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A Genetic Algorithm Procedure for Optimizing Supply Chain under Quality Measures

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Abstract: In this study, we study a model for computing the Cost of Quality (CoQ) across a single-product three-echelon serial Supply Chain (SC). The proposed model deals with the impact of various parameters such as inspection error rate, fraction defective at suppliers and rework rate on the CoQ function as well as the overall quality level and the effect that these internal variables has on the CoQ categories according to the PAF classification. A Genetic Algorithm (GA) based method was developed to optimize the model for determining the optimal CoQ point that reduces costs for the whole supply chain while maintaining an overall quality level QL. Results obtained from Genetic algorithms method are illustrated with numerical examples to highlight the use of these parameters on SC and provide an aid for decision makers to select reliable suppliers and retailers from among many and manage the cost of quality across the logistic route.

Key words: Cost of quality, genetic algorithm, mathematical modelisation, supply chain, supply chain management, illutrated

INTRODUCTION

In the present business environment where quality is a crucial competitive factor, providing high quality products or services is becoming a goal of all supply chains. Measuring the Cost of Quality (CoQ) in the Supply Chain (SC) context is considered as a key performance measurement tool to examine SC performance in monetary terms. The CoQ approach gives a way to reconcile two organizations objectives which are conflicting: maximizing quality and minimizing cost and then to have one objective: the cost of quality minimization.

Based on the literature, Juran (1951) and Feignebaum (1957) were the first researchers who demonstrated the necessity of CoQ measurement. Since, then many researchers proposed quality cost models, methods and techniques, to estimate the CoQ into the SC. Schiffauerova and Thomson (2006) presented a litterature review on CoQ Models. Their work classifies CoQ Models into four groups of generic models. These are: P-A-F or Crosby's Model, opportunity cost models, process cost models and ABC (Activity Based Costing) Models. They concluded that the classical P-A-F approach is the most commonly model implemented in practice where prevention costs are the costs associated with any activity to avoid poor quality in products and services, appraisal costs are the costs engaged to ensure the conformance of products and services to predefined specifications, internal failure costs are the costs with any activity to avoid poor quality in products and services, appraisal costs are the costs engaged to ensure the conformance of products and services to predefined specifications, internal failure costs are costs resulting from the nonconformance of product and service to the predefined specification before delivery or shipment of the product or service to the customer and external failure costs are costs of nonconformance to the predefined specification after the product or service has been delivered to the customer (Dale and Plunkett, 1995). According to Srivastava (208) who gives the first step towards estimating CoQ in a Supply Chain (SC), COQ is considered as the sum of the losses incurred across a supply chain to prevent poor quality, to ensure and evaluate that the quality requirements are being met and any other costs due to poor quality. Ant Colony Optimization (ACO), Tabu Search method (TS), etc. As observed by Altiparmak *et al*. (2006) in a Supply Chain Network (SCN), managers need to make strategic decisions that are viable for the business to reduce costs and maintain profit margins while the quality is kept at pre-specified level, through a multi objective optimization of Supply Chain Network Design (SCND) (Douiri *et al*., 2016). Several studies have been conducted to optimize SCND problems and there has been a growing interest of using evolutionary algorithms to solve these problems such as Genetic Algoritms (GA), Simulated Annealing (SA), GA is one of the well known evolutionary

