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# Techno-Economic Analysis of a Material Recovery Facility Employing Robotic Sorting Technology

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***Abstract***

Over the past decade, robots have emerged as a new sorting technology for material recovery facilities (MRFs), enabled through dramatic advances in robotics and artificial intelligence (AI). These advances allow robots to become 'smart' by coupling them with AI driven vision systems, able to distinguish recyclables by material type. By integrating robotics, MRFs hope to increase sorting speed and accuracy, reduce their residuals, and to become more resilient towards worker shortages. To better understand the economic implications, this study presents a techno-economic analysis of a representative MRF in the U.S. that integrates robotics and compare it to a similar MRF without robotics integration. We compare the metrics net present value, discounted internal rate of return, and payback period for a mid-size MRF with and without robotic integration and add an uncertainty analysis to inform about the most important factors to consider. The results of the techno-economic analysis can inform MRF operators in their future decision-making.

***Keywords*:** Techno-economic analysis (TEA), material recovery facility (MRF), recycling, municipal solid waste (MSW), robotic sorting, net present value, discounted internal rate of return, payback period



## 21.1 Introduction

Efficient recycling is the cornerstone of a circular economy. The idea of minimizing the use of primary raw materials depends on a sufficient supply of high-quality recyclables, in other words, recyclables have to be collected and sorted in quantities sufficient to meet current demand while ensuring that the quality requirements in material production are met [1, 2]. The economics of recycling favor material groups where the commodity price for virgin (primary) materials is substantially higher than that of secondary (scrap) materials. This is true for metals, but rarely the case for plastics. Metal recycling is further favored since well-established technologies exist to separate ferrous (through magnets) and non-ferrous (through eddy current separators) metals from each other and from other materials. Plastics, in turn, are much harder to separate into clean streams of recyclables despite

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advanced optical sorters since economies of scale are hindered by the plethora of different compositions that exist, reflecting, to name a few, different plastic types, additives (differing by product group and manufacturer), color, and stringent requirements to keep food-grade and non-food-grade recyclables separate.

Municipal solid waste (MSW) is one of the largest and most complex waste streams in the U.S., and material recovery facilities (MRFs) are central for sorting its different waste components into valuable recyclables. The number of MRFs in the U.S. has grown to more than 350 [3] varying widely in size, throughput (100-900 tons/day), employment (large automized MRFs employ fewer workers per throughput than small MRFs), and cost [4]. The average MRF size has grown, too, in response to an increase in absolute MSW generation [5], and the incentives of economies of scale. Yet, the potential for growth remains large considering that in 2018 only 24% of the 292 million tons MSW generated were collected for recycling while 50% were disposed of in landfills (down from 89% in 1980) [6] and the remainder was incinerated or composted [5].

Most MRFs receive the recyclables from single-stream collection in a mixed material stream that contains metals, plastics, glass, and paper and cardboard, but excludes organics, textiles, and electronics. Separating these diverse materials requires a series of different separation steps that are largely automized, with workers doing the remaining sorting [7, 8]. The level of automation depends on the size of the MRF, with large MRFs generally having substantially higher levels of automation than small MRFs.

Over the past years, the role of manual labor in MRFs has become a growing issue of concern, both from a worker and MRF employer perspective. Working conditions are hard, summarized by Gibson [9] as "dull, dirty, and dangerous". Repetitive sorting, exposure to strong odors and seasonal temperature swings, and hazards from sharp and potentially contaminated objects create work conditions that are unattractive [10, 11], leading to high sick rates and turnovers in many MRFs and making the filling of open positions difficult [10]. Other challenges for the MRF economics include the high volatility of scrap market prices, changes in quality requirements for the output recyclables, and the large regional and seasonal variability in the composition of the incoming waste stream [12].

