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Research Article

Collection System of Air Conditioners Remanufacturing: Development and Optimization under Probabilistic Uncertainty

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The need for air conditioners (ACs) is increasing every year, particularly in the Kingdom of Saudi Arabia (KSA). The annual sales of ACs clearly indicated either buying new conditioning systems or replacing existing ACs. When air conditioners are replaced for any reason, a large number of used air conditioners are available, which leads to the necessity of remanufacturing these ACs for economic and environmental purposes. The current research focuses on investigating the collection system of used window ACs as a part of the reverse logistics of remanufacturing window ACs under the uncertainty of demand and production rate. To optimize the average inventory and fulfill the need of the ACs remanufacturing unit, this current research explained many operations in the collection system and their relationship to the remanufacturing unit. These objectives were investigated using a combination of simulation, mathematical, and optimization techniques. After developing the model using Arena software, the simulation model for the initial solution was run. The theoretical and mathematical concepts of inventory have been exploited to find an initial solution for the objectives under investigation. The Optquest tool was used for the simulation model of the initial solution to improve the iterative search technique. Finally, a sensitivity analysis was carried out to determine each input parameter's magnitude and individual impact on the results. The findings suggest that simulation and optimization strategies are effective in improving average inventory and lost demand. As a result, the average inventory has been reduced significantly.

1. Introduction and Literature Review

Remanufacturing of window air conditioners (ACs) consists of collection, remanufacturing, recycling, supplier, and distributor in which each of them is self-contained and has their own set of goals. As a result, each unit was assessed and upgraded separately in order to ameliorate the reverse logistics system. The literature on remanufacturing of ACs is part of a well-known topic called reverse logistics. It has been well investigated in the literature based on its potential importance in research and industry. It deals with the flow of material, knowledge, and money in the reverse direction, as shown in Figure 1. The researchers in the field of reverse logistics have investigated various aspects, such as reverse logistics design [1], barriers during implementation [2, 3] and optimization [4], and performance evaluation [5]. Furthermore, these studies use a variety of methodologies and investigational instruments, including fuzzy research [6], multiobjective optimization [7], and decision making [8].

The first agent in reverse logistics is the collection system, which refers to the process and location for collecting discarded window air conditioners for remanufacturing [10]. The remanufacturing of air conditioners involves multiple units or agencies that interact with one another. The collection system is the most significant component of the remanufacturing system that must be properly built to respond optimally to other system components, such as the remanufacturing unit. The consumption of air conditioners in the Kingdom of Saudi Arabia (KSA) increases every year, depending on the number of units sold. Because a substantial portion of these sales is for replacements, there are

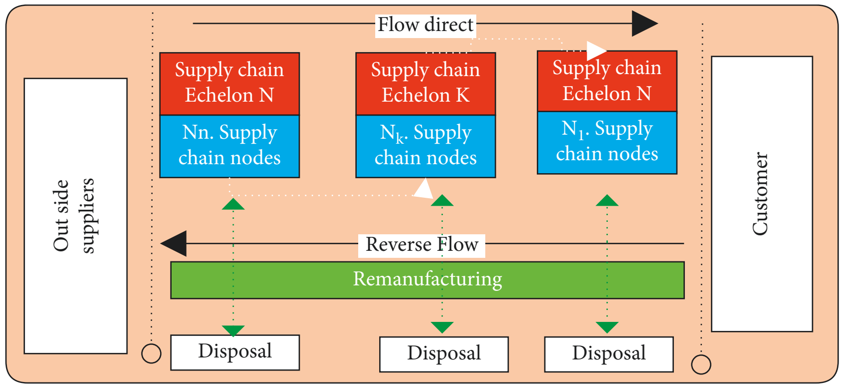


Figure 1: The supply chain conceptual model including the reverse flow of products [9].

many ACs that can be remanufactured. The remanufacturing of used ACs has a positive impact on the economy, environment, and society. Because they contain poisonous and other toxic components, used air conditioners are considered a waste of resources and are harmful to the environment.

In addition, remanufactured ACs provide a good alternative for low-income people. These facts mentioned above compel the researchers to look into the prospect of remanufacturing air conditioners at a lower cost and with higher output. The technique of remanufacturing air conditioners is still in its early stages and needs to be explored by research from various professions. Several aspects should be considered in this industry, including the behavior of used air conditioner owners, government laws, and remanufactured air conditioner market competitiveness [11–14]. The procedures of the collection system and its connections to other units, such as the remanufacturing unit, contain numerous interconnected tasks that impact one another, which can be assessed through a simulation method that provides an easy way of conducting many alternatives. The system's bottleneck can be pinpointed through simulation tools, recommending ways to improve performance. Because of various circumstances, factors, and high cost, this technique outperforms physical implementations and the possibility of modifying the real system. Furthermore, computer simulation saves time when it comes to investigating and comprehending model parameters for complicated systems [15].

