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ORIGINAL ARTICLE

Effect of inspection performance in smart manufacturing system based on human quality control system

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Abstract Quality control at every stage of manufacturing is a key aspect of the quality management system of any organization. Inspection at different stages of manufacturing is essential to achieve required quality of the product. This knowledge area has been studied extensively in the past with respect to inspection strategies, inspection location, and inspection intervals to minimize inspection cost. However, there is a lack of literature that examines the relationship between inspection performance and factors related to human labor and inspection time of different products. Here, offline inspection is investigated to achieve the process target values by determining the optimal number of inspectors for different products. Three skill levels for inspectors are selected on the basis of their inspection errors, inspection quantities, and inspection cost. The purpose of this study is to achieve the optimum results of objective functions that consist of inspection cost, outgoing quality, and inspection quantity by determining the optimal value of decision variables, i.e., the number of inspectors with respect to their skill. A multi-objective optimization model is developed using a stochastic approach to determine the optimal results of the objective functions and decision variables. Firstly, goal programming is employed to verify the optimization model by using numerical examples. Secondly, sensitivity analysis is considered to illustrate the effect of incoming quantity on inspection performance and optimal combination of decision variables.

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1 Introduction

The inspection process and skill of inspector are important for any manufacturing system [1]. Even though, the recent advancements in manufacturing systems have been characterized by precision of work through automation [2]. However, it is very difficult to automate any manufacturing system due to budget constraints, space constrains, or lack of skilled labor. Thus, the inspection process is controlled by human labor and it is the necessity that the judgment of the human labor is skilled, semi-skilled, or low-skilled inspectors. The job, in the complex manufacturing sector, should be assigned according to the skill of the inspector such that different skill levels may have different inspection loads [3]. Due to the availability of funds, the manufacturing system can be made automated in several countries. However, for other countries, the labor cost is much cheaper due to the availability of manpower. Thus, for some countries, manufacturing industries prefer to use human labor for inspection purposes with minimum cost rather than the automated system. Therefore, the skills of those inspectors should be judged properly before assigning any job. That major research gap is solved by this research problem.

Two types of inspections are most commonly used during the manufacturing process: online inspection and offline inspection [4]. Online inspection facilitates to monitor quality level during the manufacturing process, while offline inspection inspects the finished products [5, 6]. This study has investigated the offline inspection case, where human labor of different skill levels performs the process of inspections. Offline inspection has been extensively examined in past to decrease inspection cost by considering inspection errors, inspection location, and inspection strategies [7]. Duffuaa and Khan [8] revised previous research works and provided a general repeat inspection plan for products that have critical components with multi-characteristics [9, 10]. The optimum number of cycles was determined to reduce the total expected cost. Similarly, the K-stage Inspection-Rework (K-IR) system was also studied, and the optimum number of cycles was determined to minimize the inspection and rework cost [11, 12]. However, both studies considered different assumptions like the effect of lot formation on the outgoing quality level [11] and imperfect inspection with time-based flow analysis [12]. The present study has worked on the multi-objective optimization problem by considering the inspection skill of human inspectors, and a solution is achieved by determining the required manpower with respect to their skill levels.

In the optimization problem, the inspection plan/strategy plays an important part that defines how the process of inspection should be conducted. Since the optimal inspection rule is not static for all type of manufacturing setups, different types of inspection plans have been developed. The continuous sampling plan (CSP) is one of the earliest methods to control the quality of the product. It consists of 100% inspection followed by a sampling inspection [13]. Studies have been done to join the inspection policies between precise inspections and CSP-1 with inspection error and return cost [14]. On the basis of parameters and decision variables, analytical results suggested three policies: no inspection, 100% inspection, and any proportion of non-defective and non-inspected items in CSP-1. Yu and Yu [15] assumed that each defective item sent to the end customer would be the cause of a return cost. The fifth variable, defects identified by CSP-1, was considered and suggested two inspection plans for CSP-1, one not to inspect, and the other 100% inspection.

Development of the inspection policies, under different assumptions and parameters, has been done in the recent past. Anily and Grosfeld-Nir [16] and Wang and Meng [17] determined the optimal inspection policy and lot size for a batch production process to minimize the expected total cost [16] and total cost function [17]. The theoretical aspect was extended to inspection error to develop an optimal inspection policy [4]. Vaghefi and Sarhangian [18] considered misclassification errors but worked on the multi-stage manufacturing system. Avinadav and Perlman [19] investigated a batch production process to find the optimal inspection interval that minimizes the total inspection cost.

Similarly, other types of inspection strategies that have been discussed in literature are “inspection disposition” (ID) policy and “inspection disposition and rework” (IDR) policy. The pioneer ID policy was developed by Raz et al. [20] to minimize the inspection cost of the batch. Their ID policy was extended by many authors with different assumptions [21–26]. This study has considered the inspection strategy, which is similar to CSP where 100% inspection will be performed by human labor of varying skill levels followed by sampling inspection.

Multi-objective optimization models have been developed in the recent past for process target values of offline inspection. These values are profit per item, income per item, and the uniformity of product to increase customer satisfaction [27–30]. The first model was developed using 100% inspection to control the quality of the product and maximized the objective functions. Recently, a modification was proposed in the inspection system by incorporating the measurement errors [30]. An extension was done in the previous model to optimize the same objective functions by considering inspection with a sampling plan [29]. Further, a study was conducted to assess the impact of inspection error on the values of optimal parameters and objective functions [28]. The present study has also focused on three objective functions of the offline station that include inspection cost, inspection quantity, and outgoing quality. These objective functions are optimized by determining the efficient combination of inspectors with respect to their skill levels. Previous work on offline inspection has been summarized in Table 1, which shows a brief comparison of published work and the present study.

