A switching rule for plastics identification in electronics recycling

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The looming obsolescence of 3 billion consumer electronics by 2010 calls for effective recycling of 10 billion pounds of high-value engineering thermoplastics. Because general shredding operations generate mixed plastics of low value, a switching rule is needed rapidly to identify plastics for sortation by colour and type to increase plastics-to-plastics recycling value. The current paper develops a heuristic rule to determine the thresholds for a switching rule that reduces set-up time while managing queue space. Our recycling system is modelled as a multiclass queuing network in a simulation model. Results indicate that laser identification probe utilization, setups, and queue space are sensitive to the switching rule. Our work contributes important insights into the relationship between traffic intensity, setup time, and queue capacity, and generalizes to multiclass queuing systems in other applications.

Keywords: Multiclass queuing network; Scheduling; Switching rules; Plastics identification; Electronics recycling

1. Motivation for multiclass queuing analysis in recycling

Three billion consumer electronic components will reach obsolescence by 2010. This will create a crisis requiring a comprehensive approach to the effective management of electronics waste (International Association of Electronics Recyclers (IAER) 2003, Williams 2007). Today, even though discarded electronic components represent billions of pounds of high-value engineering thermoplastics (Grenchus et al. 2000), current electronics recycling processes separate less than 1% for plastics-to-plastics recycling.
recycling (National Safety Council (NSC) 1999, Dillon and
Aqua 2000, Kui and Forssberg 2003, Kang and Schoenung
2005, Qu et al. 2006, Williams 2006). The remaining 99% are
processed for waste-to-energy conversion or discarded
(Fisher et al. 2005). Two factors will motivate increased
plastics separation for reuse: environmental and economic.
First, separating and removing contaminate plastics such as
polyvinyl chloride (PVC) eliminates them from waste-to-
energy streams where they have been shown to release
hazardous dioxins (Karasek and Dickson 1987, Stein 1992).
Second, the mixed plastics from general shredding opera-
tions have a value no greater than $0.01–0.04/kg while
plastics separated by type, polycarbonate (PC) versus high-
impact polystyrene (HIPS), can yield returns as much as an
order of magnitude higher (US Environmental Protection
2006). Further separation for natural-coloured plastics may
increase worth another order of magnitude.

To recover separated plastics from end-of-life electronics,
the current metals recycling process is extended to include
limited disassembly of plastic cover components in Rios et al.
(2003), Rios and Stuart (2004) and Williams et al. (2006) and
laser identification of each plastic component’s Raman
spectrum through comparison to a library of standards
demonstrate the efficiency and potential economics of their
process design for the plastics problem without colour
sortation. It is important to extend this new recycling process
design and recycling scheduling management to separate
natural-coloured plastics, because electronics manufacturers
are now marketing equipment with a diversity of colourful
covers (Ogando 1999). In the current paper, we aggregate
coloured and black plastics to form a group called dark
plastics, as blenders tend to mix coloured plastics with black
dyes when molding black recycled plastics.

Queuing natural and dark plastic pieces separately prior
to identification is also important since dark plastics take an
average of 10 times longer to identify by Raman spectro-
scopy. Identification problems arise when there is a coating
on one side of the cover plastic or the cover is an unusual
type of plastic whose spectrochemical image is not among
those in the library of standards. In such cases, the
unidentified plastic is modelled as a re-entrant flow.
Unidentified natural and dark pieces are queued separately
for an additional identification attempt that requires a
longer identification processing time. Since identification
processing times are dependent on colour and re-entrant
flow, we model this process as a multiclass queuing network.

Further complicating the system is a significant setup
cost incurred at the laser probe identification station when
switching from first- and second-entrant natural plastic
identification to first- and second-entrant dark plastic
identification. The main source of this setup cost is material
handling. In general, plastic cover pieces for computers,
printers, monitors, and televisions weigh 50 g to 2800 g and
are sorted to 122 cm × 122 cm × 122 cm (4′ × 4′ × 4′) boxes.
Because recycling facilities do not have elaborate material
handling systems, a worker processing plastics after laser
identification tosses each piece into the corresponding box.
Hence, when switching between colours, boxes are manually
switched to avoid mixing between natural and dark
plastic types.

