A Simulation-based Optimization for Production Planning of Dedicated Remanufacturing System

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Abstract—**This paper presents a study of a dedicated remanufacturing system using a simulation-based optimization approach. The remanufacturing system performs various rework processes such as inspection, assembly, disassembly, testing, and repair on used-products and transforms them to be as-new products. In this study, the original production line of this dedicated remanufacturing system is shared with multiple products and has a limited space to accommodate arriving used products. Therefore, an appropriate inventory capacity should be set and a proper switching rule should be introduced to set up the production line. Otherwise, excessive line switching time and cost would be incurred. The objective of this study is to sequentially improve and suggest a method to optimize the production planning of this dedicated remanufacturing system under uncertain conditions, i.e., uncontrollable product arrival and stochastic operational time. A case study is used to demonstrate and identify possible solutions, to show the advantages of the proposed approach. This approach can assist in decision making for the planning and management of remanufacturing systems.**

Index Terms—**Meta-Heuristic Algorithm, Production Planning, Remanufacturing System, Simulation-Based Optimization, Switching Rule**

I. Introduction

Remanufacturing is a critical choice that can help to reduce the wastes that are generated from manufacturers. Remanufacturing systems are viewed as green processes that could develop environmental sustainability and economic growth. It is a significant market strategy that can avoid adverse effects (which impact the environment) and make more profit for manufacturers [1].

Remanufacturing can be separated into two different strategies. The first strategy is a combined model where the original manufacturer operates the remanufacturing, combined with their normal production processes. This strategy is mostly used in European countries [2]. The second strategy is a dedicated model where remanufacturing is operated by third-party remanufacturers. This dedicated outsourcing is more capable and productive, in terms of the collection and recovery of used products. The third-party remanufacturers have more knowledge in recovery processes, which can minimize the waste and operate with full capability in the recovery of used products.

This paper presents a study of a dedicated remanufacturing system. It operates under different used-product conditions such as different patterns of arrival and different priorities for each product type. This study provides an in-depth analysis of a dedicated remanufacturing system, concerning the material flow, remanufacturing process, and associated problems. A simulation-based optimization model is applied to find and optimize the significant factors that can affect the efficiency of a dedicated remanufacturing system of electronic products. A meta-heuristic algorithm is introduced to determine the optimal operating parameters that yield the near or possibly highest, system profit.

The remainder of the paper is organized as follows. The literature review, which consists of a review of a remanufacturing system, uncertainties in remanufacturing, and system optimization, is provided in Section II. Section III explains a simulation-based optimization approach for the dedicated remanufacturing, including an objective function and the OptQuest optimization tool. Section IV illustrates a case study including the model parameter assumptions, decision variables, and simulation model. Section V presents the results and discussion of this study. Finally, Section VI provides the conclusion and recommendations for further study.

II. Literature Review

A. Remanufacturing Systems

Remanufacturing systems have been studied by many researchers in the past because they can make more value for used products, reduce production costs, and promote environmental sustainability. Remanufacturing, which is an industrialized circular economy, can be considered an important solution to environmental degradation and global warming [3]. For the automotive industry, a remanufacturing system can help reduce the costs of manufacturing by up to 50%, the consumption of energy by up to 40%, and consumption of materials by up to 30%, as compared to manufacturing with new materials. Therefore, it can provide benefits in both environmental and economic aspects [4].

Regarding research on remanufacturing systems, Fathi et al. [5] studied a remanufacturing system that has two streams of used products, which are remanufactured with a dedicated capacity and a merged capacity. They used different variability levels including (1) high variability in returned product arrival that follows a hyper exponential renewal process, and (2) low variability in returned product arrival that follows a Poisson process. The total expected profit of the remanufacturing system was optimized, and the important effects of the model parameters on the admission decisions were illustrated.

B. Uncertainties in Remanufacturing Systems

A significant problem in remanufacturing systems is their inherent uncertainties, which make planning more difficult. A major drawback of a dedicated remanufacturing system is the incoming flow of arriving used products that is not stable and not certain [6]. For a dedicated remanufacturing company, the arrival pattern of used products is uncontrollable. Used products have a variety of product types with different residual values. Therefore, the production planning and control of such a dedicated remanufacturing system are more complex because of the effects of high uncertainty and variation. Daniel and Guide [7] built production planning and control activities for remanufacturing where the production planning and control activities are more complex for remanufacturing companies due to uncertainties. These uncertainties are stochastic returned product arrival, return unbalancing, demand rates, and the unknown conditions of returned products. Fang et al. [8] considered a hybrid production system of new and remanufactured products with two production processes. For optimizing the hybrid production strategy, the recycling uncertainty, demand rate, limitation of capacity, component durability, and differences between new and remanufactured products were considered to obtain the lowest costs in the system.

Wang and Huang [9] explored an optimal disassembling policy under demand uncertainty. They illustrated that after the disassembly process, the used products can be fixed and sold to the secondary market, or remanufactured, or reused to gain raw materials, or discarded. They applied a two-stage robust programming model to find the recycling volume and recovery strategies. Shabanpour and Colledani [10] varied the used-product conditions that affect the remanufacturing efficiency and profit to find the optimal design of a disassembly line under the uncertainty of disassembly processing time. They applied a mathematical optimization model to maximize the profit and optimize the sequence of disassembled components, assignment of disassembly tasks to workstations, and allocation of buffers.

