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# IDENTIFYING ECONOMIC AND SCRAP REUSE BENEFITS OF LIGHT METALS SORTING TECHNOLOGIES

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## Abstract

The constantly changing and evolving patterns of aluminum scrap usage have created material reuse challenges for the industry. For instance, mixed scraps consisting of wrought and cast fractions often cannot be directly re-melted and reused in many applications due to compositional incompatibility. Further processing and materials separations are required. Various sorting technologies currently being developed promise to address these challenges. Because of the added expense of deploying sorting technologies, it is critical to understand how, when, and to what extent sorting should be applied in different circumstances. Potential factors affecting such decisions include the mix of scrap supply, the nature and mix of finished goods demand, sorting recovery rate, and sorting costs. This paper examines the use of linear programming methods to identify economically efficient sorting strategies and their impact on scrap usage. Economic efficiency was tested for various states of scrap material supply, finished good demand, sorting technology type, and sorting performance. The model can be used to identify specific sorting schemes including for which scraps and to what extent those scraps should be sorted. The overall goal is to support industry decision-making regarding the application of sorting technologies to increase scrap use and lower production costs.

## Introduction

Several authors have raised concerns about maintaining high levels of aluminum scrap reuse in the face of changing patterns of aluminum consumption [1-3]. While these concerns do not likely point to any imminent surplus of aluminum scrap, they do point to current or emerging inefficiencies in scrap reuse [2]. In particular, economic inefficiencies occur when high value alloys are repurposed into compositionally tolerant alloys. In the absence of technological changes, current usage trends would suggest an increase in this practice.

To avoid this loss of value, several firms and institutions have been developing alloy sorting methods [4-8]. For these technologies to see wide-scale deployment, they will need to add economic value to the secondary processing business. Although it is clear that sorting methods provide real technical benefits, it can be difficult to determine whether those benefits outweigh the required investments. Secondary processors are confronted with real operational questions: What types of sorting technologies warrant investment? Which scrap streams require sorting? What types of production benefit the most from sorted scrap?

This paper presents an optimization based methodology which attempts to answer those questions by both identifying scenarios for which sorting add value and quantifying that value. To explore the usefulness of this method, a specific case study is presented in which a cast / wrought sorting technology is evaluated for upgrading four actual scrap types available within the European market today. The data used in this analysis derives from experimental work examining elemental and alloy composition of a number of scrap sources throughout Europe.

### Modeling Remelter Decisions: Sorting and Raw Material Allocation

To quantify the value which sorting brings to a remelter, it is necessary to attempt to model the set of production decisions with which that remelter is confronted. For the purposes of modeling, the primary decisions involve composing alloy batches by carefully selecting and mixing various amounts of both scrap and primary materials. Sorting technologies overlay on to this context, affording the secondary processor the opportunity to upgrade the materials which they have at hand. The model presented here simultaneously assess these two questions – what raw materials to use and which to sort – across a portfolio of alloys which are to be produced. In practice, sorting may not occur at the secondary processing facility, but rather at the scrap supplier. From an analytical perspective, the methods and results presented here are equally applicable to this arrangement. For a scrap supplier, it is still critical to identify those markets for whom sorting provides added value and which technologies are able to deliver that most effectively.

The model presented here is an extension of one developed to examine strategic raw material allocation decisions. Emphasis will be placed on extensions to the analysis of sorting. Interested readers are referred to [9] for discussion of this approach in those contexts. The model developed here assumes that sorting occurs as a single stage 1-to-*j* stream operation. In a physical sense, this means that for any scrap stream entering the sorter, *j* possible output streams can be modeled where the characteristics of the *j* output streams are determined by both the constituents within the incoming stream and the performance of the technology of interest.

Figure **1** shows this graphically, identifying both the key variables and indices that will be detailed subsequently.