The combination of these factors explains why the integration of sorting robots for MRFs has grown rapidly over the past years. Robots, coupled with artificial intelligence (AI)-driven vision systems, offer the potential of fast and reliable sorting [13, 14]. They can be considered part of the envisioned Industry 4.0 that improves the overall sustainability of a system [15] by increasing the circularity of materials [16]. Robots can be used either as the main sorters or positioned as quality control (negative picking of unwanted materials) at the end of the sorting line. Though in a different context, a recent techno-economic analysis (TEA) that evaluated the sorting of cast and wrought aluminum alloys scrap showed promising results, estimating the payback period for the sorting installation to be between 3-5 months [17].

In a MRF set-up, robots offer the opportunity to substantially reduce the need for manual labor while increasing the sorting efficiency, thus increasing the resilience of the MRF operator towards the risks associated with fluctuations in worker availability and growing labor costs. This study provides a preliminary techno-economic analysis to test the economic implications of adding robots to a mid-sized MRF, with the role of robots assigned to quality-control functions.

## 21.2 Methodology

The objective of this study is to evaluate the economic impact of introducing robots in a medium-sized MRF by comparing it to a similar MRF without robots. We define this medium-sized MRF to have an annual throughput of 93,600 metric tons (MT), a size that would make it the 50-th largest MRF in 2021 [18]. This estimate is based on an hourly throughput of 30 tons per hour, 1.5 shifts per day at 8 hours per shift, and 260 days per year of operation (5 days per week for 52 weeks).

### 21.2.1 System Boundary

Figure 21.1 presents schematic diagrams of a non-robotic and a robotic MRF, starting from the municipal solid waste (MSW) entering the MRF gate to the recovered materials that are ready to be sold to the market for further downstream processing. The role of the robots is assumed to be limited to negative sorting, in which the quality of the outgoing material from the respective sorting technologies will be upgraded by precise picking up of the unwanted entries.

A typical MRF includes the following steps: after weighing, the recyclables are placed on the tipping floor and are later loaded onto the infeed conveyor belt with a front-end loader. After presorting by human workers, the glass breaking screen separates glass while the other materials continue to be carried over to the fiber screen, which separates fiber from the metal and plastic fractions. Magnets separate the steel cans followed by an eddy