C. System Optimization

Optimization can be divided into two groups: mathematical or analytical optimization and simulation-based optimization. Each method has its advantages and disadvantages, depending on the usage purpose. The mathematical optimization model can get the global optimal solution, but it is more difficult to build when the problems are under uncertain conditions. Simulation-based optimization is suitable to solve big problems under uncertainties in which they are too complex or too difficult to be solved by the mathematical models. However, it may not get the global optimal solution.

1) Mathematical Optimization

A mathematical model can normally be used to solve certain optimization problems. It can be solved with a single objective function or multiple objective functions in both deterministic and stochastic (within a certain level) situations. There are many mathematical methods such as Linear Programming (LP) model, Integer Programming (IP) model, and Mixed Integer Linear Programming (MILP). Lee et al. [11] explored the organization and design of a chilled water network with improved efficiency, using mixed-integer nonlinear programming models to solve the problem. Their objectives were to improve the flexibility of the network and reduce the complexity of the network. Tahirov et al. [12] constructed a mathematical model for a remanufacturing system to find which strategies (among pure remanufacturing, pure production, and mixed production) are more workable for multi-items with returned subassemblies.Nuamchit and Chiadamrong [13] then used the possibilistic linear programming approach to optimize a problem of hybrid manufacturing and remanufacturing systems by incorporating fuzziness of data,represented by the triangular distribution in their mathematical model.

2) Simulation-based Optimization

A typical simulation model can only simulate a system of interest but it cannot provide an optimal solution to the problem. Therefore, simulation-based optimization embedded with meta-heuristic algorithms is applied to simulate the model and seek the near or possibly optimal solution. Meta-heuristic algorithms, such as Simulated Annealing (SA), Tabu Search (TS), Scatter Search (SS), and Genetic Algorithm (GA) are popular among researchers. Simulation-based optimization has an advantage over the mathematical optimization due to the fact that it can optimize big and complex problems, especially with the NP-hard problems as well asit can solve the problems under a wide range of uncertainties. However, its results cannot always guarantee the optimal solution.

Mazzuco et al. [14] applied simulation-based optimization with SA to the vehicle routing problem. They optimized the product delivery schedules, to find the best route that reduces the cost, delivery time, or distance. Chu et al. [15] applied simulation-based optimization with a cutting-plane algorithm to multi-echelon inventory systems, which are under uncertainty. They minimized the inventory cost while sustaining satisfactory service levels, quantified by the fill rate.

3) OptQuest

In this study, a simulation model of a dedicated remanufacturing system is built and simulated by the Arena simulation program, which has optimization software, "OptQuest". OptQuest is a meta-heuristic algorithm that combines three meta-heuristics which are a neural network, Scatter Search (SS), and Tabu Search (TS) [16]. Jie and Li [17] used OptQuest to solve and optimize the (s, S) inventory model. They showed that OptQuest can effectively solve the stochastic constrained optimization problem. Sadeghi et al. [18] studied a three-echelon supply chain system of a blood sugar strip manufacturer. They used the OptQuest in the Simio software package to optimize the inventory factors and cell utilization to minimize the total costs. Their results showed that the Re-Order Point (ROP) values generated from OptQuest are different from the ROP values from mixed-integer linear programming. However, the results are more realistic, as uncertainties in the supply chain can be included.

III. Simulation-Based Optimization for the Dedicated Remanufacturing

The main objective of constructing and simulating a dedicated remanufacturing system is to identify the factors that affect the efficiency of the system. Major features in this model consist of the inventory space, number of operators in each station, buffer size in each station, and run size of each product type. These factors affect the production revenue and costs, including raw material cost, redistribution cost, remanufacturing cost, holding cost, and batch transferring cost. Considering the size of the studied problem with a large number of decision variables as well as many uncertainty conditions, it is considered to be an NP-hard problem. Hence, the simulation-based optimization is deemed to be suitable for solving this problem over the mathematical optimization.

A. Objective Function

To optimize the profit of our dedicated remanufacturing system, important control variables are separated into four categories: received arriving product inventory capacity, run size of each product type, number of operators in each station, and buffer size of each station in the production line. As the objective of this model is to optimize the profit from these controllable variables, the objective function of the dedicated remanufacturing model can be formulated as follows:

$$Max\ f(I, W, B, Q) = TR - TC \tag{1}$$

where I represents the inventory capacity of received arriving used products, $W=(w_1,w_2,\ldots,w_n)$ represents the number of operators in station 1 to n, $B=(b_1,b_2,\ldots,b_n)$ represents the buffer size of each station, $Q=(Q_1,Q_2,\ldots,Q_m)$ represents the run size of product type 1 to m, TR represents the expected total revenue, and TC represents the expected total costs of the dedicated remanufacturing system. The expected total revenue is calculated as:

$$TR = \sum_{i=1}^{m}(R_i \times V_i) \tag{2}$$

where R_i is the selling price of product type i and V_i is the total amount of product type i that is remanufactured per replication length. The expected total costs are:

$$TC = C_C + C_R + C_L + C_S + C_B + C_I + C_H \tag{3}$$

where C_C is the raw material cost (including the purchasing cost of used products from consumers and the transportation cost from transporting the used-products to the remanufacturing factory), C_R is the redistribution cost that is incurred when the inventory capacity is not enough to hold the arriving used products, C_L is the labor cost (cost of operators for used products), C_S is the set-up cost (cost for setting up the production line when it is switched), C_B is the batch transferring cost (cost for handling and transporting a run size (batch) of used products from the received arriving product inventory to the production line), C_I is the operator idle cost (cost incurred when the operators in each station are free), C_H is the holding cost (including the holding cost of parts in the arriving used-product inventory and work-in-process inventory in each station, as well as inventory space cost).

