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Minimization of inspection cost by determining the optimal number of quality inspectors in the garment industry

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This study has been aimed at developing a model to reduce inspection cost by determining the optimum number of quality inspectors with respect to their skill levels using goal programming. A mathematical model is proposed to find out the optimal combination of decision variables. It is concluded that inspection cost may be reduced by optimising the skill level of the quality inspectors.

Keywords: Goal programming, Inspection cost, Inspection error, Offline inspection, Quality control

Quality management system (QMS) plays an important part in manufacturing industry like textile by maintaining good quality with controlled production cost[1]. QMS comprises four parts viz quality planning, quality assurance (QA), quality control (QC) and quality improvement. Part of quality control setup, that decides the conformance and non-conformance of product through the process of screening, is inspection[2]. In garment industry, inspection process is performed at different stages of manufacturing including incoming inspection, online inspection and offline inspection, depending upon the inspection plan[3]. The complete setup and execution of inspection activities increase total production cost. Every organization wants to keep this cost low without compromising the quality. Although online inspection is economical, it is sometimes not practical. In this case, offline inspection is the only option for evaluating product quality[4].

Much work has been done on offline inspection and inspection cost has been studied by evaluating inspection strategies, inspection location and inspection intervals. Wang *et al.*[5] optimized offline inspection by considering the rework and repair of defective products. A mathematical model was developed to generate both the optimal check points and the number of units to be inspected. Bendavid and Herer[6] developed an optimal inspection policy by using dynamic programming. Avinadav and Perlman[7] considered a batch production process to find the optimal inspection interval for single sampling plan to prove that expected total cost is the function of the inspection interval. An optimal frequency of inspection was determined to reduce the cost of inspection and rework that was performed throughout the K-IR inspection system[8]. An optimal frequency of inspection at the end of each assembly line was determined, which minimizes the cost of inspection as well as the cost of rework. On allocation of quality control station (AQCS) in a multi stages manufacturing system, Shetwan *et al.*[9] conducted literature survey. The approaches and models were reviewed for all AQCS and it was found that heuristic algorithm gave acceptable solution faster than the optimization method. Vaghefi and Sarhangian[10] worked on the optimization of inspection plans and developed a mathematical model to minimize the inspection cost while maintaining good quality.

In previous studies, off line inspection was considered at macro level in manufacturing and supply chain industry, but there is a lack of micro level work. There have been many manufacturing industries like textile and garments that still rely on human labour for QC and inspection. In their recent work, Khan *et al.*[11] identified a lack of work on human factors in inspection with respect to their effect on total inspection cost. The present study deals with inspection at micro level to study the effect of human factors that stimulate inspection cost of single offline station in a garment manufacturing industry. This study seeks to minimize the inspection cost by determining the optimal number of human inspectors that are major sources of increase in inspection cost as well as inspection error rate and quantity inspected.

Experimental

Model Description

The set of activities performed at offline inspection station of garment manufacturing industry is shown in

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Fig. 1. Here, the finished product from the production line with fix defect rate moves towards inspection area where 100% inspection is done by inspectors of QC department. These quality inspectors belong to three different skill levels, namely low, medium, and high. The skill level is determined on the basis of error in inspection and quantity inspected per day. After 100% inspection, good quantity is moved for lot sampling process which is performed by a QA person. A sample size "n" from the presented batch was selected and decision of acceptance or rejection was made on the basis of defective quantity in lot 'd' compared with the threshold value of 'c'. The rejection or acceptance of lot depends on the skill level of inspector, i.e. low skill inspector has a high rejection rate as compared to medium and high skill inspectors.

Every quality inspector is paid according to his inspected quantity, as accepted by the sampling process. In this study, a contractual system is used, based on the per dozen inspected quantity. During the 100% inspection, every quality inspector separates the defective items from good items that are either rejected or reworked. However, defective quantity may contain good items as well due to probability of type I error. Since quality inspectors of different skill level are working in inspection station so, low and medium skill inspectors may consider good item as defective. This good quantity is sent back to the inspection station and follows the same process of sampling inspection.