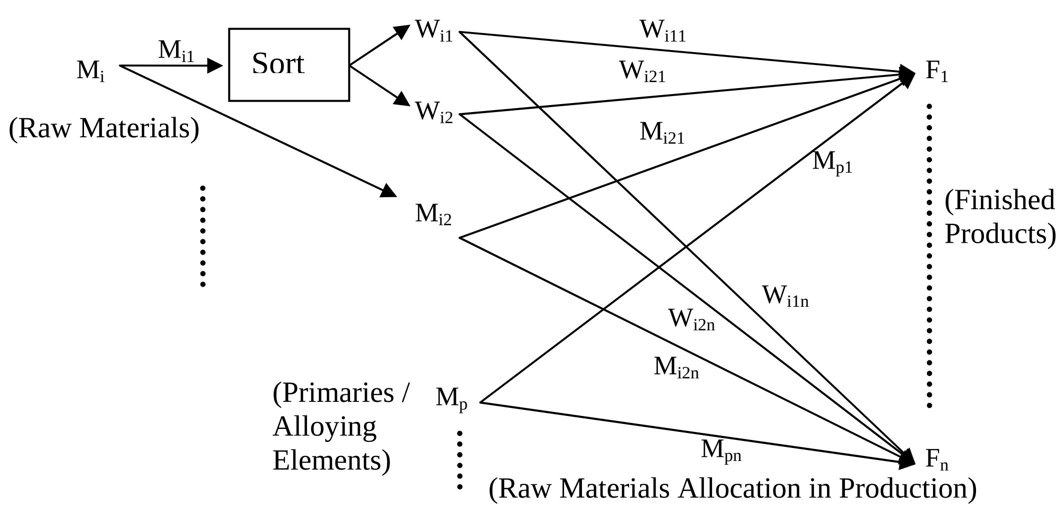


**Figure 1. Schematic of materials sorting and allocation of sorted and unsorted material streams towards production.**

The decisions regarding what scrap material to sort; how much to sort; and, finally, allocating material streams to production batches is modeled using linear optimization [10]. This method is widely applied in operational batch production decisions throughout the aluminum industry. The model presented here differs from those operational tools primarily in its simultaneous assessment of multiple production goals and its extension to explicit sorting decisions. This research also differs from other optimization studies [4-8,11-15], in that instead of focusing on the optimization of processes, technologies, and overall resource cycles, sorting technologies are examined from the point of view of the economic value – cost savings and scrap utilization – provided to key stakeholders. The following set of equations (1 – 14) describes the various elements of the model, including the decision-making objective and constraints with explanations of the variables and indices to follow. Operational options are evaluated within the model based on their ability to minimize specific operating costs. Mathematically this can be represented as:

$$\text{Min:} \left(\sum_i C_i M_i + \sum_p C_p M_p\right) + \sum_i Z_1 M_{i1} - \sum_i R_i \left(M_i - \sum_{j,n} W_{ijn} - \sum_n M_{i2n}\right) \tag{1}$$

(Raw Material Costs) (Sorting) (Residual Scrap Salvage Value)

Included in the objective function, Eq 1, are the cost contributions from raw materials purchase, sorting operation, and the net value of any residual input scrap into the system that was unallocated in final production (i.e., the salvage value of residual scrap). The model could be readily adapted to accommodate other objectives, such as profit or scrap use maximization. To capture the physical realities of batch construction and sorting performance, the objective function is subject to the following constraints on materials supply, demand, compositions, conservation of mass and sorting recovery rates.

Raw materials supply constraints:

$$M_p \leq A_p \tag{2}$$

$$M_i \leq A_i \tag{3}$$

Pre-sorting and post-sorting mass conservation:

$$M_{i1} + M_{i2} = M_i \tag{4}$$

$$\sum_j W_{ij} \leq M_{i1} \tag{5}$$

Sorted and unsorted material streams allocation for production:

$$\sum_n M_{pn} \leq M_p \tag{6}$$

$$\sum_n M_{i2n} \leq M_{i2} \tag{7}$$

$$\sum_n W_{ijn} \leq W_{ij} \tag{8}$$

Batch production requirements:

$$\sum_i \sum_n \sum_e \left(M_{i2n} M_{i2}^{e,ave} Y_{i2}^e + \sum_j W_{ijn} W_{ij}^{e,ave} Y_{ij}^e\right) + \sum_p \sum_n \sum_e M_{pn} M_p^{e,\min} Y_p^e \geq F_n \tag{9}$$

Compositional specifications requirements:

$$\sum_i \sum_n \left(M_{i2n} M_{i2}^{e,ave} Y_{i2}^e + \sum_j W_{ij}^{e,ave} W_{ijn} Y_{ij}^e\right) + \sum_p \sum_n M_p^{e,\min} M_{pn} Y_p^e \geq F_n^{e,\min} F_n \tag{10}$$

$$\sum_i \sum_n \left(M_{i2}^{e,ave} M_{i2n} Y_{i2}^e + \sum_j W_{ij}^{e,ave} W_{ijn} Y_{ij}^e\right) + \sum_p \sum_n M_p^{e,\max} M_{pn} Y_p^e \leq F_n^{e,\max} F_n \tag{11}$$

Quantities of materials recovered through sorter:

$$W_{ij} = M_{i1} \sum_m C_{im} R_{jm} \tag{12}$$

Compositional determinants for unsorted material streams:

$$M_{i2}^{e,ave} = M_i^{e,ave} \tag{13}$$

Compositional determinants for sorted material streams:

$$W_{ij}^{e,ave} = \frac{\sum_m C_{im} R_{jm} M_m^{e,ave}}{\sum_m C_{im} R_{jm}} \tag{14}$$

All variables are non-negative. The indices and variables used above are shown in

Figure 1 and defined as:

$i,n,m$ = Input scrap material index, finished alloy index, materials component index
$p,q,j$ = Primary material and alloying element index, sort stage index, stage one sort output stream index
$C_i$ = Cost (per unit wt.) of scrap material $i$
$C_p$ = Cost (per unit wt.) of primary material $p$
$R_i$ = Residual salvage value (per unit wt.) of scrap material $i$
$Z_q$ = Cost of sorting (per unit wt.) for sort stage $q$
$M_p$ = Quantity of input primary material or alloying element $p$ acquired
$M_i$ = Quantity of input scrap material $i$ acquired
$M_{i1}$ = Quantity of input scrap material $i$ that went through stage one sorting
$M_{i2}$ = Quantity of input scrap material $i$ that did not go through stage one sorting
$M_i^{e,ave}$ = Average wt. % content of element $e$ in stream $M_i$
$M_{i2}^{e,ave}$ = Average wt. % content of element $e$ in stream $M_{i2}$
$M_m^{e,ave}$ = Average wt. % content of element $e$ in material component $m$
$Y_{i2}^{e}$ = Metal yield (%) for scrap material $i$ that did not go through stage one sorting
$Y_{ij}^{e}$ = Metal yield (%) for sorted scrap material stream $W_{ij}$
$Y_p^{e}$ = Metal yield (%) for primary or alloying element $p$
$A_p$ = Quantity of availability primary material or alloying element $p$
$A_i$ = Quantity of availability scrap material $i$
$W_{ij}$ = Quantity of output into stream $j$ from stage one sorting with input $M_i$
$C_{im}$ = Wt. % representation of material component $m$ in scrap material $i$
$R_{jm}$ = Recovery rate (%) of material component $m$ in stage one sort output stream $j$
$W_{ij}^{e,ave}$ = Average wt. % content of element $e$ in stream $W_{ij}$
$M_p^{e,max}$ = Maximum wt. % content of element $e$ in primary material $p$
$M_p^{e,min}$ = Minimum wt. % content of element $e$ in primary material $p$
$F_n^{e,max}$ = Maximum wt. % content of element $e$ allowed in product $F_n$
$F_n^{e,min}$ = Minimum wt. % content of element $e$ allowed in product $F_n$
$M_{pn}$ = Quantity of primary material or alloying element $p$ allocated towards production of $F_n$
$M_{i2n}$ = Quantity of unsorted scrap material $i$ allocated towards production of $F_n$
$W_{ijn}$ = Quantity of scrap material $i$ that went through stage one sorting and ended up in stream $j$ that was allocated towards production of $F_n$