B. *Simulation-based Optimization with OptQuest*

OptQuest combines the simulation with three meta-heuristics, to optimize the problem. It is in the ARENA simulation program. The parameters which OptQuest requires are upper bound, lower bound, suggested value, and step size value for each decision variable. For the upper bound and lower bound, there is the area for searching. It must be large enough to guarantee that an optimal solution is inside the area. In each iteration, all decision variables are generated. The decision variables are simulated, to get a value of the objective function where the decision variables and the value are a solution in this iteration. Then, this solution is used to generate the decision variables in the next iteration. For the terminating condition of the OptQuest optimization, automatic stopping of the search occurs when the objective function value has no improvement for 100 iterations.

IV. Case Study

To simulate and optimize a dedicated remanufacturing system, a case study of a dedicated remanufacturing company adapted from Li et al. [2] is used to be our base model for the experiment. In the case study, this plant recovers, reuses, and recycles two used-product types laptops and desktops. Both products are remanufactured under the same production line. Operations of the dedicated remanufacturing system consist of nine stations as illustrated in Fig. 1 product receiving, inspection, inventory handling, testing, teardown, repairing, labeling, packing, and shipping.

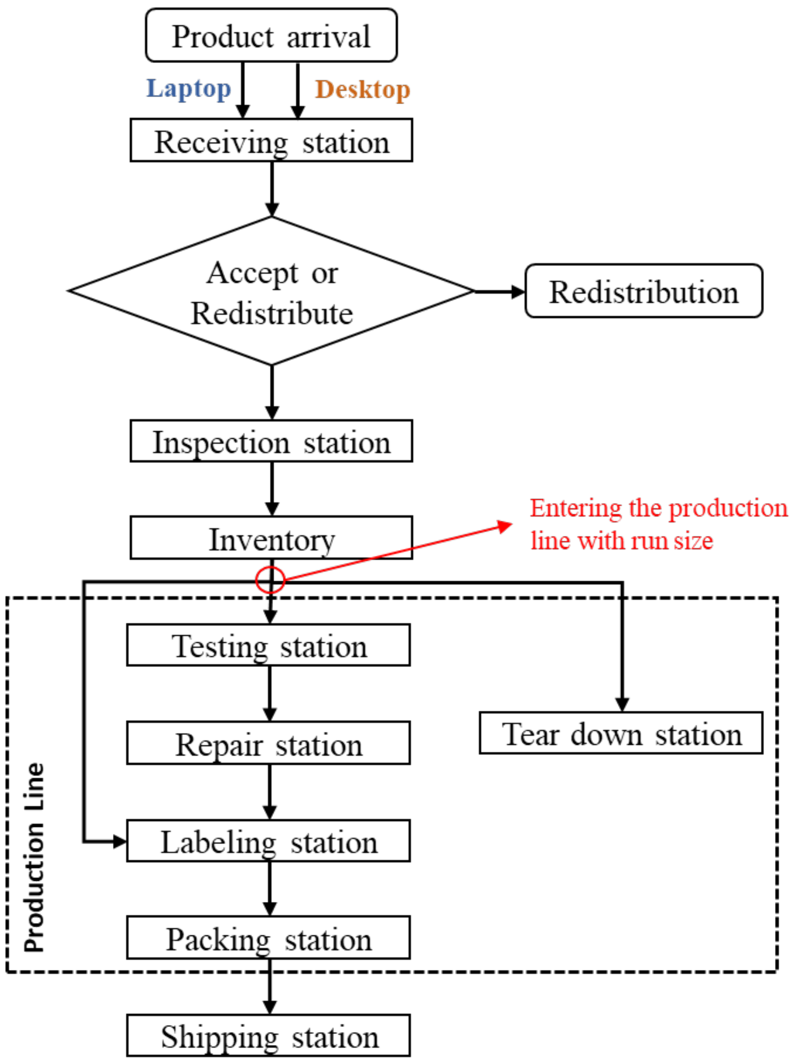

Fig. 1. Basic processes of the dedicated remanufacturing system

Product receiving is the first operation that has one receiving area to temporarily store arriving used-products. These units are transported to the receiving area by trucks. The characteristics of arriving used-products are stochastic with a variety of product types, uncertain arrival time, and uncertain quantities in each arriving batch. Then, the received product inventory is checked that it has enough space to hold the entire batch of arriving used products. If it has enough space, all arriving used products in this batch are received. If not, as many as possible used products are received considering the priority of each product type. Then, the overflow units of the batch are redistributed and a redistribution cost would incur. Next, the received products are sent to an inspection station to investigate and collect related information before sending them to the received product inventory. For the production line of this system, two different product types are shared, to be remanufactured in the same line with 5 stations. There is a proportion of products (10%) that cannot be remanufactured. These used products are sent to the teardown station for further recycling. The other used products are tested and repaired before sending them to the labeling station. In each station, there are one or more identical operators (number of operators in each station is a decision variable) working with uncertain processing time, which is exponentially distributed. The operators immediately start a job when they are available, and the product leaves a station only when the next station becomes available. Finally, the finished products are shipped out from the shipping station and sold to customers.