Although offline inspection has been comprehensively studied in last one and half decades (as shown in Table 1), little attention has been given to human inspection skill and inspection time. This study has contributed to the existing literature by focusing on both of these factors and investigated their effects on inspection performance. In spite of the deficiencies of human fatigue and inconsistency in performance, many manufacturing industries still rely on human labor for the inspection process [39]. Thus, quality of the inspection process depends much on the skill of inspectors that effect inspection performance. A second factor is inspection time [21], which can affect the performance of the individual inspector as well as the overall inspection station. Inspection time depends on the product type and its complexity. As the product type varies from basic to complex, its number of operations performed, a variety of components, size, type, and design will also change [44]. In this way, the inspector will need to check more quality characteristics that will increase the inspection time and affect its daily inspection performance.

The present study optimizes the inspection performance in terms of three indicators: cost, quantity, and average outgoing quality. Mathematical expressions are formulated for each indicator of inspection performance by considering three skill levels of inspectors and inspection time. The objective of this study is to propose an optimization model to obtain the optimal number of inspectors with respect to their skill levels for different products. This optimal combination will assure that all the objectives have been achieved that include minimization of the inspection cost, maintain outgoing quality, and achieving daily inspection target.

Table 1 Contributions of several authors

Authors	Inspection			Human inspection skill	Inspection time	Study objective
	Strategy	Error	Cost			
Finkelshtein et al. [25]	Sampling	✓	✓			Optimal inspection disposition policy
Duffuaa and Khan [9]	100%	✓	✓			Performance measures of repeat inspection plan
Elshafei et al. [10]	100%	✓	✓			Optimal inspection sequence for repeat inspection plan
Wang [24]	Sampling	✓	✓			Optimal inspection disposition policy
Grosfeld-Nir et al. [31]	Both	✓	✓			Optimal lot size
Duffuaa and Khan [8]	Both	✓	✓			Optimal inspection cycles
Wang and Hung [23]	Sampling	✓	✓			Optimal inspection disposition policy
Colledani and Tolio [32]	Sampling	✓				Analytical method of evaluation
Tzimerman and Herer [4]	Sampling	✓	✓			Optimal inspection policy
Bendavid and Herer [22]	Sampling	✓	✓			Optimal inspection disposition policy
Wang et al. [21]	Sampling	✓	✓		✓	Optimal inspection disposition policy
Yu et al. [14]	Both	✓	✓			Optimal inspection policy
Khan et al. [33]	100%	✓				Economic order quantity with learning in production
Yang [11]	Both		✓			Optimize K- stage inspection system
Khan et al. [34]	100%	✓	✓			Economic order quantity
Tsai and Wang [26]	Sampling	✓	✓			Optimal inspection disposition and rework policy
Yu and Yu [15]	Both	✓	✓			Optimal inspection policy
Khan et al. [35]	100%	✓	✓			Effect on human factors on total cost of supply chain
Galindo–Pacheco et al. [36]	Both		✓			Cost minimization of supply chain
Avinadav and Sarne [37]	Both	✓	✓			Selection of costly and unreliable inspections
Avinadav and Perlman [19]	Sampling	✓	✓			Optimal inspection interval
Duffuaa and El-Ga'aly [27]	100%		✓			Maximization of profit, income, product uniformity
Duffuaa and El-Ga'aly [29]	Sampling		✓			Maximization of profit, income, product uniformity
Bouslah et al. [38]	Sampling	✓				Joint production control and economic single sampling plan design
Khan et al. [39]	100%	✓	✓	✓		Integrated supply chain model
Liu et al. [40]	Sampling	✓				Resubmitted sampling scheme based on the process yield index
Aslam et al. [41]	Sampling	✓				Mixed acceptance sampling plan
Yang and Cho [12]	100%		✓			Optimal inspection cycles
Mohammadi et al. [42]	Sampling	✓	✓			Effective robust inspection planning
Duffuaa and El-Ga'aly [28]	Sampling	✓	✓			Maximization of profit, income, product uniformity
Sarkar and Saren [43]	Sampling	✓	✓			Product inspection policy
Ramzan and Kang [1]	Both	✓	✓	✓		Minimization of inspection cost
Duffuaa and El Gaaly [30]	100%	✓	✓			Maximization of profit, income, product uniformity
This paper	Both	✓	✓	✓	✓	Optimal inspectors for different products

2 Model formulation

The details of the optimization model is described here by defining the problem, model assumptions, model development, objective functions, and solution methodology.

2.1 Problem definition

A brief flow chart of manufacturing setup is shown in Fig. 1. The raw material is converted into the finished goods by a production unit that has an imperfect manufacturing process. Finished products move to an offline inspection station, where two types of inspections are performed: 100% inspection and sample-based inspection. One hundred percent inspection is performed by the inspectors of quality control that have different skill levels. Their skill levels are defined according to their inspection errors and inspection quantities per day. The number of inspectors and their skill levels vary as the product type changes from a basic to a complex structure. Every

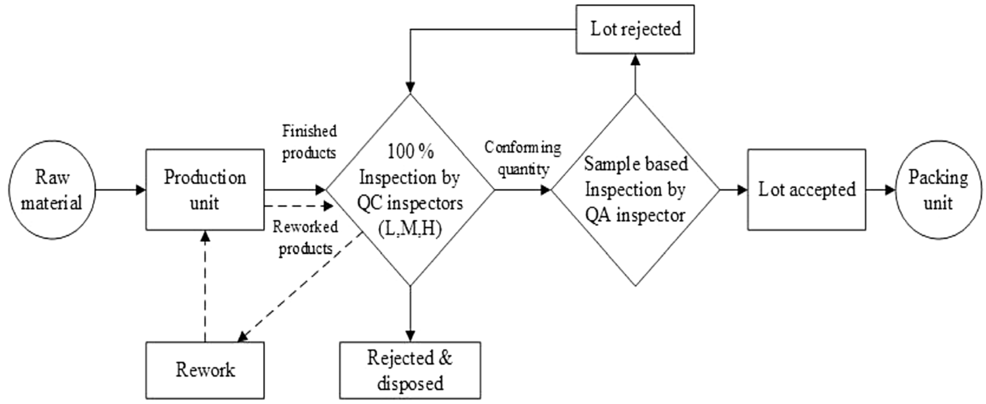

Fig. 1 Flow chart of production and inspection process of a manufacturing setup

inspector classifies the incoming products as confirming or non-confirming products. A lot of confirming products, with fixed quantity N, is then moved for sample-based inspection. Non-confirming products are either reworked or rejected [45].