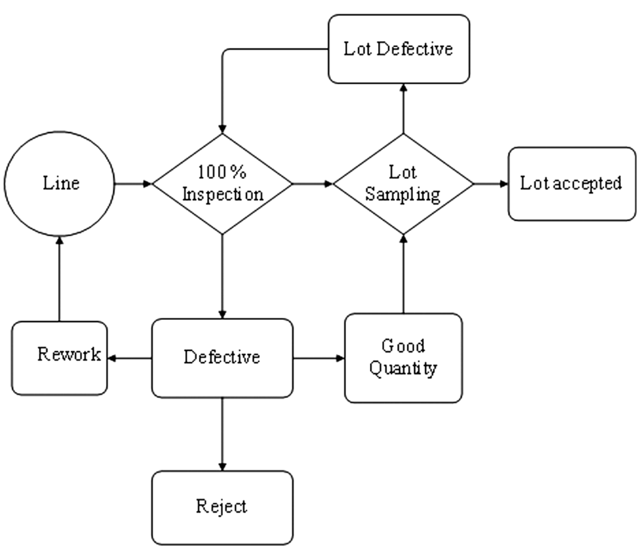

Fig. 1—Flow chart of the inspection process for garment industries

Model Development

Basic Relationship

From sewing line, "Q" is the total number of garments per day that are moved to inspection station, and Q_i is the quantity inspected by each inspector per day. If p_i is the probability of defects that are separated by inspector i, then the total number of defective garments per day D_i and the total number of accepted garments per day A_i separated by inspector i is given as

$$D_i = p_i \times Q_i \; i = 1,2,3 \ldots\ldots I$$

$$A_i = (1 - p_i) \times Q_i \; i = 1,2,3 \ldots\ldots I$$

This accepted quantity (A_i) separated by each inspector is presented for sampling process, while the defective quantity (D_i) is sent for either reworked or scrap.

Inspection Error

There are two types of inspection errors, viz type I error "α", and type II error "β". The value of β of each quality inspector is calculated by a QA person during lot sampling process, as shown below:

$$\beta = P\,(Type \text{ II } error) = P\,(\text{take as good}|\text{product is defective}) \quad \ldots (1)$$

The average value of all final inspectors of one skill level β_l is calculated using the following equation:

$$\beta_l = \frac{1}{L}\left[L\left(\frac{d_l}{n_l}\right)\right] \quad \ldots (2)$$

where L is the low skill quality inspectors; d, the defective items; and n, the sample size. Similarly, the average value of "β_o"for the entire inspection station can be calculated by following equation:

$$\beta_o = \frac{1}{I}\left\{L\left(\frac{d_l}{n_l}\right) + M\left(\frac{d_m}{n_m}\right) + H\left(\frac{d_h}{n_h}\right)\right\} \quad \ldots (3)$$

where L, M, and H show the total number of inspectors having low, medium, and high skill respectively, while "I" shows the total number of quality inspectors. Similarly, the value of "α_o" for the whole inspection station can be calculated by following equation:

$$\alpha_o = \frac{1}{I}\left\{L\left(\frac{g_l}{D_l}\right) + M\left(\frac{g_m}{D_m}\right) + H\left(\frac{g_h}{D_h}\right)\right\} \quad \ldots (4)$$

Inspection Capacity

Inspection capacity is a quantity accepted by lot sampling process and sent to the next process. This accepted quantity includes first time inspected quantity and reinspection quantity due to rework and rejected lot from the sampling process. Total inspected quantity "*IQ*" by all inspectors of one skill level can be calculated by following equation:

$$IQ_L = L\,(\mathrm{IQ}_l) \quad \ldots (5)$$

where IQ_l is the inspected quantity by one low skill inspector. Thus, total quantity inspected by the inspection station IQ_o is the sum of the quantity inspected by inspectors of all types of skill levels, as shown below:

$$IQ_o = L\,(\mathrm{IQ}_l) + M\,(\mathrm{IQ}_m) + H\,(\mathrm{IQ}_h) \quad \ldots (6)$$

