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Techno-Economic Assessment of Robotic Sorting of Aluminium Scrap

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Abstract

Due to shifting material use in several sectors, such as the automotive sector, the demand for wrought aluminium alloys is significantly increasing. Because of their low weight and desirable mechanical properties, wrought aluminium alloys find their use in many different applications. However, the primary production of aluminium is extremely energy intensive. Therefore, using secondary aluminium yields major environmental benefits. Hence, in order to avoid degradation of the aluminium quality during recycling, sorting aluminium alloys, based on their alloying elements, is necessary. Today, various non-ferrous metal fractions are either still sorted manually in unhealthy working conditions, resulting in either high labour costs, or the export of this waste stream to countries with a lower labour cost. With the emergence of novel spectrometric techniques, such as laser-induced breakdown spectrometry (LIBS) and deep learning computer vision techniques, the technical feasibility of classifying different aluminium alloys has been demonstrated. Therefore, the techno-economic viability of a robotic sorting process, that could be combined with such advanced classification systems, is presented. This study presents the development and evaluation of a robotic sorting system consisting of; a vision system, a conveyor, a SCARA robot and a pneumatic gripper. The vision system recognises the dimensions and positions of the objects on the conveyor and communicates with an innovative sequence planning algorithm. The use of experimental data enables to obtain realistic insights in the sorting efficiencies that can be obtained. The initial economic analysis illustrates the substantial potential of the proposed robotic sorting approach. To overcome saturation of the conveyor belt, two of the proposed systems are assumed to be capable of sorting 20.000 tons of aluminium annually each equipped with 6 robots creating a total added revenue up to 1,95 million euro per year.

Keywords: *robotic sorting; techno-economic analysis; aluminium; alloys; computer vision*

1. Introduction

Nations worldwide have the objective of minimising pollution and avoiding the depletion of raw materials. To achieve these objectives, low emission mobility targets have been established resulting in the production of more electric and lighter vehicles [1]. Both composite materials and high purity aluminium alloys are used to achieve weight reduction because of their very high strength-to-weight ratio. Therefore, the production of wrought aluminium alloys is increasing, while the production of cast aluminium alloys, mainly used for the production of combustion engines, is stabilising [2]. Already today aluminium is the most produced non-ferrous metal [3]. Despite all the benefits of using aluminium, primary

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aluminium production is a very polluting process and is responsible for 3,5% of global electricity consumption and 1% of the global CO_2 emission [3].

Recycling aluminium has a significantly lower environmental impact than producing primary aluminium. However, by mixing different aluminium alloys and impurities, quality losses typically occur during recycling [4], limiting the applications for which recycled aluminium can be used today. Consequently, the aluminium is downcycled instead of recycled. Paraskevas et al. show that this downcycling practice and the rising need for high purity aluminium will result in an excess of low purity aluminium for which there is no demand [5]. This excess of aluminium scrap will likely end up to a large extent in landfill and will need to be replaced by new primary aluminium, resulting in additional environmental impact. At this point, the generated amount of mixed, low purity aluminium scrap will exceed the amount that can be recycled, either directly for the production of cast alloys or through dilution for the production of wrought alloys [2] .

In order to use recycled aluminium for applications where primary aluminium is typically used, current sorting methods need to be drastically improved [6]. Diaz et al. demonstrated that neural networks are capable of classifying cast and wrought aluminium with high accuracy using only colour and depth images [7], providing new opportunities for enhanced automated aluminium sorting systems.

Therefore, this research investigates the combination of such vision systems with a robotic sorting system for aluminium recycling, addressing the following aspects:

- Technical analysis:
  The system design and plant layout, i.e., to answer questions such as how many robots could be used in each system and how many systems are needed to sort a provided annual throughput.
- Economic analysis:
  The analysis of the potential economic advantages of the proposed system and a sensitivity analysis on the economic estimation to indicate further business potential.