The recycling scheduling metric differs from the manu-
facturing scheduling metrics related to due dates and
maximizing throughput of finished goods (Potts and
Kovalyov 2000). The metric for disassembly scheduling in
recycling is queue size space, because random supply in
recycling calls for a scheduling rule to manage incoming
goods (Stuart and Christina 2003). As shown in Stuart and
Christina (2003) and Rios and Stuart (2004), queue size
space for incoming products awaiting cover disassembly
may be reduced significantly with a weighted processing
time scheduling rule where the weights are related to
product size. Following the selective disassembly of plastic
components is a new identification process that also
requires a scheduling rule.

We model this new identification system as a re-entrant,
multiclass queuing network with set-ups. To reduce set-up
time, we propose a basic threshold ‘switching rule’ that is
easy to implement. Hall (1991) provides a threshold
’switching rule’ when processing times per class are a fixed
constant and work-in-progress (WIP) space is uncapaci-
tated, Hall (1991) also finds the optimal thresholds for his
’switching rule’ when overall traffic intensity is high or the
traffic intensity of each of two classes is equal. Highway
traffic light switching rules have been shown to reduce
average queue size and waiting time (Edie et al. 1965). A
priori minimum and maximum times for switching light
settings are reviewed in Darroch et al. (1964). Schutter and
Moor (1998) derive a traffic light switching rule to
reduce queue lengths for a single intersection. In produc-
tion scheduling of one worker to two machines, a
regenerative process model is used to solve for the optimal
switching value (Kulkarni 1995). Unlike the problems
discussed in the above traffic control and production
scheduling literature, our multiclass queuing network
contains prioritized entities differentiated by potential
value, processing times, significant setup times, and more
than two classes. We seek a switching rule that minimizes
laser setup time while monitoring queue size space.
Calculating an optimal switching rule for this network
becomes increasingly difficult owing to the number of
classes considered, the significant set-up times when
switching between classes, re-entrant flows, and the
disparity in the processing times between natural and
dark plastics at the laser identification station (Banks and
Dai 1997). Furthermore, it is often the case that optimal
policies are extremely complex, and therefore difficult to
implement (Henderson et al. 2003). Owing to time and budget constraints in the recycling industry, a complex policy is not a practical solution. Thus, we develop a heuristic threshold switching scheduling rule for laser Raman plastic part identification. The results generalize to multiclass queuing systems in other applications that involve scheduling a resource to multiple customer classes or machines classes. However, in this paper, we focus on the motivating problem.

In the sections to follow, we describe the electronics recycling process, define the switching problem in plastics recycling, and present two switching rules, base cyclic versus threshold, for a laser probe that provides plastics identification for five queues of incoming flows in a recycling centre. We present an intuitive method to determine the thresholds in the threshold switching rule. The experimental design tests the performance of the switching rules when colour diversity increases in a recycling centre. The results indicate that the switching rule affects the system performance in terms of laser set-up time and WIP level.

2. Classes in an electronics recycling process

Reverse distribution systems for electronics seek to lower collection costs by locating the most expensive capital equipment, the general shredders, in individual recycling centres that saturate local collection markets. Within each recycling centre in figure 1, the general shredding capacity for bulk processing should be balanced with the disassembly, identification, and plastics shredding capacities. To represent market saturation, we consider a system with incoming equipment arrivals to utilize 70–90% of the general shredding capacity. Rios et al. (2003) find that purchasing one laser Raman spectroscopic identification system is adequate for a recycling facility with one general shredder receiving approximately 190 000 units per year if plastics identification is used for two classes: first and re-entrant plastics without colour sortation. This paper extends the analysis to include colour sortation and final quality control (QC) sampling as illustrated in figure 1.