The remanufacturing of ACs depends on the demands of the new ACs. As the demand for selling new ACs is increasing, the remanufacturing of products will be growing in which good strategic planning must be conducted for such an industry [16]. Researchers and industry experts can benefit from best practices in well-known industries like electronics remanufacturing [17–19] and household recycling [20]. In order to compare the application of numerous inventory rules, the literature has looked into reverse logistics inventory [9, 21]. Many research studies in the literature have investigated the various problems of reverse logistics. In this regard, Liao and Deng [1] provided a very good alternative to the traditional EOQ under the uncertainty of demand. They also published a recent paper [22] and studied the uncertainty of acquisition. It mainly focuses on the tradeoff between manufacturing and remanufacturing on the basis of profitability. Furthermore, the uncertainty of demand has been investigated with environmental impacts [23]. Also, the quality of returns [24] and market demand have been investigated [25]. However, there are still many limitations in the literature in the field of reverse logistics. Some of these limitations include the need for general studies on specific product remanufacturing and the uncertainty of production rate.

This research aims to construct and evaluate the first stage of the collection procedure in remanufacturing window air conditioners. Besides, it is also directed to studying the relationships between processes in the collection system, selecting the best parameters in the direction of performance measures, and investigating its relation to other units in the remanufacturing system. Inventory expenses and the percentage of orders filled are two of the performance indicators. The model is based on the data from one of the leading ACs manufacturers in KSA and academic experts in ACs logistics. However, the study intended to provide/propose general solutions for ACs remanufacturers. To achieve the research objectives mentioned above, industry and expert opinions have been collected and converted to a computer simulation model. After the collection, the Optquest tool optimized the model by minimizing inventory costs and the percent of lost orders. Finally, the system factors have been investigated using sensitivity analysis to specify the most influential factors affecting the system to be addressed to the stakeholders to reduce costs and save time.

2. The Proposed Methodology

There are two primary stages in the proposed methodology: simulation of the collection system and optimizing the average inventory and the lost demands, as shown in Table 1. First, the collection system will be simulated using simulation software to track the system's outputs, particularly the average inventory and lost needs. After that, decision variables like reorder point, batch size, and target stock are tweaked to optimize average inventory and lost demands. Finally, the sensitivity analysis is examined in order to determine the model's robustness.

Table 1: The proposed methodology.

Stages	Steps	Notes
Simulating the collection system	Determining the simulation limits	Riyadh city
	Explaining the processes in the collection system	Various process from receiving ACs to storing
	Implementing the simulation	Simulation software and assumptions
	Stating inputs data	Various times and quantities
	Setting up simulation experimentation	Periods, replications, and outputs
Optimizing the collection system	Specifying the objective functions	Minimizing average inventory and lost demands
	Decision variables	Reorder point, batch size, and target stock
	Optimization method	Iterative search using the Optquest tool
	Sensitivity analysis	By reducing and increasing input parameters

The goal of the research paper is to reduce both average inventory and lost demand. The optimal solution can be researched by changing the reorder point, batch size, and target stock. However, the model's demand and production are not constant. As a result, applying exact mathematical inventory models to arrive at the best option is impossible. Furthermore, without the use of computer optimization tools, scanning for the optimal choice factors is difficult. As a result, the Arena software's Optquest optimization tool is utilized to optimize the objectives. The mathematical model can be expressed as follows:

$$\text{minimize} \sum f(Q, R, T) S.T.\text{lost demand} \leq 1 \text{ where } Q \text{ is the batch size, } R - \text{reorder point, and } T \text{ is the target stock level.} \quad (1)$$

2.1. Simulating the Collection System

2.1.1. Simulation Limits. The current study model was limited to the central city of KSA (Riyadh) and included only collection system-related processes involved in receiving used ACs for remanufacturing. According to the status of the AC, it can be one of the three categories when it arrives at the collection system (good, moderate, and bad). Good air conditioners arrive in a good working condition to the collection system. On the other hand, moderate air conditioners do not operate but may be remanufactured depending on the results of examinations. The ACs proceeding for the inspection process may also reveal that the inspected AC is bad and either needs to be accepted for remanufacturing or should be placed in the waste. The simulation takes 240 hours representing 30 working days at a shift of eight (8) hours, to complete from the start time (zero) when the system is inactive and the inventory is at zero. However, the first demand arrives at time zero and is registered as lost demand.

2.1.2. The Processes of the Collection System. The demand originating from the remanufacturing unit and the collection unit are the two stages of the collection system model, as shown in Figure 2. The procedure begins with the remanufacturing unit sending the demand. When a demand request is received by the collection system, the system checks the inventory level. The request is fulfilled, and the inventory level is updated if the inventory meets the demand. Otherwise, the demand will be marked as unfulfilled. In both cases, the system will check the inventory level, and if it reaches the reorder point, it will send a request to the collection unit for ACs to be delivered until the inventory target is met.