A. Model Parameter Assumptions

Based on the case study of Li et al. [2], the inter-arrival time of trucks, which transport the arriving used-products, follows an exponential distribution with a mean time of 4 hours, operating 8 hours a day. For pick-up trucks, parts are randomly mixed with two product types (laptop and desktop) in which the capacity of one truck equals 260 sq. ft. The size of one laptop and desktop is 0.5 and 1 sq. ft., respectively. Hence, the number of laptops and desktops in one shipment follows 0.5 x (number of laptops) + 1 x (number of desktops) = 260. Then, the number of laptops is randomized by a uniform distribution between 0 and 520 units. The number of desktops is also randomized with 260 – 0.5 x (number of laptops). The finished products are instantly shipped and sold after finishing the packaging process so there is no need to hold the finished products in the inventory. The prices of the finished laptops and desktops are \$45 and \$20 per unit, respectively (finished products are sold in form of semi-product components). Other parameters of the dedicated remanufacturing system are described in Table I.

1) Existing System

The inventory capacity for storing arriving used products was set to 1,000 sq. ft. The dedicated remanufacturing-system problem is to find the optimal workforce level and optimal buffer size of each station in the production line, to maximize the profit.

TABLE I
PARAMETERS OF THE DEDICATED REMANUFACTURING SYSTEM

Labor	Working time	480 minutes per day
		350 working days per year
Truck	Inter-arrival time	Exponential (240 minutes)
	Truck capacity	260 sq. ft.
	Used laptop	0.5 sq. ft. per unit
	Used desktop	1 sq. ft. per unit
Inventory	For arriving used products	1,000 sq. ft.
	For finished products	None
Production line	Setup time per switch	60 minutes
	Laptop run size	q_L
	Desktop run size	q_D
Selling price	Laptop	\$45 per unit
	Desktop	\$20 per unit

2) First Improvement: Inventory Capacity

After investigating the existing system, it is found that there are many overflow units from the received product inventory due to its limited space. The first improvement is to optimize the capacity of the received product inventory. Therefore, the inventory capacity is considered to be another decision variable. It is optimized to reduce the number of redistributed used products that cause a high redistribution cost. By increasing the inventory capacity, the number of redistribution units and their cost are reduced. A high immoderate inventory capacity can cause the space cost and holding cost to be too high.

3) Second Improvement: Switching Rule

The next improvement is to further improve the profit of the system and reduce the flow time of remanufacturing by applying the priority batch switching rule to optimize the run sizes of laptops and desktops for the production line. Since the production line is shared between the laptops and desktops, it needs to switch between the two products with a set-up time of an hour. This switch happens when the production line is free and all items of the current product type in the batch (run size) are finished. The priority batch switching rule is presented as follows:

a) If IL (number of laptops in the arriving used-product inventory) > qL, the production line will keep processing laptops. The priority is given to the laptops as it has a higher selling price.

b) Else if IL <qL and ID (number of desktops in the arriving used-product inventory) >qD, the production line will be switched to process desktops and vice versa.

c) Otherwise, it will wait for the arrival of laptops and desktops to complete their run sizes before the next production can be started.

B. Processing Time

Table II presents the processing time of each station in minutes. The processing time of operators in each station of the production line is assumed to follow an exponential distribution, which is applied when it is expected that they have a large variation [19].

TABLE II
PROCESSING TIME FOR EACH STATION AND EACH PRODUCT TYPE

Station	**Mean processing time (minutes)**	
	Laptop	**Desktop**
Receiving	3.24	3.24
Inspection	1.05	1.23
Inventory	0.543	0.543
Testing	6.5	7.32
Repairing	15	20
Labeling	5.66	5.66
Packing	9.146	9.146
Teardown	5.025	5.725
Shipping	1.65	1.65

C. Remanufacturing Costs

The operating costs that are related to this dedicated remanufacturing plant are presented in Table III. The raw material costs of arriving used products are estimated to be \$20 per laptop and \$5 per desktop. The redistribution cost is incurred when the arriving used-product inventory does not have enough space to hold the arriving used products for the current batch. The redistribution cost is \$5 for a redistributed laptop and \$1 for a redistributed desktop.

The remanufacturing costs of the system are separated into four parts. The labor cost is \$15 per hour per operator for the inspection, inventory, testing, and repairing stations and \$12 per hour per operator for the receiving, teardown, labeling, packing, and shipping stations and also the production line switching. The set-up cost is incurred when the production line is switched. This set-up cost is \$150 per time. The batch transferring cost for internal logistics and transferring equals \$50 per batch. The last cost is the labor idle cost that is incurred when the operators in each station are free. This labor undertime cost is 30% of the normal labor cost.

The inventory holding cost is divided into two components. The first component is the cost of capital for holding the arriving used products in the received product inventory and work-in-process inventory in each station. This component equals 50% of the selling prices per year. This is based on the value of the units held. The other component is the inventory space costfor storing arriving used productsthat is \$0.15 per hour per sq. ft., which depends on the space occupied by the inventory. This component represents the construction cost of the inventory space that needs to be built for holding the inventory.

TABLE III
RELATED REMANUFACTURING COSTS

Raw material cost (C_C)	Laptop	\$20	per unit
	Desktop	\$5	per unit
Redistribution cost (C_R)	Laptop	\$5	per redistribution
	Desktop	\$1	per redistribution
Remanufacturing cost	Labor cost (C_L)	\$15	per hour per operator
		\$12	per hour per operator
	Set-up cost(C_S)	\$150	per time
	Batch cost (C_B)	\$50	per batch
	Idle cost (C_I)	\$4.5	per hour per operator
		\$3.6	per hour per operator
Inventory cost (C_H)	Holding cost	50% of selling price	per year
	Space cost for the received product inventory	\$0.15	per hour per sq. ft.