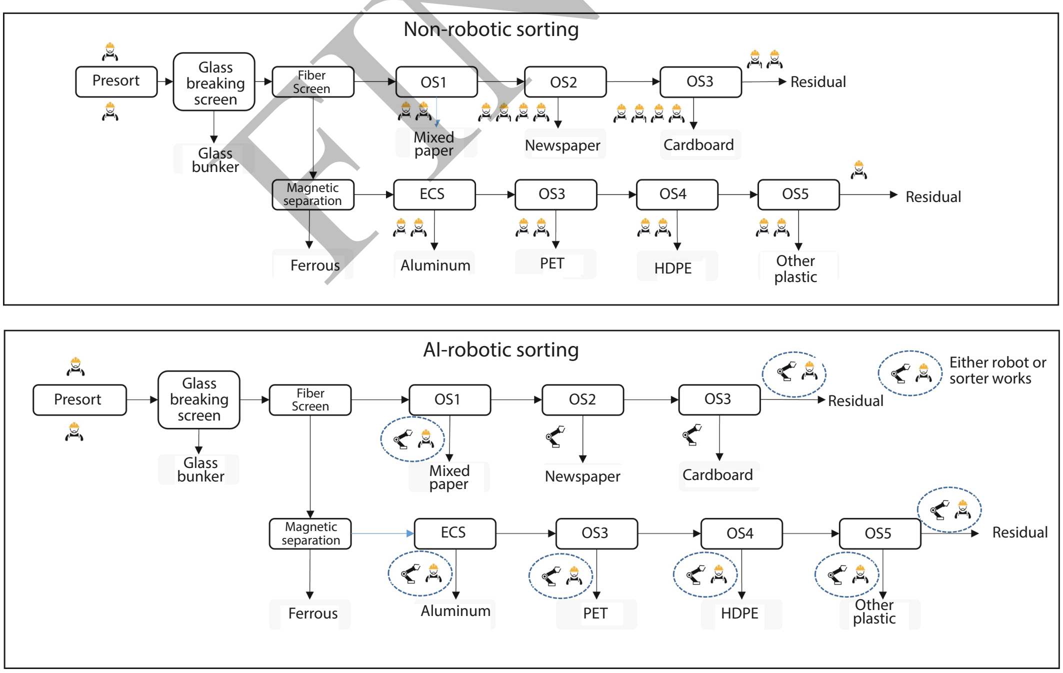


**Figure 21.1** Schematic diagram of a medium sized non-robotic MRF and a robotic MRF. The dotted oval represents workstations that can be served by either a human worker or a robot. OS: Optical Sorter, ECS: Eddy Current Separator.

current separator (ECS) that separates aluminum used beverage cans (UBC). With six optical sorters in total, three optical sorters separate the fiber stream into mixed paper, residential papers and cardboards, while the other three separate PET, HDPE, and mixed plastics (plastic types #3-7). The residuals are sent to the landfills. The input composition of the MSW is taken from Metro Waste Authority [19] and EPA [5]. The material balance is hypothetically done based on a matrix for the nine output commodities with a purity achievable in each MRF; the purity rate is assumed to be 95% [14] and 80% for the robotic and non-robotic MRF while the material recovery rate is assumed to be 90% and 85% [19].

### 21.2.2 Data Collection and Assumptions for the Techno-Economic Analysis (TEA)

The TEA is intended to compare the economic benefits of the introduction of robots in a traditional MRF setting, using 20-year discounted cash flow analysis with an internal rate of return of 20%. To estimate the economic metrics such as net present value (NPV), discounted internal rate of return and payback period, several assumptions have been made as shown in Table 21.1. During the start-up year, 50% production is considered while 75% production level is considered for the second year. The construction period is estimated to be 1 year with 100% capital investment and 75% operating cost.

**Table 21.1** Main assumptions used for the TEA of the robotic and non-robotic MRF.

| **Main assumptions for the TEA** | |
|---|---|
| Main assumptions | Value |
| Lifetime (years) | 20 |
| Operating days (days/year) | 260 |
| Number of Shifts per day | 1.5 |
| Number of hours per shift | 8 |
| Depreciation method and recovery period | Straight-Line depreciation |
| Construction period | 1 year (100% spending) |
| Start-up time (Years) | 1 ((Year 1, OPEX 75%, Revenue 50%, Year 2, Revenue 75%)) |
| Internal rate of return | 20% |
| Loan interest rate (%) [20] | 8 |
| Total Equipment Purchase Cost (TEPC) | |
| Robot cost ($) [21] | 300,000 |
| **Direct capital costs [22]** | |

(*Continued*)

**Table 21.1** Main assumptions used for the TEA of the robotic and non-robotic MRF. (*Continued*)

| **Main assumptions for the TEA** | |
|---|---|
| Main assumptions | Value |
| Installation and contingency [22] | 50% of the TPEC |
| Land [22] | 6.5% of the TPEC |
| Yard improvement [22] | 6% of the TPEC |
| Buildings [22] | 47% of the TPEC |
| Electrical [22] | 20% of the TPEC |
| Piping [22] | 30% of the TPEC |
| Instrumentation and control [22] | 26% of the TPEC |
| Service facilities [22] | 55% of the TPEC |
| **Indirect capital costs** | |
| Construction expenses [22] | 34% of the TPEC |
| Cost of contractor fees [22] | 19% of the TPEC |
| Cost of engineering and supervision [22] | 32% of the TPEC |
| Contingency [22] | 37% of the TPEC |
| Legal expenses [22] | 4% of the TPEC |
| Start-up costs [22] | 8% of the TPEC |
| Royalties [22] | 6.5% of the TPEC |
| Annual throughput (Tons/year) | 93600 |
| Price of commodities (Steel Cans, Aluminum UBC, PET, HDPE, mixed plastic (3-7)) [23] | 10 Year average |
| Price of commodities (Glass, Mixed paper, Newspaper and Cardboard) [23] | 6-7 Year average |
| Waste disposal cost ($/ton) [19] | 51 |



In a non-robotic MRF, a total of 36 sorters are employed in the sorting lines while in a robotic MRF, 12 sorters and 8 robots have been employed [4].