When air conditioners arrive at the collection system, they can be in one of the three states: good, moderate, or bad. With the support of experts in the fields of conditioning, reverse logistics, and remanufacturing, the arrival rate was projected based on people's behavior in changing and selling their old air conditioners. First, the technician inspects the arriving ACs for functioning conditions, and the functional ACs are labeled as good air conditioners. Next, a skilled worker inspects those that are not working to see if the unit can be remanufactured. This process assigns the AC to one of the two categories: moderate, which means it is good for remanufacturing, or bad, which means it is difficult or expensive to remanufacture. Then, the owners of both good and moderate ACs receive their compensation, and the AC stores the collection system inventory, which is updated regularly. Finally, the system checks the inventory level once more to ensure that the inventory objective is met; otherwise, the process of obtaining ACs will stop. These regulations aim to meet the demand for the remanufacturing units without exceeding the finite capacity of the collection system inventory. Manipulation of inventory decision variables such as reorder point and batch size can help achieve this goal.

2.1.3. Simulation Implementation. The development of this research model has been finalized with the cooperation between the authors and industrial partners, which serves as a real case study for the research model. The industrial partner is one of the leading ACs manufacturing companies in Saudi Arabia. However, independent of the manufacturer, the remanufacturing method is designed for remanufacturing numerous types of window air conditioners. After designing the actual model, Arena Simulation Enterprise Suite version 14.0 was used for the implementation. It is

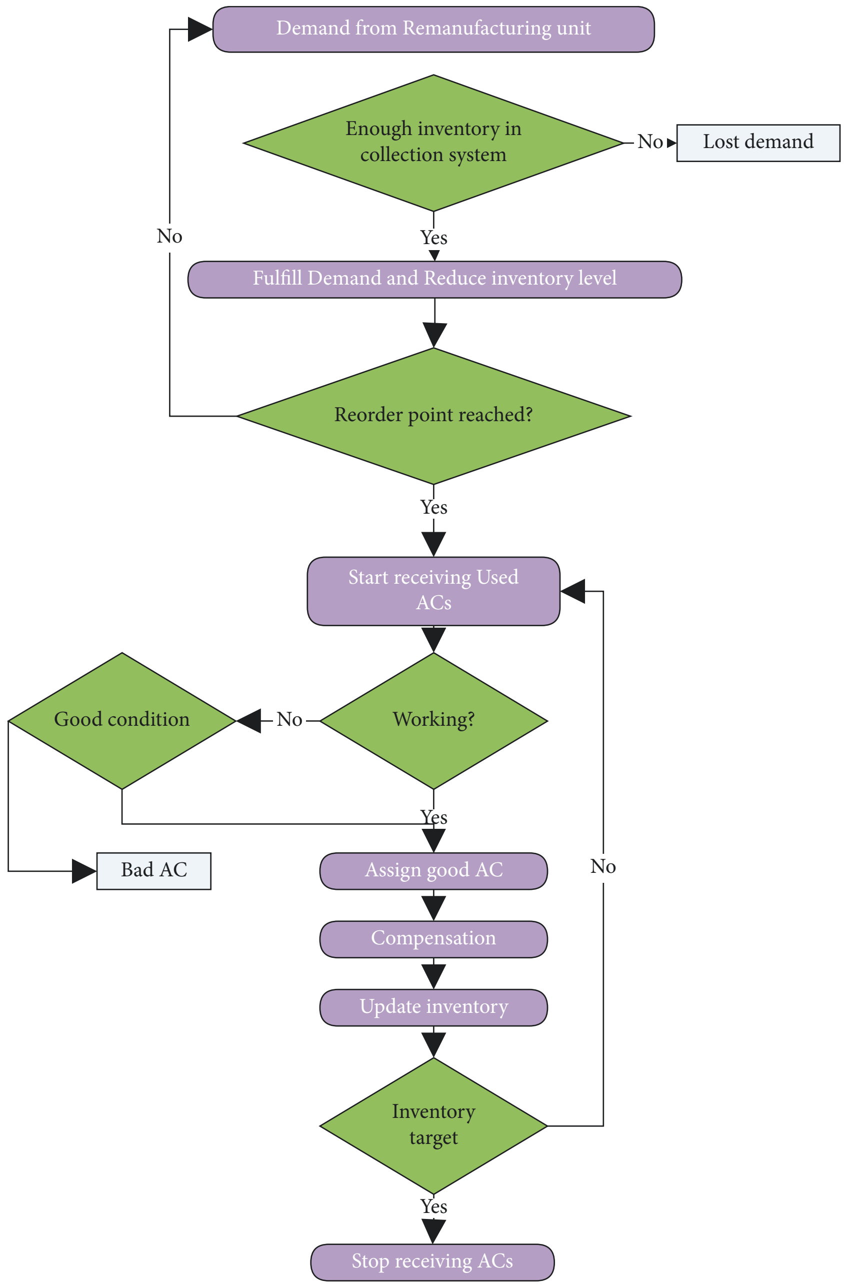


Figure 2: Activity diagram of collection system processes.