D. Decision Variables

To optimize this dedicated remanufacturing system, ten decision or control variables are searched for their optimality by OptQuest: (1) the capacity of inventory, (2) the buffer size of the repairing station, (3) the buffer size of the labeling station, (4) the buffer size of the packing station, (5) the number of operators in the testing station, (6) the number of operators in the repairing station, (7) the number of operators in the labeling station, (8) the number of operators in the packing station, (9) the run size of laptops, and (10) the run size of desktops. The required decision variables in each model and their bounds are shown in Table IV. The bounds of all control variables are affirmed to certify that the optimal values are within these bounds.

TABLE IV
DECISION VARIABLES AND BOUNDS OF EACH SYSTEM

System / Control variables	Existing System	First Improvement model	Second Improvement model	Bound: Lower	Bound: Upper	Unit
Inventory capacity	-	✓	✓	1	2,000	Sq. ft.
Buffer size of repairing station	✓	✓	✓	0	50	Units
Buffer size of labeling station	✓	✓	✓	0	50	Units
Buffer size of packing station	✓	✓	✓	0	50	Units
# operators in testing station	✓	✓	✓	1	50	Operators
# operators in repairing station	✓	✓	✓	1	50	Operators
# operators in labeling station	✓	✓	✓	1	50	Operators
# operators in packing station	✓	✓	✓	1	50	Operators
Run size of laptops	-	-	✓	1	250	Units

E. *Simulation Model*

The simulation model runs under non-terminating conditions with 10 replications. The simulation length of each replication is 42,000 minutes (3 months) and has another 42,000 minutes (3 months) for a warm-up period to generate a stable estimate of the steady-state results. Based on 10 replications, the 95% confidence interval of the flow times has a width of less than 5% of its mean. The simulation model runs on a PC with CPU AMD Ryzen 7 2700 3.20GHz and RAM 16.0 GB.

V. RESULTS AND DISCUSSIONS

The results are obtained from the simulation-based optimization by using the ARENA program to simulate the system (under uncertainties) and the OptQuest optimization tool to search and optimize the decision variables of the system, to maximize the total profit. The results are separated into three cases: existing system, first improvement model, and second improvement model.

A. *Case1: Existing Dedicated Remanufacturing System*

In this case, the original inventory capacity is fixed at 1,000 square feet, and there is no switching rule to switch the line between the two products. As lot-for-lot production is used, the line is switched to produce a new product when the current product is finished. This can happen quite frequently as arriving used products come randomly. However, OptQuest is used to maximize the profit of the system by determining the optimal number of operators and buffer size in each station (see Table V for the optimal settings obtained by OptQuest). For the results of the existing system, Fig. 2 shows the breakdown of the profit and costs. It shows a profit of $168,746.41, resulting from the difference between the total revenue of $2,039,762.50 and the total costs of $1,871,016.09. The redistribution cost of $11,078.10 is high since a lot of overflow units are redistributed. This is due to the limited space in the inventory capacity for new incoming used products. In addition, high set-up and batch transferring costs are a result of an inappropriate transferring batch size. In this instance, all remaining products similar to the current product in the inventory space (an entire lot of similar model) would be transferred when the current product in the line is about to be finished. As a result, there are higher batch transferring and line switching costs.

TABLE V
OPTIMAL OPERATING PARAMETERS OF THE EXISTING DEDICATED REMANUFACTURING SYSTEM

Control variables	Fixed inventory capacity (square feet)	Decision Variables: Buffer size of repairing station (units)	Buffer size of labeling station (units)	Buffer size of packing station (units)	# operators in testing station (operators)	# operators in repairing station (operators)	# operators in labeling station (operators)	# operators in packing station (operators)
Values	1,000	34	48	26	15	41	15	24

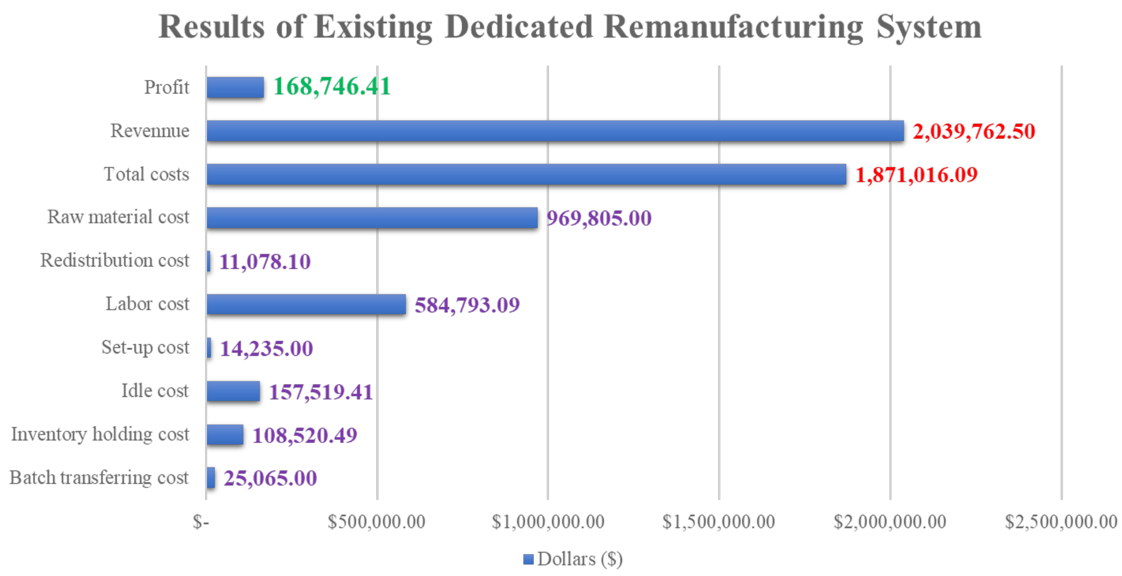

Fig. 2. Profit and cost distribution of the existing dedicated remanufacturing system

