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A HYBRID SIMULATION OF PRODUCT RECONDITIONING: A CASE STUDY

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ABSTRACT

To gain economic competitive advantage from the closed loop supply chain (CLSC), firms must ensure that the cost of reconditioning products does not exceed the cost of purchasing new products. The uncertainties associated with product returns (i.e., product condition, quantity etc.) make it difficult for managers to efficiently allocate resources. This study develops and employs a hybrid simulation (HS) model as a decision support tool in a case study from industry. We demonstrate via our HS that the company could save significant money each quarter by converting their existing schedules from two shifts to single shifts and redistributing resources. Furthermore, we found maximizing the subprocess output doesn't necessarily reduce costs. The company's focus on output-oriented subprocess evaluation could impede cost-saving efforts. Future research will explore how the mix of new and returned items affects process yield, different resource configurations, prioritization of product types, and processing time disparities.

1 INTRODUCTION

Environmental, social, and economic pressures are driving an increasing interest in the study and application of closed loop supply chains (CLSCs). However the current state of CLSC literature is characterized by a lack of industrial case studies (Kazemi et al. 2019). Furthermore, methodological limitations force researchers to simplify the complexity of CLSCs into problems that are interesting from an academic perspective, but have limited applicability to industry (Govindan et al. 2015; Guide and Wassenhove 2001; Kazemi et al. 2019). This study fills these gaps in the existing literature by employing hybrid simulation (HS) to model and analyze a complex product reconditioning process from an industrial case study. HS is a combination of system dynamic simulation, discrete-event simulation (DES) and agent-based simulation (ABS). In the current study we utilize a combination DES and ABS. The approach enables us to analyze the interactions between parallel and serial subprocesses, identify opportunities for cost reduction, and provide practical recommendations to the company at the center of the case study.

To implement CLSC strategies, supply networks need to navigate the process of returning products from customers to points of recovery. The high level of uncertainty associated with the returns process presents a significant obstacle to implementation of the CLSC (Guide and Wassenhove 2001). Managers of reverse supply chains must contend with the uncertainties that challenge forward supply chains, as well as additional uncertainties pertaining to the quantity of products that customers will return, the manner in which they will return them, the associated costs, the condition of the returned equipment, and the retained value of the returned items (de Brito and Dekker 2003; Gobbi 2011; Savaskan and Van Wassenhove 2006; Toktay et al. 2000). This uncertainty further complicates the process of determining the appropriate EoL (end of life) strategy (or combination of strategies) for the CLSC, resulting in the type of large, complex, “real-sized” problems described by Govindan et al. (2015). The complexity of the CLSC often leads researchers to make restrictive assumptions that limits a work’s usefulness to industry (Govindan et al. 2015; Guide and Wassenhove 2001; Kazemi et al. 2019).

This paper is organized as follows: We first review literature on reverse logistics and CLSCs. We then provide a brief description of the industry case and our methodological framework. Lastly, we discuss our results and recommend areas for future research.

2 LITERATURE REVIEW

2.1 Reverse Logistics and The Closed Loop Supply Chain

De Brito and Dekker (2004) define reverse logistics (RL) as “the process of planning, implementing and controlling backward flows of raw materials, in process inventory, packaging and finished goods, from a manufacturing, distribution or use point to a point of recovery or proper disposal’ (p. 3). Several factors drive RL. Companies may adopt RL practices in order to oblige regulatory pressures, promote public health, recapture value in their products, create jobs, and protect the environment (Govindan and Hasanagic 2018; Kazemi et al. 2019). Our research is slightly different from existing research because we not only consider the uncertainty in the reverse supply of products, but we also consider the uncertainty that arises when new products enter the refurbishment process alongside returned products.

The Closed Loop Supply Chain model integrates the concept of reverse logistics with remanufacturing, which involves restoring products to a condition where they can be resold (Kazemi et al. 2019). Carrasco-Gallego et al. (2012) identify a subset of returned products as "reusable articles" (RAs). These products have a shorter consumer usage period and do not suffer significant loss in quality after use. After use, RAs are reconditioned and made available for the next consumer. In contrast to extant research, this research considers a significant quality loss in several of these returned products, which are then replaced by new products.