The ecological impact is a third aspect, it is however not covered in this work. The remainder of the paper is organized as follows: The hardware setup and the developed software are explained in detail in Section 2. In Section 3, the method adopted in the performed experiment is explained. Section 4 analyses the results and discusses different scenarios, while in Section 5 a sensitivity analysis is described to quantify how the waste stream composition and the value of the sorted fractions influence the yearly revenue. Finally, Section 6 presents the conclusions and future work.

2. Materials and methods

The experiments are performed on a set of shredded aluminium flakes with a size ranging from 40mm to 120mm and an average sample weight of 47g, which is determined by weighing 840 metal particles. The origin of the scrap samples is automotive and construction waste. The sample set consists of almost exclusively aluminium alloys, a waste stream known as Twitch [8].

The test setup, shown in Figure 1, consists of six main components: 1) A five meter long conveyor, with a width of 0.6 meter, which is driven by a servo motor that allows accurate speed control and is randomly filled with metal pieces at the beginning of the conveyor. 2) The vision system consists of a 3D line camera and an RGB + NIR camera. 3) A computer running a custom developed computer vision algorithm, whose functioning is out of the scope of this paper, to process and analyse the captured images in order to define the size, location, height, rotation and class of the objects. 4) After processing, the developed Python program on the same desktop computer encodes the data and sends these to the robot. 5) An encoder, used to synchronize the system (including the robot and cameras) and 6) A PLC to synchronize the camera system, robot and processing software.

The developed software for the proposed sorting process consists of multiple subprograms that were all implemented in Python: image processing, combining, sorting, planning and encoding. Within the robot controller, three main processes are running: decoding, processing and performance logging.

After the PLC triggers the camera, it captures an image which, in turn, is sent to the first subprogram. The image processing algorithm builds a list with all the recognised objects together with their identification number, X-, Y- and Z-coordinates, angle of the object with respect to the conveyor axis, and both the width and class of the object. Only the width dimension is sent to the robot since a parallel gripping device is considered to be used. It represents the magnitude of the object perpendicular to the longest axis of the object through the centre of the object.

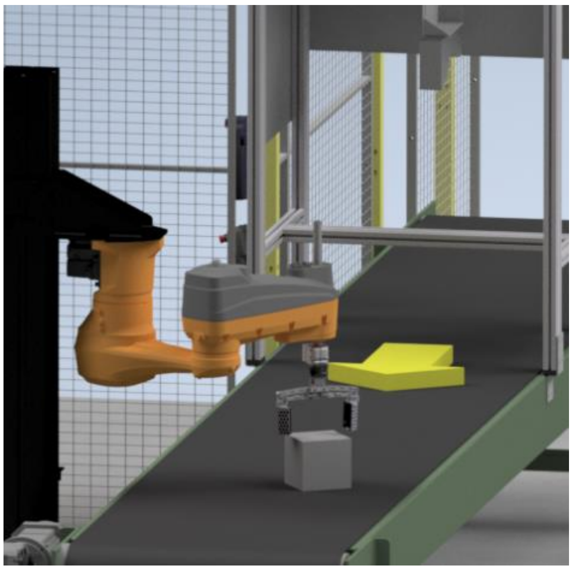

Figure 1: Render of physical test setup with the gripper attached to a Staubli TS2-80 (middle) and the camera box (top right).

An identification number is a unique number starting from 0 assigned to every object. After the image processing, the data list, comprising the data of multiple images, is constructed and sorted based on the object's location along the conveyor in the direction of the movement, represented by the Y-coordinate. This way, the first object data represent the object on the conveyor that reaches the robot first. Next, a novel planning algorithm calculates all the possible sequences and the total idle time within subsequent picks based on state-of-the-art algorithms for sequence planning [9] . The most extensive sequence will be selected every time to maximize the number of objects picked. Since two equally long sequences could be found, an additional selecting criterion is needed. For this purpose, the total idle time will be used. The sequence with the longest idle time will be selected since the robot is assumed to consume less energy when idling, even though the amount of energy preserved by this is considered marginal.

