| **As Published** | [http://www.cmmigranteeconference.org/2009CMMI/](http://www.cmmigranteeconference.org/2009CMMI/) |
| **Publisher** | National Science Foundation |
| **Version** | Author's final manuscript |
| **Accessed** | Fri Feb 01 06:02:17 EST 2019 |
| **Citable Link** | [http://hdl.handle.net/1721.1/61339](http://hdl.handle.net/1721.1/61339) |
| **Terms of Use** | Attribution-Noncommercial-Share Alike 3.0 Unported |
| **Detailed Terms** | [http://creativecommons.org/licenses/by-nc-sa/3.0/](http://creativecommons.org/licenses/by-nc-sa/3.0/) |
Separation and Energy Use Performance of Material Recycling Systems

Timothy Gutowski
Malima I. Wolf
Massachusetts Institute of Technology
77 Massachusetts Avenue, Room 35-234
Cambridge, MA 02139

Abstract: This paper outlines current research on the performance of recycling processes and systems. Several aspects of performance are explored, including the separation performance and energy use of recycling processes. Descriptive terminology for separation performance is presented. The goal of this project is to develop a basic understanding of the factors affecting the separation and energy performance of recycling systems, with the eventual ambition of developing techniques for predictive analysis of these systems. These analysis techniques will allow us to evaluate the economic, ecological, and energy impact of recycling systems. This increased understanding will help guide the design of products and recycling systems.

1. Introduction: In the United States, as well as other industrialized nations, material consumption takes place at an unsustainable rate. The end-of-life treatment of products is a significant concern when evaluating material flows. Product recycling can alter material flows by displacing the required inputs of manufacturing systems with parts or materials reclaimed from end-of-life products.

This project focuses on material recycling and its role in material flows and consumption. Here, material recycling is defined as the recycling of end-of-life products and industrial scrap for use as material feedstock. This does not include the reuse of parts from end-of-life products, remanufacturing, or the use of end-of-life products as a fuel for energy production.

Several analyses of material recycling are presented in this paper. The potential of material recycling to supply the required material input to product manufacturing is explored. A convention for separation efficiency is presented, along with a model for the distribution of separation efficiencies within a process. This paper also presents a framework for exploring the variability of separation efficiencies within processes. This paper also compares the energy use of recycling systems to other manufacturing processes.

2. Material Supply Percentage: Closing the loop of material consumption will require significant changes in the way materials and products are handled at end of life. However, other factors may impact the ability of end-of-life products to supply the material needs of industry. Even in an ideal situation, where all products from an industry are captured for recycling, not all the materials contained within these products will be reusable. Growth in industry may have the effect that the number of end-of-life products returning at the end of their expected lifespan is different than the number of new products being manufactured.

The material supply percentage is a rough measure of the ability of end-of-life products to supply the materials required for new products. This measure assumes that materials from end-of-life products are used as feedstock for the same industry to make equivalent products. The measure takes into account the reusable material fraction of the products as well as the growth rate in the industry. In its most basic form, the material supply percentage (MSP) is a measure of the ratio of materials returning to an industry through end-of-life products to the current material requirements of the industry:

\[ \text{MSP} = \frac{M_{\text{out}}}{M_{\text{in}}} \]

Here, \( M_{\text{out}} \) is the material returning from end-of-life products, and \( M_{\text{in}} \) is the material demand for new products. A given product has an average product lifespan, \( n \). The material returning from end-of-life products is roughly the amount of material used to create the products \( n \) years ago. Of this returning material, the reusable material fraction, \( R \), can be used as feedstock to supply the industry. Thus, the material recovered from used products is

\[ M_{\text{out}} = RM_{-n} \]

where \( M_{-n} \) is the material used for production \( n \) years ago. The amount of material required for current product production is related to the amount of material required \( n \) years ago by
\[ M_{in} = M_{n}(1 + i)^n \]

where \( i \) is the yearly growth rate of the industry in terms of unit production. Thus,

\[ M_{SP} = \frac{R}{(1 + i)^n} \]

