached as to the average life-span changes of buildings, as is shown in **Fig** 2(b): once a unit of 1987-steel(car steel first been used in car-making in 1987) has been used in buildings, the peak of the in-use stock of the steel recycled from these buildings appears 38 years later. It implies that the gap between production and reuse peak is 38 years, consistent with the average life-span of building in 1980s, 37.9. The corresponding gaps for the new buildings in the year 1997 and 2007 are 45 and 59 years, respectively, which are correspondent with the average life-span of buildings, 48.5 in 1997 and 56.3 in 2007.

In order to reconfirm that the peak position changes are merely induced by the changes of polices on average lifetime of cars and buildings, the two subgraphs in **Fig** 3 show the result under the situation where polices on average lifetime of cars and buildings both unchanged while IOTs in different years being different, the positions of peaks stay unchanged. In conclusion, adjustment of life-span of final products may be a new break to low consumption.



(a) Recovered car steel used back into cars (b) Recovered car steel used into machines

Figure 4: EoL cars and machines generated

The two peaks on the line of *EoL cars/machines generated* labeled by $h2$ and $h3$ in **Fig** 4, illustrate the EoL cars and machines generated in the second-round generation, respectively, the majority of which were produced at the time of the first peak by the EoL car steel, labeled by $h1$. The profiles in different years have the same tendency: both $h2/h1$ and $h3/h1$increase over time indicating that a lager percentage of car steel is allocated to car-making and machine-making, which are correspondent to the matrix of allocation of refined materials to the final products, D, in selected years. **Table** 4 and **Table** 5 show the value of $h2/h1$ and $h3/h1$, and the value of D, respectively. Since auto-industry and mechanical industry both have high standards of steel quality, the increase of allocation to cars/machines implies the quality enhancement of refined car steel during 1987 and 2007 along with the development in technology and economic structure of China.

Table 4: *Percentage of car steel allocated to car-making and machine-making*

Year	1987	1992	1997	2002	2007
h2/h1	2.12	3.42	3.4	5.45	6.12
h3/h1	17.59	17.44	17.45	21.03	32.92

Table 5: *Allocation of refined material to cars and machines presented in D*

	Cars	Machines
1987	0.0352	0.2722
1992	0.0552	0.2141
1997	0.0561	0.3160
2002	0.0568	0.3054
2007	0.0611	0.3967

4 Discussion

This paper proposes a dynamic MaTrace model with 3 decreasing peaks, indicating the increasing amount of loss which we have not handled with. 3 major kinds of losses occurred during the whole cycle, recovery losses, refinery losses and production losses, among which refinery losses account for a large proportion in theory. We can put emphasis on losses in further research and check whether the integrating flow of car steel satisfies mass balance. Limited by the scarcity of yearly data, here in this paper, parameters θ, Γ and λ remain consistent meaning that the technology improvement is not considered except in the IOTs in different years. In empirical analysis, a set of assumptions on the improvements in technology, including refining and production technology can make up for the scarcity of data. What's more, the fact is there are more than one kind of refinery process rather than the only one with one kind of output as supposed above in MaTrace model, and each has one or more outcomes, so outcomes in (2.3) should be a n_R-dimensional-vector where n_R is the number of process outcomes, such as basic oxygen furnace(BOF) steel, electric arc furnace(EAF) steel, etc. More details in share of recovered scrap allocated to refining processes are needed to strengthen the model.

Matrace is a useful evaluation tool for sustainable resource management for it provides a microstructure for material flows in standard dynamic MFAs. Its ability to trace the fate of materials can help to design recycling policies or regulations focusing on scarce materials used in cars and others. Since the development of carbon-mitigation technologies has increased the complexity of scrap streams, MaTrace model would increase the area of its application in policy planning as well as in industry. Allowing for the shortages and future directions above, a number of datum need to be found and a series of assumptions need to be relaxed in order to be more relevant to policy.

Extending lifetimes of cars and buildings are shown to have significant effects on the residence time of car steel in products. Since the expenditure for these items occupies a significant portion of GDP, their life extension would have far-reaching effects on the size and composition of final demand, and alter not only the lifetime density function $\varphi(s)$, but matrix D, the allocation of materials to final products. In this paper, we can infer that an improvement in the quality standard of recycled steel and the recycling technology can help to raise the purity of car steel and increase the cycling times before the car steel been occupied by losses; the coefficient of utilization thereby increases. New policies on quality standard of recycled steel are imperative for energy-efficiency economy.

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