Inspection Cost

Total Inspection cost (TIC) is the sum of the fixed cost and the variable cost, in which the variable cost "*VC*" is related to the quantity inspected per day. This quantity will vary as the number of quality inspectors with respect to their skill level varies. On the other hand, the fixed cost "*FC*" includes the setup cost and salaried workers of the inspection area. In this study, we are more concerned with the variable cost as it is related to our research problem. Since the inspected quantity varies as the skill level varies, the inspection cost is different for each skill level. The inspection cost of all inspectors of one skill level can be calculated using the following equation:

$$VC_l = \left[\frac{1}{12}\{L(\mathrm{IQ}_l)\}\right] \times I_r \quad \ldots (7)$$

where VC_l is the value of variable cost for low skill inspectors; and I_r, the inspection rate. Total inspection cost of all quality inspectors working in inspection station is calculated using the following equation:

$$VC_o = \left[\frac{1}{12}\{L\,(\mathrm{IQ}_l) + M\,(\mathrm{IQ}_m) + H\,(\mathrm{IQ}_h)\}\right] \times I_r \quad \ldots (8)$$

Objective Functions

Goal programming (GP) is a widely used method for multi objective decision making. Each objective has a target value that must be achieved. GP has three commonly used methods, namely preemptive method, nonpreemptive method, and fuzzy method. Their selection is related with the available information of the objective functions[12]. In this study, preemptive GP is used. The basic four objectives of this study are:

(i) To minimize the total inspection cost per day by finding the optimal number of quality inspectors of each skill level [Eq. (10)].

(ii) To maintain the daily quality target of inspection station [Eq. (11)].

(iii) To meet the daily inspection target as well as to avoid bottleneck in inspection station [Eq. (12)].

(iv) To formulate the goal programming to determine the optimal values of the decision variables, consisting of two minimization problems and one maximization problem [Eq. (9)], *d*. Indicates the amount by which the target value is under achieved, and d^+ indicates the amount by which the target value is exceeded as shown below:

$$Min\,Z = p_1 d_1^+ + p_2 d_2^+ + p_3 d_3^- \quad \ldots (9)$$

Subject to

$$\left[\frac{1}{12}\{L\,(\mathrm{IQ}_l) + M\,(\mathrm{IQ}_m) + H\,(\mathrm{IQ}_h)\}\right] \times I_r + d_1^- - d_1^+ = TIC_T \quad \ldots (10)$$

$$\frac{1}{I}\left\{L\left(\frac{d_l}{n_l}\right) + M\left(\frac{d_m}{n_m}\right) + H\left(\frac{d_h}{n_h}\right)\right\} + d_2^- - d_2^+ = \beta_T \quad \ldots (11)$$

$$L\,(\mathrm{IQ}_l) + M\,(\mathrm{IQ}_m) + H\,(\mathrm{IQ}_h) + d_3^- - d_3^+ = IQ_T \quad \ldots (12)$$

$$d_n^-, d_n^+ \geq 0\ \forall \mathrm{n} \in \{1, \ldots, 3\} \quad \ldots (13)$$

Results and Discussion

Numerical Example

To describe the application of proposed model via a numerical example, a basic t-shirt manufacturing unit was selected. The relevant data of the last three months have been collected and are given in Table 1.

This data is then analysed by using optimization software QM for Windows according to the decision variables and objective functions described above. Goal programming module of QM for windows is used to find out the optimal values of decision variables. The values of the decision variables also give optimized values of objective functions that include inspection cost per day, inspection quantity, and inspection error rate. Optimized results produced by QM for windows are shown in Table 2.

The table explains the decision variable analysis, priority analysis and constraint analysis. The decision variable analysis shows the optimal combination of decision variables by providing the number of quality inspectors of each skill level. These results indicate a lower number of low skill quality inspectors as compared to medium and high skill inspectors. This information is realistic because if the inspection

Table 1—Data of garment manufacturing industry

Description	Value
Inspection error (upper threshold)(β_T)	0.05
Avg of inspection error	
Low skill inspector (β_l)	0.1
Medium skill inspector(β_m)	0.06
High skill inspector(β_h)	0.02
Target value of variable cost for all inspectors (Rs)(VC_T)	5500
Avg of variable cost	
Low skill inspector(Rs)(VC_l)	250
Medium skill inspector (Rs) (VC_m)	417
High skill inspector (Rs) VC_h)	583
Target value of inspection quantity for all inspectors(IQ_T)	6000 pieces
Avg value of inspection quantity	
Low skill inspector (IQ_l)	300 pieces
Medium skill inspector(IQ_m)	500 pieces
High skill inspector (IQ_h)	700 pieces
Lot or batch size (N)	100
Sample size (n)	20
Threshold value for lot acceptance or rejection (c)	1
Cost of inspection (Rs) (Ir)	10