The uncertainty involved in the reverse logistics process greatly impacts remanufacturing (Goltsos et al. 2019). CLSCs must contend with uncertainty in (customer) demand downstream, as well as uncertainty in the flow of products upstream. Specific uncertainties pertaining to upstream flows deal with the quantity and quality of products entering the remanufacturing process (Ferguson et al. 2009; Goltsos et al. 2019; Ponte et al. 2021). This leads to high variability in the remanufacturing effort, which is costly to manage due to the larger commitment of labor, material, and equipment. To be profitable, the acquisition price for remanufactured products must be less than that of new products (Guide and Van Wassenhove 2009). Consequently, more empirical research is necessary to assist firms in framing the acquisition price of goods and allocating resources to reduce this cost (Guide and Wassenhove 2001; Huscroft et al. 2013). In our research, we consider the cost of remanufacturing and if it might be better to use new products instead of spending time reconditioning the products.

3 CASE STUDY

3.1 Overview

GoodComm is a telecommunications provider that leases telecommunications hardware to its residential and corporate customers. When a customer finishes its contract, it either mails its equipment back to GoodComm, or hires a technician to uninstall and return the equipment. GoodComm owns regional fulfillment centers (RFCs) that gather customer returns and forward them to the company's product reconditioning center (PRC). By reconditioning this equipment, and re-leasing it to new customers, GoodComm recovers value from these returns. The reconditioned products are perfect substitutes for new products. The product reconditioning process takes place in a large warehouse. It is comprised of five sequential sub-processes. These sub-processes consist of separating returned items from their packaging materials (detrashing), scanning these items into a Warehouse Management System (WMS), evaluating these items on test benches, remedying cosmetic damage to items by buffing them, and cleaning and kitting the items. The cleaning and kitting tasks occur at the same workstation and are therefore combined into the same sub-process. Figure 1 shows a bird's eye view of the returns process. Here, blue rectangles represent equipment racks, yellow rectangles are boxes of equipment, and dashed lines represent movement lanes. Figure 2 (next page) is the 3D representation of the returns process from the model used in this research.

GoodComm's forecasting division uses historical data to predict customer demand and establish weekly production targets for the number and type of units returning through the process. If this demand cannot be met with reconditioned equipment, GoodComm procures and distributes new equipment. The performance of the overall returns process is assessed based on whether it meets its weekly production targets. However, managers evaluate individual subprocesses based on their total throughput. They reward workers who meet throughput targets with favorable performance reports, cash bonuses, or both.

Corporate leadership at GoodComm is interested in reducing labor and materials costs by minimizing bottlenecks and backups in the returns process. To facilitate process improvement, the researchers used systems analysis and HS. Systems analysis examines the individual components of a complex system in the context of their interaction with other components. (Forrester 1958). HS is well-suited for complex system applications (Brailsford et al. 2019; Khan and Abonyi 2022).

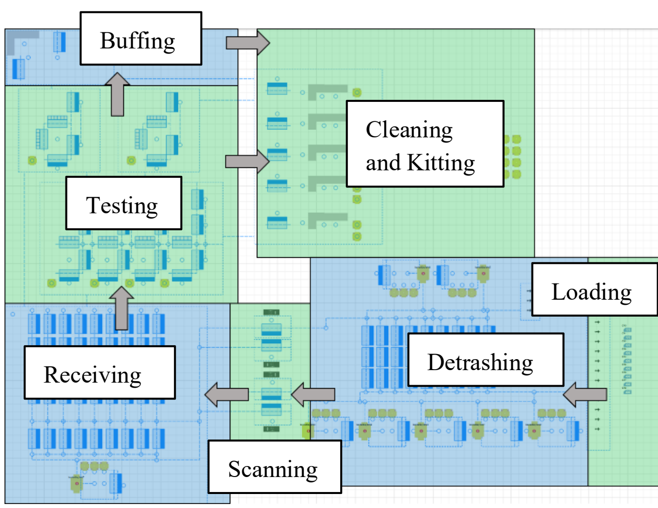

Figure 1: Overview of GoodComm's product refurbishment process.