## Model Application: Base Case – Typical EU Production

Assessing the strategic decisions surrounding sorting requires answering three fundamental questions:

- Which scrap streams should be sorted?
- How extensively should those streams be sorted?
- In which production batches should sorted scrap be used?

The algorithm described above answers these questions to generate the optimal – lowest cost – production strategy. Clearly, many possible factors ultimately affect the optimal decision. These factors include the sorting recovery rates, sorting costs, scrap types mix and products mix. The importance of some of these factors will be examined in more detail subsequently.
To demonstrate the basic information that can be provided by the sorting algorithm, an example case (i.e., Base Case) was run using the production scenario defined by Tables I, II, III and IV.
<u>Scrap Characterization</u>

In order to have realistic input to the model, four different Al-scrap types available in the European market today were examined, i) Old rolled, ii) Al-ELV scrap, iii) Shredded extrusion and (iv) Co-Mingled respectively. Samples of these scraps were collected from up to ten different suppliers and assessed regarding their aggregate composition and the distribution of constituent alloys within the overall sample. Information on the type and amount of alloys present in a scrap sample is critical to assessing how it will be affected by a sorting technology. The weight of each test load investigated was in the range 300-500 kg. The characterization work included screening, followed by manual sorting and finally remelting of the sorted fractions.

Specifically, each screened size fraction was manually sorted into the following categories: Al-extrusions, Al-casting, Al-sheet and others, which included "foreign" (i.e., non-aluminum) metals and some non-metals. After manual sorting, the different fractions were weighed and remelted in a resistance heated furnace. The scrap was melted, stirred and held at 720 °C for 10 minutes before two samples for chemical analysis were collected. No salt was added during remelting or holding. The chemical composition was determined by spectrographic analysis. The amount and type of "foreign" metals and non-metals were also recorded.

Model Inputs

Table I describes each of the four scrap types considered in terms of the amount of Cast, Wrought Sheet, Wrought Extrusion, and foreign material present. Notably, the actual set of scrap alloys present under each of these headings varies for each scrap type. The scrap compositions (Table I) are based on data collected on actual scrap materials as described above. The scrap availabilities by type are estimated based on the sourcing needs of a producer focusing on cast products. Aggregate scrap availability is set at a level to satisfy 60% of production capacity. For the purposes of the model, the salvage value of unallocated sorted scrap material is assumed to equal the original cost of that scrap. In reality, salvage value may run higher or lower than the original value depending on the nature of the sorted scrap and the sorting process. The modeled production schedule (Table II) represents 100kT of production with 70% being cast products, reflecting roughly the split between wrought and cast products in the secondary market [16]. Intensities for individual alloys were set based on expert opinion and are intended to be representative of production trends within the European market. Historically typical prices on primaries and scrap materials as well as recent prices on alloying elements were taken from the London Metals Exchange [17]. Unit prices indicated throughout this paper have been normalized to emphasize economic trends rather than absolute dollar amounts. For the purpose of the model, melt yields ($Y_{i2}^e$, $Y_{ij}^e$ & $Y_p^e$) were assumed to be 93% for all scraps and 98% for primaries and alloying elements. In Table III, relevant compositions are stated according to international standards [18]. In practice, the often limiting effects on scrap usage due to high Mg content in scrap can be offset by the volatility of Mg at aluminum melt temperatures. In order to allow for this effect, the maximum specifications for Mg employed in the model was raised compared to industry standards. Other alloying elements do not exhibit this level of volatility in the melt and were modeled based on the composition listed.

**Table I. Quantity and Make-up of Available Scrap Types Used in Model**

| **Scrap Type** | **Normalized Price / Ton**[1] | **kT** | **Alloy mass fraction wt.%** | | | |
|---|---|---|---|---|---|---|
| | | | **Wroughts** | | **Casts** | **Others*** |
| | | | **Sheets** | **Extrusions** | | |
| Base Casts | 1.04 | 30 | 30% | | 56% | 14% |
| Base Extrusions | 1.24 | 10 | 15% | 70% | - | 15% |
| Base Sheets | 1.09 | 10 | 75% | 15% | 4% | 6% |
| Co-Mingled | 1.00 | 10 | 30% | 30% | 16% | 24% |

[1] Price per ton in this document are normalized to the price per ton of co-mingled scraps.

