

Production and Remanufacturing of Returned Products in Supply Chain using Modified Genetic Algorithm

Siva Prasad Darla, C. D. Naiju, K. Annamalai, and Y. Upendra Sravan

Abstract—In recent years, environment regulation forcing manufactures to consider recovery activity of end-of- life products and/or return products for refurbishing, recycling, remanufacturing/repair and disposal in supply chain management. In this paper, a mathematical model is formulated for single product production-inventory system considering remanufacturing/reuse of return products and rate of return products follows a demand like function, dependent on purchasing price and acceptance quality level. It is useful in decision making to determine whether to go for remanufacturing or disposal of returned products along with newly produced products to satisfy a stationary demand. In addition, a modified genetic algorithm approach is proposed, inspired by particle swarm optimization method. Numerical analysis of the case study is carried out to validate the model.

Keywords—Genetic Algorithm, Particle Swarm Optimization, Production, Remanufacturing.

I. INTRODUCTION

WIDE competition in the global markets, shorter product life cycles, and higher customer expectations with respect to product capability, reliability, delivery lead times, flexibility, and service led all business firms to focus on their supply chains. Supply chain management (SCM) is the term used to describe the management of the flow of materials, information, and funds across the entire supply chain, from suppliers to component producers to final assemblers to distribution (warehouses and retailers), and ultimately to the consumer. In fact, it often includes after-sales service and returns or recycling. Effective management of suppliers can reduce transaction costs and promote recycling and reuse of raw materials. Also, the production of waste and hazardous substances can be cut, preventing corporations from being fined as a result of violating environmental regulations.

Consequently, the relevant handling and operational cost involved can be further reduced and, in the mean time, the efficiency of using resources can be enhanced. In this case other than the basic elements of a supply chain, the remanufacturing facility and inventory for returned items are considered. The used up items from the customers travel to the inventory of returned items once they are bought back from customers. After being judged on the basis of the purchasing price and quality some items travel to remanufacturing shop while some are disposed off. The items that are remanufactured again move to the inventory of the serviceable stock and are hence resupplied to the market. It usually comprises those activities related to the disposal and sale of excess stock, including recovery and recycling opportunities.

Inventory management of produced, remanufactured/ repaired and returned items has been receiving increasing attention in recent years [1]. In a study on supply chain flexibility is widely seen as one major response to the increasing uncertainty and competition in the marketplace [2]. According to study using relatively simple and widely used models, the paper illustrates how carbon emission concerns could be integrated into operational decision-making with regard to procurement, production, and inventory management [3]. The drivers of environmentally friendly practices in the supply chains of public and private sector organizations, and the barriers these organizations face in implementing GSCM practices [4]. In another study on manufacturing operations have a major contribution to environmental degradation at various stages in the product lifecycle, from resource extraction to manufacturing use, reuse, recycling and disposal [5]. The proposed algorithm is inspired by the particle swarm optimization technique [6]. A group (swarm) of virtual particles is moving in discrete intervals through the search space. Particles represent solution instances in the search space. Each particle keeps track of the best solution (location) it encountered in its path (pbest, particle's best) and the best location encountered by all particles (gbest, global best). The next move of each particle is controlled by a velocity vector that is influenced by both pbest and gbest. Kennedy and Spears have concluded through rigorous experimentation that PSO is able to accomplish the same goal as GA optimization in a new and a faster way [7].

Siva Prasad Darla is Assistant Professor(SG) in School of Mechanical and Building Sciences at VIT University, Vellore, 632014, India (Phone: 0416 220 2136; Fax: 0416 22430 92; e-mail: sivaprasaddarla@vit.ac.in).

Dr. C.D. Naiju is Associate Professor in School of Mechanical and Building Sciences at VIT University, Vellore, 632014, India (Phone: 0416 220 2136; Fax: 0416 22430 92; e-mail: naijud@gmail.com).

Dr. K. Annamalai is Professor in School of Mechanical and Building Sciences at VIT University, Vellore, 632014, India (Phone: 0416 220 2136; Fax: 0416 22430 92; e-mail: kannamalai@vit.ac.in).

Y. Upendra Sravan is student of B.Tech Mechanical Engineering at VIT University, Vellore, India (e-mail: upendra.sravan@gmail.com).

II. METHODOLOGY

There is growing consensus that carbon emissions (emissions from carbon dioxide and other greenhouse gases) are a leading cause of global warming [8]. Governments are under growing pressure to enact legislation to curb the amount of these emissions. Firms worldwide, responding to the threat of such legislation or to concerns raised by their own consumers, are undertaking initiatives to reduce their carbon footprint. In order to help such firms reduce the emission from waste, our project formulates the return rate of the used item as a demand like function of purchasing price and accepted quality level of returns. Here, a model is developed considering production, remanufacture, waste -disposal and EPQ model where a manufacturer serves a stationary demand by producing new items of a product as well as by remanufacturing collected used and returned items. The model developed will help in decision making in determining whether to go for remanufacturing or disposal by calculating the remanufacturing cost which includes the cost involved in collecting the used items to bringing them in the market. Based on our calculations we will be able to decide whether a firm should opt for remanufacturing of a certain item or go for its disposal taking into account the condition that once the product is used its disposal is the sole responsibility of the company to avoid environmental pollution and thereby reduce waste.