B. Case2: First Improvement Model with the Inventory Capacity

Optimal settings of the parameters in the system by OptQuest to maximize the profit are shown in Table VI. Table VII shows the costs and operating performance comparison between the existing system and the first improvement model. For a fair comparison, all models were set to have similar seeds and streams of random numbers when creating the arrival of used products. As a result, similar arrival times and the number of arriving units are created, resulting in the same raw material cost. From Table VI, it was found that the inventory capacity needs to be enlarged to 1,530 sq. ft. to accommodate the arriving batches of received products (the existing system has only 1,000 sq. ft.). This would result in a 21.28% and 66.80% reduction of the batch transferring cost and redistribution cost, respectively. This is a result of a larger inventory capacity. As a result, there would be fewer units of overflow products to be redistributed and fewer batch transferring times. However, the total revenue is higher because a higher number of units can be sent to the remanufacturing processes. From this improvement, it was found that profit can be increased by 19.67%, as compared to the existing system. However, it was also found that the average flow time in the system is much longer and the inventory cost is higher because there is more inventory at the arriving inventory area.

TABLE VI
OPTIMAL OPERATING PARAMETERS OF THE FIRST IMPROVEMENT DEDICATED REMANUFACTURING MODEL

Control variables	**Decision Variables**							
	Fixed inventory capacity (square feet)	Buffer size of repairing station (units)	Buffer size of labeling station (units)	Buffer size of packing station (units)	# operators in testing station (operators)	# operators in repairing station (operators)	# operators in labeling station (operators)	# operators in packing station (operators)
Values	1,530	42	38	47	14	39	14	23

TABLE VII
RESULTS OF THE FIRST IMPROVEMENT DEDICATED REMANUFACTURING MODEL

Profit & cost breakdown	Existing system	First improvement model	%improvement
Profit ($)	168,746.41	201,937.02	19.67%
Total revenue ($)	2,039,762.50	2,109,665.50	3.43%
Total costs ($)	1,871,016.09	1,907,728.48	-1.96%
- Raw material cost ($)	969,805.00	969,805.00	0.00%
- Redistribution cost ($)	11,078.10	3,677.70	66.80%
- Labor cost ($)	584,793.09	603,788.01	-3.25%
- Set-up cost ($)	14,235.00	11,895.00	16.44%
- Idle cost ($)	157,519.41	133,752.28	15.09%
- Inventory holding cost ($)	108,520.49	165,080.50	-52.12%
- Batch transferring cost ($)	25,065.00	19,730.00	21.28%
Operating performance			
Average part flow time in the system (minutes)	706.34	863.07	-22.19%
Average part flow time in testing station (minutes)	113.40	155.31	-36.96%
Average part flow time in repair station (minutes)	18.08	18.10	-0.12%
Average part flow time in labeling station (minutes)	6.53	6.65	-1.86%
Average part flow time in packing station (minutes)	9.82	9.75	0.69%
Number of line set-ups (times)	94.90	79.30	16.44%
Number of finished laptops (units)	36,999.00	38,217.50	3.29%
Number of finished desktops (units)	18,740.00	19,493.90	4.02%
Average inventory in the arriving inventory space (units)	412.00	541.47	-31.42%

Remarks: These results are averaged from 10 replications

C. Case3: Second Improvement Model with the Switching Rule

Table VIII shows the optimal settings of the parameters in the system. Table IX presents a cost and operating performance comparison between the existing system, the first improvement model, and the second improvement model. By simultaneously imposing the inventory capacity and run size of each product as the decision variables, the inventory cost is decreased by 17.47% from the case of the first improvement model. Even though the batch transferring cost increases by 20.73% due to a smaller inventory capacity and more transfers from the arriving inventory capacity to the production line, the average flow time has improved by 13.08%. In addition, the switching rule and appropriate run sizes help to reduce the number of line set-ups from 79.30 times in the case of the first improvement model without the switching rule to 70.00 times. This is a 26.24% reduction and significantly reduces the flow time in the testing station (77.01% reduction), which is the first station in the production line (as the entire lot would not be transferred at a time). In all, this improvement helps to increase the system's profit by 7.21% as compared to the first improvement model, or by up to 28.29% as compared to the existingsystem.