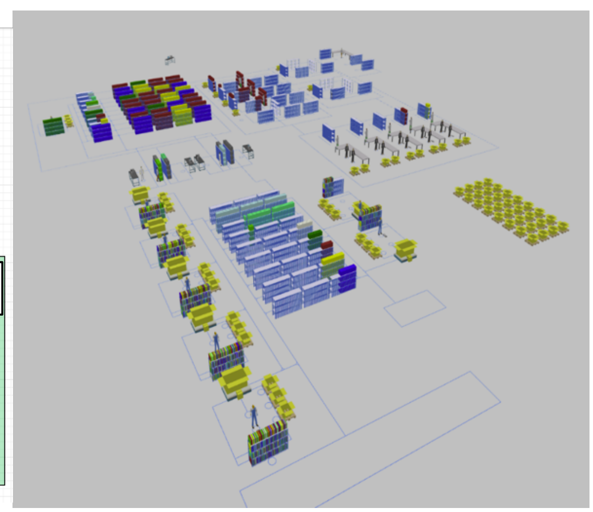

Figure 2: 3D Model of returns process.

Next, we will describe each part of the returns processes in detail, using graphics from our returns model to illustrate these processes.

3.2 Processes

The reconditioning process starts when customer returns arrive at the PRC loading dock. The returned products come in gaylord boxes, with each box containing 200 products. These products are boxed together only with other products from the same return source. For instance, returns sent through the mail ('post') are crated only with other mailed returns, technician returns are crated only with other technician returns, and returns from RFCs are crated only with other returns from RFCs. There are 18 (zero-indexed) different item types that customers return. Items 0, 4, 5 and 6 are cable boxes. Item 1 is an internet router. Items 2 and 3 are cable modems. Items 9-17 are obsolete. These items are discarded during the returns process.

Prior to the start of each day, GoodComm's forecasting division assigns unit testing priority based on forecast shortfalls with respect to the weekly production targets. Managers assign a higher priority to items that are anticipated to have a larger shortfall. Equipment racks containing higher priority items are pulled through the returns process ahead of equipment racks which contain lower priority items.

During the 'detrashing' process, technicians remove products from the boxes in which they were returned. They dispose of packaging material, discard obsolete model types, and remove any ancillary equipment (connection cables, power adapters, or extraneous items included by the customer). The technicians then place the detrashed products on equipment racks. Each of these racks can hold up to 300 units. Once an equipment rack is full, the technicians sort the products on the rack into a centralized collection of equipment racks. In the centralized collection of equipment racks, each rack contains only one model type.

The returns process includes three detrashing stations for post returns, two stations for tech returns, and an additional two stations that handle RFC returns. Each of these stations employs one technician, and services its own return type, exclusively. Returns from RFCs arrive at the refurbishment warehouse with less extraneous packaging material. Consequently, the detrashing process for these returns is 15% faster than it is for post and customer returns.

When a centralized rack in the detrashing area reaches its capacity, a technician from one of the three scanning stations retrieves the rack and takes it to the scanning area. Here, technicians scan the serial number on each returned item to check whether it is still associated with a customer's account. They then upload this item's information to the warehouse management system (WMS). The items that are still associated with a customer's account are set aside at the end of the returns process and are not distributed to new customers until the prior association is resolved. Once the scanning process is finished, technicians advance the equipment racks to a receiving area. In the receiving area, items await testing or follow-on cleaning and kitting. When GoodComm's inventory of a particular item type exceeds three times the safety stock (one week's worth of demand), managers inform the scanners. The scanners set aside items of this type to prevent them from crowding out the receiving area.

GoodComm uses three types of testing stations. These stations are not interchangeable between item types. Two item types, items 6 and 7, do not require testing and are sent directly from the receiving area to cleaning and kitting. To simplify matters, we shall refer to each of the testing stations as 'TS' followed by a numerical designator corresponding to the station number. Table 1 summarizes this convention, according to the item type serviced at each TS, the capacity of that TS, and the number of workers servicing that TS. TS1 is configured as three parallel processes. Each of these processes incorporates one 20-unit test bench. TS2 and TS3 each have only one 48-unit test bench.