Sample-based inspection is performed by a highly skilled quality assurance person. Sample size n is selected from the presented batch of confirming products with quantity N. The decision of acceptance and rejection will be made on the basis of defective items d compared with the threshold value c. If $d \leq c$, then the lot is accepted and moved to the next process; however, if $d > c$, then the lot is rejected. The rejected lot is sent back to the same inspector, and he will have to re-inspect the whole lot again. Non-confirming products are replaced by confirming products to complete the lot size N which is again presented for sample-based inspection. The total number of accepted lots is then used to calculate the quantity inspected per day by individual inspector and the offline station. Labor cost per day is calculated by using this accepted quantity of each inspector. Similarly, sample-based inspection provides the value of outgoing quality (OQ) of individual inspectors as well as the offline station. Outgoing quality per day, accepted quantity per day, and labor cost per day depend on the number of inspectors working in inspection station and their skill levels.

In the abovementioned scenario, the number of inspectors based on their skill level has a major contribution to achieve the required inspection performance. If the offline station consists of more low skill inspectors, then inspection cost may be minimized; however, the target of OQ and inspection quantity cannot be achieved. On the other hand, a high-skill inspector will increase the inspection cost even though the target of OQ and inspection quantity will be achieved. It is very rare to observe that an inspection station only consists of high-skill inspectors. Thus, organizations always would like to maintain a combination of manpower with respect to their skills to achieve required objectives of offline inspection.

2.2 Notation and assumptions

2.2.1 Notation

The nomenclature of model is stated below:

Index

$j$type of inspectors
j = low, medium, and high skill
$l$low skill inspector
$l = 1,2,3,\ldots,L$
$m$medium skill inspector
$m = 1,2,3,\ldots,M$
$h$high-skill inspector
$h = 1,2,3,\ldots,H$

Parameters

Q	quantity per day moved from manufacturing unit to inspection station
N	lot size (units)
n	sample size (units)
V	cost of inspection (\$/min) according to the product type
MI	maximum number of inspectors
VC_T	target value of variable cost of all inspectors (\$/day)
OQ_T	target value of outgoing quality of all inspectors (percentage/day)
IQ_T	target value of accepted quantity of all inspectors (units/day)

Input variables

$E(d_j)$	expected number of defective items in sample size n inspected of j^{th} inspector
$E(q_j)$	expected number of accepted lots inspected by a j^{th} inspector
$d_1^{\pm}$	deviational variable for cost of inspectors
$d_2^{\pm}$	deviational variable for outgoing quality
$d_3^{\pm}$	deviational variable for inspection quantity
$E(OQ_j)$	expected value of outgoing quality of j^{th} inspectors

$E(IQ_j)$ expected value of accepted quantity of j^{th} inspectors
VC_j variable cost of j^{th} inspectors ($/day)
OQ_O average outgoing quality of offline station (percentage/day)
IQ_O total accepted quantity of offline station (units/day)
VC_O total variable cost of all inspectors of offline station ($/day)

Decision variables

NI_j number of j^{th} type of skilled labor

2.2.2 Assumptions

In this study, the following assumptions have been made:

- A fixed quantity of finished products per day is moved from production unit to inspection station in the form of the batch with quantity Q [4, 19]. However, as the product changes from simple to complex, the output of the production unit is reduced and supply of finished products to inspection station per day will also be reduced.
- The production unit is imperfect, and there is a definite quantity of defective products in the finished quantity [46]. Output received by inspection station has a varying percentage of non-confirming quantity with respect to products as assumed by Wang and Hung [23]. However, this quantity will depend on the type of product as well.
- Inspection (100%) is performed by human inspectors of three different skill levels (low, medium, and high). Their skill levels are defined on the basis of their inspected quantities and inspection errors reported by sample-based inspection processes because of defective products present in the inspected batch [28].
- It is assumed that inspected quantity by each inspector and defective products found from each presented lot by sampling process are random variables, and follow a triangular distribution with parameters (a, b, c). The parameters a and c are the inferior and superior values, respectively, and b is the mode of the triangular distribution [47]. For a triangular distribution, it is well known that the expected value of $E(OQ)$ or $E(IQ) = (a + b + c)/3$.
- The process of sample-based inspection is used for quality assurance of batch/lot of confirming products with size N and inspection is assumed to be error free [48]. Thus, sample size n and threshold value c are also fixed for each batch that will be used to decide the acceptance and rejection of lot [18].
- Non-confirming quantities are reworked. However, the quantities that cannot be reworked are discarded with negligible cost. However, this discarded quantity also depends on the product type as simple product has less rejection percentage as compared to complex product.
- Different payment systems are used to pay the human labor that includes fixed salary per month, the contractual system, and fixed salary with incentives. This study has considered the contractual system for calculating the daily wages based on the accepted quantity of each inspector. This quantity varies from inspector to inspector according to their skill levels and product type that helps to calculate the inspection cost of each inspector.

2.3 Model development

This section describes the basic relationship of manufacturing system shown in Fig. 1. In the complete process, different types of costs are involved and organizations like to keep their expenditures in control by minimizing these costs. In this study, the objective is not only to minimize the inspection cost but also to maintain good OQ and inspection quantity as well. These objectives depend on the skill level of inspectors and inspection time of the product being inspected. Therefore, we present a model that considers both these factors. Basic relationships discussed here include inspection time, outgoing quality, inspection quantity, and inspection cost.