worth mentioning that any simulation model contains a number of assumptions that must be met in order for the model to be used in software to reflect the real-world system under examination. Both the authors and the industrial partners agreed with the assumptions, which include the following:

(i) The remanufacturing unit accepts only good and moderate ACs, in which bad ACs will leave the system after the inspection process without consuming any additional resources.

(ii) Regardless of the time spent in the system or any conceivable incidents that can modify their status, the ACs' status will remain as assigned for the first time.

(iii) In the collection system, both good and moderate ACs have the same resources and priority. However, in the remanufacturing unit, they use a different remanufacturing method.

(iv) The demand of the manufacturing unit is fulfilled by good and moderate ACs randomly.

(v) The collection system's inventory was considered zero at the beginning of the system simulation, which starts with the first demand from the remanufacturing unit. As a result, the first demand will be reinstated as a lost demand, allowing the collection system to begin accepting ACs.

(vi) Any required equipment in the collection system rather than ACs was assumed to be enough in all simulation periods.

(vii) The acquisition of ACs was assumed to be available all time, and there is a cost for storing each AC and it is computed in predetermined periods. In contrast, the inventory process requires no other resources.

(viii) The process of shipping and transferring demand to remanufacturing is not included in the collection system activities, and the remanufacturing unit handles it completely.

(ix) Only one type of the AC model is considered. This assumption seems reasonable given that many AC models available on the market have the same major components.

2.1.4. Data Inputs. The inputs required to drive the model include ACs parameters, processing time, and resource levels. The data input and simulation model are summarized in Table 2. Detailed literature review and a questionnaire survey were among the sources for the input parameters. The demand arrival is the demand that comes from the remanufacturing unit, and it might take one to three days. Furthermore, the quantity of each demand is not constant, and each demand follows a Poisson distribution with a mean of 100 ACs. Therefore, when the initial demand arrives, the system and the inventory level has zero value. With the support of industry and academic specialists, the processing timeframes for each procedure, demand, and different percentages were determined.

2.1.5. Simulation Experimentation. The goal of this study's model was to optimize the collection system's inventory problem. In terms of meeting demand with the least inventory level, the model is considered efficient. As a result, two key outcomes are used to assess the model's performance:

(i) The average inventory of the simulation period

(ii) The number of lost demands because of shortage inventory

These two measures are the objective of this research and require to be minimized. Table 3 shows the setup of the simulation parameters. At the end of the iterative search, the best 25 solutions are shown by the software. This solution is then used as input to run the simulation model. In addition to the given number of solutions, the Optquest optimization tool's stopping criteria are set to be manual and auto-stopped. Auto-stop takes place after searching 500 solutions without significant improvement using a 95% confidence level (CI). The simulation model was programmed to run for 240 hours or 30 working days at 8 hours per day.

3. Results and Discussion

3.1. Initial Solution of Decision Variables. As previously stated, the goal of this study is to reduce both average inventory and the number of lost demands. The reorder point (ROP), batch size, and goal stock are the decision variables that influence the two objectives (minimizing average inventory and number of lost demands). Before using Arena software's Optquest tool to optimize these objectives, we must first discover an initial solution to be utilized as boundaries for lowering the optimization time. The batch size equals

$$\sqrt{\frac{2 * \text{period demand} * \text{setup cost}}{\text{holding cost peritemper period}}} = \frac{2 * (66 * 30d * \$1)}{\$1} = 60. \tag{2}$$

This research model is a probabilistic inventory model since the demand and lead time are both variable (not constant). Therefore, as shown in Figure 3, the probabilistic inventory model is used when there is uncertainty in demand, lead time, or both.