Workers at each TS remove items from the equipment racks and connect them to the test bench(es) located at that TS. After completing the test, technicians remove the item from the test bench. Items that pass the testing processes are placed onto a new equipment rack, while items that fail the testing process are collected in a box co-located with each test bench. Testing takes place concurrently at TS1, TS2, and TS3. Due to the complexity of the testing process at TS1, it takes an average of 10 times longer than the testing at TS2 and TS3. Technicians from the Cleaning and Kitting (C&K) station retrieve entire equipment racks of processed items after testing.

Table 1: Testing stations by item type.

Item Number	Testing Station	Test Station Capacity	# Test Station Workers
0	Station 1 (TS1)	20 units	2 workers
1	Station 1 (TS1)	20 units	2 workers
2	Station 1 (TS1)	20 units	2 workers
3	Station 1 (TS1)	20 units	2 workers
4	Station 2 (TS2)	48 units	1 worker
5	Station 3 (TS3)	48 units	1 worker

GoodComm purchases new units to fill any demand that cannot be met with reconditioned units. The lead time for these new units is one week. New model types that need testing are tested at the appropriate station, while items that do not require testing are passed through the testing station based on the established model priority rules. During testing at station 1, workers update firmware for some items. Units with more outdated firmware require longer testing. New items have more recent firmware and need less updating. Although GoodComm did not possess specific information on differences between new and returned unit testing times, researchers estimated, based on throughput data, that staged units undergo testing ten times faster, on average, than customer returns. GoodComm's management agreed with this estimate.

One cleaning technician and two kitting technicians comprise each of the five CK stations. The cleaning technician selects an item from its respective equipment rack and then vacuums, cleans, and polishes it before passing it to the kitting technicians. These technicians package the item with its necessary documentation and ancillary equipment such as cables, power supply, and remote controls. New items do not undergo cleaning and are passed directly to the kitting team.

Occasionally, item 2 returns require buffing to ameliorate cosmetic damage. When this is the case, workers from the buffing station retrieve the item 2 equipment at the completion of the testing process. A buffer polishes the damaged items on the equipment rack before advancing it to the C&K station. GoodComm estimates that 40% of item 2 returns require buffing.

4 SIMULATION MODEL CONSTRUCTION

After gaining familiarity with the returns and reconditioning process at GoodComm, the research team made several noteworthy observations. First, they identified that disparities in cycle times among subprocesses resulted in idle periods for one subprocess while others were busy. Second, they identified that the limited capacity and long cycle times at TS1 (~100 times greater than its preceding subprocess and 4-5 times longer than its follow-on subprocess) represented a potential bottleneck. This was confirmed by GoodComm's management. Third, they found that the quantity of item 2 returns exceeded the demand for model 2 units by a factor of four.

Based on these observations, the researchers investigated four areas of potential process improvement:

1. Resource sharing between subprocesses
2. The addition of a testbench at TS1
3. The addition of an additional scanning station
4. Eliminating the buffing subprocesses, discarding damaged model 2 units, and using surplus, non-damaged model 2 units to meet customer demand.
5. Different combinations of shift schedules across subprocesses.

Researchers proceeded by building a floor plan of the returns process to approximate scale in AnyLogic® University Edition. v 8.8. In the operational schema proposed by GoodComm, equipment racks serve as a critical component for queuing, batching, and facilitating item transitions across stations. As such, these were replicated to scale and capacity. Discrete-event simulation (DES) process flows were employed to model individual subprocesses. Each of these DES process flows was defined within an agent, whose state was a function of the DES process. This enabled the containing agents to manage the prioritization, batching, and transportation of items between subprocesses.

4.1 Parametrization

Worker input was gathered through a time study. To accomplish this, the subprocesses were divided into subtasks and the researchers recorded the time taken for each subtask. At least 30 observations were made for each subtask. Additionally, a filmed walkthrough of the returns facility was provided by management. However, time study data was not available for the buffing station. To estimate the time taken for the buffing process, researchers relied on rules of thumb provided by warehouse managers. Comparable process times from the available time studies were used to estimate the time taken for a worker at the buffing station to remove a unit from the equipment rack and place it back on the rack.