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algorithms for its easy concept, the effectiveness of this algorithm was tested for various real life problems and is found to be very effective. Many comparisons were set up by researchers between GA and other methods; Seyed Chandrasekaran *et al*. proposed a GA based approach to optimize supply chain network by reducing operating costs. He considered a four echelon system composed by suppliers, plants, distribution centers and retailers. The GA parameters are set with the following values where sample size = 20, crossover = 0.2, mutation = 0.02 and number of generations = 50. The software used: MATLAB 7.5. The experimental results showed the effectiveness of GA to provide an optimal solution within few minutes while running on a standard PC. Ramezani *et al*. (2013) employed GA technique to optimize a multiple products and multiple suppliers supply chain model. The objective function consists on maximizing the total profit for the whole supply chain, in order to determine the products to order, the quantities, the suppliers and the periods to order. The results obtained were compared (global best satisfactory) with lingo results. The GA method gives more solutions with higher level information. Altiparmak *et al*. (2006) suggested a solution procedure based on GA to solve supply chain network design problem. The researchers presented a generalized mathematical programming model as a multi-objective mixed-integer non-linear programming model to optimize three objective functions: minimizing the total cost, maximizing the service level and maximizing the capacity utilization balance. Castello-Villar *et al*. (2014) designed and optimized a capacitated supply chain network including quality measures; the researcher developed a Genetic algorithm to solve the model so that firms could improve their profitability and quality simultaneously. Farahani and Elahipanah (2008) developed a genetic algorithm to optimize the total cost and service level in a supply chain. Lin *et al*. (2007) compared flexible supply chains and traditional supply chains with a hybrid genetic algorithm and mentioned advantages of flexible ones. Also, several studies have been developed about optimization SC using GA by different researchers. Gen and Syarif (2005) considered the total cost as an objective function in their supply chain network design, the problem was solved by a Hybrid Genetic algorithm. Sourirajan *et al*. (2009) developed a multi objective stochastic programming approach. The objective function is to minimize safety stock costs and to locate distribution centers in the network. They proposed a solution method based on genetic algorithms to solve the model. GA performs very well in terms of both quality of solutions obtained and computational time. In this study which is basically inspired by Ittner (1996) and Castillo-Villar *et al*. (2012), we will present a mathematical model in order to forecast quality costs in three echelon manufacturing supply chain. Model utilizes COQ as a performance measure of all of the entities within supply chain and uses GA as solution procedure. Our proposed GA optimization depends on various internal parameters such as fraction defective, error rate inspection and rework rate.

MATERIALS AND METHODS

Problem description: In this study, we seek to determine the required fraction defective at manufacturing and error rate at inspection to attain the minimum total quality costs as well as meeting a required quality level of customer. We consider a supply chain consisting of three tiers namely suppliers, manufacturers and retailers. The model computes the good and defective units at each stage of the SC as shown in Fig. 1, in order to select one supplier among a set of suppliers and likewise for plants and retailers.

Notations

Sets:

- I = Set of suppliers (i = 1, ..., I)
- J = Set of manufacturers (j = 1, ..., J)
- K = Set of retailers (k = 1, ..., K)

The CoQ parameters:

- W = No. of components
- Y_{si} = Fraction defective at supplier i
- Y_{rk} = Fraction defective at retailer k
- Dem = Customer Demand
- Af = Fixed costs for prevention activities
- Av = Variable costs for prevention activities
- Bf = Fixed costs of inspection
- Bv = Variable costs of inspection
- Cf = Fixed internal failure costs
- Cs = Loss due to failure of purchased components
- Cm = Direct manufacturing cost per rework element
- Cr = Rework cost per item
- Φ = Rework rate
- C_{EF} = Cost per defective item repaired or replaced
- K = Coefficient of Taguchi loss function
- P1 = Price per sold item
- P2 = Price per 'sold as defective' item

Decision variables: Decision variables are the variable which could vary during the time interval and could have a critical impact on the objective function, these variables change if the process characteristics change. The model decision variables are defined as follows:

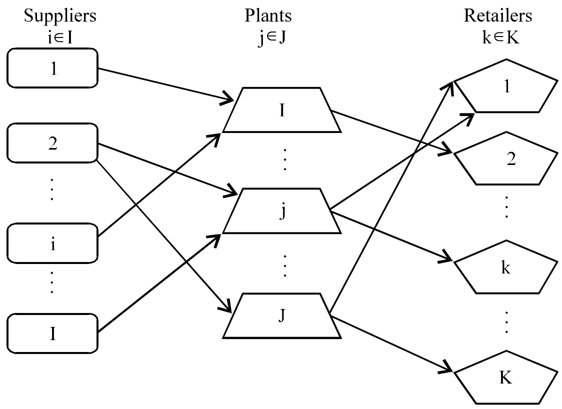

Fig. 1: CoQ Model flowchart (Castillo-Villar *et al*., 2014)

- Y_{pj} = Fraction defective at manufacturing plant j
- Y_{ij} = Inspection error rate at the manufacturing plant j