*Include tubes, wires, etc.

**Table II. Modeled Alloy Products Demand**

| Alloy | Qty. Demanded (kT) |
|---|---|
| 230 | 20 |
| 226 | 20 |
| 239 | 30 |
| 6111 | 10 |
| 6082 | 2 |
| 6060 | 14 |
| 3104 | 2 |
| 3105 | 2 |

**Table III. Chemical Compositions Specifications (wt. %) of Relevant Alloys [18]**

| Alloy | Si | Fe | Cu | Mn | Mg | Cr |
|---|---|---|---|---|---|---|
| 230 | 12.5-13.5 | <0.4 | <0.03 | <0.35 | <0.05 | <0.05 |
| 226 | 8-11 | <1 | 2-3.5 | 0.1-0.4 | 0.1-0.5 | <0.05 |
| 239 | 9-11 | <0.8 | <0.08 | 0.001-0.4 | 0.2-0.5 | <0.05 |
| 6111 | 0.6-1.1 | <0.4 | 0.5-0.9 | 0.1-0.45 | 0.5-1.0 | <0.1 |
| 6082 | 0.7-1.3 | <0.5 | <0.1 | 0.4-1 | 0.6-1.2 | <0.25 |
| 6060 | 0.3-0.6 | 0.1-0.3 | <0.1 | <0.1 | 0.35-0.6 | <0.05 |
| 3104 | <0.6 | <0.8 | 0.05-0.25 | 0.8-1.4 | 0.8-1.3 | <0.05 |
| 3105 | <0.6 | <0.7 | <0.3 | 0.3-0.8 | 0.2-0.8 | <0.2 |

| Alloy | Zn | Ti | Ni | Pb |
|---|---|---|---|---|
| 230 | <0.1 | <0.15 | <0.05 | <0.05 |
| 226 | <1.2 | <0.15 | <0.3 | <0.2 |
| 239 | <0.1 | <0.15 | <0.05 | <0.05 |
| 6111 | <0.15 | <0.05 | <0.05 | <0.05 |
| 6082 | <0.2 | <0.1 | <0.05 | <0.05 |
| 6060 | <0.15 | <0.1 | <0.05 | <0.05 |
| 3104 | <0.25 | <0.1 | <0.05 | <0.05 |
| 3105 | <0.4 | <0.1 | <0.05 | <0.05 |

**Table IV. Normalized Price / Ton Assumptions for Primaries and Alloying Elements**

| Si | Fe | Cu | Mn | Mg | Cr | Zn |
|---|---|---|---|---|---|---|
| 1.88 | 0.32 | 2.66 | 2.02 | 2.27 | 9.95 | 0.98 |

| Ti | Ni | Pb | P1020 | P0508 |
|---|---|---|---|---|
| 10.67 | 15.11 | 0.76 | 1.36 | 1.36 |

<u>Modeled Sorting Technology</u>

The sorting technology considered in the Base Case was modeled as having three output streams — bins 1, 2 and 3. Bin 1 receives 95% of the wrought alloys within the incoming scrap stream and 5% of incoming cast constituent. Bin 2, receives 95% of the cast alloys and 5% of the wrought. The final Bin 3 is assumed to receive 100% of all the other remaining scrap components. These values approximate the sorting recovery rates reported for the "hot crush" technique with prior separation of the “Other” fraction [19]. The Base Case sorting cost was estimated at $30/Ton. This figure is rather conservative compared to contemporary sorting techniques such those for stainless steel and iron[2]. With future development in light metal sorting technologies, this cost is likely to come down. The impact of this assumption is thoroughly explored in subsequent analysis.

## Results

Table V indicates the optimal production allocation of sorted and unsorted scraps and sorting decisions as determined by the model for the Base Case inputs. The balance of production raw materials were made up by appropriate primaries and alloying elements. The utilization of sorted scrap is summarized in Table V and Table VI.

As Table V indicates, at 95% sort recovery rates, scrap usage is pervasive throughout all of the alloys considered with *sorted* scrap being used for all alloys save one (i.e., 6082). In aggregate, all available scrap is used for this Base Case scenario with sorting available. Notably, only Base Cast scraps were sorted and used in final production (Table V). Base Cast scrap is the most commingled of those considered with wrought and cast material making up 30% and 56% by mass, respectively. Generally speaking, sorting is more applicable when the scrap components are more commingled.

**Table V. Allocation of Sorted & Unsorted Scraps Streams in Production (Base Case)**

| Alloy | Scrap materials allocations (T) in alloy production | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Base Casts | | | | Base Extrusions | | | | |
| | Bin 1 | Bin 2 | Bin 3 | Un-sorted | Bin 1 | Bin 2 | Bin 3 | Un-sorted | |
| 230 | - | 152 | - | - | - | - | - | - | |
| 226 | - | 9,668 | 2,202 | 9,417 | - | - | - | - | |
| 239 | 3,375 | 255 | - | - | - | - | - | 9,097 | |
| 6111 | 428 | - | - | 1,669 | - | - | - | - | |
| 6082 | - | - | - | - | - | - | - | 903 | |
| 6060 | 1,662 | 103 | - | - | - | - | - | - | |
| 3104 | 177 | - | - | 158 | - | - | - | - | |
| 3105 | 182 | - | - | 150 | - | - | - | - | |