To find an informative reorder quantity (batch size), the authors will use the economic order quantity (EOC) concept. As demand fluctuates and the lead time is not constant, the reorder point calculation should incorporate this variation. Moreover, since the cost of stockout cannot be determined, ROP will be calculated using a service level, which is derived using the following equation:

$$\text{ROP} = (\text{Average daily demand } x \text{ Average leadtime}) + Z\text{sdLT}. \tag{3}$$

Here, $Z -$ represents the service level sing the normal curve

$$\begin{aligned} \sigma\ d &= \text{Standard deviation of demand per day}, \\ \sigma LT &= \text{Standard deviation of lead time in days}. \end{aligned} \tag{4}$$

$\sigma\text{dLT} = \sqrt{(\text{Average lead time } x\sigma d^2)}$ $+ (\text{Average daily demand})^2 \sigma_{LT}{}^2$. The demand in this model depends on the demand arrival distribution and the demand amount in each demand request (arrivals). The arrival of demand follows the uniform distribution with a minimum of one and a maximum of three days. The demand amount in each arrival follows a Poisson distribution with a mean of 100 ACs (pois(100)). However, this is not the daily demand since demand arrivals follow a uniform distribution with parameters 1 and 3 days (UNIF(1.3)). The mean of demand arrivals is $1 + 3/2 = 1.5$. Every 1.5 days, there are 100 demands of ACs; therefore, the daily demand is $100/1.5 = 66.667$.

The lead time in this model depends on the time of the processes in the collection system. These processes include turn-on, inspection, and compensation processes. It is worth noting that 30 percent of ACs did not undergo any inspection since they are working and directly moved to the compensation process. However, the remaining 70 percent of ACs are inspected during the inspection process. Then, only 70 percent of inspected ACs are accepted for the compensation process. The remaining 30%, on the other hand, are rejected because of the significant damage they

Table 2: Input parameters of the simulation model.

Input parameter	Input description
Demand arrivals	Uniform distribution ($a = 1$, $b = 3$ days)
Demand quantity	Poisson distribution (*lam da* $= 100$ ACs)
Initial inventory	Zero ACs
Turn-on process	Uniform distribution ($a = 1 *$ batch size, $b = 2 *$ batch size minutes)
Expected % of working ACs	30%
Inspection process	Triangular distribution ($a = 3 *$ batch size, $c = 5 *$ batch size, $b = 7 *$ batch size minutes)
Expected % of good inspected ACs	70%
Compensation process	Uniform distribution ($a = 1 *$ batch size, $b = 2 *$ batch size minutes)
Target stock	Initial value = 215, best value = 127
Batch size	Initial value = 60, best value = 7
Reorder point	Initial value = 67, best value = 219

Table 3: Parameters of simulation run setup.

Parameter	Setting
Solution method	Iterative search using Optquest tool
# of searched solutions	2000 solutions
Replications for each solution	3 replications
Date and time stamp	Present day
Statistics collection	End of run
Warm-up period	0 minutes
Replication length	240 hours
Hours per day	8 hours
Base time units	Hours
Inputs	Defined in Table 1
Queue management	First in first out

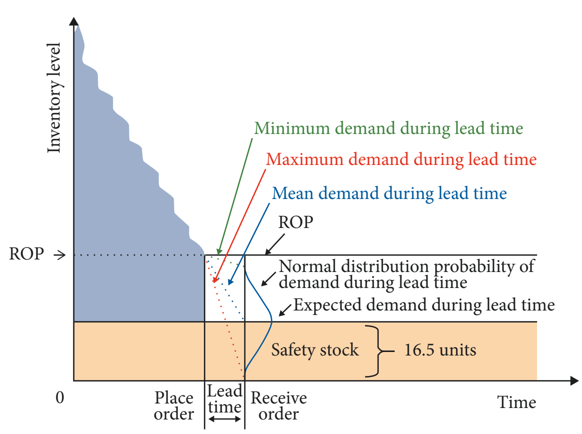


Figure 3: Probabilistic inventory model.

have sustained and the exorbitant expense of remanufacturing. The processing time in these processes is variable. For turn-on and compensation processes, it follows a uniform distribution with parameters of one and two minutes. At the same time, the processing time durations of the inspection process follow the triangular distribution with parameters of 3, 5, and 7 minutes. Considering all these time durations and percentages, the average, lower, and upper lead time durations for storing a batch of 60 ACs are 0.82, 0.48, and 0.99 days, respectively, where there are eight working hours in a day. Suppose we take the service level equal to 95%; the z-value equals 1.645. Then, the reorder point is as follows:

$$\text{ROP} = (66\,x\,0.82) + 1.64 * \sqrt{(0.82 * 370) + (66)^2 * 0.022} = 67\text{units}. \tag{5}$$

The target inventory level can be calculated by expecting the average inventory level during the run period. The average inventory level =
Total produced during the production run −
Total used during the production run = 73 ∗ 30
−66 ∗ 30 = 215. At this stage, the initial solution for the inventory in the collection system has been obtained, which is 60, 67, and 215 for batch size, reorder point, and target inventory level, respectively. This initial solution will be used in the next section to optimize the inventory level and the number of lost demands. Before running the optimization tool in simulation software, the initial solution will enter and register the values of our objectives (average inventory and number of lost demands). The average inventory value is 117, whereas the number of lost demands is 5, respectively. However, because we need to obtain 95%, this solution is not practical.