Table 2—Optimum values of objective functions and decision variables

Decision variable analysis	Value	Priority analysis	Non achievement
L	2	Priority 1	0
M	5	Priority 2	0
N	5	Priority 3	0
Constraint analysis	RHS	d^+ (Exceed)	d^- (under achieved)
Inspection quantity (pieces)	6000	600	0
Inspection error	0.05	0	0
Inspecting cost (Rs)	5500	0	0

Table 3—Sensitivity analysis conducted on the inspection target

Target value	Decision variables			Objective functions		
(IQ_T)	L	M	H	IQ	VC	B
6000	2	5	5	6600	5500	0.05
7500	3	5	6	7600	6333	0.05
9000	4	6	7	9100	7583	0.05
10500	4	6	9	10500	8750	0.05

stations have greater numbers of low skill inspectors then we may apparently claim that the inspection cost per day is low, but the daily inspection target and quality level of the inspection station cannot be achieved. Therefore, the inspection station must consist of an efficient combination of quality inspectors of all skill levels, so that all the objectives can be achieved. It is also observed that in the manufacturing setup where the inspection still depends on human labour, presence of high and medium skill inspectors motivate the low skill inspectors to learn quickly and increase their skill level at a faster rate. However, this learning and skill improvement depends on the type of product, i.e. either it is a basic type of garments or highly fashioned or complex garment[13].

The priority analysis gives idea about the achievement and non-achievement of the already given priority targets. For the proposed model, priorities are mentioned in Eq. (9) and analysis shows zero value for all priorities. It means all of our set targets that include minimization of inspection error and inspection cost and maximization of inspection quantity are achieved. Lastly, the constraint analysis shows achievement of each goal by giving under achieved value as d^- and exceeded value as d^+. GP has come out with optimized results of decision variables, indicating that there is no under achievement or exceeded values for any constraints, except inspection quantity. Although Table 2 shows the exceeded value of the inspection quantity d^+as 600, it is still fulfilling the constraints mentioned in Eqs (9) and (13). Inspection quantity per day should not be less than the target value, but our result shows exceeded value, which is a positive aspect of the findings.

Sensitivity Analysis

It is observed that as the incoming quantity from the production line increases, the required daily target also increases to avoid bottleneck. Therefore, the number of quality inspectors of each skill level and daily inspection cost will change as well. Sensitivity analysis is done to evaluate the effect of daily target value on other objective functions and decision variables. Results of the sensitivity analysis conducted on the daily inspection targets are shown in Table 3.

The inspection target per day (IQ_T) is increased by 25% and changes in the optimal values of each objective function and decision variable are mentioned. As the manufacturing capacity of the sewing section increases, the load on inspection stations will also increase, which in turn, will increase the required number of quality inspectors, if a bottleneck is to be avoided. Sensitivity analysis shows the values of the decision variables and objective function for increasing demand of inspection quantity. However, the number of quality inspectors can be increased to a specific limit according to space available for inspection station. This study also shows that the increase in production with time will also improve skill level of inspectors and each quality inspector will be able to inspect more garments per day with low inspection error as well. So, future work should be conducted in this area by considering time varying factors like skill level, inspection target and learning behaviour.

In this study, a multi objective optimization model has been developed to minimize the inspection cost in an offline garment inspection station. It also focuses the minimization of inspection error rate and encourages getting daily inspection target. Cost of inspection depends upon the skill level of the quality inspectors and their number. Since the garment industry is a labour intense sector, it makes the problem more severe. The proposed model takes into account the human factors like inspection error and daily efficiency to find out the optimal number of quality inspectors of low, medium and high skill. This study is helpful in planning the required manpower in offline inspection in garment manufacturing setup and also it provides minimum skill level that every new quality inspector should have before transferring from training section to production section.

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