This definition of MSP allows for an investigation into the ability of end-of-life products from different industries to supply the necessary material for current production. Table 1 shows the MSP for several products. For all the products shown, it would be possible to supply at least half of the feedstock material for new production with material recycled from returning end-of-life products. However, real products are not typically constructed from a percentage of used materials as high as the MSP. Table 2 shows the percentage of recycled content typically used in several new products, as well as the recycling rates for these products. The products with the highest recycled content percentages, such as aluminum cans and newspapers, contain at best 50% of their MSP. These products are ideal recycling candidates, with one dominant, easily recycled material. Other products with moderate recycled content, such as automobiles and refrigerators, have recycled content percentages dominated by their steel content. The steel industry uses roughly 35% scrap in its feedstock, and thus any product using steel has inherent recycled content [19].

There are a variety of reasons that products do not use as much captured material as suggested as the MSP. End-of-life products may be disposed of as waste instead of entering recycling or reuse systems. Product material recycling does not typically return as much material as suggested by the useful material fraction, due to the high costs often associated with material recovery, or technical difficulties with separation. Some products, such as tires, shed material during their useful life. Other factors that may change the amount of material required by new production include changing product material mix and product light-weighting.

Recycled materials may be used in different industries than from which they were recovered.

The MSP provides an estimate of the percentage of virgin materials used for product manufacturing that could be replaced by recycled materials. Comparing the actual recycled material percentage in a given product against its industry MSP provides an idea of how much room for improvement in the use of recycled materials an industry may have. This performance gap can be closed through applying a variety of techniques, from improving recycling programs to improving the separation efficiency and energy performance of recycling systems and processes.

<table>
<thead>
<tr>
<th>Product</th>
<th>Recycled Content</th>
<th>Recycling Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum cans</td>
<td>50% typ</td>
<td>45%</td>
</tr>
<tr>
<td>Newspapers</td>
<td>30% typ</td>
<td>70%</td>
</tr>
<tr>
<td>Pet bottles</td>
<td>3% typ, 30% best</td>
<td>23%</td>
</tr>
<tr>
<td>Automobiles</td>
<td>20% typ</td>
<td>95%</td>
</tr>
<tr>
<td>Refrigerators</td>
<td>25% typ</td>
<td>90%</td>
</tr>
<tr>
<td>Cell Phones</td>
<td>1% typ, 20% best</td>
<td>1%</td>
</tr>
</tbody>
</table>

**Table 2:** Recycled content percentage and recycling rate for several products [2, 6, 16-20].

3. **Bayesian Material Separation Model:** The Bayesian material separation model provides a simple characterization for the separation efficiencies of a recycling process. [21, 22] This model assumes a binary mixture of a target material and a non-target material as an input stream to a separation process. The separation efficiency of the target material is \( r \), that is, the probability of correctly identifying and capturing the target material is \( r \). Similarly, the separation efficiency for the non-target material, or probability of correctly rejecting the non-target material, is \( q \). Figure 1 shows the separation process from the point of view of the target material.

![Figure 1](image1.png)

<table>
<thead>
<tr>
<th>Product</th>
<th>Yearly Growth Rate</th>
<th>Useful Material Fraction</th>
<th>Life Span</th>
<th>Material Supply Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum cans</td>
<td>0% for 1996-2006</td>
<td>100%</td>
<td>6 weeks</td>
<td>100%</td>
</tr>
<tr>
<td>Newspapers</td>
<td>-3% for 2006-2007</td>
<td>99%</td>
<td>1 week</td>
<td>99%</td>
</tr>
<tr>
<td>HDPE bottles</td>
<td>2.5% for 1991-2006</td>
<td>100%</td>
<td>1 year</td>
<td>98%</td>
</tr>
<tr>
<td>Pet bottles</td>
<td>10.5% for 1991-2006</td>
<td>100%</td>
<td>1 year</td>
<td>90%</td>
</tr>
<tr>
<td>Automobiles</td>
<td>2.8% for 1999-2009</td>
<td>87%</td>
<td>10 years</td>
<td>66%</td>
</tr>
<tr>
<td>Auto Battery</td>
<td>2.8% for 1999-2009</td>
<td>70%</td>
<td>4 years</td>
<td>63%</td>
</tr>
<tr>
<td>Refrigerators</td>
<td>3.2% for 1983-2001</td>
<td>88%</td>
<td>15 years</td>
<td>55%</td>
</tr>
<tr>
<td>Cell Phones</td>
<td>10% in 2008</td>
<td>73%</td>
<td>4 years</td>
<td>50%</td>
</tr>
<tr>
<td>Solar Panel</td>
<td>40% for 2001-2008</td>
<td>100%</td>
<td>25 years</td>
<td>0.02%</td>
</tr>
</tbody>
</table>