TABLE VIII
OPTIMAL OPERATING PARAMETERS OF THE SECOND IMPROVEMENT DEDICATED REMANUFACTURING MODEL

Control variables	Decision Variables							
	Fixed inventory capacity (square feet)	Buffer size of repairing station (units)	Buffer size of labeling station (units)	Buffer size of packing station (units)	# operators in testing station (operators)	# operators in repairing station (operators)	# operators in labeling station (operators)	# operators in packing station (operators)
Values	1,530	42	38	47	14	39	14	23

TABLE IX
RESULTS OF THE SECOND IMPROVEMENT DEDICATED REMANUFACTURING MODEL

Profit & cost breakdown	Existing system	First improvement model	Second improvement model	%improvement a.	%improvement b.
Profit ($)	168,746.41	201,937.02	216,487.74	7.21%	28.29%
Total revenue ($)	2,039,762.50	2,109,665.50	2,102,879.00	-0.32%	3.09%
Total costs ($)	1,871,016.09	1,907,728.48	1,886,391.26	1.12%	-0.82%
- Raw material cost ($)	969,805.00	969,805.00	969,805.00	0.00%	0.00%
- Redistribution cost ($)	11,078.10	3,677.70	4,615.60	-25.50%	58.34%
- Labor cost ($)	584,793.09	603,788.01	601,959.32	0.30%	-2.94%
- Set-up cost ($)	14,235.00	11,895.00	10,500.00	11.73%	26.24%
- Idle cost ($)	157,519.41	133,752.28	139,454.64	-4.26%	11.47%
- Inventory holding cost ($)	108,520.49	165,080.50	136,236.70	17.47%	-25.54%
- Batch transferring cost ($)	25,065.00	19,730.00	23,820.00	-20.73%	-4.97%
Operating performance					
Average part flow time in the system (minutes)	706.34	863.07	750.22	13.08%	-6.21%
Average part flow time in testing station (minutes)	113.40	155.31	35.70	77.01%	68.52%
Average part flow time in repair station (minutes)	18.08	18.10	17.88	1.24%	1.12%
Average part flow time in labeling station (minutes)	6.53	6.65	6.67	-0.29%	-2.15%
Average part flow time in packing station (minutes)	9.82	9.75	9.71	0.42%	1.10%
Number of line set-ups (times)	94.90	79.30	70.00	11.73%	26.24%
Number of finished laptops (units)	36,999.00	38,217.50	38,122.20	-0.25%	3.04%
Number of finished desktops (units)	18,740.00	19,493.90	19,369.00	-0.64%	3.36%
Average inventory in the arriving inventory space (units)	412.00	541.47	574.14	-6.03%	-39.35%

Remarks: These results are averaged from 10 replications
a. %improvement of the second improvement model as compared to the first improvement model
b. %improvement of the second improvement model as compared to the existing system

D. *Sensitivity Analysis*

For a study dealing with the profit and cost optimization, a sensitivity analysis based on different cost structures is required to confirm the conclusion that has been made. Even though there are many costs used to calculate the system's profit, not all of them have a major influence on the outcome. Therefore, we do the sensitivity analysis on four main costs, which are redistribution cost, set-up cost, inventory holding cost, and batch transferring cost. These costs are varied ±20% from their initial settings at a time, and we observe the outcomes from varying these costs. Table X presents the profits obtained from varying these costs in each model, relative to their initial values. The overall results show that the second improvement model still outperforms the other models, in terms of a higher profit, despite varying these four costs by up to ±20% from their initial values. This can confirm the appropriateness of our findings and conclusion. For instance, when the redistribution cost and set-up cost are reduced by 20%, this should favor the existing system as it has many redistribution units due to its small inventory capacity and a greater number of line set-ups. However, its profit still cannot outperform the first and second improvement models.

TABLE X
RESULTS OF ADJUSTING EACH EFFECTIVE COST FOR EACH MODEL

Effective costs		Profit ($)		
		Existing system	**First improvement model**	**Second improvement model**
± Redistribution cost	-20%	$162,052.57	$193,585.29	$220,639.19
	Initial value	$168,746.41	$201,937.02	$216,487.74
	+20%	$159,458.73	$201,987.04	$215,841.27
± Set-up cost	-20%	$180,402.29	$198,350.58	$210,759.47
	Initial value	$168,746.41	$201,937.02	$216,487.74
	+20%	$153,252.60	$194,013.04	$206,656.09
± Inventory holding cost	-20%	$192,670.35	$230,928.76	$238,784.69
	Initial value	$168,746.41	$201,937.02	$216,487.74
	+20%	$149,241.15	$162,416.73	$179,522.10
± Batch transferring cost	-20%	$177,535.81	$195,877.23	$206,093.77
	Initial value	$168,746.41	$201,937.02	$216,487.74
	+20%	$154,955.46	$188,252.47	$203,655.92

VI. CONCLUSION

The remanufacturing system has proven to help environment as well as contribute to a higher company's return. However, it is unstable and hard to control due to uncontrollable inputs. This paper purposed to explore the problems of the remanufacturing system based on a case study of a dedicated remanufacturing system. A simulation-based optimization approach was applied to this system incorporating uncertainties of part arrival and operating conditions. While, ARENA was used to simulate the system under uncertain conditions, OptQuest was used to optimize the operating parameters of the system.

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A few sequential steps of improvement have been applied to the system, starting from recommending optimal buffer size and an appropriate number of operators in each station. We also enlarged the size of arriving inventory space to accommodate more arriving used products and imposed the switching rule for setting up the production line with an appropriate run size in each model. The findings showed that adjusting one operating parameter would affect the other parameters. The final step where all improvements were applied increased the profit of the system by up to 28.29% with a shorter average part flow time and fewer line set-ups. This improvement should not be the end as this method can be applied to other parts of the system. A case study is used to demonstrate and identify possible solutions and their advantages of utilizing the simulation-based optimization approach. These findings can help decision makers to make the right decisions on the near, or possible optimal, or feasible solution in a certain situation under an uncertain environment.