A. Mathematical Formulation

Cost of raw materials required to produce a single new unit of the product is denoted by C_n , where the monetary value of purchasing price for a returned item is $P_M = p \times C_n$. Mathematical model developed assumes a single production cycle and a single remanufacturing cycle per interval T . Return rate of used items follows a demand-like function dependent on two decision variables which are the purchasing price, P , and acceptance quality level, q , for returned items. Other notations used in this formulation are given in the Appendix I.

Market demand D is satisfied from the serviceable stock, which is a collection of newly produced and remanufactured item which are represented in fig. 1 Over an interval of length T , $R(P, q) \times T$ (or RT for simplicity) used/returned units are collected in the returned stock facility, where $0 < R/D < 1$, and $D > 0$. In this facility, activities such as disassembly and sorting are carried out. The waste disposal amount of the returned items is decided once the acceptance quality level is determined, i.e., disposal increases as the acceptance quality level decreases and vice-versa, with the number of used / returned items disposed per interval is $(1 - q)RT$. The remaining collected used/returned units, qRT , are transferred to the remanufacturing facility in the first shop. The term C_r here represents the cost to repair one unit (which includes cost components such as labour, energy, machinery, etc.) excluding the cost to purchase a used item $P_M = p \times C_n$. We assume that remanufactured used/returned items are considered as-good-as new and are part of the serviceable stock. The remaining serviceable stock, $(D - Rq)T$, is replenished by newly produced

items, where DT represents the total demand in an interval of length T .

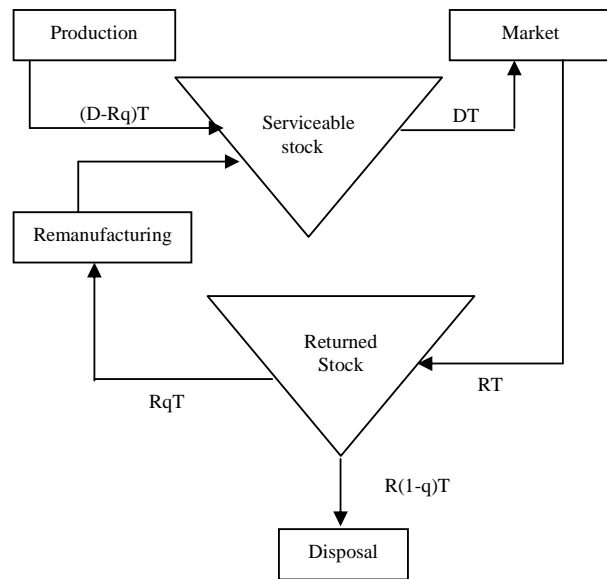


Fig. 1 Material flow in an interval of Length T

Note that the case when $(R > 0$ and $q = 0)$ is technologically infeasible since it considers that all the returned/used items are non-remanufactured and would be disposed. Although this case is valid mathematically, it is costly and therefore never optimal. On the other extreme, $q=1$ means that a returned/used item must be of an identical quality to that of a newly produced one, for example, returns during trial periods or returns due to obsolete technology. Here, the return rate of used/returned items, $R=R(P, q)$, is a portion of the demand rate D , i.e., $(0 < R(P, q)/D < 1)$, where this portion is dependent on the purchasing price (P) and its corresponding level of acceptable quality (q) of returns. The price factor of the demand function is $f_p = (1 - ae^{-\theta P})$, where $0 < a < 1$ and > 1 are parameters. This price factor models the behavior of returns for a fixed quality level. The return rate of used/returned items (demand of the reverse flow) is modelled as a function of price and quality factors f_p and f_q , and is expressed as $R = R(P, q) = D(1 - ae^{-\theta P})be^{-\theta q}$. There is one repair cycle of length T_R and one production cycle of length T_P in the time interval T , where $T = T_R + T_P$. The inventory of serviceable stock builds up at a rate of $(1/\gamma - 1)D$ units per unit of time with remanufacturing ceases when an inventory level of $I_{R,1} = (1 - \gamma)DT_R$ is attained. The production cycle commences once $I_{R,1}$ units are depleted. Similarly, the inventory of newly produced items builds at a rate of $(1/\beta - 1)D$ units per unit of time with production ceasing when an inventory level of $I_{P,1} = (1 - \beta)DT_P$ is attained. Once $I_{P,1}$ units are depleted, a new interval of length T is initiated.