To minimise the time needed for a picking motion, the zone in which the robot is able to pick objects, referred to as the *picking zone*, has been limited. Usually, the picking zone is defined as the intersection between the workspace of the robot and the conveyor surface. However, to better control the picking motion and to minimise the time needed for the robot to return and to pick the following object in this zone, a thin band is defined at the beginning of the original picking zone. Figure 2 shows the picking zone with a white box. The robot always starts its picking movement in this picking zone. This also assures that there is sufficient time for the robot to pick the object after synchronizing before the object passes too far on the conveyor, resulting in an inefficient operation of the robot. Picking objects too far on the conveyor is inefficient, because of the robot's fixed righty configuration, which causes the first and slowest axis of the robot to be moved the most when working down the conveyor belt. In addition, when switching from righty to lefty configuration and back would also introduce extra time required for a certain pick. Therefore, a time loss. A fictive boundary is used which the robot will not surpass to prevent this, as shown by the dotted line in Figure 2. Working in front of this boundary enables the robot to use its second and faster axis more intensively, leading to more efficient picks. The extra speed also seems to help with throwing the objects at the drop of location since the objects have a higher speed when released.

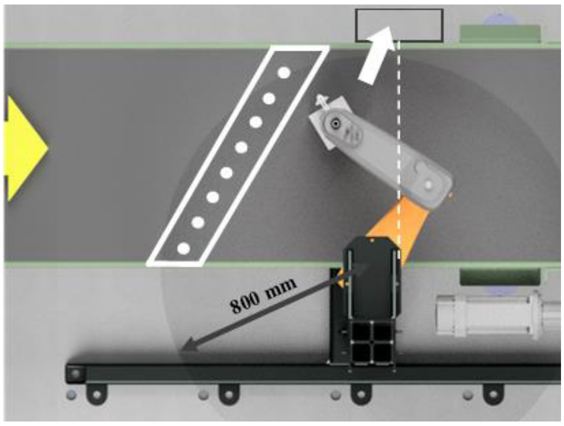

Figure 2: Top down robot view with picking zone (white square) and drop-off location (arrow).

Within the picking zone a certain number of equally spaced points, illustrated in Figure 2 by dots, are defined to experimentally determine the time needed for a certain pick. A pick movement is performed starting from all these points while recording the time needed. The data are then kept in an array and used to estimate the needed picking time for all random object locations in the picking zone, using interpolation as presented in Han et al. [9], whereas, in this study, a limited picking zone is used. This approach yields some benefits, namely: 1) Using the predefined picking time is a less computationally demanding approach and, therefore, it is suitable for a real-time system as the one proposed in this work. 2) The robot only receives data from the objects which it can pick and, therefore, the system knows which objects are pickable by a particular robot and which objects could be passed on to another robot. 3) It is a robotic-type independent approach, which means that it does not depend on the robot manufacturer and, therefore, it is more flexible.

To define the picking sequence, the first object to be picked has to be selected. This can be either the first object from the combined data of the images or the first possible object after picking the last object from the previously combined data. In Figure 3, this first object is represented by *A*. All cells in the table contain the spare time available to pick a specific object (row header) after picking another object (from the column header). The first circled value within this figure represents the first positive spare time in the column after picking *A* and getting ready to pick the next object, *B* in this case. If this spare time is negative, the robot will never be able to pick this object after picking *A*. In that case, the negative cell is skipped and the next cell in the column is calculated to consider this object as an option to be picked next in the sequence. Since *B* has a positive value, it is considered a viable option in this example and the algorithm will stop calculating the spare times (robot idle time) for alternative options and will repeat the same steps starting from column B. In this example, picking *C* is not an option after picking *B*. Therefore, object *C* will be skipped, in this example, *D* is a viable option. This method continues until the last column is reached (or skipped). To make sure all possible sequences are checked, all the objects that where skipped after defining the first succeeding object, non in this example, are used as a first object to define a sequence for these since starting with object A (which is the first viable option) is not necessarily the best option. As explained before, the resulting sequences are compared to check if starting with a later object could yield a benefit.