Total equipment purchase cost (TEPC) has been estimated by taking into account the equipment required for the sorting lines of robotic [19, 21] and non-robotic MRF [19] as shown in Figure 21.1. The difference in TEPC between the MRFs is the cost of a robot.

Fixed capital cost (direct and indirect) for robotic and non-robotic MRF has been estimated based on a percentage basis of the TEPC, while the value of some items (piping, buildings, yard improvement, service facilities, and land acquisition cost) have been kept constant, irrespective of TEPC, as robot involvement does not influence those costs. The total capital cost is in agreement with the MRF pro-forma model by RRS [24].

The operating cost (OPEX) involves no raw material acquisition cost. Labor, facility maintenance and utilities, equipment operation and maintenance, insurance, residual disposal and contingency and annual debt service has been included in the OPEX. Labor, residual disposal and robot utility and maintenance has been calculated by the authors, while Facility maintenance and equipment operation and management has been taken from a MRF feasibility study [19]. The non-robotic MRF workforce includes 14 high skilled employees and 36 sorters [4] while the robotic MRF includes 18 high skilled employees and 12 sorters. The hourly rate has been taken from the MRF feasibility study [19]. Debt servicing is estimated based on a loan interest rate of 8% [20] and for 20 years. The lifetime of the MRF equipment is expected to be the same for the non-robotic and robotic MRF.

Robot acquisition cost has been estimated as $300,000 [17, 21, 25]. The annual maintenance cost and energy consumption, lifetime years, and downtime cost (all based on [26]) have been estimated. The workload is considered to be the equivalent of three sorters, but the net purity increase has not been internalized in the revenue estimation. The revenue generation has been based on the increased material recovery and reduced landfill disposal fees.

## 21.3 Results and Discussion

Figure 21.2 summarizes the values of major parameters for an annual throughput of 93,600 MT. TEPC and total capital cost are higher for robotic MRF by 80% and 55% respectively, due to the cost of robot added to the TEPC. For the robotic MRF, the OPEX is higher by only 2% due to lower workforce cost (20%) and higher debt service (55%). In contrast, revenue generation is higher for the robotic MRF by 6%, leading to a net revenue of $5.2 million as opposed to $4.7 million for the non-robotic MRF.

To estimate NPV, discounted internal rate of return (IRR) and payback period, we use a 20-year model with a discount rate of 20%. It shows that the NPV is $31 million for the robotic MRF while $30 million for the non-robotic MRF including tipping fee $51/ton (Table 21.2). Discounted IRR is less favorable for the robotic MRF as the capital investment is 55% higher compared to the non-robotic MRF. Similarly, the payback period is greater

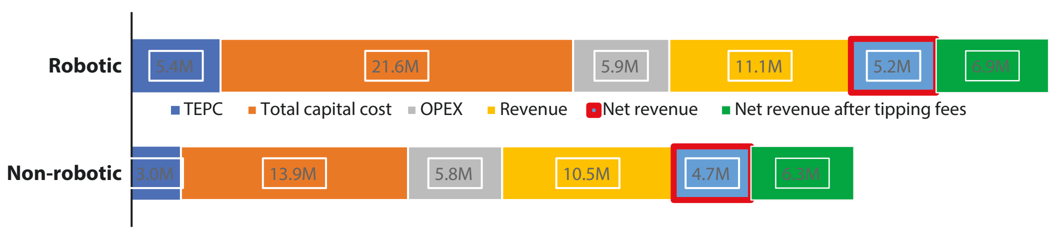


**Figure 21.2** TEA results for robotic and non-robotic MRF for an annual throughput of 93,600 MT. TEPC: Total Equipment Purchase Cost, OPEX: Operating Cost.