A remanufacturing cycle commences once the inventory level of the returned stock reaches $I_{r1} = qRT(1 - qR\gamma/D)$, which depletes at a rate of $(qR - D/\gamma)$. By the end of a remanufacturing

cycle, I_r , 1 units would have been depleted, and a new collection cycle of used/returned items commences building up inventory at a rate of qR . It is assumed that the screening and sorting of collected used/returned items occur prior to storage, and terms not conforming to quality standards are disposed, totaling $(1-q)RT$ units. The total inventory holding cost per unit of time is given as:

$$H_{T,1} = (H_p + H_R + H_r)/T = TD\psi(\lambda/2)$$

$S = S_r + S_p$, where S is the total setup cost and S_r and S_p are the remanufacturing and production setup costs, respectively. The cost per unit of time function is given as:

$C(\lambda, T) = S/T + TD\psi(\lambda/2)$. The optimal remanufacturing and production cycle times are given respectively as:

$$T_R^* = \lambda \quad T^* = \lambda \sqrt{2S/D\psi(\lambda)}$$

$$T_P^* = (1-\lambda)T^* = (1-\lambda)\sqrt{2S/D\psi(\lambda)}$$

The overall costs are determined. The total cost per unit of time is the sum of the following unit time costs:

Setup cost per unit time: $(S_r + S_p)/T = S/T$

Holding costs per unit of time: $TD\psi\lambda/2$

Disposal costs per unit of time: $(1-q)RC_w$

Remanufacturing costs per unit time: qRC_r

Production costs per unit time: $(D-qR)C_p$

Purchasing costs per unit time: $RPC_n + (D-Rq)C_n$

Objective Function

Total cost per unit of time is expressed as:

$$C(p, q) = \sqrt{2SD} \psi(\lambda) + R[q(C_r - C_w - C_p - C_n) + C_w + PC_n] + D(C_p + C_n)$$

Subject to:

$$0 < \gamma < 1$$

$$0 < \beta < 1$$

$$0 < \lambda < 1$$

$$0 < R/D < 1, \text{ and } D > 0$$

$$0 < a < 1 \text{ and } \theta > 1$$

$$0 < b < 1 \text{ and } \Phi > 1$$

$$df_p/dp > 0 \text{ \& } df_p^2/dp^2 < 0, \text{ for every } p > 0$$

$$df_q/dq < 0 \text{ \& } df_q^2/dq^2 < 0, \text{ for every } q > 0$$

III. PARTICLE SWARM-BASED GENETIC ALGORITHM

Conceptually, particle swarm optimization technique seems to lie somewhere between genetic algorithms and evolutionary programming. It is highly dependent on stochastic processes, like evolutionary programming. The adjustments toward pbest (local best) and gbest (global best) by the particle swarm optimizer are conceptually similar to the crossover operation utilized by genetic algorithm. It uses the concept of fitness, as do evolutionary computation paradigms. In this proposed approach, the chromosomes in the initial genetic algorithm population are treated as particles in a swarm and crossover operator of GA is done in two steps. In the first step, a particle is crossing with its local best and one of new child particle is crossing with its (parent particle) global best. Mutation operator of GA is not considered in this proposed approach.

Initial population is generated randomly. Evaluation and selection process aims to associate each individual with a fitness value so that it can reflect the goodness of fit for an individual. In this proposed approach, the objective function has been taken as fitness function. Two parents are selected from the population by the binary tournament selection

mechanism in every generation. The crossover is done to explore new solution space and the crossover operator corresponds to the exchanging parts of the strings between selected parents. In this proposed algorithm, new generation is created by crossing each particle (here the chromosome is treated as the particle in a swarm) with its local best solution and the global best solution. In PSO, each solution is adjusted based on the best chromosome in its search path through the generations (pbest) and the best chromosome generated up to that point (gbest). A chromosome is first crossed with pbest resulting in two children of that one is chosen randomly. The chosen chromosome is then crossed with gbest using the same operator. Again, one of the resulting two children is chosen randomly and copied to the new generation. Therefore, the outcome of a crossover operator assumes a location in the search space in the average space that includes the parent particle, the best solution in its search path and the best solution found over the whole population. Procedure of the proposed Particle Swarm-based Genetic Algorithm and overall pseudo-code procedure for solving the problem is outlined in Appendix II.