Expressions
Tier 1: Supplier
Good Component (GC):

$$GC = (1\text{-}Y_{si})W \tag{1}$$

Bad Component (BC):

$$BC = Y_{si}\ W \tag{2}$$

Tier 2: Manufacturer
Good component with successful Manufacture (GgM):

$$GgM = (1\text{-}Y_{si})W\ (1\text{-}Y_{pj}) \tag{3}$$

Good component with failed Manufacture (GbM):

$$GbM = (1\text{-}Y_{si})\ W\ Y_{pj} \tag{4}$$

Bad component with a successful Manufacture (BgM):

$$BgM = Y_{si}\ W\ (1\text{-}Y_{pj}) \tag{5}$$

Bad component with a failed Manufacture (BbM):

$$BbM = Y_{si}\ W\ Y_{pj} \tag{6}$$

Good product after successful Rework (GaR):

$$GaR = \varphi(1\text{-}y_{Ij})W\left[(1\text{-}Y_{si})Y_{pj}+Y_{si}\right] \tag{7}$$

Sold as Defective products (SaD):

$$SaD = (1\text{-}\varphi)(1\text{-}Y_{Ij})W\left[(1\text{-}Y_{si})Y_{pj}+Y_{si}\right] \tag{8}$$

No. of bad products after entering the manufacturing process (BcGC):

$$BcGC = Y_{Ij}W\left[(1\text{-}Y_{si})Y_{pj}+Y_{si}\right] \tag{9}$$

Tier 3: Retailer
No. of Good products after the Retailer (GaRe):

$$GaRe = (1\text{-}Y_{rk})\begin{bmatrix}(1\text{-}Y_{si})W\ (1\text{-}Y_{pj})+\\ \varphi(1\text{-}Y_{Ij})W\ ((1\text{-}Y_{si})Y_{pj}+Y_{si})\end{bmatrix} \tag{10}$$

No. of Bad products after the Retailer (BaRe):

$$BaRe = Y_{rk}\begin{Bmatrix}(1\text{-}Y_{si})W\ (1\text{-}Y_{pj})+\varphi(1\text{-}Y_{Ij})+\\ W\left[(1\text{-}Y_{si})Y_{pj}+Y_{si}\right]\end{Bmatrix} \tag{11}$$

Quality cost function
Prevention Costs (CP): Prevention costs are related to the number of good product and are divided into three components: supplier prevention activities, manufacturer prevention activities and mutual prevention activities between supplier and manufacturer. The overall quality level will increase as well as the number of good products increases.

Prevention costs include: System development, quality engineering, training, Statistical Process Control (SPC), planning, implementation and controlling quality system in the organization, etc. Prevention costs are given by Eq. 12:

$$CP = Af+Av\left[(1\text{-}Y_{si})W\ (1\text{-}Y_{pj})\right] \tag{12}$$

Appraisal Costs (CA): Previous studies demonstrated the relationship between appraisal costs and inspection error rate. Thus, the appraisal cost increases when inspection is more accurate. The appraisal cost includes: Test and inspection of purchased materials, final product testing and inspection, Supervision of inspecting activities, Maintenance of test equipment, etc. and it is given by Eq. 13:

$$CA = Bf+Bv\times W\left[(1\text{-}Y_{si})+(1\text{-}Y_{sj})\right] \tag{13}$$

Where:
Bf = The fixed cost
Bv = The variable cost
W = The No. of items going throw the inspection system

Internal Failure Costs (CIF): These are the costs incurred in the supply chain as a result of manufacturing defective products. They are calculated based on the probable amount of defective products at each tier of supply chain and their relative rework costs. We can cite as for example: cost of scrap, rework, reinspection and retesting of reworked products, down time caused by quality problems, analysis of the cause of defects in the production, debugging software errors, etc. internal failure cost is given by Eq. 14:

$$\begin{aligned} CIF = {} & Cf+(Cm+Cr)\varphi(1-Y_{Ij})GbM+(Cs+Cm+Cr)+ \\ & \varphi(1-Y_{Ij})(BgM+BbM)+(P1-P2)SaD \end{aligned} \quad (14)$$

External Failure Costs (CEF): The external failure cost in our model is composed by two terms. The first term models the cost related to customer returns which involve the action to either repair or replace the defective item. The second term models losses owing to defective items (e.g., complaints from customers, warranty claims, loss of reputation, etc.) and is based on the Taguchi (Quigley and McNamara, 1992) loss function concept. The external failure cost is given by the Eq. 15:

$$CEF = \bar{C}_{EF}\left[BaRe+BcGC\right]+k\left(Y_{rel}\right)^2 \quad (15)$$

Where:

- k = The loss constant coefficient
- Y_{rel} = The relative value of the quality characteristic to compute the loss for the supply chain by subtracting the target value or lower bound from the current overall percentage defective:

$$Y_{rel} = \left(\begin{matrix}\left[\left(BaRe+BcGC+SaD/Dem\right)\right]- \\ \left[Y_{rk}+Y_{si}\left(1-\varphi\right)\left(1-Y_{rk}\right)\right]\end{matrix}\right)\times 100\% \quad (16)$$

Total CoQ function: The total COQ is computed as the sum of the prevention, appraisal and internal and external failure expressions as given by:

$$CoQ = CP+CA+C_{IF}+C_{EF} \quad (17)$$

Quality level

We assume that the parameter QL: Overall quality level that represents SC quality is the proportion of good products among all products delivered to final customers. QL is given by :

$$QL = \left(1-Y_{rk}\right)\left[\begin{matrix}\left(1-Y_{si}\right)\left(1-Y_{pj}\right)+\varphi\left(1-Y_{Ij}\right) \\ \left(1-Y_{si}\right)Y_{pj}+\varphi\left(1-Y_{Ij}\right)Y_{si}\end{matrix}\right]=1 \quad (18)$$

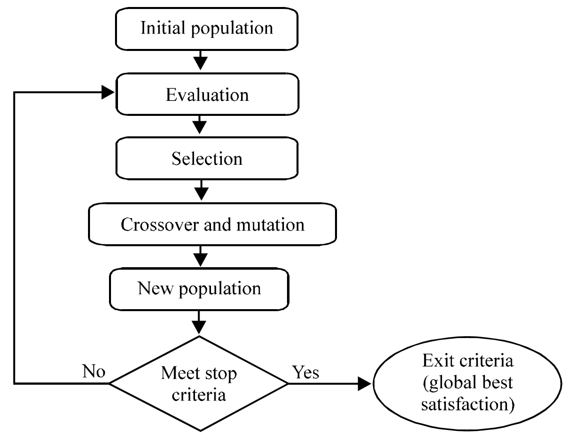

Fig. 2: A optimization flowchart (Holland and Arbor, 1975)

Developing a GA based solution: Genetic Algorithm (GA) is adaptive heuristic search algorithm based on the evolutionary process of natural selection and genetics. The GA technique was developed by Holland and Arbor (1975) and his collaborators in the 1970s. It represents an intelligent exploitation of random search used to solve large scale conventional combinatorial optimization problems. In other words, GA simulates the survival of the fittest among individuals (candidates solutions) over consecutive generations for an optimization problem, each candidate solution is represented by character string which is analogous to the chromosome. A population of these individuals in this case composed of two variables Y_{ij} and Y_{pj} presented in a string-bit block and a fitness score is assigned to each solution that gives information about the relative merit of each individual g^s (Y_{ij}, Y_{pj}). GA operators such as: selection, crossover and mutation are applied to these individuals to explore new solution space. In this way, solutions tend to improve over successive generations leading to optimal or near optimal solution. The basic concept of the algorithm can be represented as follows (Fig. 2).

Individual representation: Y_{ij} and Y_{pj} are real numbers which are converted to the string-bit block. This crucial encoding phase allows us to apply crossover and mutation operations to the individuals. Once the GA operators are applied the binary string are reconverted finally to decimal base. Equation 19 allows us to find the corresponding number of x. The x can be Y_{ij} or Y_{pj}):

$$x' = \left(x+2\right)\frac{\left(2^{22}-1\right)}{4} \quad (19)$$

Where 2^{22} and 4 depend on the required precision. x' is then converted to a binary form. For example, a solution-string block for a fraction defective of 0.729 is obtained by inserting this value into Eq. 19 above as x and solving for x'.The x' is then transformed into a binary string as follows:

$$0.729 = -2 + x' \times \frac{4}{\left(2^{22}-1\right)}$$

$$x' = \left(0.729+2\right) \times \frac{\left(2^{22}-1\right)}{4} = 2861560.5 = \left(2861561\right)_{10}$$

The binary form of $2861561 \rightarrow 1010111010100111111001$.

Initialization: This stage aims to generate feasible solutions space of a desired size (popsize). Y_{ij} and Y_{pj} are generated randomly between the limits 0.05 and 0.95.