| | Base Sheets | | | | Co-Mingled | | | | Primary & Alloying |
|---|---|---|---|---|---|---|---|---|---|
| | Bin 1 | Bin 2 | Bin 3 | Un-sorted | Bin 1 | Bin 2 | Bin 3 | Un-sorted | |
| 230 | - | - | - | 1,504 | - | - | - | - | 18,837 |
| 226 | - | - | - | - | - | - | - | - | 207 |
| 239 | - | - | - | 3,253 | - | - | - | - | 15,448 |
| 6111 | - | - | - | - | - | - | - | 8,571 | 81 |
| 6082 | - | - | - | 1,231 | - | - | - | - | 15 |
| 6060 | - | - | - | 4,012 | - | - | - | - | 8,804 |
| 3104 | - | - | - | - | - | - | - | 1,429 | 367 |
| 3105 | - | - | - | - | - | - | - | - | 1,726 |

To best guage the impact of sorting on overall cost and scrap usage, it is necessary to compare the above scenario to one in which the sorting process is not made available within the model.

[2] Industry estimates the sorting cost for stainless steel and iron to be approximately $20/T.

Table VIII summarizes such a comparison, showing the aggregate scrap usage differences for the Base Case with and without sorting capabilities made available in the model. When sorting is not available, the pattern of scrap material consumption changes markedly. In fact, not only does the amount of scrap used change, but also the *types* of scrap used change (Table VII). The magnitude of these changes varies for different products. In aggregate, scrap utilization drops to 88% of the 60kT available mass without sorting from 100% with sorting. Clearly there are economic impacts from this scrap utilization, the effects of which will be discussed in more detail below. Furthermore, this drop in scrap usage highlights the key advantage of sorting technologies – allowing a material processor to cope with scrap input compositions such that they can be used in otherwise unaccommodating circumstances. It is exactly this property of material "upgrading" through sorting that can makes it valuable in a production environment.

**Table VI. Amount and Percentages of Scraps Used[3] and Sorted (Base Case)**

| Scrap Type | % Used | Qt. (kT) Used | % Sorted | Qt. (kT) Sorted | Shadow price / Ton [4] |
|---|---|---|---|---|---|
| Base Casts | 100.0% | 30.0 | 62.0% | 18.6 | 0.09 |
| Base Extrusions | 100.0 | 10.0 | 0.0 | 0.0 | 0.05 |
| Base Sheets | 100.0 | 10.0 | 0.0 | 0.0 | 0.19 |
| Co-Mingled | 100.0 | 10.0 | 0.0 | 0.0 | 0.29 |
| **Overall Total** | **100.0%** | **60.0** | **31.0%** | **18.6** | |

**Table VII. Allocation of Unsorted Scraps in Alloys Production**

| Alloy | Raw Materials Allocations (T) in Production Without Sorting | | | | |
|---|---|---|---|---|---|
| | Base Casts | Base Extrusion | Base Sheet | Co-Mingled | Primaries & Alloying Elements |
| 230 | 219 | - | - | - | 20,201 |
| 226 | 19,550 | - | - | - | 1,855 |
| 239 | 538 | 9,097 | 5,081 | - | 16,648 |
| 6111 | 1,735 | - | - | 8,925 | 88 |
| 6082 | - | 903 | 1,231 | - | 15 |
| 6060 | 310 | - | 3,688 | - | 10,491 |
| 3104 | 177 | - | - | - | 1,873 |
| 3105 | 183 | - | - | 1,075 | 848 |

**Table VIII. Comparison of Scrap Usage With and Without Sorting**

| Scrap type | With Sorting | | Without Sorting | |
|---|---|---|---|---|
| | % Used | Qt Used (kT) | % Used | Qt. Used (kT) |
| Base Casts | 100.0% | 30.0 | 75.7% | 22.7 |
| Base Extrusions | 100.0 | 10.0 | 100.0 | 10.0 |
| Base Sheets | 100.0 | 10.0 | 100.0 | 10.0 |
| Co-Mingled | 100.0 | 10.0 | 100.0 | 10.0 |
| **Overall Total** | **100.0%** | **60.0** | **87.8%** | **52.7** |
| **Total Costs** | $128,267,000 | | $129,561,000 | |

## Scrap Utilization and Cost Impacts

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[3] Scrap used includes mostly sorted and unsorted material streams allocated for production as well as amounts of unallocated sorted materials that are ultimately resold.

[4] Shadow price represents the amount that the objective will improve (i.e., production cost reduction) had there been an extra unit of that material available.

To provide a more detailed look on the economic impact sorting can make by altering scrap usage patterns, Figure 2 examines the magnitude of scrap usage with and without sorting for each of the individual alloys which were investigated. As evident in the figure, scrap utilization for almost all products increased or stayed flat with sorting. Interestingly, there was a decrease in scrap usage for alloy 3105. The cause of this is probably limited scrap supply. In particular, with sorting all available scraps are completely utilized, leading to competition among products for similar scraps. Specifically, as can be noted from a comparison of Table V and Table VII, there was competition for Co-Mingled scrap between alloys 3104 and 3105. This led to the opposite scrap utilization effects observed for these two products in Figure 2 with and without sorting.