2.3.1 Inspection time

Inspection time is related to the product type and its complexity. As the complexity increases, inspection time will also increase that will affect the inspection performance. Therefore, this study has described the method for finding the standard inspection time (ST) of a particular product in three steps. Firstly, cycle time (CT), which is defined as "average inspection time (seconds) taken by an inspector for a particular product," is evaluated first by using Eq. (1).

$$CT = \frac{1}{R}\sum_{r}^{R} t_r \qquad r = 1, 2\ldots\ldots R \tag{1}$$

where t_r is the inspection time of single reading and R is a set of observations. Secondly, the value of CT is converted to basic minutes (BM) using Eq. (2).

$$BM = \frac{CT \times Rating\ percentage\ (RP)}{60} \tag{2}$$

Where the purpose of RP is to convert the actual time into standard time that is appropriate and at a defined level of performance. Finally, the ST is calculated Eq. (3).

$$ST = BM\left(1 + \frac{PF}{100}\right) \tag{3}$$

where PF is personal fatigue due to continuous inspection. The allowance for PF is added to standard time to recover personal needs, fatigue, and unavoidable delays during the inspection process. The complete equation to calculate the ST for a particular product is given in Eq. (4).

$$ST = \left\{ \frac{\left(\frac{1}{R} \sum_r^R t_r \times RP \right)}{60} \right\} \left(1 + \frac{PF}{100} \right) \tag{4}$$

2.3.2 Outgoing quality

Organizations would like to maintain a good level of OQ of finished products before going to end customers. The value of OQ of the inspection station and each inspector can be determined by a sample-based inspection process. Suppose Q is the total number of finished products per day moved from the production line to inspection station, and Q_j is the quantity inspected per day by j^{th} inspector. If p_j is the probability of separating the non-conforming products by j^{th} inspector, then the total non-conforming products per day NC_j and conforming products per day C_j can be calculated by Eqs. (5) and (6), respectively.

$$NC_j = p_j \times Q_j \qquad \forall j \tag{5}$$

$$C_j = \left(1 - p_j\right) \times Q_j \tag{6}$$

A part of NC_j is sent for rework while rest are rejected/disposed of. Thus, the rework quantity RE_j and rejected/disposed quantity RD_j separated by j^{th} inspector can be determined using Eqs. (7) and (8), respectively.

$$\begin{aligned} RE_j &= \alpha_j \times NC_j \\ RE_j &= \alpha_j \times \left(p_j \times Q_j\right) \ \forall j \end{aligned} \tag{7}$$

$$\begin{aligned} RD_j &= \left(1 - \alpha_j\right) \times NC_j \\ RD_j &= \left(1 - \alpha_j\right) \times \left(p_j \times Q_j\right) \end{aligned} \tag{8}$$

where α_j is the probability of reworkable quantity in NC_j. On the other hand, confirming quantity C_j separated by each inspector is presented for sample-based inspection process in the form of batches/lots of size N [49]. The value of "OQ" of j^{th} inspector is obtained as:

$$\begin{aligned} OQ_j &= \frac{Number\ of\ defective\ products}{Sample\ size} \\ OQ_j &= \frac{d_j}{n_j} \qquad \forall j \end{aligned}$$

It is assumed that the value of d_j is a random variable and follows a triangular distribution [47]. The expected value of defective products $E(d_j)$ will vary.

$$E\left(d_j\right) = \frac{d_{j,a} + d_{j,b} + d_{j,c}}{3}$$

Thus, the expected value of OQ_j of j^{th} inspector is calculated by Eq. (9).

$$E\left(OQ_j\right) = \frac{E\left(d_j\right)}{n_j} = \frac{d_{j,a} + d_{j,b} + d_{j,c}}{3n_j} \tag{9}$$

As inspectors are divided into three groups (low, medium, high) and the value of OQ vary as the skill level and product type changes. Thus, (OQ_O) of offline station is obtained using Eq. (10):

$$\begin{aligned} OQ_o &= \frac{OQ_L + OQ_M + OQ_H}{NI_L + NI_M + NI_H} \\ &= \frac{NI_L \times E(OQ_l) + NI_M \times E(OQ_m) + NI_H \times E(OQ_h)}{NI_L + NI_M + NI_H} \end{aligned} \tag{10}$$

where NI_L, NI_M, and NI_H are the total number of inspectors with low, medium, and high skills, respectively. The value of OQ_o can be calculated by Eq. (11):

$$OQ_o = \frac{\sum_j NI_j \times E\left(OQ_j\right)}{\sum_j NI_j} \qquad \forall j \tag{11}$$

2.3.3 Inspection quantity

Inspection quantity is the number of items accepted by sample-based inspection and sent to the next stage. The value of IQ_j by j^{th} inspector is calculated by Eq. (12).

$$IQ_j = q_j \times N \qquad j = 1, , 2 \ldots J \tag{12}$$

However, this value of IQ changes from one inspector to other inspector because of their varying skills and follows triangular distribution [47] as described above. Thus, the expected value of IQ can be calculated as:

$$E\left(IQ_j\right) = \frac{IQ_{j,a} + IQ_{j,b} + IQ_{j,c}}{3}$$

Total accepted quantity per day (IQ_o) of the offline station can be calculated using Eq. (13):

$$\begin{aligned} IQ_o &= \sum_j IQ_j = IQ_L + IQ_M + IQ_H \\ IQ_o &= NI_L \times E(IQ_l) + NI_M \times E(IQ_m) + NI_H \times E(IQ_h) \end{aligned} \tag{13}$$

The value of IQ_o with all NI_j number of inspectors can be estimated by Eq. (14),

$$IQ_o = \sum_j NI_j \times E\left(IQ_j\right) \quad \forall j \tag{14}$$

2.3.4 Inspection cost

Total inspection cost of offline inspection consists of fixed cost and variable cost VC. This study focuses more on VC, which is calculated by using accepted quantity per day IQ. If the accepted quantity per day of j^{th} inspector is IQ_j, then total time earned per day TE_j and VC_j can be calculated by Eqs. (15) and (16), respectively.