Figure 1. Electronics recycling centre with plastics identification and separation.
The electronics recycling process in figure 1 begins with receiving and sorting. The research presented in (Rios and Stuart 2004) shows how to sequence products for disassembly to more quickly accumulate plastic components. Next, the disassembly process sorts cover pieces by colour to feed the first two classes awaiting identification, natural first-entrant plastic cover pieces and dark first-entrant plastic cover pieces. Following the plastics identification process, plastics are sorted into 10 different queues. Eight of the queues await accumulation for shredding densification while two of the queues, natural re-entrant and dark re-entrant, await a re-entrance to plastics identification. When a plastics inventory accumulates 500 kg in one of the six ABS (acrylonitrile butadiene styrene), PC/ABS (poly-carbonate/ABS), HIPS natural and dark plastics inventory queues, it progresses to shredding and then the QC queue for plastics identification sampling. The other and contaminant queues, which contain mixed natural and dark plastics, do not send samples to the QC queue prior to shipment.

In figure 2, \( \lambda_j \) represents the mean arrival rate to queuing class \( j \), and \( \mu_{jk} \) represents the service rate to the subgroup \( k \) in queuing class \( j \). The distributions of the random variables for plastics identification processing time, \( p_{jk} \) are given in table 1. Tables 1 and 2 show that dark plastics require a longer processing time to identify each piece, incur a slightly higher probability of no identification on the first entrant flow, and most significantly, require a 12 min material handling setup time, \( s_{jj'} \), to exchange boxes collecting specific natural plastics from class \( j \) with boxes collecting specific dark plastics from class \( j' \) and vice versa. A five-minute handling set-up is required for QC samples. During QC, natural second-entrant, and dark second-entrant identifications, the laser is dismounted for more flexible contact with the plastic pieces. Dismounting the laser for re-entrant flows and QC as well as remounting the laser for faster natural first-entrant and dark first-entrant flows requires a one-minute setup. For example, as shown
for $s_{32}$ in table 2, the box exchange set-up and the laser remount setup sum to a total setup time of 13 min.

3. Laser identification switching problem in plastics recycling

By modelling the plastics identification process as a multiclass queuing network with setups and re-entrant flows, we are specifically interested in answering the questions posed in table 3. The metrics used to analyse the questions posed are also described in table 3.

The first investigation question addresses the spatial needs for products awaiting materials separation. The spatial needs may be impacted by the percentage of time the laser probe(s) is (are) idle during set-ups versus busy processing products. Thus, the second question seeks to measure the total set-up time while the third question seeks to measure the laser probe utilization which also impacts the number of probes needed. The last investigation question explores how the shipment fill times for different plastics are impacted by the switching rule. Next, we develop and propose switching rules.

Table 1. Plastics identification process steps and time for each of the five classes (Williams et al. 2006).

<table>
<thead>
<tr>
<th>Queue class</th>
<th>Queues for Raman spectrochemical identification</th>
<th>Sub-Group</th>
<th>Alternative 1</th>
<th>Alternative 2</th>
<th>Identification success % of total flow</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Natural 1st-entrant</td>
<td>1 p_{11} \sim \text{BETA}(1.2, 3.0, 3.0, 5.6, 6.2)</td>
<td>3 p_{13} \sim \text{UNIF}(5.6, 6.2)</td>
<td>80.0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Dark 1st-entrant</td>
<td>2 p_{12} \sim \text{BETA}(1.2, 3.0, 7.5, 8.3)</td>
<td>3 p_{14} \sim \text{BETA}(9.3, 10.2)</td>
<td>9.00%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Natural re-entrant</td>
<td>1 p_{21} \sim \text{BETA}(1.2, 3.0, 7.4, 8.1)</td>
<td>3 p_{23} \sim \text{BETA}(14.7, 16.2)</td>
<td>15.0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Dark re-entrant</td>
<td>1 p_{31} \sim \text{BETA}(1.2, 3.0, 11.1, 12.2)</td>
<td>3 p_{33} \sim \text{BETA}(11.1, 12.2)</td>
<td>25.0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 QC (natural)</td>
<td>1 p_{41} \sim \text{BETA}(1.2, 3.0, 14.7, 16.2)</td>
<td>3 p_{43} \sim \text{BETA}(16.6, 18.3)</td>
<td>9.75%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>QC (dark)</td>
<td>2 p_{51} \sim \text{BETA}(1.2, 3.0, 64.3, 70.7)</td>
<td>3 p_{53} \sim \text{BETA}(64.3, 70.7)</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*0.25% of the total natural plastic pieces and 0.25% of the total dark plastics pieces remain unidentified.