Figure 3 correlates the changes in scrap usage patterns to cost savings/increases associated with such changes. Generally speaking the cost savings are associated with an increase in scrap utilization. Once again the dramatic difference observed between 3104 and 3105 can be attributed to competition for scraps. Overall the cost saving for wrought products is 1.4%, which is greater than that of cast products at 0.9%. In most cases, the increase in cost savings should be correlated directly with increase in scrap usage when scrap supply is unconstrained. Furthermore, it should be noted that the cost savings/increases on individual alloys in Figure 3 does not include the revenues obtained from the resale of unused sorted scrap, of which there were roughly 0.4kT in the Base Case.

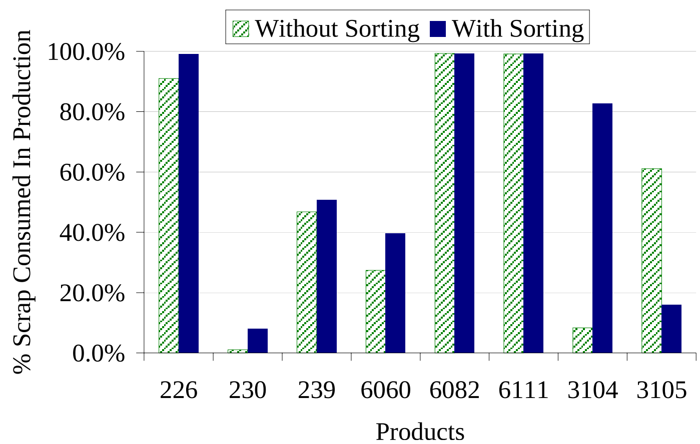


**Figure 2. Base Case changes in percentage of scrap consumption in production for individual products with and without sorting.**

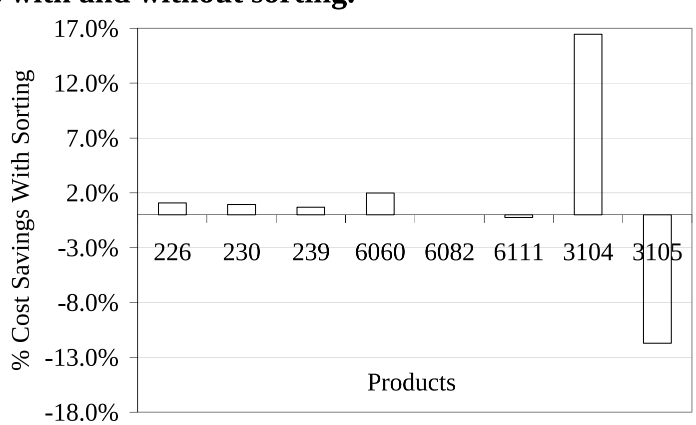


**Figure 3. Base Case cost savings/increases due to changes in scrap usage pattern of various products with sorting.**

## Sensitivities of Sorting Technology Utilization Rate on Sorting Recovery Rates

Many factors ultimately affect the optimal decisions surrounding scrap allocation and sorting. Key factors include the sorting recovery rates, sorting and raw material costs, scrap characteristics and production mix. The effects of sorting recovery rates and sorting costs are examined for the Base Case in Figure 4 and Figure 5 which show the percentage of available mixed scrap[5] that is sorted. In essence this is a measure of the sorter utilization rate. It should be noted that in these figures, Bin 3 is invariant in that it always collects 100% of the "Other" fraction. Furthermore, as the wrought recovery rate was decreased, the Bin 2 grade[6] was becoming less cast-like since it was increasingly "contaminated" by wrought fractions. Similar logic follows with Bin 1 grade for decreases in the cast recovery rate.

Interestingly, the utilization rate in Figure 4 and Figure 5 never reached above 60%. This is a result of the fact that, out of the four types of scraps considered, only the Base Cast scraps had *both* wrought and cast representation equal to or greater than 30% by mass. Since Base Cast scraps made up 60% of the mixed scrap supplies, this effectively capped that amount of material sorted at this level. In fact, while some Base Cast scraps were sorted throughout the entire range of sorting costs and cast sort recovery rates considered in Figure 4, only up to 30% maximum of the Base Sheet scraps were sorted for sorting costs below $11/T and for the range of 72.5% to 85% cast recovery rates. Outside this range, none of the Base Sheet scraps were sorted. Furthermore, none of the Co-Mingled scraps were ever sorted within the ranges of sorting cost and sort recovery rates considered, even though it had a more diverse mix of cast and wrought materials compared to Base Sheet scraps. Finally, none of the Base Extrusion scraps or Co-Mingled scraps was ever sorted for the ranges of sort recovery rates shown in Figure 4.

While these results are specific to these scrap types and products, there are general observations that can be made. From Figure 4 and Figure 5, it is clear that on average the sorting utilization rate remained much higher for the entire range of wrought sort recovery rates compared to similar levels of the cast sort recovery rates. This difference in sensitivity is driven by several factors. As recovery rates drop, Bin 1 (wrought bin) gets contaminated with more cast fractions and Bin 2 (cast bin) gets contaminated with more wrought fractions. However, the tolerance for alloying content is generally higher in cast products than wrought products. The combined effect in the Base Case where only 30% of the alloys produced are wrought is that the sorting utilization rates were more sensitive to cast recovery rates than wrought recovery rates.