**Table 1:** Material supply percentage for several products [1-15].

Proceedings of 2009 NSF Engineering Research and Innovation Conference, Honolulu, Hawaii  
Grant #0423484
A mass of target material, $m_T$, enters the separation process. If the separation efficiency of the process for the target material is $r$, the portion of the target material that is separated into the target output stream is $r m_T$. The portion of the target material that is sorted into the non-target output stream is thus $(1-r) m_T$. A similar relationship exists for the non-target material stream and the process separation efficiency for the non-target material, $q$, as shown in Figure 2.

The performance of recycling separation processes can be characterized using these separation efficiencies. Figure 3 shows the performance of a variety of typical separation processes described in terms of the separation efficiencies $r$ and $q$.

4. Distribution Model for Separation Efficiencies:
Separation processes sort particles of input stream materials based on one or more material properties. In some cases, the determining property is a body property of the particles, such as density or magnetic permeability, a surface property, such as spectroscopic response or surface charge capacity, or a combination of these and other factors. The properties of the particles vary, creating a distribution of responses to the separation mechanisms. The recycling processes divide the input materials into separate output streams based on this distribution. In some cases, a splitter physically divides the material stream. In other cases, a rating of the properties of the particles is used to trigger physical mechanisms that divert the particles into different streams. If the property distributions of the target and non-target materials are separate, then it can be possible in an ideal process to create a stream splitting mechanism based on these properties that can completely separate the target and non-target materials. However, in the case that the property distributions overlap, the separation efficiencies will be determined by the selection of the separation point. Figure 4 shows two overlapping property distributions.
Let the distribution on the left represent the property distribution of the target material, and the distribution on the right represent the non-target material. Using the dashed line as a separation point, the shaded area under the left curve represents the fraction of target material that can be separated into the target stream based on this property distribution. The shaded area under the right curve represents the fraction of the non-target material that can be separated into the non-target output stream. These areas represent the separation efficiencies in an ideal process that relies on the properties represented in these distributions. The area under the left curve represents the target separation efficiency, \( r \), while the area under the right curve represents the non-target separation efficiency, \( q \).

With this basic concept, we can model the separation efficiencies of recycling processes. Of particular interest are processes where the separation point varies. In these cases, the separation efficiencies of the process acting at different points reflect the shape of the underlying property distributions. A simple first approximation for many property distributions is a normal distribution. Figure 5 shows two overlapping normal distributions.

These normal distribution parameters shown in this figure can be estimated for a variety of processes from separation data. Analysis of the data gives a family of pairs of normal distributions that yield the same separation parameters. For convenience of comparison, all parameters are given for a distribution pair with \( \mu_2 - \mu_1 = 1 \) for the two normal distributions.

Figure 6 shows the separation efficiency progression for an electrostatic separation of PVC and PC plastic with each point representing a different division of the process output. Here, \( r \) is the separation efficiency of PVC, and \( q \) is the separation efficiency of PC for this process. The line is generated by the continual variation of the dividing position between the two normal distributions with the given parameters. The progression of the division from left to right yields first low \( r \), high \( q \) separation efficiency pairs progressing through to high \( r \), low \( q \) efficiencies. In the case of this separation process, the distribution of the target material, PVC, has a larger standard deviation than that of the non-target material, PC. This creates an asymmetric separation efficiency curve, leaning toward the non-target separation efficiencies.