Evaluation: The objective of this step is affecting a score to each individual solution (Y_{ij} and Y_{pj}) in order to minimize quality cost function. To do so, a competitiveness score is assigned to each solution calculated as follows:

$$g^i(s) = f^s_{max} - f^i(s) \tag{20}$$

Where:

$f^i(s)$ = The objective function of a solution (Y_{ij}, Y_{pj})

f_{max}^s = The least function value of the current solution space

A probability selection Pi is then calculated with the following equation:

$$Pi = \frac{fi(s)}{\sum_{k=1}^{popsize} fi(s)} \tag{21}$$

Selection: According to Egelese (Collins, 1988), there are six alternatives selection schemes. In this researchwe have opted for the remainder stochastic sampling without of replacement strategy. A fractional part ei is calculated as follows:

$$e_i = \frac{f(s)}{\sum f(s)/popsize} \tag{22}$$

It represents the probability of each string to have copies in the next generations.

Genetic operators

Crossover: This operation consists of taking two chromosomes (called parents) and producing child individuals from them. It is a mechanism for diversification that encourages GA to examine unvisited regions. When two individuals are selected, the program generates two random cut points of the block string and extracts the segment from these two individuals. To achieve this operation, segments are exchanged and finally two new individuals are produced. The operation is done with a Crossover Probability (PC). Example: the crossover operator generates two new strings as follows (where (^) represents the cross positions):

- String 1: 0000000000000001^001^110
- String 2: 0000000000000001^101^100

After crossover operation, the newly created strings are:

- New String 1: 000000000000001^101^110
- New String 2: 000000000000001^001^100

Mutation: This operation allows the algorithm to explore the space of solutions for any initial solution space and guarantees the possibility of avoiding the local minima by preventing the population of individuals from becoming too similar to each other. The mutation is performed with a probability Pm. If an individual is selected, a random point is generated and the bit concerned is transformed.

RESULTS AND DISCUSSION

Computational results: The aim of this study is to explore the effect of supplier's fraction defective Y_{si},the fract ion defective at the retailer Y_{rk} as well as Rework rate φ on Cost of Quality (CoQ). As initiated in Castillo-Villar *et al.* (2012), this study allows us to determine which of these parameters has a considerable impact on CoQ. To do so, we propose an optimization tool based on GA wich is developed on Python 3.0 and it is inspired from works developed by Jabri *et al.* (2013). We regroup in Table 1 the values of various parameters used to develop the GA. We use the set of data reported in Ittner research, Table 2 for a quality level between 0.1 and 0.7 as the base for the numerical examples (Fig. 3).

The impact of decision variables on QL constraint: This study aims at presenting the QL curves depending on Y_{ij} and Y_{pj}. The optimisation of the model presented in Eq. 17 subject to the quality constraint (QL = l) were achieved in terms of the range of the quality level which is delimited by the lower bound and the upper bound on QL. The parameters Y_{si}, Y_{rk} and ô are varied to specify QL limits according to Y_{ij} and Y_{pj}. The upper bound is attained when both Y_{pj} and Y_{ij} are zero in Eq. 18, in other words, when there are zero defects at manufacture and no error at

Table 1: Input fixed parameters for the GA

Parameters	Values
Population size (popsize)	20
No. of iterations	200
Crosseover rate (pcross)	0.7
Mutation rate (pmutate)	0.2

Table 2: Parameters used to generate GA instances

Parameters	Values
W	2000
Bv	5
Cm	5
Cs	22.5
Cr	70
Phi	0.7
Cs	22.5
P1	1.2
P1	228.8
P2	P1/4
P2	1/4*P1
Af	5000
K	1/10
Bf	15000
C_{EF}	57.2
Cf	10000
Y_{si}	0.05
K	1/10
Y_{rk}	0.05
W	50
Av	5
C_{EF}	5

inspection. The lower bound is attained when both Y_{pj} and Y_{ij} are one in Eq. 18. We show in Fig. 6a the quality level plots for three levels of Y_{si}.

It can be observed that when Y_{si} increases the optimal quality level decreases. When the supplier fraction defective is small, there is a need to improve the manufacturing process by improving prevention activities. Figure 6b shows that as the fraction defective at retailer increases, the maximum overall quality level attained by the logistic route decreases. For $Y_{rk} = 0.2$ the lower bound of QL is on 0.6 where QL is $<1-Y_{rk}$. This can be explained by the relationship between Y_{rk} and the good products delivered to the customers. It can be seen also from Fig. 6c that increasing the rework rate will not return significant benefits to the logistic route.