3.2. Iterative Search Optimization. The optimization tool included in Arena software called Optquest is used to optimize the inventory level and the number of lost demands. The Optquest optimization tool uses an iterative heuristic method to search for better solutions that optimize the given objective concerning a given constraint. This model aims to minimize the average inventory during the run time concerning the service level. The service level refers to the level of demand met, as measured by the lost demands. The model needs to meet 95% of demands as the CI, or the service level should be 95%. It is worth noting if the first arrival demand in this model is lost since the initial inventory is zero. As a result, the first demand will not be computed in the 5% lost demand range. There are 15 demands during the simulation run that allowed loss of one demand in addition to the first demand. Then, the objective of this model is to minimize the average inventory to not exceed the lost demand from two demands. Figure 4 shows the iterative solutions of Optquest that have been processed for 2000 runs. The best solution is gained by adjusting the batch size to 7, reorder point to 219,

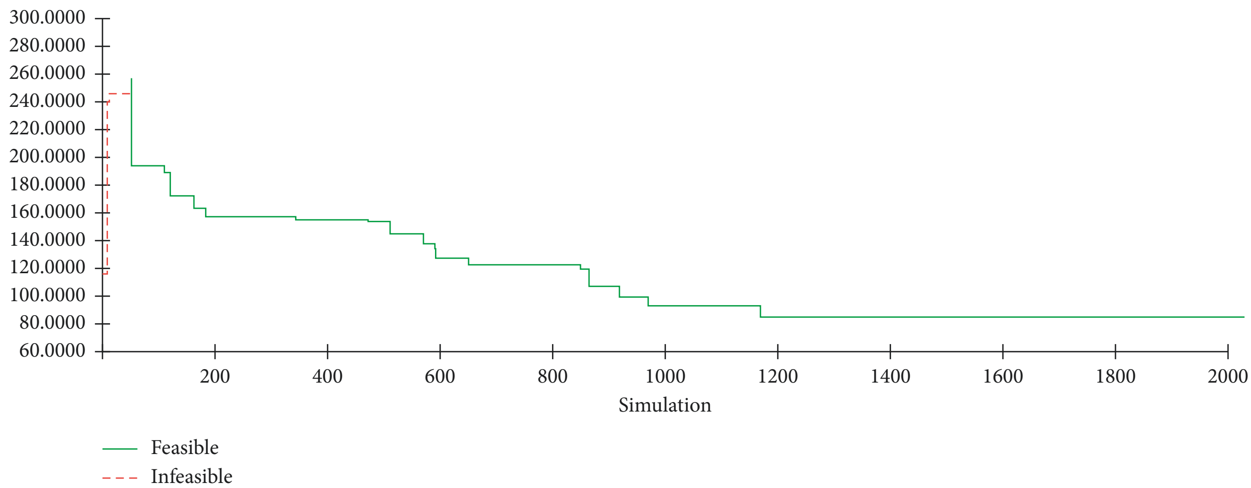


Figure 4: Solution improvement using Optquest optimization.

and target stock to 127. This solution reveals an average inventory of 84.72 units and two lost demands. The solution is obtained after 1352 runs, yet the simulation continues without any improvement until 1915 runs.

The idea behind improving the solution is to coincide the inventory level with the arrival demands. The concept of level of inventory for initial and improved solutions can be seen in Figure 5. Besides, Figure 5(a) shows the inventory level and demand of the initial solution along the simulation run. The inventory level itself, as well as the demand and inventory level, has high variations. However, in the optimum solution offered by the Optquest optimization program, this variance has been avoided, as shown in Figure 5(b). As a result, the inventory level variance has been decreased from a maximum of 270 units in the original/initial solution to roughly 130 units in the modified/improved solution.