**Table 21.2** Comparison of TEA metrics between robotic and non-robotic MRF. NPV net present value, IRR internal rate of return.

| **Economic TEA metrics** | | |
|---|---|---|
| | **Robotic** | **Non-Robotic** |
| NPV | $31M | $30M |
| Discounted IRR | 35% | 55% |
| Payback period (Years) | 2.14 | 1.54 |

for the robotic MRF. Under the given revenue generation assumption, it is important to note here that although NPV is slightly better for the robotic MRF, the investment into robots is not as attractive in terms of discounted IRR.

Revenue estimate is carried out based on the incoming mass composition [5], outgoing commodity composition [5, 19], transfer coefficient calculation and price information [23]. EPA recyclable composition has been adjusted to exclude food, wood, and textiles. Paper and cardboard (75%), plastics (5%), metal (14%) and glass (5%) were further distributed into nine outgoing commodities. For paper and cardboard, three categories are mixed paper (55%), sorted residential paper (20%) and cardboard; for metal, two categories are steel cans (75%) and aluminum (24%); for plastic, four categories are PET (52%), HDPE natural (22%), HDPE color (21%) and Mixed plastics (#3-5). The outgoing composition is taken from a MRF Feasibility Study [19]. To estimate the transfer co-efficient, we have assumed the recovery rate 85% and 90% for non-robotic and robotic MRF respectively, with a purity of 80% and 95%. Since the prices of recycled commodities fluctuate widely, we have chosen to use a 10-year average except for glass and paper products. For glass, we use a fixed price of -0.12 $/ton and for papers, an average of 6-7 years.

Total revenue estimated for the robotic MRF is $11.1 million whereas it is $10.5 million for the non-robotic MRF, 6% value addition by introducing robots. Aluminum cans share maximum revenue of 39%, followed by cardboard with 13%. A negative value is generated for mixed glass, about 0.004%.



## Uncertainty Analysis

Three important parameters - robot price, purity-based value addition, and commodity market value - were analyzed for their uncertainties to understand the effect of the assumptions on the three metrics NPV, discounted IRR and payback period. In our uncertainty analysis, the robot price ranges between $100k and $300k, the value addition ranges from a 0% to 30% increase, and commodity prices are current, 5-year, and 10-year averages [23].

**Robot price.** The effect of the robot price on NPV shows that the robot price cannot exceed $300k, beyond which the NPV is lower for the robotic MRF. At a robot price of $100k, the NPV is $5 million higher than in the non-robotic MRF. In contrast, discounted IRR is lower for the robotic than the non-robotic MRF unless the robot price drops to $100k. Therefore, given the other parameters being the same, the robot price is required to be below $100k for the robotic MRF to be favorable over the non-robotic MRF. Like the discounted IRR, the payback period appears to be better only when the robot price is below \$100k (Figure 21.3).

**Purity-based value addition.** The value addition due to high purity assumed to be achievable in the robotic MRF is discussed by increasing 10%, 20% and 30% of its base value. We find that with the base value, the NPV is \$1 million higher than in the non-robotic MRF and it increases to \$45 million, surpassing the non-robotic MRF by \$15 million. However, the discounted IRR is lower at the base value, and it surpasses only when the value generation increases by more than 30%. Similarly, the payback period is greater at the base value, and it gets lower than the non-robotic MRF when the value generation exceeds 30%.

**Commodity prices.** The historic fluctuation of commodity prices is captured in this variable. We analyze the effect of using the current price, 5-year average, or 10-year average commodity price on the TEA metrics. We find that the current price has lowered NPV value down to \$20 million from \$31 million. Similarly, discounted IRR is also lower from about 35% to 20%. From this analysis we conclude that if commodity prices fall below the current commodity prices, the robotic MRF would not be attractive.