To obtain worker inputs, the research team conducted a time study by recording times for each subtask within each subprocess. They used at least 30 observations for each subtask. The buffing station was not observed. In the absence of this data, the researchers used rules of thumb implemented by warehouse managers to approximate the buffing process. Comparable process times from available time studies were used to estimate the time required for a worker at the buffing station to remove a unit from the equipment rack and place it back on the rack. For processes that happened too quickly to make accurate observations, such as the time between picking processes at the testing station, a one-second, uniform distribution was used for approximation.

Collecting time studies for the testing benches was challenging due to their different capabilities. The test benches at TS1 capture data for each tested unit, including the model type, test duration, and pass/fail outcome. To estimate process times for these models, the researchers analyzed three months of historical data containing 24,167 individual tests. Testing stations 2 and 3 do not capture this data, so the researchers used GoodComm's prior time studies to model the testing process times for these models.

The researchers used four months of demand data to model a consistent, weekly demand for each model type. GoodComm's initial inventory on model startup was set to two weeks' worth of inventory. Table 2 (below) displays information on the demand and initial average inventory. The model initializes at equilibrium, with a week's worth of new equipment scheduled to arrive at the end of the first week.

Table 2: Average weekly demand and initial inventory, by model type.

Model	Weekly Average Demand	Initial Inventory/Desired Inventory Level
1	3,976	7,953
2	1,855	3,711
3	2,624	5,248
4	7,549	15,099
5	565	1,130
6	705	1,411
7	190	380
8	502	1,005

4.2 Resource Sharing and Inventory Policy

GoodComm's management supported the research team's interest in resource sharing to increase worker utilization and reduce costs but raised concerns about sharing resources across jobs with varying skill requirements, or between subprocess that were far apart. Notably, GoodComm distinguishes between 'physical' task types (detrashing, buffing, cleaning & kitting) and 'technical' task types (scanning, testing). The research team entertained these concerns and decided to share resources only between scanning and testing. These subtasks are similar in nature and adjacent to each other.

Based on these considerations, the research team formulated a resource sharing plan between scanning and testing stations. It was important to develop criteria that would be practical and easily implemented by workers. Therefore, researchers decided to initiate resource sharing from TS2 or TS3 (characterized by low worker utilization rates) to the scanning stations (characterized by higher worker utilization rates), so long as the respective TS had no pertinent equipment at its station or in the receiving area, and resources were not already being shared (i.e. a worker from TS3 will not go to scan station 4 if a worker from TS2 is already there). If any of the criteria that initiate resource sharing are violated, resource sharing ends. Note that resource sharing is not appliable for any scenario which already includes a fourth scanning station.

4.3 Inventory Policy

GoodComm's reconditioning process operates on a periodic review and order-up-to inventory policy. Each week, managers place an order up to an inventory level that meets the demand for the next week. Since GoodComm holds safety stock for each item type that is equivalent to one week's worth of demand, the order up to level for each model type simplifies to twice its safety stock for that model type (equation 1). Managers also evaluate the discrepancy between the desired inventory levels and the actual inventory levels of each product type. If the actual inventory levels are below the order up to point, they add this difference to the order. Otherwise, no order is placed (equation 2). Each new item of inventory costs GoodComm \$200.

$$S_{w=}^{i}2D_i \tag{1}$$

$$Q_w^i = \begin{cases} S_w^i - I_w^i \quad , & I_w^i < S_w^i \\ 0 \quad , & I_w^i \geq S_w^i \end{cases} \tag{2}$$

Where:
S_w^i is the order up to quantity for item i in week w
D_i is the expected demand for item i (assumed constant)
Q_w^i is the order quantity for item i in week w
I_w^i is the on-hand inventory for item i in week w

4.4 Cost

The cost function used in this research is composed of two major factors: labor expenses and the expense of acquiring new units to meet unsatisfied customer demand. The worker wages at each workstation are consistent, but differ based on the shift worked, with the options being a regular shift (6:00 AM-2:30 PM), an extended overtime shift (2:30 PM-6:00 PM), or the addition of a second shift (3:00 PM-11:30 PM).