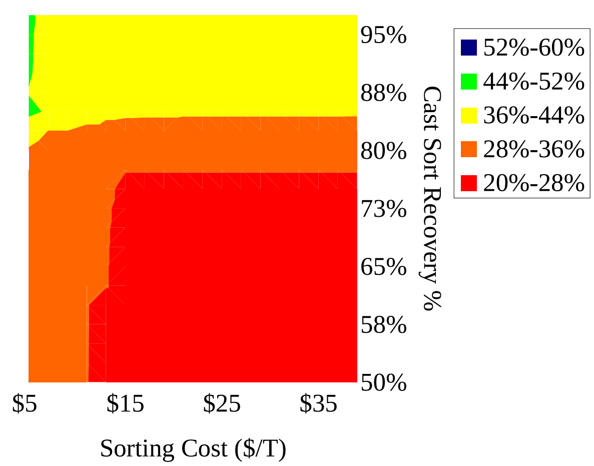


**Figure 4. Sensitivity of percentage of available mixed scrap sorted with variations in cast sort recovery rate (Wrought sort recovery rate is held constant at 95%).**

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[5]Mixed scrap is defined as scrap that has both representations of wrought and cast fractions. Therefore Base Extrusions scrap is excluded from this definition.

[6] Grade is defined as the weight (concentration) of the desired product in the output stream.

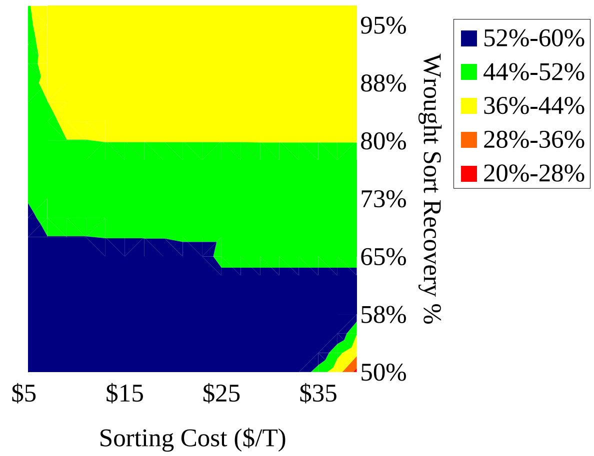


**Figure 5. Sensitivity of percentage of available mixed scrap sorted with variations in wrought sort recovery rate (Cast sort recovery rate is held constant at 95%).**

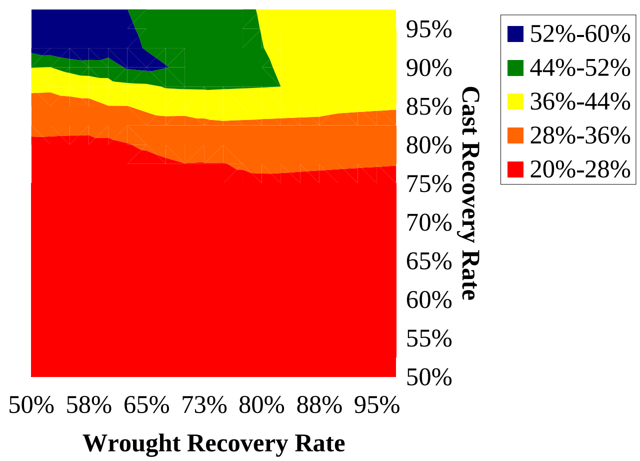


**Figure 6. Percentage of available mixed scrap sorted under various wrought and cast sort recovery rates (Base Case, $30/T sorting cost).**

Another interesting observation from Figure 4 and Figure 5 is that the sorter utilization rate does not monotonically increase with recovery rates. For the Base Case examined, Figure 5 indicates that the recovery rates at which sorting were utilized most peaked below 65% wrought sort recovery rates. In fact, following this peak, as the sorting cost approached $40/T and the wrought recovery rate dropped towards 50%, the sorter utilization rate decreased back below 30%. This shows that having the highest recovery rates does not always lead to the highest utilization rate for this sorting technology. This effect is made even more pronounced in Figure 6 which examines the effects of simultaneous variations in wrought and cast sort recovery rates on the significance of sorting utilization, assuming a uniform sorting cost of $30/T. These results might seem counter-intuitive, especially if one associate higher sorting recovery rates to better control over sorted scrap stream chemistry.

To clarify this issue, one can examine the allocations of sorted and unsorted streams along two different points along the top edge of Figure 6. Table IX and Table X illustrate the allocation of sorted and unsorted materials streams for the production of selected products for two different levels of wrought recovery rates with cast recovery rate fixed at 95%. For the sake of clarity, the operating point corresponding to a wrought recovery rate of 55% will be identified as point L (low wrought recovery) and wrought recovery rate of 90% will be identified as point H (high wrought recovery). Furthermore, only those products with significant materials usage changes are shown. In particular, the amount of sorted materials that was consumed by alloys 226 and 6111 in this constrained material system at point L was 20.9kT and 2.3kT versus only

**Table IX. Allocation of sorted and unsorted materials for production with 55% wrought and 95% cast recovery rates (Base Case, sorting cost = $30/T).**

| Alloy | Scrap materials allocations (T) in alloy production | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Base Casts | | | | Base Extrusions | | | |
| | Bin 1 | Bin 2 | Bin 3 | Un-sorted | Bin 1 | Bin 2 | Bin 3 | Un-sorted |
| 230 | 1,242 | - | - | - | - | - | - | 1,173 |
| 226 | - | 17,195 | 3,656 | 422 | - | - | - | - |
| 239 | 2034 | 293 | - | - | - | - | - | 7,924 |
| 6111 | 349 | 1,910 | - | - | - | - | - | - |

| | Base Sheets | | | | Co-Mingled | | | | Primary & Alloying |
|---|---|---|---|---|---|---|---|---|---|
| | Bin 1 | Bin 2 | Bin 3 | Un-sorted | Bin 1 | Bin 2 | Bin 3 | Un-sorted | |
| 230 | - | - | - | - | - | - | - | - | 18,116 |
| 226 | - | - | - | - | - | - | - | - | 220 |
| 239 | - | - | - | 4,727 | - | - | - | - | 16,398 |
| 6111 | - | - | - | - | - | - | - | 8,403 | 86 |