Supplier's fraction defective (Y_{si}) impact: First, we study the impact of supplier's fraction defective on the COQ curves. To simplify the model, we suppose that one supplier is selected from among many. In this first example, we vary the fraction defective at supplier between 0.1 (Fig. 4a) and 0.7 (Fig. 4b).

In order to meet a given quality level (l) and minimize the total cost of quality, we optimize the parameters Y_{pj} and Y_{ij} which are the internal decision variables of our model; Fig. 4 presents the curves associated with each cost category: the curve COQ represents the total cost, CP the appraisal costs, CIF the internal failure costs and C_{EF} is the external failure costs curve.

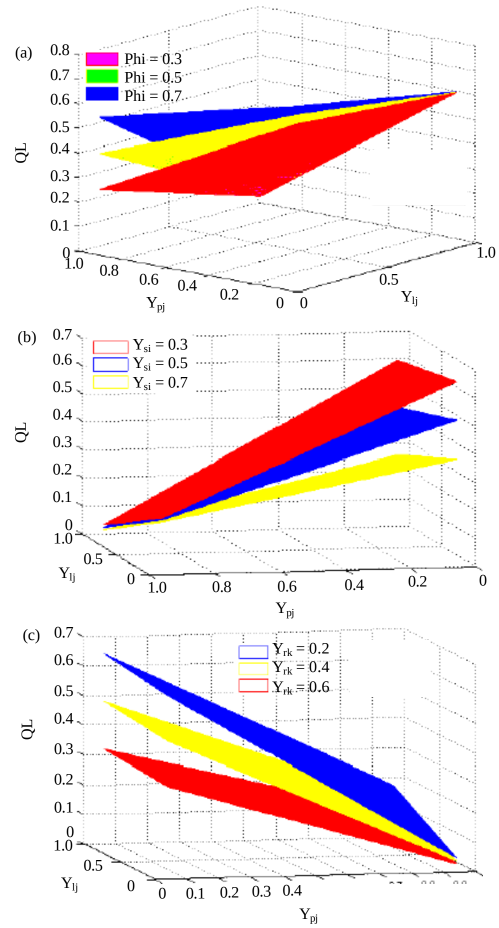

Fig. 3: QL level plots for three levels of Y_{si}, Y_{rk} and Φ: a) Phi = 0.3, 0.5, 0.7 and Y_{rk} = 0.2, Y_{si} = 0.2; b) Y_{si} = 0.3, 0.5, 0.7 and Y_{rk} = 0.1, Phi = 0.2 and c) Y_{rk} = 0.2, 0.4, 0.6 and Y_{si} = 0.1, Phi = 0.2

Figure 4 shows that the greater the supplier's fraction defective rate, the slower is QL which minimizes the total CoQ. In other words, if we want to meet the fixed QL, we have to invest more on appraisal and internal failure activities, this is due to the quantity of bad components received from the supplier. The minimal CoQ point is obtained for QL = 0.6 and 0.35 when Y_{si} = 0.1 and 0.5, respectively and the CoQ becomes important because the internal failure costs in this case increase considerably. This result confirms that when selecting suppliers, it is important to take into account the fraction defective in order to avoid inspection and rework process and to meet the quality requirements at minimum cost. We conclude that the supplier fraction defective has an economic impact on the supply chain by avoiding decisions based solely on price and reducing the total quality costs that achieve a high quality level in the supply chain.