Workers executing a regular shift earn $15.00/hr. This increases to $22.50/hr during extended shift hours. Second shift workers make $19.00/hr.

$$
\begin{aligned}
Cost \\
= \Bigg[& n_{wD}\left(h_{rs}\sum_{t_{rsD}\in T} + h_{ts}\sum_{t_{tsD}\in T} + h_{ds}\sum_{t_{dsD}\in T}\right) + n_{wS}\left(h_{rs}\sum_{t_{rsS}\in T} + h_{ts}\sum_{t_{tsS}\in T} + h_{ds}\sum_{t_{dsS}\in T}\right) \\
& + n_{wC}\left(h_{rs}\sum_{t_{rsC}\in T} + h_{ts}\sum_{t_{tsC}\in T} + h_{ds}\sum_{t_{dsC}\in T}\right) + n_{wT}\left(h_{rs}\sum_{t_{rsT}\in T} + h_{ts}\sum_{t_{tsT}\in T} + h_{ds}\sum_{t_{dsT}\in T}\right) \\
& + n_{wC}\left(h_{rs}\sum_{t_{rsC}\in T} + h_{ts}\sum_{t_{tsC}\in T} + h_{ds}\sum_{t_{dsC}\in T}\right) + C_{new}\sum_{t\in T}\sum_{m\in M} S_{mt}\Bigg]
\end{aligned}
\tag{3}
$$

Where:
n_{wD} = number of Detrashing Station workers
n_{ws} = number of Scanning Station workers
n_{wT} = number of Testing Station workers
n_{wB} = number of Buffing Station workers
n_{wC} = number of Cleaning and Kitting Station workers
h_{rs}= worker regular shift hourly rate ($/hr)
h_{ts} = worker time and a half shift hourly rate ($/hr)
h_{ds}= worker second shift hourly rate ($/hr)
T= set of all time periods
t_{rsD}= Number of regular shifts worked at the detrashing station.
t_{tsD}= Number of extended shifts worked at the detrashing station.
t_{dsD}= Number of second shifts worked at the detrashing station.
t_{rsS}= Number of regular shifts worked at the scanning station.
t_{tsS}= Number of extended shifts worked at the scanning station.
t_{dsS}= Number of second shifts worked at the scanning station.
t_{rsT}= Number of regular shifts worked at the testing station.
t_{tsT}= Number of extended shifts worked at the testing station.
t_{dsT}= Number of second shifts worked at the testing station.
t_{rsB}= Number of regular shifts worked at the buffing station.
t_{tsB}= Number of extended shifts worked at the buffing station.
t_{dsB}= Number of second shifts worked at the buffing station.
t_{rsC}= Number of regular shifts worked at the cleaning and kitting station.
t_{tsC}= Number of time and a half shifts worked at the cleaning and kitting station.
t_{dsC}= Number of second shifts worked at the cleaning and kitting station.
m= model type
M=set of all model types
S_{mt}= shortage penalty for model m during time period t
# of new products = delta b/w returns throughput and demand
C_{new}= cost of purchasing a new unit of inventory.

Therefore, our objective is:

$$Obj[Min(Cost)] \tag{4}$$

4.5 Verification and Validation

Throughout the modelling process, the framework proposed by Manuj et al. (2009) for maintaining rigor in logistics and supply chain simulation was employed. To ensure the accuracy of the code, the lead researcher held weekly meetings with two skilled programmers and process modelers, discussing the underlying assumptions and logic of the model. Program traces were utilized to verify the proper execution of the model logic, which supplemented the detailed process model that accompanied the underlying code.

In addition, the researchers conducted several sensitivity tests. Firstly, they confirmed that the total labor cost increased as the levels of scheduling for relevant subprocesses increased. They then ensured that the utilization rate of the fourth scanning station, fourth TS1 testbench, and buffer stations was zero when not in use. The researchers also verified that the utilization rate of the TS2 and TS3 workers increased during resource sharing, while ensuring that the utilization rate did not increase when resource sharing was active in scenarios that utilized four scanning stations. This was necessary to avoid any potential leakage of resource sharing into the four scan station scenarios. Once all these conditions were verified as expected, the researchers proceeded with the analysis.