Table 2. Set-up changeover time matrix for plastics identification process.

<table>
<thead>
<tr>
<th>From queue</th>
<th>Queue No.</th>
<th>To queue</th>
<th>Setup time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural plastic first-entrant queue</td>
<td>1</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Dark plastic first-entrant queue</td>
<td>2</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Natural plastic re-entrant queue</td>
<td>3</td>
<td>1</td>
<td>13</td>
</tr>
<tr>
<td>Dark plastic re-entrant queue</td>
<td>4</td>
<td>13</td>
<td>1</td>
</tr>
<tr>
<td>QC queue</td>
<td>5</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3. Investigation questions.

<table>
<thead>
<tr>
<th>Investigation question</th>
<th>Description of metric</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) What impact does the switching rule have on the WIP inventory in the queues awaiting the laser identification station?</td>
<td>Queue size space (number of boxes) for each of the queue classes awaiting processing at the laser identification station.</td>
</tr>
<tr>
<td>(2) What impact does the switching rule have on total setup time?</td>
<td>Set-up time</td>
</tr>
<tr>
<td>(3) How many laser probes are required to process colour sorted plastics and verify their quality for a typical recycling center housing one general shredder?</td>
<td>Laser probe utilization and number of probes</td>
</tr>
<tr>
<td>(4) What impact does the switching rule have on shipment fill time for finished plastic goods?</td>
<td>Shipment fill time for finished plastic goods in terms of the time (weeks) to fill a truckload shipment (10 000 kg) of a specific finished good such as Natural ABS.</td>
</tr>
</tbody>
</table>
4. Proposed switching rules

The base switching rule for laser identification, denoted 'base,' is to cycle through queues as shown in figure 3(a). Each queue is visited in sequence until it is depleted. Beginning with QC, queuing class 5, the cycle proceeds to queuing class 1 for first-entrant natural plastics followed by queuing class 3, re-entrant natural plastics. Next, queuing classes 2 and 4 which contain dark plastics are selected. The sequence places the two natural plastic queues and the two dark plastic queues adjacent in order to lower set-up times.

However, if any queues grow slowly, then a setup is incurred in each cycle for small sets of WIP. As a result, a large number of setups may occur with the base cycling rule with queue depletion.

In this problem, the 'switching rule' simply implies that the laser probe resource should process a given product class if an initial WIP queue size accumulates. For some traffic control rules, including the base cyclic and the 'threshold' switching rules, switching may occur with queue depletion. After all parts in a class have been processed in the threshold switching rule in figure 3(b), the laser resource probe is re-directed to begin working on another product class that has accumulated the threshold conditions or a default class.

To determine the thresholds to switch to a class, we develop an intuitive rule based on setup time, traffic intensity, and WIP storage capacity. We begin with calculating the threshold $X_1$ to switch from natural to dark class first-entrant flow in figure 3(b), by deriving a heuristic rule based on traffic intensities. Let $m_1$ and $m_2$ represent the average service rate for the natural and dark first-entrant flows respectively. Next, let the traffic intensities be defined by $r_1 = \frac{l_1}{m_1}$ and $r_2 = \frac{l_2}{m_2}$ for natural and dark first-entrant flows respectively. If the relationship between traffic intensities is such that $r_1 > r_2$, then the relationship between thresholds should be $X_1 > X_2$. As a result we begin with expression (1)

$$X_1 = \frac{\rho_1}{\rho_2} X_2$$

Figure 3. (a) ‘Base’ cyclic scheduling with queue depletion. (b) ‘Threshold’ switching rule with queue depletion to schedule laser identification tasks.
Let $b$ represent the average number of pieces to fill a box. Let $L$ be the WIP queue space goal in number of boxes for the natural first-entrant and dark first-entrant queues awaiting processing at the laser identification station. $L$ is determined by the facility layout and space available for WIP. We express the WIP level goal for the natural and dark first-entrant queues in expression (2)

$$X_1 + X_2 \leq bL$$  \hspace{1cm} (2)