For larger problems with a higher number of decision variables, this simulation-based optimization using OptQuest may need some adjustments to reduce the computation time and further improve the quality of the objective value. As the meta-heuristic algorithm cannot guarantee an optimal result, alternative algorithms such as Genetic Algorithms, Particle Swarm Optimization, Ant Colony, or hybrid optimization are worth exploring, to strive for a better solution. This can be further introduced in the model to improve its effectiveness.

REFERENCES

[1] J. W. Ho, Y. S. Huang, and C. L. Hsu, "Pricing under internal and external competition for remanufacturing firms with green consumers," *Journal of Cleaner Production,* vol. 202, pp. 150-159, Nov. 2018.

[2] J. Li, M. Gonzalez, and Y. Zhu, "A hybrid simulation optimization method for production planning of dedicated remanufacturing," *International Journal of Production Economics,* vol. 117, no. 2, pp. 286-301, Feb. 2009.

[3] R. H. Teunter and D. Vlachos, "On the necessity of a disposal option for returned items that can be remanufactured," *International Journal of Production Economics,* vol. 75, no. 3, pp. 257-266, Feb. 2002.

[4] X. Xia, K. Govindan, and Q. Zhu, "Analyzing internal barriers for automotive parts remanufacturers in China using grey-DEMATEL approach," *Journal of Cleaner Production,* vol. 87, no. 1, pp. 811-825, Jan. 2015.

[5] M. Fathi, F. Zandi, and O. Jouini, “Modeling the merging capacity for two streams of product returns in remanufacturing systems,” *Journal of Manufacturing Systems,* vol. 37, no. 1, pp. 265-276, Oct. 2015.
[6] C. D. White, E. Masanet, C. M. Rosen, and S. L. Beckman, “Product recovery with some byte: An overview of management challenges and environmental consequences in reverse manufacturing in the computer industry,” *Journal of Cleaner Production,* vol. 11, no. 1, pp. 445-458, Jun. 2003.
[7] V. Daniel and R. Guide Jr., “Production planning and control for remanufacturing: Industry practice and research needs,” *Journal of Operations Management,* vol. 18, no. 1, pp. 467-483, Jun. 2000.
[8] C. C. Fang, M. H. Lai, and Y. S. Huang, “Production planning of new and remanufacturing products in hybrid production systems,” *Computers & Industrial Engineering,* vol. 108, pp. 88-99, Jun. 2017.
[9] H. F. Wang and Y. S. Huang, “A two-stage robust programming approach to demand-driven disassembly planning for a closed-loop supply chain system,” *International Journal of Production Research,* vol. 51, no. 8, pp. 2414-2432, Apr. 2013.
[10] N. Shabanpour and M. Colledani, “Integrated workstation design and buffer allocation in disassembly systems for remanufacturing,” *Procedia CIRP,* vol. 69, pp. 921-926, Nov. 2018.
[11] J. Y. Lee, C. L. Chen, T. L. Wen el.al., “Synthesis and design of chilled water networks using mathematical optimization,” *Applied Thermal Engineering*, vol. 58, no. 1-2, pp. 638-649, Sep. 2013.
[12] N. Tahirov, P. Hasanov, and M. Y. Jaber, “Optimization of closed-loop supply chain of multi-items with returned subassemblies,” *International Journal of Production Economics,* vol. 174, pp. 1-10, Apr. 2016.
[13] K. Nuamchit and N. Chiadamrong, (2019, Jun.). Optimal inventory control policy of a hybrid manufacturing-remanufacturing system using a possibilistic linear programming approach. *International Scientific Journal of Engineering and Technology* [Online]. *3(1)*. pp. 41-59. Available: https://ph02.tci-thaijo.org/index.php/isjet/article/view/199035/
[14] D. E. Mazzuco, A. M. C. Danielli, D. L. Oliveira, et. al. (2018). A concept for simulation-based optimization in vehicle routing problems. *IFAC-Papers On Line* [Online]. *51(11)*. pp. 1720-1725. Available: https://www.sciencedirect.com/science/article/pii/S2405896318313296
[15] Y. Chu, F. You, J. M. Wassick, and A. Agarwal, “Simulation-based optimization framework for multi-echelon inventory systems under uncertainty,” *Computers and Chemical Engineering,* vol. 73, no. 2, pp. 1-16, Feb. 2015.
[16] B. Keskin, S. Melouk, and I. Meyer, “A simulation-optimization approach for integrated sourcing and inventory decisions,” *International Journal of Computers and Operations Research*, vol. 37, no. 9, pp. 1648-1661, Sep. 2010.
[17] W. Jie and L. Li, “Simulation for constrainted optimization of inventory system by using Arena and OptQuest,” in *Proc. 2008 International Conference on Computer Science and Software Engineering*, 2008, pp. 202-205.
[18] A. Sadeghi, G. Suer, R. Y. Sinaki, and D. Wilson, “Cellular manufacturing design and replenishment strategy in a capacitated supply chain system: A simulation-based analysis,” *Computers & Industrial Engineering*, vol. 141, pp. 1-22, Mar. 2020.
[19] V. D. R. Guide, M. E. Kraus, and R. Srivastava, “Scheduling policies for remanufacturing,” *International Journal of Production Economics,* vol. 48, no. 2, pp. 187-204, Jan. 1997.

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