$$\begin{aligned} VC_j &= TE_j \times V \\ TE_j &= IQ_j \times ST \qquad j = 1,,2\ldots J \end{aligned} \tag{15}$$

$$VC_j = \left(IQ_j \times ST\right) V \tag{16}$$

As described in section 2.3.3, the value of IQ is a random variable that follows triangular distribution [47]. Thus, using $E(IQ_j)$, the value of VC_j can be calculated by Eq. (17):

$$VC_j = \left\{E\left(IQ_j\right) \times ST\right\} \times V \tag{17}$$

Thus, the total variable cost VC_o of all inspectors can be obtained by Eq. (18):

$$\begin{aligned} VC_o &= \sum_j VC_j = VC_L + VC_M + VC_H \\ VC_o &= \{NI_L \times E(IQ_l) \times ST\} \times V + \{NI_L \times E(IQ_l) \times ST\} \\ &\quad \times V + \{NI_L \times E(IQ_l) \times ST\} \times V \end{aligned} \tag{18}$$

while the inspection cost of all inspectors can be calculated by Eq. (19):

$$VC_o = \left[\left\{\sum_j NI_j \times E\left(IQ_j\right)\right\} \times ST\right] \times V \tag{19}$$

2.3.5 Objective functions

Objective functions are optimized by determining the efficient combination of decision variables in Goal Programming (GP). This is a type of multi-objective decision-making that achieves target values of each objective and minimizes unwanted deviation. GP has three commonly used methods that includes pre-emptive, non-preemptive, and fuzzy [50]. This study used the pre-emptive GP method to determine optimum decision variables. In this method, each objective is given a priority number with respect to its importance and the GP method to find out the values of decision variables according to the priority number. For this purpose, the three objective functions are described below:

1. The first objective of this study is to minimize the total inspection cost per day VC_o of all inspectors (Eq. 21). Reduction in inspection cost is given the first priority (Eq. 20) because it helps the organization meet its goals in terms of revenue and profit.
2. The second objective function is to maintain the daily quality target of the inspection station (Eq. 22). Minimization of inspection error is the second priority of our model (Eq. 20) to keep the value of outgoing quality OQ less than the target value OQ_T.
3. The third objective is to meet the daily inspection target to avoid a bottleneck in the inspection station (Eq. 23). Maximization of inspection quantity is the third priority of the presented model (Eq. 20).

Finally, the GP formulations for determining the optimal values of the decision variables consist of two minimization problems and one maximization problem as shown below:

$$Min\ Z = p_1 d_1^+ + p_2 d_2^+ + p_3 d_3^- \tag{20}$$

subject to

$$\left[\left\{\sum_j NI_j \times E\left(IQ_j\right)\right\} \times ST\right] \times V + d_1^- - d_1^+ = VC_T \tag{21}$$

$$\frac{\sum_j NI_j \times E\left(OQ_j\right)}{\sum_j NI_j} + d_2^- - d_2^+ = OQ_T \tag{22}$$

$$\sum_j NI_j \times E\left(IQ_j\right) + d_3^- - d_3^+ = IQ_T \tag{23}$$

$$\sum_j NI_j = MI \tag{24}$$

$$\mathrm{d}_t^-, \mathrm{d}_t^+ \geq 0 \qquad \text{for all t} = 1, 2, 3$$

2.4 Solution methodology

The general pre-emptive GP model is written as

$$Minimize\ Z = \sum_{t=1}^{T} p_t\left(d_t^- + d_t^+\right) \tag{25}$$

subject to

$$\sum_{j=1}^{J} \mathrm{a}_{tj}\, x_j + d_t^- - d_t^+ = b_t \tag{26}$$

$$x_j, d_t^-, d_t^+ \geq 0 \quad \text{for all } t \text{ and } j \tag{27}$$

where Z is the sum of all deviations with respect to the desired target T. The p_t is the priority number given to each deviation variables d_t^- and d_t^+. In this study, priority numbers (P_1, P_2, and P_3) are given to each deviational variables (d_1^+, d_2^+, and d_3^-) as shown in Eq. (20). Here, a_{tj} shows the constant value attached to each decision variables x_j and b_t shows the target value of each goal constraint as shown in Eqs. (21)–(24).

2.4.1 Solution algorithm

The solution methodology of GP works according to the following steps [51, 52]:

1. Based on the availability of resources that may restrict achievements of the targets, the goals and constraints are identified. A priority number is assigned to each goal with respect to its importance, for example, priority number P_1 is considered the most important target, similarly, P_2 will be the next most important target, and so on.
2. According to the research problem, decision variables and constraints are defined. Formation of constraints is developed by adding deviational variables that indicate the possible underachieved or overachieved values of targets. Finally, objective function is explained in terms of minimizing a priority function of the deviational variables.
3. According to the priority number P_1, P_2, and P_3 given in Eq. (20), the value of each decision variable and c_j-z_j for each priority is calculated separately because each ranked goal has a different measuring unit. In the calculation of c_j-z_j, c_j values represent the priority factors assigned to deviational variables, and z_j values represent the sum of the product of entries in c_b column with columns of the coefficient matrix. Thus, the c_j-z_j value for each column is calculated [51]. These priority goals are listed from bottom to top, i.e., P_1 is shown at bottom and P_3 is shown at top as shown in Table 2.
4. If the value of c_j-$z_j \leq 0$ for P_1 row, then the optimal solution has been obtained, whereas if c_j-$z_j > 0$ and there is no negative entry at higher unachieved priority levels, then optimal solution is not achieved.
5. The solution is optimal when the target value of each goal is zero in x_b column.
6. Examine the value of c_j-z_j row of highest priority P_1 to select the largest negative value and select that column as key column. Otherwise, move to the next higher priority P_2 to select the largest negative value. Similarly, the key row is the row with the minimum non-negative value, which is obtained by dividing the x_B value with the positive coefficient in the key column. This complete process gives the idea of the key column, key row, and key elements which is the intersection point of key column and key row.
7. To choose a variable that needs to leave the solution mix, apply the usual procedure for calculating the minimum ratio.
8. Any negative value in the c_j-z_j row that has a positive c_j-z_j value under any lower priority rows is ignored. This is because deviations from the highest priority goal would be increased with the entry of this variable in the solution mix.