Solving for $X_2$ in expression (2), we obtain expression (3) for the threshold $X_2$ to switch from dark to natural class first-entrant flow

$$X_2 \leq bL - X_1$$  \hspace{1cm} (3)

Substituting expression (3) into expression (1), we obtain expression (4)

$$X_1 = \frac{\rho_1 \times (bL)}{\rho_2 + \rho_1}$$  \hspace{1cm} (4)

If the set-up time between queuing classes 1 and 2 is sufficiently large, then expression (4) could produce a threshold that results in a processing time less than the set-up time. To prevent this from occurring, we can modify expression (4) to seek the maximum of either the number of pieces processed during the setup time $(s_{12} \times \bar{\pi}_1)$ or the minimum of the difference between total capacity and setup capacity $(bL - (s_{12} \times \bar{\pi}_2))$ or expression (4). To make the scheduling policy practical for implementation, we convert the threshold expression from number of pieces to number of boxes. If a box holds $b$ pieces, let $\lceil \rceil$ represent rounding up to the nearest multiple of $b$ pieces. Combining these results, the threshold $X_1$ is calculated in number of boxes according to equation (5)

$$X_1 = \max \left\{ \left\lceil s_{12} \times \bar{\pi}_1 \right\rceil, \min \left\{ bL - (s_{12} \times \bar{\pi}_2), \frac{\rho_1 \times (bL)}{\rho_2 + \rho_1} \right\} \right\}$$  \hspace{1cm} (5)

As illustrated in figure 3(b), identification of class 3 may be sequenced to follow class 1, since the setup time between classes 1 and 3 is small. Likewise, class 4 may be sequenced to follow class 2.

Since class 5 QC precedes shipment and occurs relatively infrequently, it is prioritized as the most important class in figure 3(b). Within QC, subgroup natural is prioritized over subgroup dark based on the higher value of natural plastics. In figure 3(b), class 1 for first-entrant natural plastics is prioritized second based on value and relatively low processing time, and class 3 is prioritized third based on value. Next, classes 2 and 4 are prioritized fourth and fifth based on value and processing time. Within classes 1 and 3, the subgroups are scheduled as first-come first-serve, because they are not differentiated until the identification process begins. In the next section, the cycling and threshold switching rules are compared for current and future product return scenarios.

5. Simulation study of laser scheduling

To evaluate our multiclass queuing network under the maximum potential setup conditions when WIP space is constrained, the number of natural and dark incoming pieces should be approximately balanced, which is the current case for returns. Since marketing initiatives are increasing the popularity of black and dark coloured plastics, this future returns case is also investigated.

The experimental design for our simulation in table 4 shows the four parameters that are varied: switching rule, distribution for truck interarrival time, colour distribution of plastic pieces, and processing time distribution. The scenarios for colour distribution of plastic pieces are described in table 5. The product arrival compositions are shown in table 6 based on data in (US EPA 1999). As indicated in table 6, some data from (US EPA 1999) were scaled so that the distribution for truck interarrival time generates between 600 000 pounds and 1 million pounds of electronics, which is consistent with reported processing quantities (GIE Media, Inc. 2006). Since the processing times were derived from MTM evaluations, we only had the mean (Konz and Johnson 2000, Magnusson 1972). Thus, we tested two alternative distributions for processing times as shown in table 1 to check the sensitivity of our results to the choice of the processing time distribution (Law and Kelton 2000).

In each case, our total WIP space goal for the laser identification station area could not exceed a floor space allocation of 37 m². Since the queues for re-entrant flows in classes 3 and 4 grow very slowly, it is highly unlikely that they will each exceed 1 box of pieces. Assuming a goal of 1 box each for queue classes 3 and 4 in table 1, the WIP space goal $L$ for queue classes 1 and 2 totals 18 boxes. If the boxes are 122 cm × 122 cm (48 × 48) and it is assumed that a box holds 30 pieces, then the total WIP space goal for queue classes 1, 2, 3, and 4 are 20 boxes (29.76 m³). Since QC samples arrive relatively infrequently in small containers, they do not contribute to space concerns.