Figure 7 shows the distribution of material in the output stream of the electrostatic process. The material distribution closely resembles the normal distribution used to approximate the separation curve shown in
Figure 6. The distribution of the PC matches the estimated normal distributions better than that of the PVC. However, it is most important for the estimated distributions to match in areas where the two material distributions have the most overlap, in this case where the right tail of the PVC distribution enters into the body of the PC distribution. The overlapping sections shape the response of the separation efficiencies \( r \) and \( q \). From this perspective, the estimated and real distributions match well.

Figure 7:

\[
\mu_2 - \mu_1 = 1 \\
\sigma_1 = 0.25 \\
\sigma_2 = 0.62
\]

Figure 8: Efficiencies for the electrostatic separation of ABS and HIPS [23].

Figure 8 shows an example of a process with a separation efficiency model that leans toward the target separation efficiency. Here, \( r \) is the separation efficiency of ABS, and \( q \) is the separation efficiency of HIPS. Figure 9 shows the actual distribution of ABS and HIPS in the output of an electrostatic separation, spread through an array of output segments. The shape of real material distribution is very similar to the estimated property distribution presented in Figure 8.

Figure 9: Distribution of ABS and HIPS in the output of an electrostatic separation based on fraction of material in each output segment [23].

Figure 10 presents the separation efficiencies for the separation of aluminum and LDPE using rare earth magnetic rollers. In this case, the actual separation efficiency curve is much closer to ideal than for either of the electrostatic separations. The normal distributions used to approximate the property distributions have much tighter standard deviations, creating less overlap in these distributions.

Figure 10: Efficiencies for the rare earth magnetic roller separation of aluminum and LDPE.

In general, the distributions of materials in recycling processes are similar to normal distributions. Truncated normal distributions may fit the real separation data more accurately.

Understanding the form of these property distributions provides insight into the properties of process separation efficiencies. The property distributions will be specific to each process based on the physical processes used within each separation process. Knowing the approximate forms of these distributions allows for estimation of the separation efficiencies. The basic shapes of the distributions also provide a qualitative key into the behavior of the process for these materials. If the standard deviation of the target distribution is the smaller of the two, the separation efficiency curve is more favorable for high target material recovery. If the standard deviation of the non-target distribution is smaller, the opposite is true.

5. Effect of Input Material Variation on Separation Efficiencies: Most literature about separation processes describes the performance of a process under a single set of conditions. Most of the separation processes shown in Figure 3 show processes’ separation efficiencies under a single operating point. These processes are operating with a single set of operating conditions, including feed rate and process-specific parameters, and with a single type of input material.
stream, with specific material concentrations, particle sizes, and particle shapes. If these operating conditions vary in any dimension, there is a possibility that these process separation efficiencies will not be consistent under the new conditions.

While machine-specific operating parameters are typically intended to affect the separation efficiencies of a process (e.g. changing the division point in the output stream for an electrostatic separator), the effects of varying the properties of the input stream are less clear. The variation of some input material properties is known to have an effect on some processes. For example, particle sizes and shapes have been shown to affect the travel distance of particles in eddy-current separators [30]. Determining the input material properties that affect the performance of a process is a critical part of modeling separation efficiencies.

Many input material stream factors can be considered when investigating separation performance. The possible factors that can be investigated include the size and shape of particles, the relative concentrations of materials in the stream, moisture content of the materials, and many more. For our research, we have chosen to investigate concentration dependence. Concentration dependence is a good choice for several reasons. Literature review provides some guidance in the role of concentration in separation performance. Based on the physical details, there is reason to believe that some processes will be concentration dependent while others will be concentration independent. Concentration independence is also an important factor in several theoretical models, particularly for modeling the repeated application of separation steps, with or without internally recycling streams [21, 31].