Table 2 shows the 3 × 6 matrix to calculate the optimal criterion c_j-z_j values by using the three priority levels and six variables as shown in Eqs. (20)–(24). These variables include both decision variables (L, M, *and* H) and deviational variables (d_1^+, d_2^+, and d_3^-).

3 Results and discussion

This section is organized by describing the numerical example and sensitivity analysis. Numerical example briefly discussed the results obtained from the presented model for three

Table 2 The 3 × 6 matrix to calculate the optimal criterion c_j-z_j values

		c_j	0	0	0	P_1	P_2	P_3	Min ratio (x_b/ x_i)
c_b	Variables in basis	Solution values x_B	l	m	h	d_1^+	d_2^+	d_3^-	
P_1	d_1^+	VC_T	VC_l	VC_m	VC_h	-1	0	0	
P_2	d_2^+	OQ_T	OQ_l	OQ_m	OQ_h	0	-1	0	
P_3	d_3^-	IQ_T	IQ_l	IQ_m	IQ_h	0	0	1	
0	0	MI	1	1	1	0	0	0	
c_j-z_j	P_3	IQ_T	IQ_l	IQ_m	IQ_h	0	0	1	
	P_2	OQ_T	OQ_l	OQ_m	OQ_h	0	-1	0	
	P_1	VC_T	VC_l	VC_m	VC_h	-1	0	0	

different products. Sensitivity analysis is conducted to evaluate the effect of incoming quantity on decision variables and objective functions.

3.1 Numerical example

The application of the presented model is described in this section. For this purpose, an offline inspection setup of a manufacturing industry is selected which mainly depends on human labor, i.e., the garment manufacturing industry. The intense labor that is required in the garment industry makes it a good sector to study the effect of human factors on process improvement activities. This is because the productivity and quality of these industries greatly depend on skill level, learning behavior, attitude, and qualifications of human labor [39]. For this study, three knitted items were used that includes the basic T-shirt (A), the long sleeve shirt (B), and the hooded shirt (C). These garments vary from each other in many ways that increase inspection time and can affect the overall performance of the inspection station. Relevant information of offline inspection setup with respect to selected garments is mentioned in Table 3.

Optimization software is required to analyze data (Table 3) to obtain the optimal results for different products. For this purpose, QM for Windows was used with the following system configuration: Intel® Core™ i5-3570 CPU @ 3.40GHz, 8.00GB of RAM. GP module was applied to determine the optimal results of the decision variables along with the optimized values of the objective functions. Optimized results for three different garments are summarized in Tables 4, 5, and 6. The results are divided into three sections that include the decision variable analysis, priority analysis, and constraint analysis.

1. The decision variable analysis shows the optimal combination of decision variables by providing the number of inspectors of low, medium, and high skill levels. According to the results, the number of low skill inspectors was less as compared to the medium and high-skill inspectors (Tables 4, 5, and 6). This evidence is relatively true because, with a greater number of low skill inspectors, inspection cost of the offline station may be low but it will be very difficult to achieve the daily inspection target and quality level. Therefore, the inspection station must consist of an efficient combination of inspectors of all skill levels so that all the objectives can be achieved.

However, this efficient combination depends on the type of product, i.e., the product complexity that effects the skill level of inspectors along with the inspection costs and outgoing quality. In order to meet the required inspection performance, the results of decision variables changed from one product to another due to the change in inspection time. The change in the value of decision variables is shown in Tables 4, 5, and 6 for three different types of products. For basic/less complex products, more low and medium skill inspectors can achieve the required objective functions as mentioned in Table 4. On the other hand, as product complexity increases, an inspection station requires a greater number of high-skill inspectors to meet required inspection performance (Tables 5 and 6).

2. The second section consists of priority analysis that describes the achievement and non-achievement of the already given priority targets. In the case of achievement, analysis will give zero value while for non-achievement, the analysis shows the value by which the priority is not achieved. For the presented

Table 3 Data of garment manufacturing industry

Notation	T-shirt (A)	Long sleeve shirt (B)	Hooded shirt (C)
ST (mins)	0.96	1.25	1.60
OQ_T	0.05	0.05	0.05
$E(OQ_{l,a})$, $\boldsymbol{E(OQ_{l,b})}$, $E(OQ_{l,c})$	0.07, **0.08**, 0.09	0.09, **0.10**, 0.11	0.09, **0.10,** 0.11
$E(OQ_{m,a})$, $\boldsymbol{E(OQ_{m,b})}$, $E(OQ_{m,c})$	0.03, **0.04**, 0.05	0.04, **0.05**, 0.06	0.05, **0.06**, 0.07
$E(OQ_{h,a})$, $\boldsymbol{E(OQ_{h,b})}$, $E(OQ_{h,c})$	0.01, **0.02**, 0.03	0.02, **0.03**, 0.04	0.03, **0.04**, 0.05
$E(IQ_{l,a})$, $\boldsymbol{E(IQ_{l,b})}$, $E(IQ_{l,c})$	250, **300**, 350	150, **200**, 250	100, **150**, 200
$E(IQ_{m,a})$, $\boldsymbol{E(IQ_{m,b})}$, $E(IQ_{m,c})$	450, **500**, 550	300, **350**, 400	200, **250**, 300
$E(IQ_{h,a})$, $\boldsymbol{E(IQ_{h,b})}$, $E(IQ_{h,c})$	650, **700**, 750	450, **500**, 550	300, **350**, 400
IQ_T (units)	6000	5500	4000
VC_T ($)	5500	7000	8500
VC_l ($)	249	250	300
VC_m ($)	415	438	500
VC_h ($)	581	625	700
V ($/min)	0.86	1.00	1.25
N (units)	100	50	32