In the simulation study we assume the product compositions, weights, and values shown in table 7. We assume that the plastic material 3 in table 7 is further composed of the specific plastics shown in table 8.

The discrete-event simulation model was developed using ARENA 8.0 (Rockwell 2006) and run on a Dell Pentium IV Dimension 3000 requiring computation times
between 5 and 10 min. We carried out a long-run steady-state simulation for each scenario. For example, figure 4 illustrates that for the ‘T 0.75 F Beta’ scenario defined in table 4, a one-year warm-up period is adequate to avoid the effect of the initial conditions on the statistical analysis of output. A test run with a one-year warm-up

<table>
<thead>
<tr>
<th>Products</th>
<th>Number of plastic cover pieces disassembled</th>
<th>Current</th>
<th>Future</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Natural products</td>
<td>% Dark products</td>
<td>% Natural products</td>
<td>% Dark products</td>
</tr>
<tr>
<td>TVs</td>
<td>1</td>
<td>2%</td>
<td>98%</td>
</tr>
<tr>
<td>Monitors</td>
<td>1</td>
<td>95%</td>
<td>5%</td>
</tr>
<tr>
<td>CPUs</td>
<td>2</td>
<td>95%</td>
<td>5%</td>
</tr>
<tr>
<td>Printers</td>
<td>3</td>
<td>90%</td>
<td>10%</td>
</tr>
</tbody>
</table>

Exp(\lambda) represents an exponentially distributed random variable with mean \lambda.

<table>
<thead>
<tr>
<th>Table 4. Experimental design.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run label</td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td>B 0.75 C Beta</td>
</tr>
<tr>
<td>B 0.75 C Unif</td>
</tr>
<tr>
<td>B 0.75 F Beta</td>
</tr>
<tr>
<td>B 0.75 F Unif</td>
</tr>
<tr>
<td>B 1.0 C Beta</td>
</tr>
<tr>
<td>B 1.0 C Unif</td>
</tr>
<tr>
<td>B 1.0 F Beta</td>
</tr>
<tr>
<td>B 1.0 F Unif</td>
</tr>
<tr>
<td>T 0.75 C Beta</td>
</tr>
<tr>
<td>T 0.75 C Unif</td>
</tr>
<tr>
<td>T 0.75 F Beta</td>
</tr>
<tr>
<td>T 0.75 F Unif</td>
</tr>
<tr>
<td>T 1.0 C Beta</td>
</tr>
<tr>
<td>T 1.0 C Unif</td>
</tr>
<tr>
<td>T 1.0 F Beta</td>
</tr>
<tr>
<td>T 1.0 F Unif</td>
</tr>
</tbody>
</table>

Table 5. Natural versus dark colour composition scenarios.

<table>
<thead>
<tr>
<th>Products</th>
<th>Number of plastic cover pieces disassembled</th>
<th>Current</th>
<th>Future</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Natural products</td>
<td>% Dark products</td>
<td>% Natural products</td>
<td>% Dark products</td>
</tr>
<tr>
<td>TVs</td>
<td>1</td>
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<td>1</td>
<td>95%</td>
<td>5%</td>
</tr>
<tr>
<td>CPUs</td>
<td>2</td>
<td>95%</td>
<td>5%</td>
</tr>
<tr>
<td>Printers</td>
<td>3</td>
<td>90%</td>
<td>10%</td>
</tr>
</tbody>
</table>

Table 6. Truckload compositions for televisions, computers, printers and monitors from (US EPA 1999).