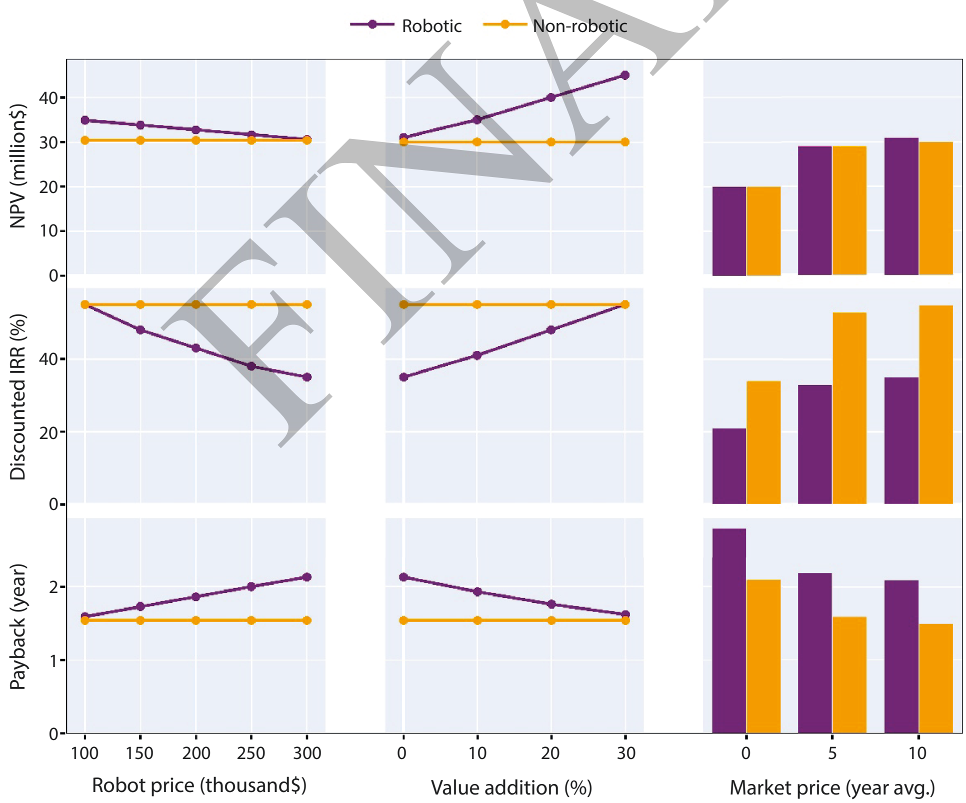


**Figure 21.3** Results of changes of NPV (Net Present Value), discounted IRR (Internal Rate of Return) and payback period due to the variation of robotic price, value addition by percentage and commodity value average. (Effect of NPV, discounted IRR and payback period is from the left to the right. The robotic price, value addition and commodity value is shown from the top to the bottom.)

## 21.4 Conclusions & Recommendations

The TEA reveals that integrating robots into a medium-sized MRF has only a minor positive effect on the net present value. It should be noted that the price of a new robot and the difference in revenue of the recycled commodities are key drivers to determine if a robotic intervention is economically feasible. The lower the robot price the better, and a robot price of less than $100k leads to favorable outcome for robot integration based on all three metrics (NPV, discounted IRR, and payback period). To perform better with respect to all three metrics, the robotic introduction should add value by more than 30%. Finally, as discussed earlier, the 10-year average is an optimistic market scenario, and if the market price falls below the current price, robotic intervention would not be interesting. It is also important to note that robotic intervention reduces human-waste interface, which might be an interesting feature, and that the economics presented here are based on highly reliable robots that do not cause downtime triggered by robotic malfunction.

We emphasize that this study is based on a range of assumptions that should be viewed critically. In addition to the estimates already discussed, another assumption to question is if the throughput is the same in robotic and non-robotic MRFs. With increasing technological maturity, the throughput of robot employing MRFs can be expected to exceed that of non-robot MRFs in the near future. Future research could also analyze if robots can play a greater contributive role rather than the quality control role discussed here; an assumption that would change the economics and likely only be attractive in smaller MRFs with low levels of automation (since it is currently unlikely that a robot could economically replace an optical sorter, magnet, or ECA). Finally, MRF operators might find the framework of this techno-economic analysis useful, by replacing our informed estimates with their own proprietary data to achieve results relevant for their future decision-making.



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