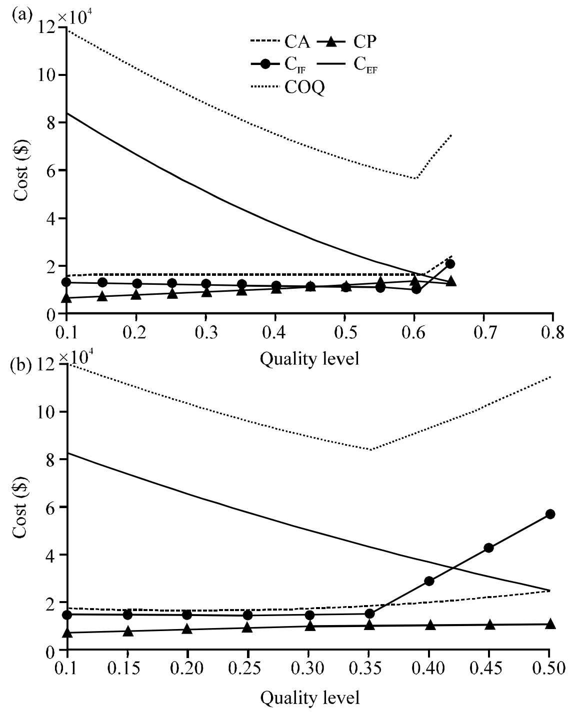

Fig. 4: CoQ curves for Y_{si}: a) 0.1 and b) 0.5

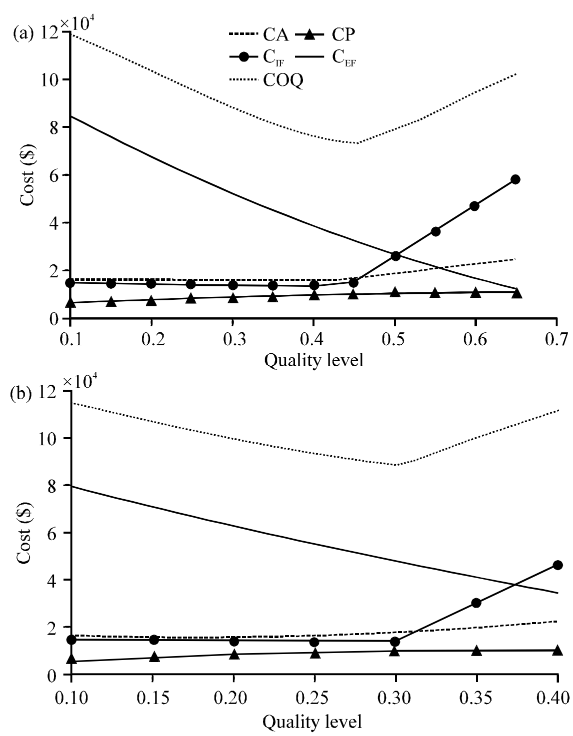

Fig. 5: CoQ curves for Y_{rk}: a) 0.1 and b) 0.4

Retailer's fraction defective (Y_{rk}) impact: Figure 5 presents the results obtained when varying Y_{rk} for two

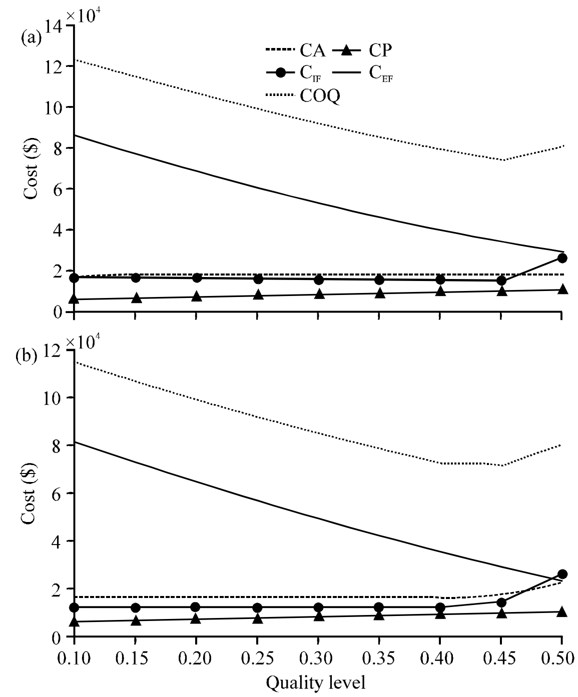

Fig. 6: CoQ curves for Φ: a) 0.2 and b) 0.7

values: 0.1 and 0.4. The results show that like Y_{si}, Y_{rk} has a negative effect on CoQ curve. In fact, when the fraction defective at retailer Y_{rk} increases, the maximum overall quality level attained by the logistic route decreases. This is due to the number of good products delivered to the final customers and its direct dependency on the fraction defective at retailer. For example when Y_{rk} increase from 0.1-0.4, the QL achieve l at 0.9 and 0.76, respectively and CoQ also increases to attain 5.2×104 for Y_{rk} = 0.4. Therefore, in order to minimize the total cost of quality, managers must take into account when selecting a retailer, its fraction defective to achieve a high quality level in the supply chain.