<table>
<thead>
<tr>
<th>Collection pilot arrival</th>
<th>Arrival No.</th>
<th>Arrival TVs</th>
<th>Arrival PCs</th>
<th>Arrival Monitors</th>
<th>Arrival Printers</th>
<th>Total weight kg/arrival</th>
</tr>
</thead>
<tbody>
<tr>
<td>NY, Binghamton 1996</td>
<td>1</td>
<td>23</td>
<td>7</td>
<td>8</td>
<td>2</td>
<td>841</td>
</tr>
<tr>
<td>NY, Binghamton 1997</td>
<td>2</td>
<td>52</td>
<td>19</td>
<td>33</td>
<td>9</td>
<td>2,187</td>
</tr>
<tr>
<td>NY, Somerville 1996</td>
<td>3</td>
<td>54</td>
<td>21</td>
<td>17</td>
<td>12</td>
<td>2,059</td>
</tr>
<tr>
<td>NY, Somerville 1997</td>
<td>4</td>
<td>61</td>
<td>72</td>
<td>52</td>
<td>40</td>
<td>3,534</td>
</tr>
<tr>
<td>MN, Hennepin 1995*</td>
<td>5</td>
<td>369</td>
<td>6</td>
<td>57</td>
<td>16</td>
<td>11,200</td>
</tr>
<tr>
<td>MN, Hennepin 1996*</td>
<td>6</td>
<td>426</td>
<td>56</td>
<td>96</td>
<td>22</td>
<td>13,920</td>
</tr>
<tr>
<td>MN, Hennepin 1997*</td>
<td>7</td>
<td>615</td>
<td>111</td>
<td>145</td>
<td>47</td>
<td>20,610</td>
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<tr>
<td>IL, Naperville 1996</td>
<td>8</td>
<td>56</td>
<td>184</td>
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<td>IL, Naperville 1997</td>
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<td>153</td>
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<tr>
<td>IL, Wheaton 1998*</td>
<td>10</td>
<td>51</td>
<td>50</td>
<td>113</td>
<td>51</td>
<td>3,990</td>
</tr>
</tbody>
</table>

*The original number of items was scaled by 8.3%. †The original number of items was scaled by 50%. 
period and a 4-year run length were conducted to estimate the run length that guarantees the widths of the 95\% confidence intervals in our output are less than 10\% of their average. In the result of the test run, the 95\% confidence interval of 580 + 80 hours for the average light ABS fill time is the widest interval in the output. Therefore, the run length must be greater than 18 years according to

\[ n > n_0 \left( \frac{t_{n-1, 0.975}}{t_{m-1, 0.975}} \right)^2 \]

where \( t_{n-1, 0.975} \) denotes the 97.5\% quantile of the t-distribution with \( n - 1 \) degrees of freedom, while \( n \) and \( h \) denote the number of replications needed and the width of the 95\% confidence interval desired, respectively. Also, \( n_0 \) and \( h_0 \) denote the number of replications and the width of the 95\% confidence interval in a test run, respectively (Kelton et al. 2004). Thus, a run length of 20 years was used for our experiment. We grouped the data into 10 batches each of size two years to obtain variance estimates for our metrics in our statistical output analysis (Banks et al. 1996).

6. Results

We compare the four metrics introduced in table 3 across the scenarios over two years, the batch length in our simulation study. The first metrics, 95\% confidence intervals (CI) for average WIP in natural and dark first-entrant queues, are graphed in figures 5(a) and 5(b) to estimate potential space requirements in number of pieces for the natural and dark first-entrant queues respectively. Figure 5 does not include the results for the other queues in front of laser identification because they receive inputs at a much slower rate; the average WIP was much less than 1 box for any other queue in front of the laser identification station. We discuss the results in terms of pieces as illustrated in figure 5 to show the slight variations. We also include the results in terms of boxes, which hold up to 30 pieces, since this is useful in visualizing the impact of the scheduling rule. In figure 5(a), the average natural first-entrant queue size ranges from 15–62 pieces (one to three boxes) regardless of the scheduling rule, colour composition, distribution for truck interarrival time, and processing time distribution. The average dark first-entrant queue size, on the other hand, is very sensitive to the scheduling rule. For the base scheduling rule, the dark first-entrant queue size ranges from 12–39 pieces (one to two boxes) for the 95\% CI while the threshold scheduling rule increases the dark first-entrant queue size range for the 95\% CI to 144–205 pieces (5–7 boxes). While the threshold scheduling rule seeks to lower switching, it does so while monitoring the WIP space limit of 20 boxes. Figure 5(b) also demonstrates that the dark first-entrant queue size is more sensitive to the scheduling rule than the colour composition or truck interarrival time and that it is insensitive to the processing time distribution.