Table 4 Optimum values of objective functions and decision variables for product A

Decision variable analysis	Value	Priority analysis	Non-achievement
Low	5	Priority 1	0
Medium	2	Priority 2	0
High	5	Priority 3	0
Constraint analysis	RHS	d^+ (exceed)	d^- (underachieved)
Inspection quantity (units)	6000	0	0
Outgoing quality	0.05	0	0
Inspecting cost ($)	5500	0	520

model, the analysis shows zero value for all priorities. This means that the goal programming module gave such optimal results that all our set targets were achieved for all three products (Tables 4, 5, and 6).

3. Finally, the constraint analysis shows the difference between the actual values and the target values of each goal. There are some underachieved and exceeded values for inspection cost and inspection quantity, but these values do not violate the given priorities. Tables 4 and 5 show the exceeded value of the inspection quantity (d^+) 50 and 150 for product A and B, respectively. However, it still fulfills the constraints mentioned in Eqs. (20) and (23). 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 results. Similarly, Tables 4, 5, and 6 indicated underachieved values of inspection cost (d^-) as 520, 63, and 200 for product A, B, and C, respectively. Since the requirement of the model is to keep inspection cost as low as possible, these underachieved values show good results.

To validate the results of the proposed model, the value of each objective of the research problem was determined for all three products using one type of inspector only. The results are shown in Tables 7, 8, and 9. Then, a comparison was done with the optimized results shown in Tables 4, 5, and 6 to verify the importance of using manpower with respect to their skill.

Table 5 Optimum values of objective functions and decision variables for product B

Decision variable analysis	Value	Priority analysis	Non-achievement
Low	3	Priority 1	0
Medium	7	Priority 2	0
High	5	Priority 3	0
Constraint analysis	RHS	d^+ (exceed)	d^- (underachieved)
Inspection quantity (units)	5500	50	0
Outgoing quality	0.05	0	0
Inspecting cost ($)	7000	0	63

Table 6 Optimum values of objective functions and decision variables for product C

Decision variable analysis	Value	Priority analysis	Non-achievement
Low	3	Priority 1	0
Medium	5	Priority 2	0
High	7	Priority 3	0
Constraint analysis	RHS	d^+ (exceed)	d^- (underachieved)
Inspection quantity (units)	4000	150	0
Outgoing quality	0.05	0	0
Inspecting cost ($)	8500	0	200

For example, Tables 7, 8, and 9 indicate that if the variable cost is to be minimized only, then this target can be achieved by taking all low skill inspectors. However, outgoing quality and inspection quantity will be overlooked in that case. If the offline station consists of inspectors with medium skills only, then results are quite satisfactory, but it is hard to believe that all inspectors of an organization have same skills. Lastly, the target of both outgoing quality and inspection quantity is well achieved if all inspectors belong to the high skill level. However, in this case cost will be very high and there is always a lack of high-skill labor in the organization. Thus, an efficient combination of human labor with respect to their skill level should be determined to achieve all the targets simultaneously.

Tables 4, 5, and 6 show optimized results of decision variables for which all the objectives have been achieved for three different products. Thus, the proposed model enables the manufacturers to determine the efficient combination of human labor for offline inspection based on their skill. This study has focused on inspection performance that is evaluated on the basis of three parameters: quality, quantity, and cost associated with human labor. It is observed that overall inspection performance is significantly affected by the individual performance of inspectors. This fact is briefly described in Fig. 2 which indicated how these varying factors (*VC*, *IQ*, and *OQ*) of human resource affect the performance for three different products. Thus, Fig. 2 indicates that as the product type changes inspection cost, *OQ* and inspection quantity change because of the changing contribution of each group of inspectors.

Figure 2a shows that inspection cost of offline station increases as product changes from basic to complex. The main

Table 7 Values of objective functions with inspectors of same skill for product A

When all inspectors are	TVC ($)	AOQ	TIQ (units)	L	M	H
Low skill	2988	0.08	3600	12	0	0
Medium skill	4980	0.04	6000	0	12	0
High skill	6972	0.02	8400	0	0	12

Table 8 Values of objective functions with inspectors of same skill for product B

When all inspectors are	TVC ($)	AOQ	TIQ (units)	L	M	H
Low skill	3750	0.10	3000	15	0	0
Medium skill	6570	0.05	5250	0	15	0
High skill	9375	0.03	7500	0	0	15

reason behind this change is the increasing contribution of high-skill inspectors as compared to low and medium skill inspectors. Figure 2b indicates the contribution of different inspectors to maintain the required *OQ* of the offline station. Since low skill human labor is more prone to inspection error as compared to medium and high-skill labor, to maintain the required quality level, an inspection station must have sufficient high-skill labor as compared to low or medium skill labor. A further increase in high-skill labor is observed as the product type changes from basic to complex.

Figure 2c shows how inspectors of different skill levels contribute to achieving the required target of inspection quantity. Low skill inspectors do not have enough experience, and their inspection quantity is less than experienced inspectors. Thus, to attend the required target of the offline station, the contribution of high-skill inspectors increases with the increase in product complexity.

3.2 Sensitivity analysis

Sensitivity analysis was conducted to evaluate the effect of the daily inspection target on the optimal results of the presented model. It was observed that finished items coming from a production line increase with the passage of time. For sensitivity analysis, the value of IQ_T changed from − 50 to + 50% and the variation in decision variables, inspection cost, and outgoing quality are measured with respect to the originally optimized results obtained in Tables 4, 5, and 6. The results of the sensitivity analysis for three different products are summarized in Table 10, and some insights of the sensitivity analysis are as follows:

(1) For the presented model, total inspection cost, outgoing quality, and optimal values of decision variables are sensitive to incoming inspection quantity. As the demand for inspection station increases, there is a need to increase the manpower to meet the target of inspection quantity. Similarly, a decrease in target value of inspection station will decrease the involvement of labor and target can be achieved with lesser labor.