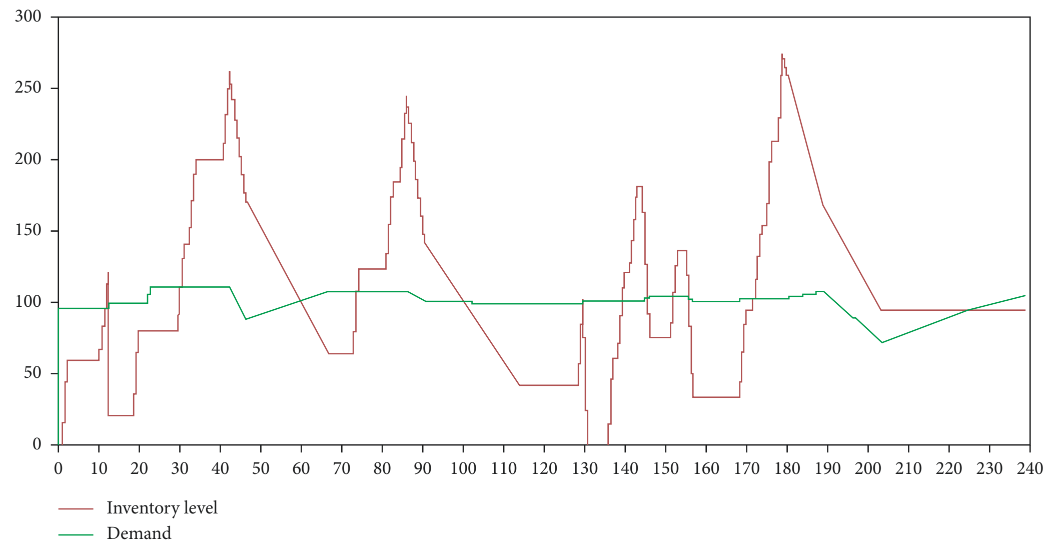
3.3. Sensitivity Analysis. In this study, sensitivity analysis was used to assess the size effect of each input parameter on the outputs under consideration (average inventory and lost demand). The simulation model can be better understood by changing the input parameters. The sensitivity analysis illustrates how much changing parameters affect the model. This extent can provide an informative guide on the robustness of the model. Consequently, these changes can be used to predict the estimation of any value of the inputs.

There are many sensitivity analysis methods, which depend on the study objective [26]. In this research, one of the most popular methods has been used to conduct sensitivity analysis. This method increases and decreases the input parameters by a constant percent one input parameter at a time and records the changes in output. Based on the literature review, the current study chose to fix 20% for both increasing and decreasing changes [15, 27, 28]. The changing process was conducted for one parameter at a time to investigate the initial effect of each parameter on output. The results of sensitivity analysis on average inventory are shown in Figure 6.

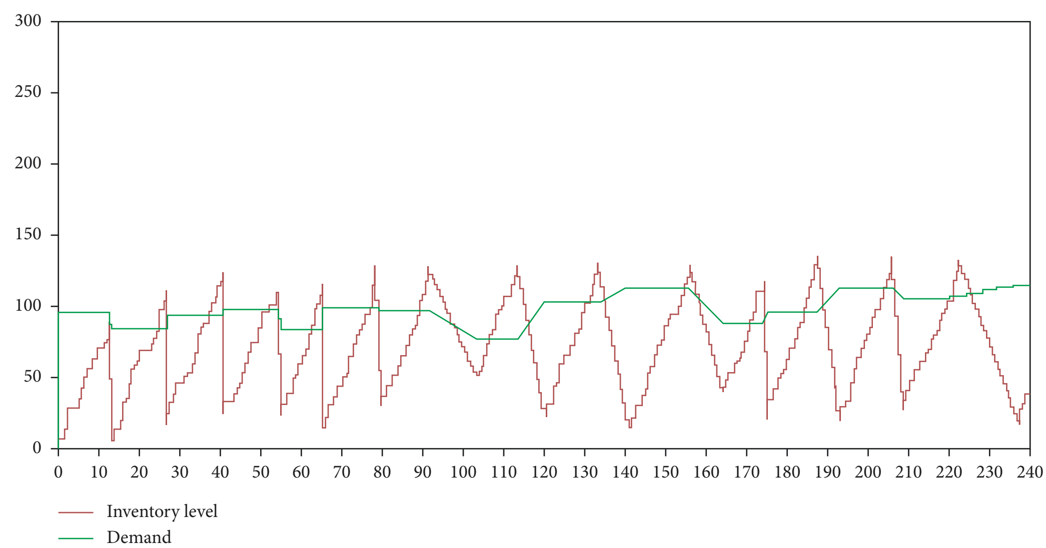
The effect of reducing/decreasing input parameters on the outcomes can be classified into large, medium, and small effects depending on the percentage of change on the outcome when reducing or increasing the corresponding parameter by 20%. For example, Figure 6 shows that the large magnitude of change in average inventory has been induced by increasing the demand quantity, which reveals an increase in average inventory by 20%. However, increasing or decreasing the reorder point does not affect the average inventory.

Furthermore, changes in input parameters have had a greater impact on the number of lost customers than on average inventory, as shown in Figure 7. Therefore, changing the demand quantity is the most influential input parameter of the lost demands. Increasing the amount of demand amount by 20% resulted in a 300% increase in lost demand. It is worth noting that the model outputs are very sensitive to the change in demand quantity. Therefore, further studies in the near future are needed for the investigation of these parameters. However, lowering the majority of the input parameters leads to a significant increase in lost demand. The decrease in target stock, compensation processing time, and the percentages of good ACs demonstrate this. In general, decreasing the input parameters is more influential than increasing. It is worth noting that the changing of reorder points does not affect the lost demand.