IV. RESULTS AND DISCUSSIONS

The Case Study which is used to validate the proposed method has been taken from [1]. In the numerical example considered, $D=1000$ Units, $h_s=1.6$ \$, $h_r=1.2$ \$, $c=0.3$, $b=0.6$, $S_p=2400$ \$, $S_r=1600$ \$, $C_r=1.2$ \$, $C_w=0.1$ \$, $C_p=2$ \$, $C_n=5$ \$, $\gamma=0.3$, $\beta=0.6$, $\beta_1=0.0272$ and $\beta_2=0.7898$. Eight pairs of chromosomes i.e. eight different values of $p(0.25, 0.15, 0.23, 0.29, 0.31, 0.31, 0.29, 0.27)$ and $q(0.68, 0.64, 0.63, 0.67, 0.60, 0.79, 0.76, 0.69)$ have been taken in order to generate the initial population. The output generated by solving the mathematical model using the above mentioned values is as shown in Table I.

TABLE I
OPTIMIZED COST MATRIX

p	q	Cost (\$)
0.153808	0.789184	169.4765
0.023632	0.664538	171.7775
0.150267	0.664538	172.3788
0.027173	0.789184	168.8751
0.023632	0.664538	171.7775
0.150000	0.907010	168.8738
0.123437	0.907010	169.4963
0.150000	0.664538	166.0121

Solving the above mentioned mathematical model, a mixed production and remanufacturing/recycling policy has the lowest cost of 166.0121\$ when compared to the cost of a pure production system which comes out to be 190\$. The cost 166.0121\$ of a mixed production and remanufacturing strategy is attained when $p = 0.15$ and $q = 0.664538$. A mixed strategy was found to be optimum as some of the returned items to be remanufactured/repared are good quality items ($q = 0.664538$ or more) that are purchased at a low price (Purchasing Price= $pxC_n = 0.15 \times 5 = 0.75$). Genetic Algorithm has been used in order to solve the above mathematical problem. The solution obtained here in terms $p=0.15$ and

$q=0.664538$ is accurate when compared to that obtained in [1] where the values are $p=0.146$ and $q=0.829$. The coding for the problem has been done using the C language.

V. CONCLUSIONS

This paper extended upon the production, remanufacturing/repair and waste disposal model by assuming a return rate of used items that follows a demand-like function of purchasing price and acceptance quality level of returns. A mathematical model was developed. The Model assumes a single remanufacturing cycle and a single production cycle and it also assumes that it is the responsibility of the company from the making of the product to the disposal of the product. An attempt was made to solve the problem using particle swarm-based genetic algorithm and in which crossing each particle (chromosome) with its local best solution and the global best solution in genetic algorithm. Numerical results showed that when considering the return rate of used items to be dependent on the purchasing price and acceptance quality level of these returns, a pure (bang–bang) policy of either no waste disposal (total repair) or no repair (total waste disposal) is not optimal. Results showed that a mixed (production + remanufacturing) strategy is optimal, when compared to either a pure strategy recycling (Pure Remanufacturing) or a pure strategy production. The model can be further extended to multiple remanufacturing and production units as scope for future work.

APPENDIX I

D/γ remanufacturing rate

D/β production rate

$\Lambda=qR/D$.the ratio of repairable items to total demand..

D demand rate (units per unit of time)

R proportion of demand which is returned to the system either for remanufacturing or disposal

p the percentage of the cost of raw materials required to produce new items.

q the quality level representing the percentage of useful parts in remanufactured items

Price factor of the demand function is $f_p = (1 - ae^{-\theta p})$ ($0 < a < 1$ and $\theta > 1$)

Return rate of used/returned items (demand of the reverse flow) is modelled as a function of price and quality factors f_p and f_q

S_r remanufacturing setup cost

S_p production setup cost

h_s holding cost per unit per unit of time for serviceable (new and remanufactured) stock

h_r holding cost per unit per unit of time for returned stock

C_n cost of raw materials required to produce a newly produced unit, note that pxC_n is the purchasing price for a single returned item

C_r remanufacturing cost per unit for qRT units

C_p production cost per unit for $(D - qR) T$ units

C_w waste disposal cost per unit for $(1 - q) RT$ units

T length of the production and remanufacturing cycles

APPENDIX II

Input: Data, Parameters

Output: best solution

Begin

$k \leftarrow 0$;

initialize the population $P(k)$;

evaluate $P(k)$;

while not (termination condition) do select P_1 and P_2 by binary tournament from $P(k)$; apply crossover to P_1 and P_2 using PSO

For each chromosome p_i in $P(k)$

$pbest_i = p_i$

End

Denote the best chromosome in P as $gbest$

Repeat over all generations while termination is not reached

For all chromosomes p_i in $P(k)$

$c =$ outcome of crossover between p_i and $pbest_i$

$p_i =$ outcome of crossover between c and $gbest_i$

If p_i is better than $pbest_i$

$pbest_i = p_i$

End if

If $gbest$ is better than $pbest_i$

$gbest = p_i$

End if

End for

End repeat

Evaluate p_i

Update $P(k)$ by deleting the worst solution and adding the p_i

End

Output best solution

End

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