Table 9 Values of objective functions with inspectors of same skill for product C

When all inspectors are	TVC ($)	AOQ	TIQ (units)	L	M	H
Low skill	4500	0.10	2250	15	0	0
Medium skill	7500	0.06	3750	0	15	0
High skill	10,500	0.04	5250	0	0	15

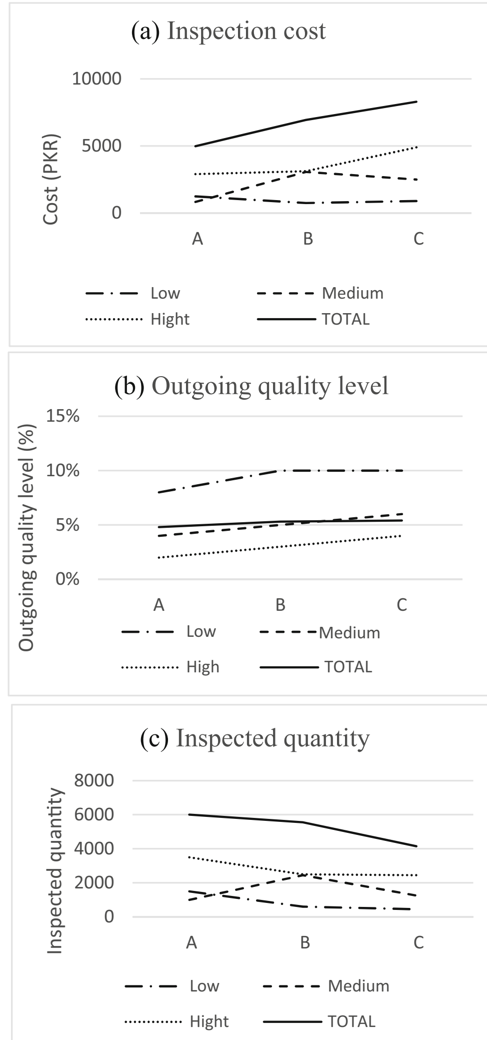

Fig. 2 Effect of varying factors on overall inspection performance

(2) This fact is again cleared that products with high inspection time required a greater number of high-skill labor as compared to low-skill labor to meet *OQ*. This result shows that as the complexity increases, there is a higher demand of high-skill labor and less of low-skill labor. But in actuality, organizations always have human labor of different skills. This gap means that there is a need to work on the fragmentation of complex product so that all type of human labor can be utilized efficiently.

(3) According to sensitivity analysis, both inspection cost and outgoing quality are sensitive to inspection quantity as well. As the required inspection quantity changes from + 50 to − 50%, inspection cost also changes at an almost similar rate. On the other hand, good outgoing quality

Table 10 Sensitivity analysis of target inspection quantity for three different products

Product type	Inspection time (ST)	Inspection quantity		Optimal value of decision variables			Change in	
		Change (%)	Revised IQ_T	Low	Medium	High	VC_O (%)	OQ_O (%)
A	0.96	+ 50%	9000	8	5	6	+ 52%	+ 6%
		+ 25%	7500	7	4	5	+ 27%	+ 6%
		− 25%	4500	4	4	2	− 23%	+ 8%
		− 50%	3000	3	3	1	− 48%	+ 13%
B	1.25	+ 50%	8250	5	8	9	+ 50%	0%
		+ 25%	6875	5	7	7	+ 25%	+ 6%
		− 25%	4125	2	5	4	− 25%	− 2%
		− 50%	2750	2	2	3	− 53%	+ 6%
C	1.60	+ 50%	6000	7	9	8	+ 47%	+ 12%
		+ 25%	5000	6	7	7	+ 21%	+ 10%
		− 25%	3000	2	4	5	− 27%	0%
		− 50%	2000	2	3	3	− 50%	+ 7%

has been maintained against change in inspection quantity. In fact, this change is likely to change the optimal value of decision variables that affect the inspection cost and outgoing quality. Organizations like to achieve such an efficient combination of inspectors with respect to their skills to keep inspection cost minimum with good outgoing quality.

4 Conclusions

This study has investigated the human-based offline inspection station with inspectors of different skills. The objective was to meet the required inspection performance by efficient use of the available human labor of different skills. A multi-objective optimization model is presented to obtain the number of inspectors of each skill level to meet demands of an inspection station. This model considered three levels of skill (low, medium, and high) and inspection time to measure the inspection cost, inspection error, and inspection quantity. The goal programming was used to obtain the optimal values of decision variables that achieved all the objective functions. Numerical examples with three different types of products, graphical illustration, and sensitivity analysis were presented to point out the significance of model for human-based offline inspection. From the results, it can be concluded that the skill levels of inspectors significantly affect the inspection performance. An inspection station must have a suitable combination of inspectors with different skill levels to meet the requirements of inspection performance. The managers of different industries will be benefited from the results of this model because it is helpful for efficient use of human labor in an offline inspection setup for products of different complexities. However, further work should be done in this research area by considering the effect of time-varying factors like improvement in skill level with the passage of time. It is also observed that efficient combination of human labor with different skill levels creates an environment of competition that will encourage low skill inspectors to learn quickly, so they will be able to increase their skill level at a faster rate. Thus, the effect of such competitive environment, i.e., learning behavior must also be considered in future for human-based manufacturing systems to propose a more realistic model [53]. Moreover, as the skill level and learning behavior improves, the inspection cost and quality levels are significantly affected. It highlights the importance of developing training methods to improve the skill and the learning process.

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