3.4. Managerial Insights. The ACs remanufacturing in Saudi Arabia needs a lot of effort to be established among people and industry. It is a very promising sector, and many international research studies have been conducted to solve various issues in this field. The starting point of ACs remanufacturing is the collection system, in which ACs are received, inspected, and stored. The quality of received ACs is almost suitable for remanufacturing, and further inspection is needed. As the market is considered currently full of used ACs, the unit worth of received used ACs is related to the demand of the remanufacturing unit, which is constrained by the remanufacturing capacity and market demand. The collection system is



(a)



(b)

FIGURE 5: Level of inventory and demand for initial and improved solutions.

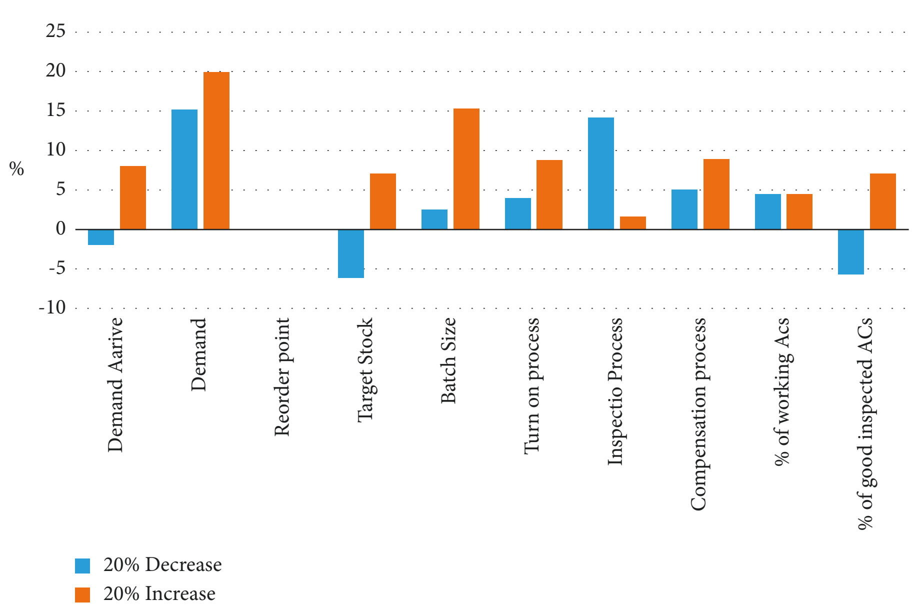


FIGURE 6: Percentages of changes in inventory levels.

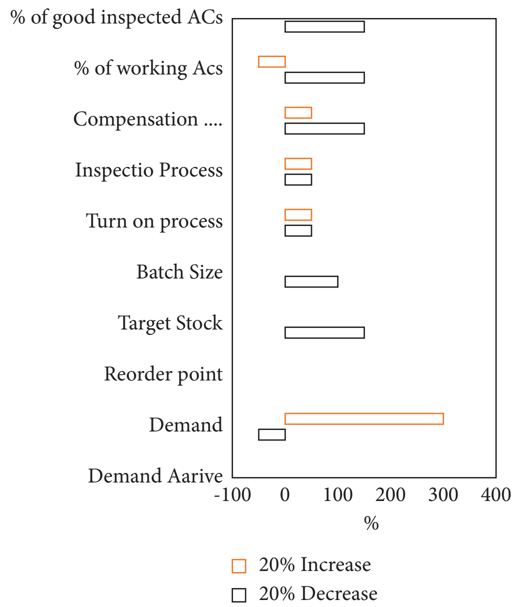


Figure 7: Percentages of changes in lost demand.

supposed to fulfil the demand of remanufacturing units along with maintaining a reasonable average inventory. The more the average inventory in the collection system, the more the expenses. To reduce the cost of the inventory, the batch size should be chosen by an appropriate method. Furthermore, the greater the batch size, the greater the average inventory, which results in great costs. Also, the reorder point plays an important role in inventory cost. On the contrary, the demand should be met to increase the service level and this will become true with more investigation of the demand curve. The presented research introduces a practical solution to these issues.

4. Conclusion

The current study investigated the collection system in ACs remanufacturing. The research was based on an actual case study from one of Saudi Arabia's largest air conditioner manufacturers. With the support of industry and academic specialists, a simulation model for the collection system was developed to optimize average inventory and lost demand. The simulation model has provided a great opportunity to improve the performance of the collection system. It is a better option because the simulation model allows for more flexibility in altering parameters and recognizing changes. Furthermore, using the Optquest optimization tool has dramatically improved the average inventory and the number of lost demands. It offers a variety of alternate ways for improving the collection system's performance. Moreover, the sensitivity analysis has provided several hints about the most influential input parameters and the most sensitive outcome to modifications, which has backed up the findings of this study.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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