Picked / Next target	A	B	C	D	E	F
A						
B	> 0					
C		< 0				
D		> 0				
E				> 0		
F					> 0	

Figure 3: Sequence planning based on idle time from robot in-between consecutive picks

After receiving the sequence, the robot picks the objects accordingly. The data from the different processing steps are saved in a database. The first data transferred are the sorted data list generated from the images. Second, the sequence list, which was sent to the robot, is saved in the same database. The robot controller saves the object data and the picking time of all picked objects. After the experiments, both databases are merged. A table is generated and evaluated in Microsoft Excel, containing all the information from the recognised objects, whether or not the data have been sent to the robot, the picking confirmation and the time needed to execute the picking task.

3. Experiments

The conveyor is not loaded during the experiment to avoid collisions and prevent intensive manual labour for loading and unloading. Instead, an image set is taken during five experiments using a conveyor speed of 0,5 m/s, when the objects are loaded with different spread densities. Within the image set, there were no overlapping objects. In industrial applications, this is commonly realized by installing a vibration feeder or brushes to make sure no objects are laying on top of each other.

The first goal of the experiment is to estimate the ideal robot plant layout in function of the annual throughput. Second, an economic analysis is performed on a case study followed by a sensitivity analysis.

For the case study, an annual throughput of 20.000 tons is assumed to be desired in 3.400 working hours. According to Van den Eynde et al., Twitch comprises approximately 35% cast aluminium and for the remainder, wrought alloys [2]. Therefore, cast alloys will be picked from the conveyor as it is the minority fraction.

As explained, different image sets are created for the five experiments with a gradually increasing filling density to imitate different throughput scenarios. During the experiments, all the objects are targeted as if they are cast objects to exclude the influence of the fluctuation in the composition of the test samples on the performance of the robot. For example, momentary higher concentrations of casts could result in a peak load for the robot, creating unrealistic results or extreme idle times.

4. Results

The total system cost is estimated for all the scenarios based on the minimum number of robots. The picked amount of material per robot is assumed linearly scalable. By scaling linear, an error is made. The indicated amount of picked objects is assumed to be higher than the capable amount. Because the current setup only includes one robot and the software is not ready to plan sequences for two or more robots, no experiment to define the error could be executed. This will be covered in future work. Moreover, other aspects, like gripper efficiency and homogeneity of the conveyor filling, are assumed to have a more significant impact on the performance of a robotic sorting system. After calculating the system's cost, the sorting benefit is calculated.

4.1. Sorting system requirements

Table 1 shows, for each scenario, the number of objects that are fed during the different experiments, as well as how many of those pieces got picked by a single robot. The number of robots needed to pick 35% of the pieces, which corresponds to the cast fraction, is calculated using this data.

Table 1: Test scenario characteristics; conveyor fill density inclines with scenario number

Scenario:	**1**	**2**	**3**	**4**	**5**
Objects detected	1720	2938	4672	4314	5676
Objects picked	405	400	334	266	391
Picked (%)	23,55	13,61	7,15	6,17	6,89
Number of robots	1,49	2,57	4,90	5,68	5,08
Throughput (tons/year)	4656	7954	12648	11679	15366

Both scenario 3 and 4 surprisingly show less picked objects, which confirms the relevance of this work. A lot of different parameters influence the efficiency of the system. For example, the relative positions of the metal objects influence the robot path so that less efficient sequences could be the best option, resulting in less picked objects.

Figure 4 shows the number of robots required to achieve the corresponding throughput. The number of robots is rounded up to determine the investment cost per system. Also, the investment cost, the yearly benefit of sorting and profit in the first year are shown for each indicated throughput and number of robots. The investment cost and the economic analysis will be further explained in Section 5.