Rework rate Φ impact: The third parameter studied in this study is the rework rate Φ. In this example Φ is varied from 0.2-0.7. Figure 6 gives the CoQ for these two cases. It can be seen clearly that the curves of Fig. 5a and b are similar. To attain any quality level, we can choose many inspection error rates for one value of supplier fraction defective. The products resulting from rework process are: good products after successful Rework (GaR) (Eq. 7) and products Sold as Defective (SaD) (Eq. 8). It means that even if managers invest more in appraisal activities it will not greatly influence the cost of quality especially for low rework rate values because few products will be reworked and most products will be SaD at low price P2 that is an internal failure cost. Only investments in

Table 3: Results for the various parameteres

Variables/QL	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65
Y_{si} = 0.5												
Y_{ij}	94.9	95.0	94.8	94.9	94.9	91.9	65.5	35.1	11.5			
Y_{pj}	74.4	60.3	45.3	30.7	16.3	5.0	5.2	5.2	5.0			
Y_{si} = 0.1												
Y_{ij}	94.9	94.7	95.0	94.8	94.7	94.8	94.8	94.7	94.9	94.9	95.0	83.0
Y_{pj}	85.8	77.7	69.5	61.5	53.3	45.1	37.0	28.9	20.5	12.7	5.2	5.0
Y_{rk} = 0.4												
Y_{ij}	94.8	94.9	94.9	95.0	92.2	61.7	29.9					
Y_{pj}	69.6	52.3	35.3	18.8	5.3	5.1	5.2					
Y_{rk} = 0.1												
Y_{ij}	95.0	94.9	94.9	94.8	95.0	94.9	95.0	91.9	71.0	49.9	28.8	7.8
Y_{pj}	81.2	70.0	58.6	47.2	35.7	24.4	12.9	5.1	5.1	5.0	5.2	5.0
Φ = 0.2												
Y_{ij}	95.0	94.9	94.9	94.9	94.9	94.8	94.6	80.7	28.0			
Y_{pj}	78.5	67.3	56.1	45.0	33.7	22.5	11.5	5.0	5.0			
Φ = 0.7												
Y_{ij}	95.0	94.9	94.8	94.9	94.9	95.0	94.8	94.8	79.1			
Y_{pj}	33.3	71.6	60.3	48.6	37.2	25.6	14.5	5.0	5.0			

prevention activities will guarantee that good products reach the retailer. In conclusion, rework rate did not greatly influence cost of quality but when Φ decreases, the inspection system will not return important benefits.

Discussion of PAF cost categories evolution: In this study, the effect that decision variables and CoQ internal parameters has on the CoQ categories (CA, CP, C_{IF} and C_{EF}) curves are discussed.

We report in Table 3, the results obtained when variying these parameters until finding the maximum QL value. External failure cost decreases as QL increases and this is due to decreasing values of fraction defective which means that more and more best items reach clients with best quality. C_{IF} increases as inspection error rate decreases. This is due to the considerably increased costs of the quantity of defective products as well as operation failure costs and purchasing failure cost which means that more inspection at manufacturing is needed in this situation to guarantee that good products reach the retailer.

When Y_{si} and Y_{rk} increase, the optimal quality level which minimises the total COQ decreases. It attains 0.35 for Y_{ij} = 91.9 and Y_{pj} = 5 and it equals to 0.65 for Y_{ij} = 83 and Y_{pj} = 5. At these QL points, CA start to increase considerably ans this is due to the need for a greater investment in appraisal activitites since more bad components are received from the supplier.

The prevention costs increases as the minimum quality level increases. As described analytically in Eq. 12, Prevention costs are related to the number of good products shipped from suppliers (Y_{si}) and the manufacturer prevention activities (Y_{pj}). As these two elements increase, at the minimum quality level, CA start to increase which justify the need to invest more in appraisal activities.

CONCLUSION

This study uses three quality variables and study what impact each has on quality costs and quality level across a single-product three-echelon supply chain. A Genetic algorithm based procedure was developed to optimize the model and the solutions was examined and validated against manufacturing supply chain data.

Based on the results, there is a relationship between supplier fraction defective and the optimal quality level as well as between retailer fraction defective and the quality level achieved. Furthermore, according to the data analysis results, the system decision variables has an impact on PAF cost categories when computing quality costs and determining the optimal COQ point. Therefore, including quality costs in supply chain modeling can provide an aid for managers for taking internal operational decisions considering the defective rates at each stage of the supply chain.

SUGGESTIONS

Future research involves the development of hybrid solution method that combines two metaheuristics procedures such as Genetic algorithms and simulated annealing. Another future research includes extending the model to include more levels in the supply chain.

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