Figure 6(a) illustrates the total laser setup time in hours for the 16 scenarios. The base scheduling rule that cycles through the queues incurs a significantly high set-up time.
For the threshold switching rule, on the other hand, the laser set-up time is much lower. Figure 6(a) demonstrates that for the threshold switching rules, the laser set-up time is insensitive to colour distribution of plastic pieces and processing time distribution, but is slightly sensitive to truck interarrival time. On the other hand, for the base switching rule, the laser setup time is sensitive to truck interarrival time, and is slightly sensitive to colour distribution of plastic pieces and processing time distribution. These results demonstrate that the decrease in truck interarrival time increases the workload of the laser probe, which affects the laser set-up time.

In figure 6(b) the 95% CIs and means for laser probe utilization show that one probe is adequate for each of the 16 scenarios. The laser probe utilization is lowest in figure 6(b) for the threshold switching rule with longer truck interarrival time. The laser probe utilization is sensitive to the scheduling rule and truck interarrival time distribution, but is insensitive to the current versus future colour composition and processing time distributions. Since the threshold switching rule provides the greatest probe identification capacity, this approach may be required if the number of plastic pieces per electronic product and/or the number of incoming electronic products increase.

Figure 7 illustrates the output metric, shipment fill time, for the four plastic types/colour combinations arriving in the highest quantities. Figure 7 does not include the shipment fill times for the other materials since their results are similar and their values are much lower. The shipment size is defined as 10 000 kg. As expected, the shipment fill times for different colour shipments are sensitive to the colour composition of the arrivals and truck interarrival time distribution. However, the shipment fill time is insensitive to the switching rules and processing time distribution since their CIs overlap for the same colour distribution of plastic pieces and truck interarrival time distribution.

7. Summary and conclusions

In summary, this paper provides the first analysis of a multi-class queuing system in a recycling facility with laser Raman probe plastic part identification and colour sortation. We develop an intuitive threshold switching rule that is based on traffic intensity, set-up time, and queue space goals. Assuming representative space goals, we test the sensitivity of our policy with respect to truck interarrival time, distribution of colour composition of incoming end-of-life products, and processing time distribution. We compare the performance of our heuristic threshold switching rule with a cyclic scheduling rule.

Our results show that recycling operations are sensitive to the scheduling rules and sorting requirements to improve material recovery value. The results in figure 5(b) indicate that the space required for the WIP in the dark first-entrant queue for the 95th CI is most sensitive to the scheduling rule, less sensitive to the truck interarrival time and the colour composition, and insensitive to the processing time distributions. Figure 6(a) indicates that set-up time is most
sensitive to the scheduling rule while figure 6(b) indicates that the laser utilization is sensitive to the scheduling rule and the truck interarrival time. Figure 7 shows that shipment fill time is sensitive to the colour composition of product arrivals and truck interarrival time, but it is insensitive to the scheduling rule and processing time distributions. Our results indicate that a good switching rule to schedule laser Raman plastic resin identification can increase probe capacity for changing colour compositions and reduce total set-up time.

Figure 5. (a) 95th confidence interval (CI) for average WIP in the natural first-entrant queue for the 16 scenarios. (b) 95th CI for average WIP in the dark first-entrant queue for the 16 scenarios.
Although our threshold switching rule was motivated by a specific plastic identification and recycling problem in the electronics industry, this paper explores the issues of traffic intensity, setup time, and capacity in scheduling multiple classes in the general case of a queuing system. For example, our approach may apply to scheduling multiple machines to one worker when the worker’s processing time distribution differs for each machine. Our work contributes important insights into the relationship between traffic intensity, setup time, and queue capacity for multiclass queuing systems.
As the relationships between manufacturers, collectors, and recyclers develop, opportunities to enhance the scheduling of demand-driven recycling will likewise develop. As Williams (2007) points out, linking activities in the reverse logistics networks will support planning and control. For example, if manufacturers and collectors use new technologies to communicate the content of incoming loads to recyclers (Thomas 2007), this scheduling work may be extended to reduce disassembly and materials identification set-up times further.

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