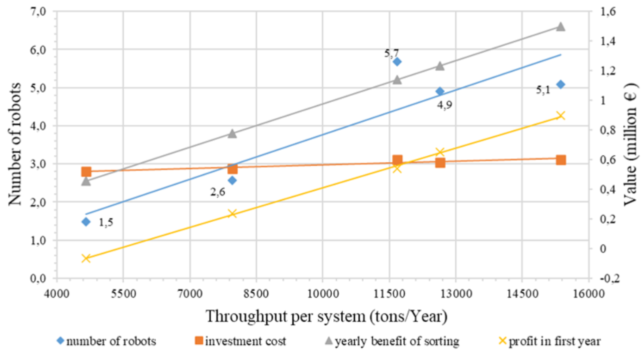

Figure 4: System requirements and economic parameters as function of required throughput

As illustrated in Figure 4, the throughput per system profoundly impacts the number of robots and, therefore, the investment cost and potential profits. While an extra robot adds a cost to the system, it also increases both the potential for higher throughput and an increased share of the aluminium fraction to be picked. Another observation is that the robots only contribute to 15-20% of the total cost of the proposed system.

Considering the presented experimental setup, the performed experiments indicate that the maximum throughput of the sorting installation mainly depends on the filling density since the width of the conveyor and the conveyor speed are constant. An increased or decreased conveyor speed directly influences the performance of the robot and would therefore require more experiments. It should also be considered that the applied gripper type limits the allowed population of pieces on the conveyor. Some grippers require more free space around the targeted object than others. For instance, parallel grippers with claws need extra free space for positioning the claws without colliding with other objects, while suction cups or other grippers may not require this spacing. Given the shredded nature of the Twitch waste stream, the gripper type considered in the experiments is a parallel gripper with custom claws.

4.2. Plant requirements

Since the fifth scenario is assumed to have the maximum conveyor fill density when using a parallel gripper, the results from the fifth scenario with the highest possible throughput are used for further analysis. Since the fifth scenario is the limitation, six robots will be considered the maximum number of robots that can be implemented in a single system.

Figure 5 shows extrapolated data for both the limits and the capabilities of multiple sorting plant configurations and indicates the increased revenue for the different configurations as function of the number of shifts the plant is operated in annual working hours.

For the selected use case, this results in the need for 11 robots to enable the sorting of 20.000 tons in 3.400 working hours. Consequently, 2 systems are required. One extra robot is added to cope with downtime or extra available material within those machines, resulting in two six-robot systems.

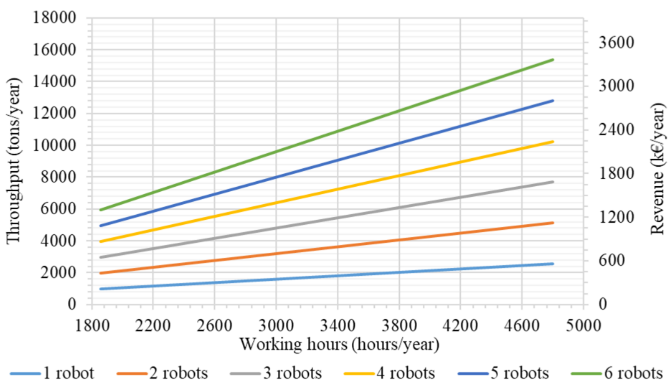

Figure 5: Plant layout

5. Economic analysis

As shown in Figure 5, the use case with two systems and, therefore, 12 robots will require around 3.400 working hours or around seven eight-hour shifts a week to sort the required throughput of 20.000 tons a year. The investment cost of one system is estimated between 600.000 and 800.000 euro consisting of 20.000 euro for the camera system, 15.000 euro for the conveyor, 6 times 20.000 euro for the robots and 445.000 to 645.000 euro for the realisation of the system, including the labour and extra material needed to build the system as well as the cost for transport, calibration, setting up the system for the customer and a possible profit margin. The development cost is not included since this cost has to be divided over the amount of systems sold which is hard to estimate.

However, some additional assumptions need to be taken to perform economic calculations. First, we assume the complete aluminium stream will never lose value by sorting it. Second, the value for the sorted cast and wrought fractions will be considered respectively 1.200 and 1.350 euro per ton, unsorted aluminium is valued at 1.200 euro per ton [8].