**Table X. Allocation of sorted and unsorted materials for production with 90% wrought and 95% cast recovery rates (Base Case, sorting cost = $30/T).**

| Alloy | Scrap materials allocations (T) in alloy production | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Base Casts | | | | Base Extrusions | | | |
| | Bin 1 | Bin 2 | Bin 3 | Un-sorted | Bin 1 | Bin 2 | Bin 3 | Un-sorted |
| 230 | 1,336 | 11 | - | - | - | - | - | - |
| 226 | - | 10,513 | 2,340 | 8,434 | - | - | - | - |
| 239 | 2,043 | 390 | - | - | - | - | - | 9,097 |
| 6111 | 431 | - | - | 1,666 | - | - | - | - |

| | Base Sheets | | | | Co-Mingled | | | | Primary & Alloying |
|---|---|---|---|---|---|---|---|---|---|
| | Bin 1 | Bin 2 | Bin 3 | Un-sorted | Bin 1 | Bin 2 | Bin 3 | Un-sorted | |
| 230 | - | - | - | 786 | - | - | - | - | 18,384 |
| 226 | - | - | - | - | - | - | - | - | 207 |
| 239 | - | - | - | 3,971 | - | - | - | - | 15,902 |
| 6111 | - | - | - | - | - | - | - | 8,571 | 81 |

12.9kT and 0.4kT at point H, respectively. These underscore the fact that with materials availability constraints, higher sort recovery rates do not always produce the most compatible sorted scrap materials for all alloys.

While the discussions above indicate that having high sort recovery rates do not automatically lead to high sorting technology utilization, it should be emphasized that overall cost savings were found to increase monotonically with both increases in cast and wrought sort recovery rates. Assuming that the cost of sorting is independent of sorting technology utilization rate, all else being equal, sorting more material always incurs greater overall costs. Therefore, the goal will always be to consume as much scrap material as possible first without sorting. It should also be noted that as both cast and wrought recovery rates increase, the amount of scrap consumed[7] increased monotonically. In this cast-heavy case, the amount of scrap consumed was found to increase more rapidly by increasing cast recovery rates (holding wrought recovery rate constant) compared to increasing wrought recovery rates (holding cast recovery rate constant). This trend is consistent with the observation that in a cast dominated product mix, the cast recovery rate is more critical for sorting technology utilization rate. From a products perspective, sorting will be most critical and applicable when the products chemical specifications are less amenable to scrap consumption. This was not the case with some of the products in this study (e.g. Alloy 226 is considered a scrap-friendly material.) as shown in Table X. In fact, between point L and point H, the total amount of Base Cast scraps used in alloy 226 stayed roughly the same around 21.2kT.

## Conclusions

Advanced sorting technologies hold promise to add considerable value to secondary aluminum streams. As a potentially expensive investment, scrap processors and remelters must apply sorting judiciously to receive maximum return. This paper has presented a decision-support algorithm which both characterizes the complex interactions of surrounding sorting in the context of aluminum reuse and provides critical insights into the economic value of sorting methods. Specifically this method answers the key business questions:

- Which scrap streams should be sorted?
- How extensively should those streams be sorted?
- For what production scenarios should sorted scrap be used?

With answers to these questions, stakeholders are able to identify economically optimal schemes to acquire, sort and allocate raw materials for alloy production.

In applying this method to a case representative of European scrap streams and production demands, it is clear that there are a broad range of conditions where efficient sorting methods (in this case cast / wrought sorting) can add value to remelt operations. Not surprisingly, it was found that sorting benefited wrought production more than cast production, in terms of cost savings and increased scrap consumption. While overall cost savings correlate positively with increased scrap consumption, not all alloys produced benefited equally from this increase in scrap consumption through sorting due to competition for limited scrap supplies. At a sorting cost of $30/T, only scraps with both cast and wrought fractions above 30% were sorted.

Assuming that sorting cost per ton is independent of sorting technology utilization rate, better wrought and cast recovery rates led to monotonically increasing cost savings and scrap consumption. However, better recovery rates do not always lead to greater sorting technology utilization. In fact, under stated material system constraints, higher recovery rates do not always lead to greater amounts of usable sorted scraps for selected products. In the case examined (i.e., production was cast dominated), higher cast recovery rates were more critical than higher wrought recovery rates to effect greater sorting technology utilization. In fact, for this case, sorting technology utilization did not change significantly relative to the wrought recovery rates for a large range of cast recovery rates.

Finally it should be noted that some of the products examined in this paper are quite scrap-friendly both because of specific alloying requirements, but also in terms of the use of broad industry specifications. It can be expected that firm-specific compositional specifications are tighter than those used in this study. Furthermore such stringent requirements will likely elicit even higher value from effective scrap sorting. Future work should include examination of the effects of altering the specific products on sorting technology utilization and associated economic impacts.

[7] Defined as scrap used less scrap resold

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