5 RESULTS

To address bottlenecks at the scanning and testing station, we evaluated various policy and configuration changes, including the addition of a fourth scanning station, a fourth TS1 testbench, and all possible combinations of work scheduling at TS1, TS2, and TS3. Management expressed concerns about high utilization rates for scanning workers, which were confirmed in pilot simulations even under double shift conditions, thus we did not consider any single or extended shift scenarios for scanners. Similarly, single shift CK operations were found to be insufficient in meeting service level requirements, leading to their exclusion from the experimental design, with CK scheduling only tested for extended and double shifts. We also examined resource sharing between scanning and testing stations, but only in scenarios with 3 scanning stations. Finally, we evaluated the elimination of the buffing station.

This culminated in a 2 (resource sharing) x 2 (buffing) x 2 (fourth scan station) x 2 (fourth TS1 testbench) x 3 (TS1 schedules) x 3 (TS2 Schedule) x 3 (TS3 Schedule) x 2 (CK Schedule) = 864 factor DoE. The simulation process encompassed a three-month production period and entailed executing the model for 30 replications on a 24-core AMD Ryzen EPYC workstation equipped with 512GB of RAM.

Table 3 provides an overview of the baseline model, the lowest cost model, and a 'max output' model designed to maximize the throughput at each subprocess. The 'max output' model is included as a point of comparison to the former two models.

The findings suggest that GoodComm can achieve quarterly savings of $114K (0.5%) by converting TS2 and TS3 schedules from two shifts to single shifts, reallocating resources from TS2 and TS3 to the scanning subprocess and eliminating the buffing subprocess. Furthermore, as evidenced by the greater expenses associated with the ‘max output’ scenario, this study implies that maximizing the throughput of individual subprocesses does not translate into lower overall costs. Therefore, GoodComm's approach of evaluating subprocesses based solely on output may hinder its efforts to achieve cost savings.

6 DISCUSSION AND CONCLUSION

There are several avenues for future research. First, the notion that the maximum output scenarios results in a smaller average daily output is very interesting, although consistent with previous research. Ponte et al. (2021) demonstrate that the introduction of higher quality items into the remanufacturing process can induce the bullwhip effect, and therefore, (unexpectedly) decrease its yield. It is likely that this is what is happening here; new items process through TS1 and cleaning and kitting more than 10x faster than returned items. Future research should examine the relationship between the mix of new and returned items and the

Table 3: Results and best treatments.

	NumTest1Stns	NumScanStations	Test1Schedule	Test2Schedule	Test3Schedule
Baseline	3	3	Second Shift	Second Shift	Second Shift
Best	3	3	Second Shift	Single Shift	Single Shift
Max	4	4	Second Shift	Second Shift	Second Shift

	CKSchedule	ResourceSharing	Buffing
Baseline	Second Shift	No	Yes
Best	Second Shift	Yes	No
Max	Second Shift	N/A	No

	TotalWorkerCost	TotalNewUnitCost	TotalCost	Avg Daily Output (Units)
Baseline	$833,752.00	$21,261,527	$22,095,279	2369.9
Best	$796,016.00****	$21,259,060	$22,055,076***	2344.7****
Max	$895,696.00****	$21,252,180	$22,147,876****	2338.4****

*p<0.05, **p<0.01, ***p<0.001, ****p<0.0001. Contrasts drawn between respective case and baseline scenario.

overall process yield. Future research might also examine other configurations in which specific resources prioritize product types. For instance, would having certain TS1 or CK stations prioritize new products (or old products) increase throughput? For what ratio of new to old returns is this effective? How does the disparity in process times between product grades affect this decision? The major limitation of this study is that it focuses only on a single company in the form of case-study, nonetheless it does provide some insights as to how resource sharing, and taking a systems approach can help reduce the over cost for a firm.

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