Figure 11 shows the separation efficiencies of two separation processes, previously shown in Figure 3. The different points on the graph represent the process being operated at various concentration points. In the case of the electrostatic separation of ABS and HIPS, the concentration of ABS varies from about 10-90%, while the concentration of tungsten in the tungsten-slurry mix is in the range of 0.3-3%.

![Figure 11: Separation efficiencies for two processes](image)

This figure shows that both of these processes are relatively concentration-independent over the ranges investigated in the studies. In the case of the centrifugal processing of slurry, the range of concentration in the study is fairly narrow. The behavior of the process outside of the window investigated in the study is unknown.

While the two studies presented above show concentration-independence for those processes, investigation into the concentration-based behavior of other processes can determine if this is typical. Our research has focused on exploring the behavior of recycling separation processes operating under typical operating conditions for these processes.

The first process investigated is metal/plastic separation by eddy-current process. The material sample used to test this process is a mix of LDPE and aluminum squares, roughly two inches square. To counter the effects of particle momentum in the process, the aluminum and LDPE samples are of different thicknesses designed to give the particles similar weights. The sample materials were mixed into test samples of varying concentrations. These test samples were run through an eddy-current separator under typical operating conditions.

With the materials used in these tests, the response of the aluminum particles was more pronounced than would be in the case of a more realistic material stream, such as an aluminum and plastic shredder waste stream. At all concentration studied, the separation efficiency for the aluminum material, $r$, was at or near 1. This is due to the ideal shape of the particles. Large, flat particles will have a stronger eddy-current response than smaller, thicker, or folded particles [30]. While there was little variation of the separation efficiency of the aluminum, the separation efficiency of the LDPE
varied significantly with concentration. Figure 12 shows the variation of the non-target separation efficiency, $q$, with the concentration of aluminum.

![Figure 12: Non-target separation efficiency for an eddy-current separation of aluminum and LDPE.](image)

Unlike the separation processes shown in Figure 11, the separation shown in Figure 12 shows a strong dependence on concentration. In terms of the distribution model, concentration varying separation parameters imply that distribution parameters are also concentration dependent. In this case, when the process is applied to the materials individually, the process identifies the material alone with a separation efficiency of 1. In terms of the distribution model, this would imply that material property distributions for these two materials with respect to this process are separate such that it would be possible to divide these two materials perfectly. However, when the two materials are mixed, an imperfect separation is created. Particle interactions may alter the material property distribution curves.

With these few studies in hand, it seems that the separation efficiencies of some processes are affected by material concentrations, while others are not. The physical details of each process may determine if a process tends toward concentration dependence or concentration independence. The operation point of the process and other material input variables may also influence concentration dependence in a given process. Further studies into separation efficiencies under varying concentrations may provide insight into the basic causes of concentration dependence.

6. Particle Interactions in Separation Processes: The experimental results shown in Figure 11 reveal that the non-target separation efficiency for that specific eddy-current separation has some form of concentration dependence. When processing a mixture with an aluminum concentration of 0, where all particles are LDPE, the separation efficiency of the LDPE was 1. Increasing aluminum concentration caused decreasing non-target separation efficiency. This suggests some sort of interaction between aluminum particles and LDPE particles causes the lowered separation efficiency. During the separation process, aluminum particles leaving the bulk material stream can affect LDPE particles nearby, carrying or knocking the particles into the target stream.

This one-sided effect can be described by the proximity effect model. The proximity effect model provides a simple description of how non-target separation efficiency could be influenced by target material concentration. This model assumes that the target separation, $r$, is 1. The target material particles in the material mixture carry particles of non-target material into the target output stream. The average number of particles affected by each target particle will be $N$. This average number of affected particles, $N$, is influenced by the presentation density of the particles. Figure 13 shows conceptually how $N$ increases with increasing presentation density.