Consequently, the unsorted material (20.000 tons) has a value of 24 million euro. The sorted material has a value of 25,95 million euro increasing the value by 1,95 million euro resulting in a payback time of 3,69 up to 4,92 months , depending on the cost of the realisation of the system. When including the development, cost this period will end up being longer.

Since the aluminium scrap prices can strongly fluctuate over time, and in order to assess the robustness of an investment under the uncertain price conditions, a sensitivity analysis is performed to estimate the influence of this fluctuation on the revenue associated with sorting cast and wrought aluminium [10].

5.1. Sensitivity analysis

During the subsequent sensitivity analysis, two scenarios are discussed. The first scenario focuses on the change of the added value created by sorting wrought aluminium, which is varied between 0 and 260 euro per ton in increments of 65 euro. Figure 6 shows the added value by separating the 35% wrought aluminium (x-axis) and the added annual revenue of sorting (y-axis), with a throughput of 20.000 ton per year.

The second sensitivity analysis focuses on how the changing waste stream composition could affect the revenue created with the sorting system. This change is depicted in Figure 6, representing different cast-wrought ratios of the waste stream.

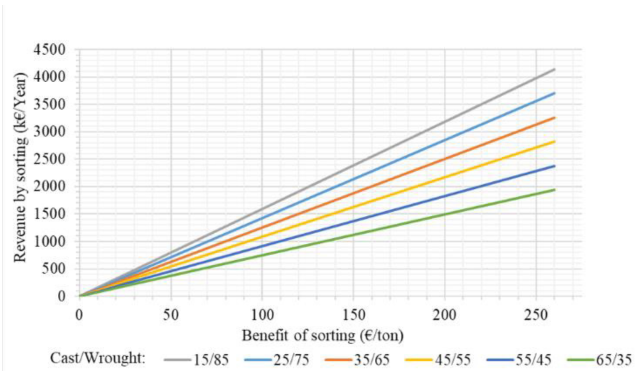

Figure 6: Sensitivity analysis on profit

Figure 6 shows that a growing share of cast alloys negatively impacts the revenue and, therefore, the profit of sorting and that the overall revenue strongly depends on the actual sorting benefits, whereas an increased value of 150 €/ton with the considered material composition (35% cast) for the sorted aluminium results in an extra revenue of 1.95 million euro per year. With an investment cost of 600 to 800 thousand euro this equates to a payback time of 3,69 to 4,92 months. The revenue by sorting, shown in Figure 6, is not unrealistic. Especially if a more advanced sensor, e.g. a LIBS sensor, could be implemented, which could be used to classify the different alloy types and, therefore, facilitate the opportunity to create an additional benefit by sorting the waste stream in more aluminium fractions [11].

6. Conclusions and future work

This study investigated the techno-economic viability of a robotic sorting system for cast and wrought aluminium alloys. First the system is constructed. Next a Python program with a novel planning algorithm was developed to enable communication between all the subsystems and facilitate sequence planning. This planning algorithm will be further tested and compared with state of the art in future work. This comparison will be made to define the error made in this work by linear scaling the throughput with the number of robots while testing the capabilities of the algorithms in terms of multi-robot collaboration.

The performed empirical experiments allow that a six robot sorting system would be capable of sorting up to around 11.000 tons a year. Within the performed case study, an installation consisting out of two six-robot sorting systems, capable of sorting 20.000 tons a year, has been evaluated. An estimated investment of 1,2 to 1,6 million euro could increase the revenue with 1,95 million euro a year. Consequently, the payback period for this sorting installation is estimated to be around 3.69 to 4.92 months.

A gripping device with a smaller footprint allows for denser conveyor filling. Consequently, more robots can operate on the same conveyor and therefore increase the throughput without duplicating the senor and control components. Future research will further explore different gripper types and adapt existing grippers.

The sensitivity analysis shows further economic potential of the sorting systems for different aluminium compositions and a range of different added values.

Acknowledgments

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