![Figure 13: $N$ increases with increasing presentation density.](image)

In this diagram, the colored particles are the target particles, while the white particles are the particles affected by the target particle with some probability. If $c$ is the concentration of the target material in the incoming stream, the fraction of particles affected by those particles is $cN$. Assuming that the affected particles are equally distributed between target and non-target materials, the fraction of the particles in the stream that are non-target particles being carried into the target stream is $cN(1-c)$. Figure 14 shows the path of the material in the system.

![Figure 14: Separation of non-target material.](image)

The fraction of the non-target material in non-target output stream, which defines the non-target separation...
efficiency, \( q \), is \( 1 - cN \). Applying this model to the eddy-current separation data shown in Figure 12 yields an average number of affected particles of \( N = 0.5 \). The trend line shown in Figure 15 represents \( q = 1 - cN \) where \( N = 0.5 \) over the range of concentrations shown.

Based on the agreement of the trend line and the separation efficiency data, the proximity effect model accurately describes the behavior of the non-target separation efficiency varying with concentration. In this case, the value of \( N \) is inferred from the separation data, but investigation into the physical effects governing the separation and presentation density of a given process may allow for predictive models for the average number of affected particle.

**Figure 15:** Non-target separation efficiency for an eddy-current separation of aluminum and LDPE, with proximity effect model trend line.

7. **Energy Use in Recycling:** The net cost of recycling has a large influence on the products and materials that are recycled. Within a recycling facility, the performance of the recycling system greatly affects the value captured and resources expended by the facility. A typical facility may include one or more size reduction devices and several separation processes. The value captured is affected by the condition of the material stream as it’s output from size reduction processes and by the layout and efficiencies of the separation processes used to sort the material into output streams. The energy used by the size reduction and separation processes contributes to the cost of manufacturing. The flow rate of materials through the processes determines the amount of products and materials that can be processed at this facility and ultimately the flow rate of saleable recycled material.

**Figure 16:** Energy intensity and mass flow rate of selected processes [32, 33, 34, 35].

The energy use of a process is a rough indicator of the cost of material processing. Figure 16 shows the energy use of a variety of processes including general manufacturing processes as well as recycling processes. The recycling processes are divided into two groups, sorting processes and shredding processes. The diagonal grid represents lines of equal process power consumption. Of the manufacturing processes, the highest flow-rate processes, in the lower right of the graph, are thermal processes, such as smelting.

This figure shows that typical recycling processes have higher process flow rates and lower specific energy than typical manufacturing processes. Within recycling processes, size reduction processes typically have higher specific energy than sorting processes, and thus will be the largest contributor to energy use in most recycling systems. This figure also provides insight into the lower level of energy used to recycle materials as compared to the manufacturing processes.

8. **Continuing Research:** The continuing study of separation performance will lead to a better understanding of recycling processes and systems and improvements in predictive process modeling. More accurate process models can improve recycling system optimization, leading to increased yields and profitability for recyclers.

Several of the models presented here can be improved by further study. The distribution model for separation efficiencies could be improved with the study of additional processes. Studying the individual distributions of each material within a process may allow us to create predictive overlapping process
distributions for that separation process. Processes with similar physical mechanisms may share similar distribution curves. We hope to continue physical studies of the distribution model.

We also plan to continue studying separation efficiencies under varying conditions. Further experiments will continue exploring concentration dependence in separation processes. The upcoming processes to be studied include magnetic drum separation and rare-earth magnet roller separation. Continuing data collection for concentration dependence may provide more data to explore and validate the proximity effect model. Further studies will explore the application of the proximity effect model to processes where particles of both target and non-target materials can affect separation efficiencies.

We also plan on continuing to collect energy use data for recycling processes. With this data in hand, we hope to create a basic model of the energy use within recycling systems, based on the type and number of process steps within a system.

9. Acknowledgements: The research presented in this paper is supported by the National Science Foundation through DMI Award #0423484.

We would also like to thank Dr. Michael Mankosa and Joseph Wernham of Eriez Manufacturing Co, for their ongoing research partnership.

We would like to thank Dr. Stanley Gershwin for his suggestion to use normal distributions to approximate material property distributions for separation processes.

10. References:


