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Selecting the best quality inspection alternative based on the quality, economic and environmental considerations

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ABSTRACT

The use of inspection is unavoidable in many situations. For example, inspection is required to satisfy government regulation, guarantee quality parameter is met by the products supplied by new suppliers whose quality history has not been built, and mitigate product liability risks. There are three quality inspection alternatives, 100 percent inspection, no inspection, and sampling inspection. No inspection brings a considerable risk of shipping non-conforming products to the consumer. 100 percent inspection involves a slight risk of delivering non-conforming products to the consumer but consumes resources significantly. Sampling inspection requires the producer to judge products based on a random sample. Therefore, it still contains the risk of sending non-conforming products to the consumer. The risk and resource consumptions can cause the producer to bear for the cost and environmental impact due to rework, scrap, and transportation. This paper proposes a mathematical model and algorithm to select the best inspection alternative based on quality, economic, and environmental considerations. We apply the model and algorithm to solve a real industrial case study. The results of the case study show that the proposed method results in a lower expected total cost and CO_2 emission and a better level of protection for the producer and consumer than the single sampling plan method widely used. We expect that the proposed model and algorithm can assist practitioners in the industry to select the best inspection alternative. It is essential to note that sampling inspection is not a substitute for proper process monitoring and control.

Abbreviations: *AOQ*: average outgoing quality; *AOQL*: average outgoing quality limit; *AQL*: acceptable quality limit; α: producer's risk; β: consumer's risk; c: acceptance number; I_{ec}: inspection cost per unit; I_{ev}: environmental impact per unit due to inspection; *LTPD*: lot tolerance percent defective; n: sample size; N: lot size; *OQ*: outgoing quality; p: proportion of non-conforming products produced by a process; p_0: average proportion of non-conforming products produced by a process; P_a: probability of acceptance; $\varphi_{s,ec}$: total cost of sampling inspection; $\varphi_{s,ev}$: total environmental impact of sampling inspection; $\varphi_{100,ec}$: total cost of 100 percent inspection; $\varphi_{100,ev}$: total environmental impact due to 100 percent inspection; $\varphi_{0,ec}$: total cost of no inspection; $\varphi_{0,ev}$: total environmental impact due to no inspection; R_{ec}: replacement cost per unit; R_{ev}: environmental impact per unit due to replacement; $\hat{\sigma}_p$: estimated standard deviation of p; T_{ec}: delivery cost per unit; T_{ev}: environmental impact per unit due to delivery

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Introduction

Although Lean Six Sigma (LSS) and Statistical Process Control (SPC) are regarded as the main tools in lean practices and quality assurance (Freitas, Costa, and Ferraz 2017; Cherrafi et al. 2016; Garza-Reyes et al. 2014; Torielli et al. 2011), the use of inspection is unavoidable in many situations (Yen, Chang, and Aslam 2015). For example, inspection is needed when there are product liability risks (Montgomery 2013) and there is a need to satisfy government regulations (e.g., for the military procurers and food processors). Also, for particular customers, not all suppliers have good quality assurance systems and products from new suppliers must be inspected before a good quality reputation is built. Furthermore, there is a situation in the manufacturing processes in which known assignable causes of defective products may not be eliminated instantly because of time or capital reasons, and consequently, an inspection must be performed (Yen, Chang, and Aslam 2015). A quality inspection may also be required to reach zero defects. For example, a consumer can build an inspection policy motivating

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its suppliers to achieve zero defects (Wang 2013; Starbid 1997; Calvin 1983). Finally, the prevalence of outsourcing and contract manufacturing practices in the industries has made inspection resumes its relevance in the industries (Nezhad and Niaki 2013).

The most effective use of inspection is as an audit tool to guarantee that the outputs of a process fulfill the requirements but not to "inspect quality into the product" (Montgomery 2013). Therefore, literature classifies inspection as a necessary but non-value added activity (Starbid 1997). It is an activity in which the consumers do not ask and want to pay for. The best approach to address this issue is by selecting the best inspection alternative based on quality and other considerations, such as economic and environmental considerations.

According to ASTM International, formerly known as American Society for Testing and Materials, to determine how much inspection is required, the alternative is between 100 percent inspection, no inspection at all, or sampling inspection (Schilling 1990). The author also stated that 100 percent inspection is not difficult to practice because of computerized automatic inspection equipment that can perform inspection at high speed. However, the machine requires costs for design, production, installation, and maintenance.

With 100 percent inspection, there is a lower risk that the producer ships non-conforming products to the consumers. The magnitude of the risk depends on the effectiveness of the 100% inspection. Juran (1999) stated that the effectiveness of 100% inspection when inspecting a large lot is about 80%. The 100 percent inspection activity will also consume significant economic, environmental, and human resources. Moreover, if the inspector finds non-conforming products in the lot, the producer needs to replace, rework, or scrap them. Replacing, reworking, and scrapping the non-conforming products will also have economic and environmental effects.

When the producer applies no inspection alternative before shipping the lot, there will be no cost and environmental impacts related to the inspection activity, rework, and scrapping the non-conforming products because there is no inspection at all. However, there is a very high risk that the producer will send batch containing numerous non-conforming products to the consumers. If the quality of the batches does not meet consumer's specifications, he will return them to the producer, and the producer will be responsible for the return transportation costs, replacing or reworking the defective products, and shipping the defect-free batch to the consumer.

Sampling inspection is between the two extremes. The producer takes a random sample from the lot and inspects the sample. Based on the sample, the producer decides whether to accept the lot and ship it to the consumer or not. The producer uses a particular parameter to judge the lot. If the lot does not meet the quality parameter (based on the sample), the producer inspects all products in the lot and replaces or reworks all non-conforming products. Then, he ships the rectified lot to the consumer. In the literature, this is known as the rectifying inspection (Besterfield 2008; Fink and Margavio 1994; Montgomery 2013; Wadsworth, Stephens, and Godfrey 2002). The inspection, rework, providing replacement, and transportation will have economic and environmental impacts. When the producer accepts the lot (based on the sample), there is still a risk that the producer will send a lot having defective products. If the consumer rejects and returns this lot, the producer is responsible for the transportation and replacing the non-conforming products found in the lot. Similarly, these activities will have economic and environmental consequences.

If we relate the cost and impact mentioned above with product delivery, when we use 100 percent inspection, the cost and impact may appear before the delivery of products. With no inspection, the cost and impact may emerge after delivering the products to the customer. With sampling inspection, the cost and impact may arise before and after the delivery. Sources of costs and impacts include scrap (loss of labor and material), rework (cost, material, and energy of correcting non-conforming), retesting (cost, material, and power for reinspection and testing), handling, and replacing non-conforming items returned by the consumer. Other effects can be downtime, delays, complaints, and sales reductions.

Currently, there is an increasing pressure from the government and the public for the industries to establish sustainable operations (Meng et al. 2017). They should reduce their ecological footprint in all their business activities while not sacrificing their financial performance. There has been abundant literature exploring ways to reduce the environmental impact of material production, manufacturing, transportation, use, and maintenance activities. However, there is still a lack of models that include the economic and environmental considerations in an inspection process. This paper attempts to fill this gap.

The goal of this paper is to develop a mathematical model and algorithm to determine the best alternative for product inspection such that the total expected cost and environmental impact associated with the inspection, repair of the non-conforming products, and transportation are minimized. The model will also provide proper protection for the producer and consumer. It is expected that this will support the industries' efforts to achieve quality enhancement, financial, and environmental goals.

Literature review

At the process level, SPC is commonly used to control critical environmental performances, such as energy usage and CO_2 emission (Cherrafi et al. 2016; Garza-Reyes et al. 2014; Torielli et al. 2011). However, SPC is just one of the tools in Statistical Quality Control (SQC). The other tool is acceptance sampling.

There are two schemes of a sampling plan, attribute, and variable sampling plans. An attribute sampling plan labels products as conforming or non-conforming, while a variable sampling plan is used when measurement data is available, and therefore it can provide more information (Aslam et al. 2014).

The simplest form of an attribute sampling plan is the single sampling plan. Other types of attribute sampling plans are double, sequential, and multiple sampling plans. Double sampling requires taking the second sample, which is not always taken, depending on the decision given by the first sample. Multiple sampling plan is an extension of the double sampling plan. The accept or reject decision is made after less than or equal to seven samples are taking. In the sequential sampling, each item is inspected continuously. After each piece is examined, the decision is to accept the lot, reject the lot, or inspect another item (Wadsworth, Stephens, and Godfrey 2002). Besterfield (2008) showed that a single sampling's Average Sample Number (ASN) $>$ double sampling's ASN $>$ multiple sampling's ASN $>$ sequential sampling's ASN. A variable sampling plan is usually a single sampling plan. Its sample size is smaller than the attribute sampling plans (Wadsworth, Stephens, and Godfrey 2002).

In selecting the best sampling plan, two criteria are usually used, cost and the level of protection provided for the producer and consumer. Sampling plan procedures aimed to minimize the expected total cost can be found in Aslam et al. (2013), Fallahnezhad and Yazdi (2016), Farooq et al. (2017), Fink and Margavio (1994), Nezhad and Niaki (2013), and Tagaras (1994). The cost function was modeled based on the average sample number (ASN) (Aslam et al. 2013), appraisal and failure costs (Farooq et al. 2017), Taguchi's loss function (Fink and Margavio 1994; Tagaras 1994), and Markovian model (Nezhad and Niaki 2013). Sampling inspection plans aimed to fulfill the stipulated level of protection required by the consumer and producer can be found in Besterfield (2008), Montgomery (2013), and Wadsworth, Stephens, and Godfrey (2002). The level of risks that can be accepted by the producer and consumer are stated together with the acceptable quality level (AQL) and Lot Tolerance Percent Defective ($LTPD$). The result provided by sampling inspection is usually compared with no inspection and 100 percent inspection.

Based on the literature review, we can conclude that quality and economic considerations have been proposed to select the best inspection alternative but environmental factor has not been touched yet as one of the criteria. However, there is pressure from the government and public to the industries to reduce all their operations' ecological footprints (Meng et al. 2017). This paper aims to fill this gap. In this paper, the mathematical model and algorithm to choose the best inspection alternative based on the quality, economic, and environmental considerations are proposed.

Problem description

The producer produces products with the lot size of N. Average proportion of non-conforming items of the producer's production process is p_0, and therefore the average percentage of non-conformity of the lot is also p_0. The consumer purchasing the products may set the most inferior quality level that he is willing to accept. The quality level is known as the lot tolerance percent defective ($LTPD$) (Montgomery 2013). The $LTPD$ is stated together with the risk that the consumer is willing to take β. The producer wants the consumer to accept such lot at least $100(1-\alpha)$ percent of the time when he supplies lot having a certain proportion of defective products or better, called the acceptable quality limit (AQL). α denotes the risk the producer willing to accept. The producer has three alternatives in examining the lot before delivering it to the consumer, sampling inspection, no inspection, and 100 percent inspection (Schilling 1990).

If the producer selects sampling inspection, he inspects the lot through a sample with the size of n and acceptance number c ($c = 0, 1, 2, \ldots$).When he finds c or fewer non-conforming products in the lot, he accepts the lot. Else, he rejects the lot.

The probability of the lot being accepted P_a can be approximated using Poisson distribution and is given by Eq. (1) (Besterfield 2008; Montgomery 2013; Wadsworth, Stephens, and Godfrey 2002). P_a is a function of p_0, n, and c. Since the lot size is large, the

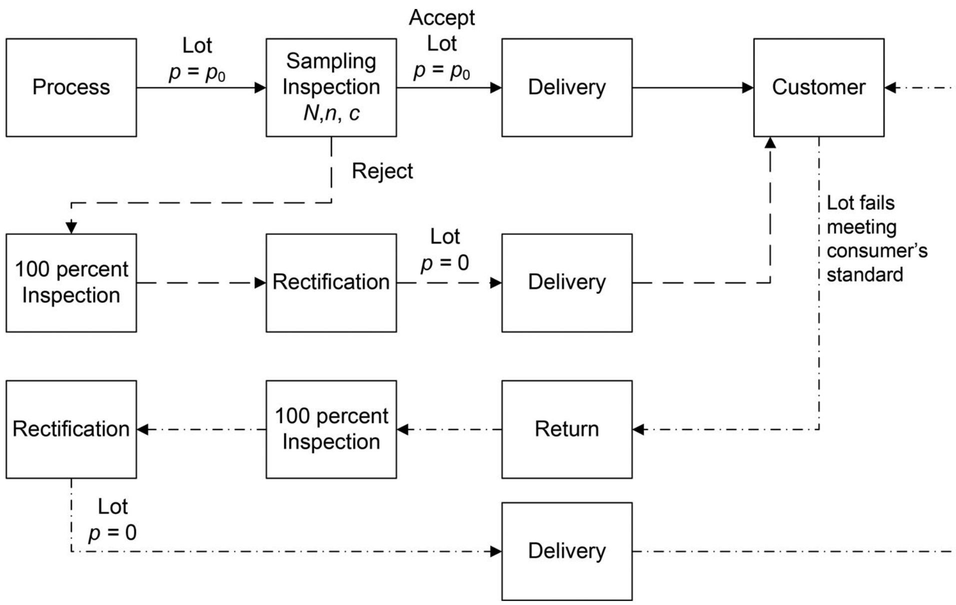

Figure 1. Sampling inspection.

binomial distribution may be used. However, when $np_0 < 5$ and $p_0 < 0.10$, the Poisson distribution can well approximate the Binomial distribution (Besterfield 2008; Devore 2000; Feldman and Valdez-Flores 2010; Montgomery 2013; and Wadsworth, Stephens, and Godfrey 2002). Moreover, when the Poisson distribution is used, the computation is easier, and it is more practical (Wadsworth, Stephens, and Godfrey 2002). In deciding the values of c and n, the producer aims not to exceed α at AQL, and β at $LTPD$.

$$P_a = \sum_{i=0}^{c} \frac{(np_0)^i}{i!} e^{-np_0} \tag{1}$$

After the producer deciding to accept the lot, he ships it to the consumer. In the lot sent by the producer, there may be non-conforming products, with the average proportion of p_0. If the decision rejects the lot, he will perform 100 percent inspection and rectify the lot. After rectification, he ships the lot and the probability of defect p of the rectified lot is zero.

Also, if the consumer finds that the number of defective products in the lot exceeds the $LTPD$, the consumer returns the lot to the producer (O'Connor and Kleyner 2012; Montgomery 2013). The producer must perform 100 percent inspection, rectification, and reship the rectified lot to the consumer.

It is clear that n items in the sample are always inspected, but the 100 percent inspection is not always performed. Here, the average number of items inspected by the producer, called Average Total Inspection (ATI), is calculated using Eq. (2) (Besterfield 2008; Montgomery 2013; Wadsworth, Stephens, and Godfrey 2002).

$$ATI = n + (N - n)(1 - P_a) \tag{2}$$

Figure 1 depicts events that may occur when the producer selects sampling inspection. In Table 1, we show the sources of cost and environmental impact that may emerge. Based on the table, we can conclude that all activities presented in the figure have economic and ecological effects.

Figure 2 presents events that may occur if the producer utilizes no inspection. He bears a high risk of sending non-conforming items to the consumer. Thus, when the consumer finds that the number of non-conforming products exceeds the $LTPD$, he returns the lot (O'Connor and Kleyner 2012; Montgomery 2013). The probability of the consumer will return the lot depends on p_0 and its variability. If this happens, the producer is responsible for returning transportation, 100 percent inspection, rectification, and reshipment. He must pay for the costs incurred and is accountable for the environmental burden.

If the producer uses 100 percent inspection, see Figure 3, he examines all items in the lot before shipping it to the consumer. When he finds non-conforming items in the lot, he rectifies them. Then, he delivers the rectified lot to the consumer. Thus, the lot is free from non-conforming items, and the probability that the consumer will return the lot is zero (assuming that 100 percent inspection is 100 percent effective). Therefore, through 100 percent inspection, there is no risk of sending a poor quality lot to the consumer. The activities causing the emergence of cost and environmental impact in this alternative are

Table 1. Sources of cost and environmental impact.

Activity	Source of cost	Source of environmental impact
Sampling and 100 percent inspections	• Operation of inspection equipment • Inspector wage • Materials consumed in an inspection activity	• Energy consumed and pollutants emitted due to the operation of inspection equipment • Loss of materials and energy due to the destructive test
Lot rectification before shipment	• Costs associated with the production of replacement products • Rework • Scrap • Retesting	• Pollutants emitted, energy, and materials consumed due to the production of replacement products • Pollutants emitted, energy, and materials consumed due to rework, scrap, and retesting
Shipment and return	• Transportation	• Pollutants emitted due to transportation activity
Lot rectification after shipment	• Costs associated with the production of replacement products • Rework • Scrap • Retesting	• Pollutants emitted, energy, and materials consumed due to the production of replacement products. • Pollutants emitted, energy, and materials consumed due to rework, scrap, and retesting • Pollutants emitted due to redelivery

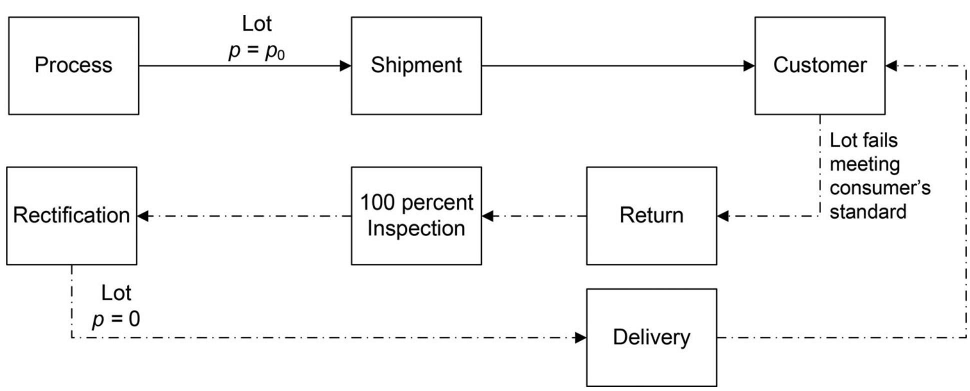

Figure 2. No inspection.

Figure 3. 100 percent inspection.

the 100 percent inspection, the rectification of the lot, and the shipment activities.

The problem is that, what alternative should the producer select such that the expected total cost and environmental impact are minimized, given the values of N, AQL, α, $LTPD$, and β? Furthermore, if he chooses sampling inspection, what are the values n and c?

Material and methods

In formulating the model, we assume that 100 percent inspection is 100 percent effective and there is no inspector error.

Sampling inspection

Figure 1 presents events that may happen when sampling inspection is selected. An inspection cost is a form of incorporation of appraisal costs in sampling inspection. It is a function of the number of items inspected and the inspection costs per unit (Besterfield 2008; Fink and Margavio 1994; Montgomery 2013; Wadsworth, Stephens, and Godfrey 2002). Table 1 gives sources of cost and environmental impact due to the inspection activity. Now let I_{ec} be the inspection cost per unit and I_{ev} be the environmental impact per unit due to the inspection. Therefore,

$$(\text{Inspection cost}) = I_{ec}ATI = I_{ec}[n + (N - n)(1 - P_a)]$$

$$(\text{Environmental impact due to inspection}) = I_{ev}ATI$$
$$= I_{ev}[n + (N - n)(1 - P_a)]$$

In the inspection step, some of the items from the sample may fail. Those items are rectified. As presented in Table 1, rectification incurs cost and environmental impact. Let the rectification cost and environmental impact per unit are R_{ec} and R_{ev}, respectively. Then, the total cost and environmental impact of this activity are,

$$\begin{pmatrix} \text{Cost of rectifying nonconforming} \\ \text{items found in the sample} \end{pmatrix} = R_{ec}np_0$$

$$\begin{pmatrix} \text{Environmental impact of rectifying} \\ \text{nonconforming items found in the sample} \end{pmatrix} = R_{ev}np_0$$

When the producer rejects the lot before delivery, he will rectify it (Fink and Margavio 1994). The rectification activity incurs cost and environmental impact, see Table 1. Total cost and environmental impact of lot rectification before shipment are,

$$\begin{pmatrix} \text{Cost of} \\ \text{lot rectfication before shipment} \end{pmatrix}$$
$$= R_{ec}(1 - P_a)(N - n)p_0$$
$$\begin{pmatrix} \text{Environmental impact of} \\ \text{lot rectification before shipment} \end{pmatrix}$$
$$= R_{ev}(1 - P_a)(N - n)p_0$$

When the lot is accepted, it will be shipped to the consumer. The transportation activity incurs cost and emits pollutants. Let T_{ec} and T_{ev} be the cost and environmental impact per unit caused by the delivery activity, then the total cost and environmental impact due to the delivery activity are,

$$(\text{Delivery cost}) = T_{ec}N$$
$$\begin{pmatrix} \text{Environmental impact} \\ \text{due to delivery} \end{pmatrix} = T_{ev}N$$

For the lots passing sampling inspection, its quality level is determined by a random variable called the Outgoing Quality OQ (Jaraiedi and Segall 1990). The estimate of its mean is the Average Outgoing Quality $AOQ = P_a\, p_0$, and the estimate of it variance is ${p_0}^2\, P_a$ $(1 - P_a)$ (Jaraiedi and Segall 1990). The probability that $OQ > LTPD$ is given by,

$$P_{OQ>LTPD} = 1 - \Phi\left(\frac{LTPD - AOQ}{p_0\sqrt{P_a(1 - P_a)}}\right)$$

Φ represents the cumulative standard normal distribution. If $OQ > LTPD$, the producer is responsible for returning transportation, performs 100% inspection, and rectifies the lot. Therefore, total cost and environmental impact of lot rectification after shipment are,

$$\begin{pmatrix} \text{Cost of} \\ \text{lot rectification after shipment} \end{pmatrix}$$
$$= [I_{ec}N + T_{ec}N + R_{ec}(N - n)AOQ]P_{OQ>LTPD}$$
$$\begin{pmatrix} \text{Environmental impact} \\ \text{of lot rectification after shipment} \end{pmatrix}$$
$$= [I_{ev}N + T_{ev}N + R_{ev}(N - n)AOQ]P_{OQ>LTPD}$$

Consequently, the expected total cost $\varphi_{s,ec}$ and environmental impact $\varphi_{s,ev}$ of the sampling inspection are given by Eqs. (3) and (4).

$$\begin{aligned} \varphi_{s,ec} &= I_{ec}[n + (N - n)(1 - P_a)] + R_{ec}np_0 \\ &+ R_{ec}(1 - P_a)(N - n)p_0 + T_{ec}N \\ &+ [I_{ec}N + T_{ec}N + R_{ec}(N - n)AOQ]P_{OQ>LTPD} \end{aligned} \tag{3}$$

$$\begin{aligned} \varphi_{s,ev} &= I_{ev}[n + (N - n)(1 - P_a)] + R_{ev}np_0 \\ &+ R_{ev}(1 - P_a)(N - n)p_0 + T_{ev}N \\ &+ [I_{ev}N + T_{ev}N + R_{ev}(N - n)AOQ]P_{OQ>LTPD} \end{aligned} \tag{4}$$

Sample size n and acceptance number c minimizing $\varphi_{s,ec}$ and $\varphi_{s,ev}$ must satisfy β at $LTPD$ and α at AQL. The n and c are calculated using Eq. (5), and α at AQL is evaluated using Eq. (6). The pair of c and n minimizing $\varphi_{s,ec}$ and $\varphi_{s,ev}$ is the solution.

$$\beta = \sum_{i=0}^{c} \frac{(n \cdot LTPD)^i e^{-n \cdot LTPD}}{i!} \tag{5}$$

$$\alpha = 1 - \sum_{i=0}^{c} \frac{(n \cdot AQL)^i e^{-n \cdot AQL}}{i!} \tag{6}$$

No inspection

For no inspection option, see Figure 2, there are no costs and environmental impacts due to the inspection activity prior to the shipment. The probability that $p > LTPD$ is determined by the mean and standard deviation of p. The mean of p is estimated using its average p_0. The standard deviation of p is estimated using $\hat{\sigma}_p = \sqrt{p_0(1 - p_0)/n_0}$. n_0 is the sample size used when measuring the quality of the process. Therefore, the probability that $p > LTPD$ is,

$$P_{p>LTPD} = \Phi\left(\frac{LTPD - p_0}{\hat{\sigma}_p}\right)$$

Additionally, when the lot does not meet the $LTPD$, the consumer returns the lot, and the producer is responsible for the return transportation, 100 percent inspection, and rectification. Consequently, the expected total cost and environmental impact ($\varphi_{0,ec}$ and $\varphi_{0,ev}$) associated with the no inspection option are,

$$\varphi_{0,ec} = (I_{ec}N + T_{ec}N + R_{ec}Np_0)P_{p>LTPD} + T_{ec}N \quad (7)$$

$$\varphi_{0,ev} = (I_{ev}N + T_{ev}N + R_{ev}Np_0)P_{p>LTPD} + T_{ev}N \quad (8)$$

$T_{ec}N$ and $T_{ev}N$ outside the parentheses are the total delivery costs and environmental impacts due to the delivery activity. $T_{ec}N$ and $T_{ev}N$ inside the parentheses are the total reshipping cost and environmental impact due to the reshipment activity.

100 percent inspection

For the 100 percent inspection option, see Figure 3, there will be no lot rectification after shipment because the producer inspects all products before being delivered. Non-conforming items found during the inspection are rectified. Therefore, the sources of cost and environmental impact are the 100 percent inspection, rectification before shipment, and transportation. Mathematically, the expected total cost and environmental impact for the 100 percent inspection ($\varphi_{100,ec}$ and $\varphi_{100,ev}$) option are,

$$\varphi_{100,ec} = T_{ec}N + I_{ec}N + R_{ec}Np_0 \quad (9)$$

$$\varphi_{100,ev} = T_{ev}N + I_{ev}N + R_{ev}Np_0 \quad (10)$$

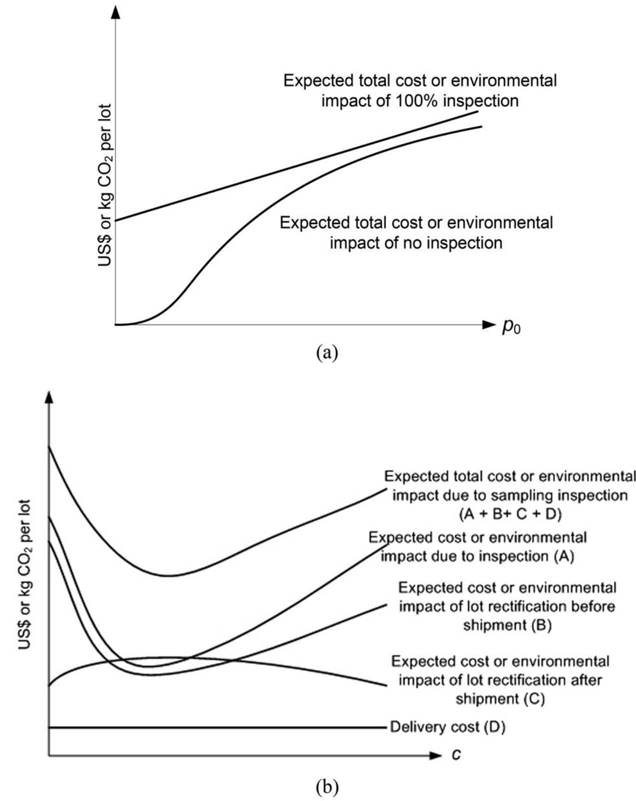

Figure 4. Expected total cost and environmental impact associated with no inspection, 100 percent inspection, and sampling inspection.

The algorithm to solve the models and find the best option

The problem presented in this paper is a multi-objective optimization problem. It can be seen from Eqs. (3), (4), (7), (8), (9), and (10). There are two objective functions for each inspection option. For no inspection and 100 percent inspection options, the calculation of the cost and environmental impact are straight forward, see Eqs. (7)–(10). When the equations are plotted, the shape of the cost and environmental curves are identical, see Figure 4a.

However, for sampling inspection, we need to decide the value of c and n such that the expected total cost and environmental impact are at their lowest points. If Eqs. (3) and (4) are plotted as a function of c, the cost and environmental curves form similar shapes, see Figure 4b. This is driven by the integer value of c. As a consequence, the lowest expected total cost and environmental impact are given by the same value of c. The above facts are used to develop an algorithm to solve the problem and not to use a multi-objective optimization technique to find a solution.

The developed algorithm compares the expected total cost and environmental impact of the three inspection options. In the algorithm, the expected total cost and environmental impact of each option are calculated separately. The algorithm starts with finding the parameters for the sampling inspection, n and c, using Eq. (5), and evaluate α at AQL using Eq. (6). The algorithm discards the pair c and n when α at AQL exceeds the stipulated α. Since there is one equation and two unknowns, the algorithm fixes the value of c and solves for n. The algorithm starts from $c = 0$ and increases c into $c = 1, 2, \ldots$. Thus, for every value of c, there will be a different value of n, $\varphi_{s,ec}$, and $\varphi_{s,ev}$.

The initial values for the minimum expected total cost and environmental impact of sampling inspection ($\varphi*_{s,ec}$ and $\varphi*_{s,ev}$) are set equal to $+\infty$. The values of $\varphi_{s,ec}$ and $\varphi_{s,ev}$ at c and n will be compared with the current values of $\varphi*_{s,ec}$ and $\varphi*_{s,ev}$. When $\varphi_{s,ec} < \varphi*_{s,ec}$ and $\varphi_{s,ev} < \varphi*_{s,ev}$, the algorithm sets $\varphi_{s,ec} = \varphi*_{s,ec}$, $\varphi_{s,ec} = \varphi*_{s,ev}$, and the current value of c and n are set as the updated optimum values of c and n, $c*_{ec} = c*_{ev} = c$, $n*_{ec} = n*_{ev} = n$. The algorithm stops increasing the value of c when $\varphi_{s,ev} \geq \varphi*_{s,ev}$ and $\varphi_{s,ev} \geq \varphi*_{s,ev}$. It means that the current values of $c*_{ec}$, $n*_{ec}$, $c*_{ev}$, and $n*_{ev}$ are the optimum values of c and n for the sampling inspection option.

Then, the minimum expected total cost and environmental impact for sampling inspection, $\varphi*_{s,ec}$ and $\varphi*_{s,ev}$, are compared with the expected total cost and environmental impact for no inspection and 100 percent inspection, $\varphi_{0,ec}$, $\varphi_{100,ec}$, $\varphi_{0,ev}$, $\varphi_{100,ev}$. The lowest values among $\varphi*_{s,ec}$, $\varphi_{0,ec}$, and $\varphi_{100,ec}$ is determined and decides the inspection option that will be selected. Similar comparison is also performed for $\varphi*_{s,ev}$, $\varphi_{0,ev}$, and $\varphi_{100,ev}$.

Based on the above logic, the following procedure has been designed to solve the models and find the best inspection option.

Step 1. Given N, p_0, $\hat{\sigma}_p$, α, β, AQL, $LTPD$, I_{ec}, I_{ev}, R_{ec}, R_{ev}, T_{ec}, and T_{ev}.

Step 2a. Set $c = 0$

Step 2b. Set $\varphi*_{s,ec} = +\infty$.

Step 2c. Set $\varphi*_{s,ev} = +\infty$.

Step 3. Solve for n using Eq. (5) and calculate P_a using Eq. (1). Evaluate α at AQL using Eq. (6). If $\alpha \leq$ stipulated α, go to step 4a. Otherwise, set $c = c + 1$, repeat this step.

Step 4a. Calculate $\varphi_{s,ec}$ using Eq. (3).

Step 4b. Calculate $\varphi_{s,ev}$ using Eq. (4)

Step 5a. If $\varphi_{s,ec} < \varphi*_{s,ec}$, set $\varphi_{s,ec} = \varphi*_{s,ec}$, $c*_{ec} = c$, $n*_{ec} = n$, $c = c + 1$, and repeat Step 3, 4a, and 5a. Otherwise, go to Step 6a, and 7a.

Step 5b. If $\varphi_{s,ev} < \varphi*_{s,ev}$, set $\varphi_{s,ec} = \varphi*_{s,ev}$, $c*_{ev} = c$, $n*_{ev} = n$, $c = c + 1$, and repeat Step 3, 4b, and 5b. Otherwise, go to Step 6b, and 7b.

Step 6a. Calculate $\varphi_{0,ec}$ and $\varphi_{100,ec}$ using Eqs. (6) and (8).

Step 6b. Calculate $\varphi_{0,ev}$ and $\varphi_{100,ev}$ using Eqs. (7) and (9).

Step 7a. $\varphi*_{ec} = \min\{\varphi*_{s,ec}, \varphi_{0,ec}, \varphi_{100,ec}\}$

If $\varphi*_{ec} = \varphi*_{s,ec}$, sampling inspection with the parameters $c*_{ec}$ and $n*_{ec}$ is the best option to minimize expected total cost.

If $\varphi*_{ec} = \varphi_{0,ec}$, no inspection is the best option to minimize the expected total cost.

If $\varphi*_{ec} = \varphi_{100,ec}$, 100 percent inspection is the best option to minimize the expected total cost.

Step 7b. $\varphi*_{ev} = \min\{\varphi*_{s,ev}, \varphi_{0,ev}, \varphi_{100,ev}\}$

If $\varphi*_{ev} = \varphi*_{s,ev}$, sampling inspection with the parameters $c*_{ev}$ and $n*_{ev}$ is the best option to minimize the expected total environmental impact.

If $\varphi*_{ev} = \varphi_{0,ev}$, no inspection is the best option to minimize the expected total environmental impact.

If $\varphi*_{ev} = \varphi_{100,ev}$, 100 percent inspection is the best option to minimize the expected total environmental impact.

Results

A case study is conducted to show the applicability of the developed model. A sensitivity analysis is also conducted to present the effect of the changes in process average and lot size to the expected total cost, total environmental impact, and the average quality level of the lots received by the consumer. Finally, we compare the results with the results obtained using methodologies widely used.

Table 2. Materials and energy inputs.

Process	Amount	Unit
Material production		
Cement	1.3600	kg/unit hollow brick
Sand	5.5900	kg/unit hollow brick
Fly Ash	6.8300	kg/ unit hollow brick
Water	0.4250	liter/unit hollow brick
Hollow brick production		
Electrical energy	0.1120	kWh/unit hollow brick
Inspection		
Electrical energy	0.0625	kWh/unit hollow brick
Delivery		
Fuel	7.0000	km/liter

Case study

The case study is done in a company producing construction materials and products. The company is located in Padang, Indonesia. The product being investigated is the hollow brick K-125 with 10 cm width. The brick is produced by using a multi-block machine. To inspect the quality of the brick, a compressive test is conducted.

Process quality, order, economic, and environmental data

Process quality and consumer's order. A particular consumer ordering the products with $N = 9{,}000$ units states that he does not want to accept more than 10% time lots that consist of more than 4.5% defective products. The producer wants the consumer to accept such products at least 95% of the time when he supplies the products at 1% defective or better. This means that the consumer's risk β is 10%, $LTPD = 4.5\%$, producer's risk α is 5%, and $AQL = 1\%$.

We measured quality of the producer's process by collecting data of percent defective of the hollow bricks produced. Seventeen samples, 50 items each, were collected. From the samples we found that the average percent defective is $p_0 = 2.24\%$ and the standard deviation is $\hat{\sigma}_p = 0.021$.

Table 2 presents material and energy inputs to produce the brick. In Table 3, we show the cost and environmental impact factors used to calculate the values of the cost and ecological parameters of the proposed model. In Table 3, the environmental impact factor for energy consumption is based on Widiyanto, Kato, and Maruyama (2003). EPA (2018) is the basis

Table 3. Costs and environmental impact factors.

Process	Amount	Unit
Material production		
Long dry process kiln to produce cement	9,000	kg CO_2/ton cement
Preheated process kiln to produce cement	9,000	kg CO_2/ton cement
Sand dryer process to process sand	9,000	kg CO_2/ton sand
Hollow brick production		
Energy cost	0.1010	US$/kWh
Environmental impact due to energy consumption	0.7200	kg CO2/kWh
Inspection		
Energy cost	0.1010	US$/kWh
Environmental impact due to energy consumption	0.7200	kg CO2/kWh
Delivery		
Fuel cost	0.3550	US$ /liter
Environmental impact due to fuel consumption	10.2100	Kg CO2/gal.

Table 4. Costs and environmental parameters of the model in the case study.

Parameter	Notation	Amount	Unit
Cost			
Inspection	I_{ec}	0.0063	US$/unit hollow brick
Rectification	R_{ec}	0.0297	US$/unit hollow brick
Delivery	T_{ec}	2.2570E-04	US$/unit hollow brick
Environmental impact			
Inspection	I_{ev}	0.0625	kg CO2/unit hollow brick
Rectification	R_{ev}	2.6070	kg CO2/unit hollow brick
Delivery	T_{ev}	1.711E-03	kg CO2/unit hollow brick

for calculating the environmental impact of the material production process. Afrinaldi et al. (2017) and EPA (2014) are the references for calculating the environmental impact factor for the delivery activity.

Inspection cost and emission. The inspection is a compressive test carried out using a machine with a 0.75 kW power rating. On average, the duration of a test is 5 minutes per product. In Indonesia, the average electricity cost is US$0.101/kWh. Using this information and the data presented in Tables 2 and 3, we calculate inspection activity's cost and environmental impact. The results are shown in Table 4.

Rectification cost and emission. In this case study, the company replaces defective products with good ones. Therefore, the rectification cost is equal to the cost of the product. CO_2 emitted due to the replacement comes from two sources, materials production and the process of making the bricks. Tables 2 and 3 present the inputs, cost, and environmental factors of the processes. On average, the time required to produce nine units of brick is 5 minutes. Using this information, we calculate the cost and environmental impact of the rectification activity. We present the results in Table 4.

Delivery and return. Cost and environmental impact due to the shipment are the cost and environmental impact caused by transporting the products from the producer's location to the consumer's area. The company uses a truck for delivery, and the price of diesel fuel in Indonesia is US$0.355/liter. Based on the above information, lot size, and data presented in Tables 2 and 3, the cost and environmental impact of the delivery activity (2-way transportation) are given in Table 4.

Application of the proposed models and algorithm

By following the algorithm and substituting all known values into the proposed equations, we present the results in Table 5. From the table, it can be seen that at $c = 23$ and $n = 677$, $\varphi_{s,ec}$ and $\varphi_{s,ev}$ are at their lowest values. At $c = 24$ they start to increase and therefore the looping stops. It is concluded that $\varphi*_{s,ec}=$ US$12.79 and $\varphi*_{s,ev}=$ 103.33 kg CO_2 and are achieved at $c*_{ec}= c*_{ev}=$ 23 and $n*_{ec}= n*_{ev}=$ 677 units. For the economic aspect, based on the table, it is found that, $\varphi*_{ec}=$ min {12.79, 18.16, 115.72} = US$12.79. Since $\varphi*_{ec}= \varphi*_{s,ec}=$ US$12.79 then sampling inspection with acceptance number $c*_{ec}=$ 23 and sample size $n*_{ec}=$ 677 is the best option. Similarly, for the environmental aspect, $\varphi*_{ev}=$ 103.33 kg CO_2, and sampling inspection with acceptance number $c*_{ev}=$ 23 and sample size $n*_{ev}=$ 677 is also the best option. The option results in 30% savings in terms of cost and CO_2 emission, compared to no inspection option. If it is compared to 100 percent inspection policy, it provides 89% savings in terms of cost and CO_2 emission.

Based on the above results, the producer is suggested to follow the following sampling procedure,

Step 1: Sample and inspect $n = 677$ products from the lot of $N = 9000$ products.

Step 2: If the number of non-conforming products found during inspection is less than or equal to 23, the lot is accepted and delivered to the consumer. Else, reject and do a 100 percent inspection of the remaining products and replace all non-conforming products with conforming products.

Table 5. Results of the designed algorithm for the case study (Lot size $N = 9{,}000$ units).

Sampling Inspection				No Inspection		100 percent Inspection	
c	n	$\varphi_{s,ec}$(US$)	$\varphi_{s,ev}$ (kg CO_2)	$\varphi_{0,ec}$ (US$)	$\varphi_{0,ev}$ (kg CO_2)	$\varphi_{100,ec}$ (US$)	$\varphi_{100,ev}$ (kg CO_2)
0	51	79.53	648.98	18.16	248.10	147.06	944.85
1	87	67.79	552.99				
2	118	58.13	473.99				
…	…	…	…				
19	576	13.44	108.67				
20	601	13.13	106.18				
21	627	12.98	104.92				
22	652	12.86	103.96				
23*	677*	12.79*	103.33				
24	702	12.80	103.44				

*Best option

The consumer's risk β at $LTPD = 4.5\%$ and producer's risks α at $AQL = 1\%$ of this plan are,

$$\beta = \sum_{i=0}^{23} \frac{(677 \times 0.045)^i e^{-677\times0.045}}{i!} = 10\%$$

$$\alpha = 1 - \sum_{i=0}^{23} \frac{(677 \times 0.01)^i e^{-677\times0.01}}{i!} = 2.17\text{E} - 07$$

It means that the consumer will not accept more than 10% time lot that is 4.5% defective or worse and the producer has a sampling procedure that at $AQL = 1\%$ will accept such lot almost 100% of the time. Since the producer rectifies the lot, the average outgoing quality AOQ of the products received by the consumer is 2.19% and the average number of products inspected by the producer (ATI) is 851.40 products.

Sensitivity analysis

Figure 5 presents the effect of the change in process average p_0 to the expected total cost and environmental impact. The figure shows that, when p_0 increases, total expected cost and environmental impact associated with no inspection and 100 percent inspection options ($\varphi_{0,ec}$, $\varphi_{100,ec}$, $\varphi_{0,ec}$, and $\varphi_{100,ec}$) rise linearly. An interesting behavior is presented by the expected total cost and environmental impact associated with the sampling inspection ($\varphi_{s,ec}$ and $\varphi_{s,ev}$). They increase when p_0 increases, but it does not have a linear pattern. Based on the behaviors of $\varphi_{s,ec}$, $\varphi_{s,ev}$, $\varphi_{0,ec}$, $\varphi_{100,ec}$, $\varphi_{0,ec}$ and $\varphi_{100,ec}$, it is suggested that, (1) no inspection policy for $0 \le p_0 < 1.75\%$ and $p_0 \ge 2.75\%$, and (2) sampling inspection with $c = 23$ and $n = 677$ for $1.75\% \le p_0 < 2.75\%$.

Figure 6 shows the effect of the change in the lot size N to the expected total cost and environmental impact. The figure presents that, when N increases, the total cost and environmental impact associated with no inspection and 100 percent inspection policies ($\varphi_{0,ec}$, $\varphi_{100,ec}$, $\varphi_{0,ev}$, and $\varphi_{100,ev}$) increase linearly. The figure also indicates that 100 percent inspection policy always results in the highest expected total cost and environmental impact. Different to $\varphi_{0,ec}$, $\varphi_{100,ec}$, $\varphi_{0,ev}$, and $\varphi_{100,ev}$, the expected total cost and environmental impact associated with the sampling inspection policy ($\varphi_{s,ec}$, and $\varphi_{s,ev}$,) increase in a nonlinear fashion as the lot size N rises. From the figure, it can be concluded that, (1) for $N < 5000$, no inspection policy is suggested, and (2) for $N \ge 5000$, sampling inspection with $c = 23$ and $n = 677$ is suggested.

Since the producer may rectify the lot during sampling inspection, therefore the average quality of lot received by the consumer (AOQ) will change as producer's process average p_0 increases. The change in AOQ follows the shape presented in Figure 7. The top point of the curve is called as the Average Outgoing Quality Limit ($AOQL$). The $AOQL$ can be said as the worst quality level that may be received by the consumer.

It is known that $AOQ = P_a p_0$. Taking the first derivative of the AOQ with respect to p_0 and set it equals to zero will result in the following equality,

$$\sum_{i=0}^{c} \frac{(np_0)^i e^{-np_0}}{i!} = np_0 \frac{(np_0)^c e^{-np_0}}{c!}.$$

It is known that $c = 23$ and $n = 677$. By substituting these values into the above equations, it is found that $p_0 = 2.71\%$ and $AOQL = 2.39\%$. The percentage implies that, by following the suggested sampling inspection plan, on average, the worst quality level that may be received by the consumer is 2.39%. The $AOQL$ is about twice lower than the $LTPD$ and will occur only when the producer's process average equals 2.71%.

A comparison with a methodology that is widely used

Since there is abundant literature for establishing a sampling plan, the results presented in this paper will only be compared with a widely used methodology

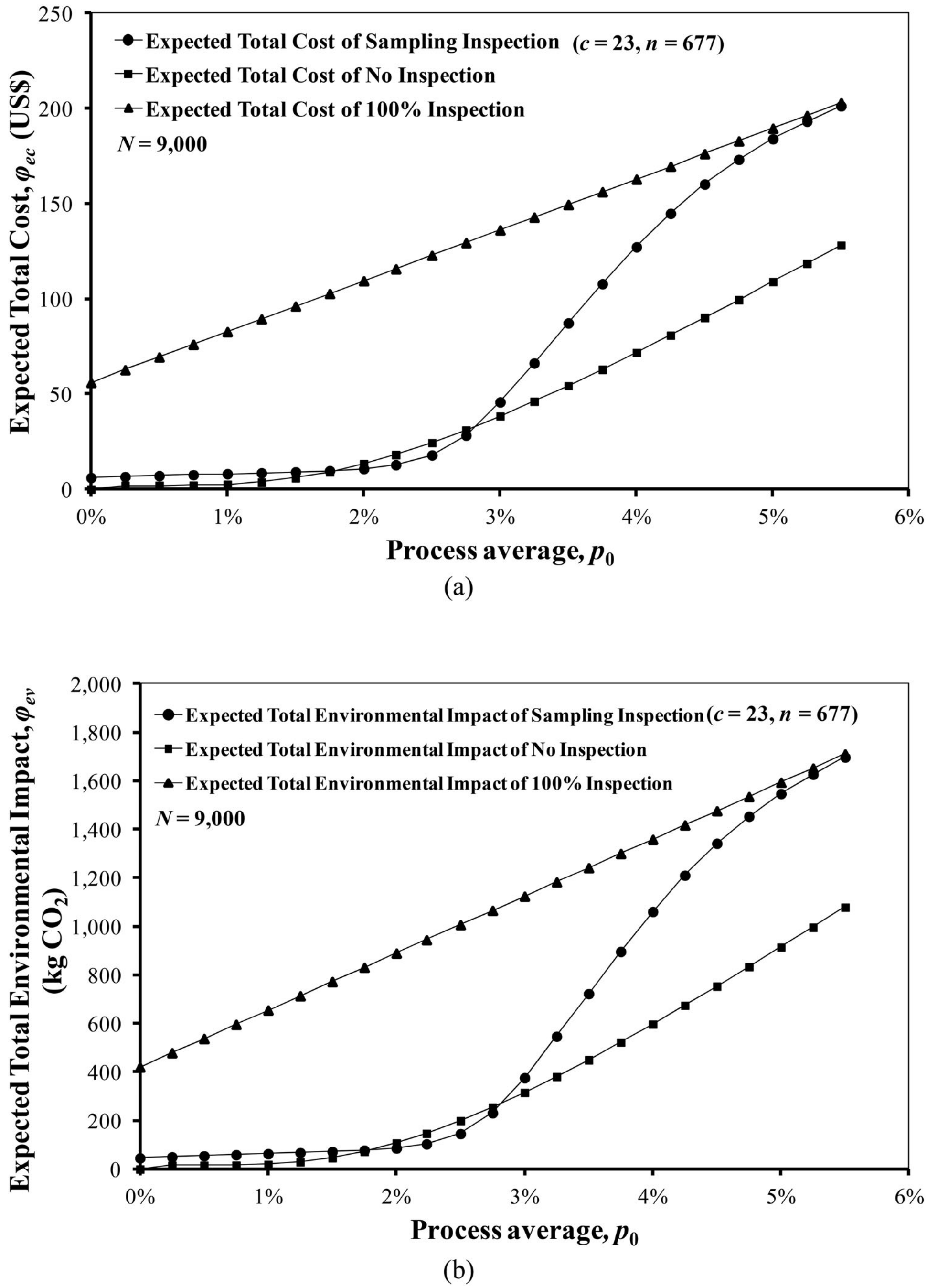

Figure 5. Effect of change in process average, p_0.

for creating a single sampling plan. We compare the proposed model with the MIL-STD-105E and *AOQL* based sampling plan. The later is the basic concept for the Dodge-Roming inspection system (Wadsworth, Stephens, and Godfrey 2002). Based on the values of n and c obtained using the above two methods, the producer's risk α at *AQL* and consumer's risk β at *LTPD* will be determined. Those values, together with the values of the economic and environmental parameters of the case study, will be substituted into Eqs. (3) and (4) to obtain the expected total cost $\varphi_{s,ec}$ and expected total environmental impact $\varphi_{s,ev}$. In this paper, for the *AOQL* based sampling plan, the sample size and acceptance number are calculated at $AOQL = 2.39\%$, the *AOQL* value of the sampling plan produced by the proposed model for the case study. Table 6 summarizes the results of the comparison.

Table 6 shows that the proposed model does not exceeds the stipulated values of $\alpha = 5\%$ at $AQL = 1\%$ and $\beta = 10\%$ at $LTPD = 4.5\%$. The reduced and normal inspection sampling plans obtained using MIL-STD-105E, general inspection level II, exceeds the value of β at *LTPD*. The tightened inspection sampling plan derived using MIL-

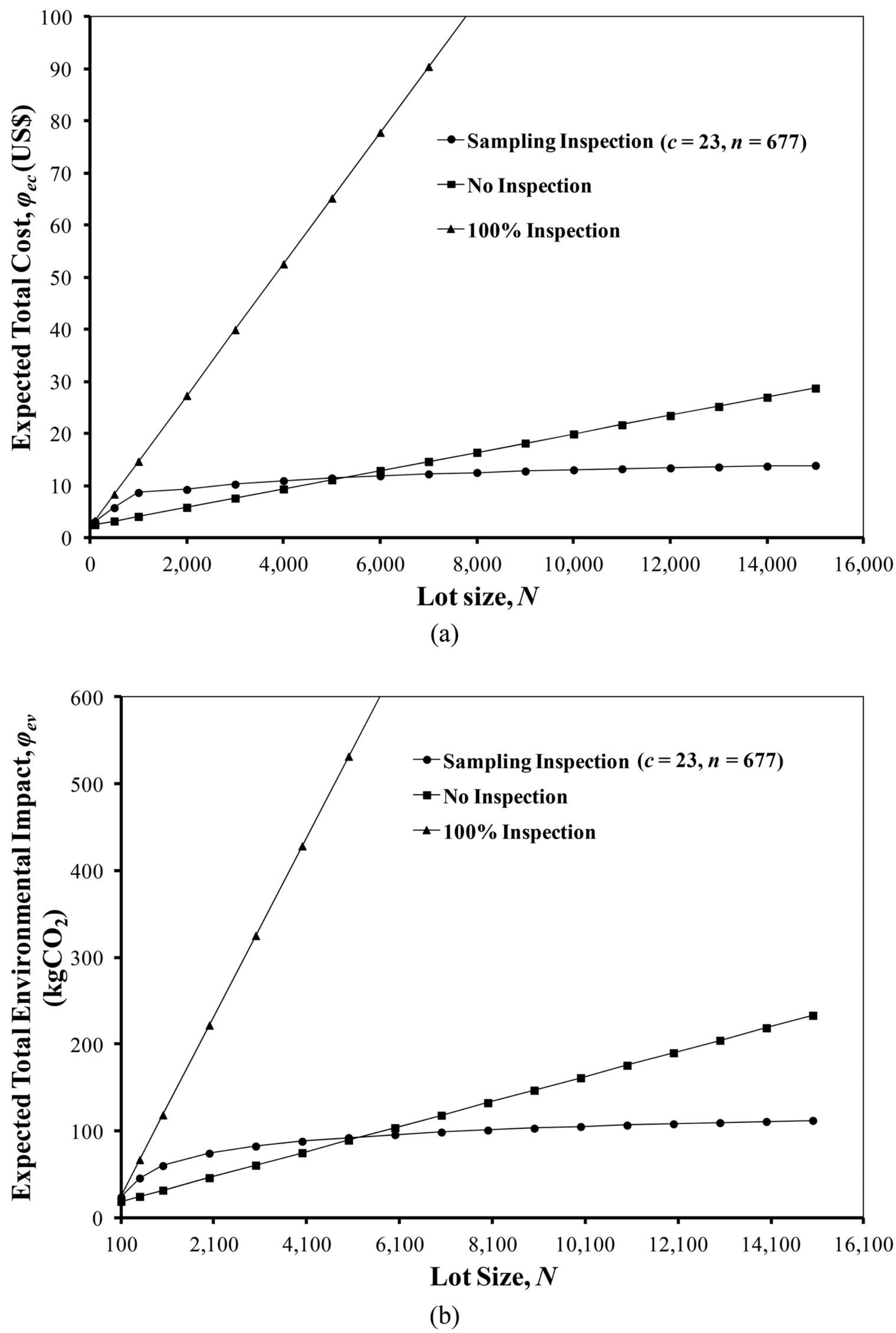

Figure 6. Effect of change in lot size, N.

STD-105E, general inspection level II, exceeds the value of α at AQL. Moreover, all three types of sampling inspection obtained using MIL-STD-105E, general inspection level II, have a higher expected total cost and environmental impact. The $AOQL$ based sampling plan has a lower expected total cost and environmental impact than the proposed method but has a higher value of β at $LTPD$. Therefore, we can conclude that the proposed model has better performance.

Discussion

The results of this research have proven that acceptance sampling, which is one of the tools in SQC, can also be used to aid the manufacturers to reduce the economic and environmental impacts associated with the inspection activity. In practice, the models and algorithm can be integrated with SPC. We can use the SPC to monitor the process, and after the final products are produced, the models and algorithm presented in this paper can be used to determine whether to accept or reject the products such that the economic and environmental consequences of the decision are minimized.

For the sampling inspection, this paper proposes a new single sampling plan model. If the widely-used single sampling plan systems are based on AQL, $LTPD$, α, and β, the proposed model includes them all and minimizes expected total cost and environmental impact, simultaneously. There is literature that includes costs in determining sampling inspection alternative, but the environmental impact aspect has not been touched yet. This paper fills the gap.

According to the results of the case study, for the current process, quality, economic, and environmental parameters, sampling inspection with acceptance number $c = 23$ and $n = 677$ is the best option. It results in the lowest expected total cost and environmental impact. A sensitivity analysis has also been conducted in order to see the effect of changes in the process average p_0 and lot size N to the current optimal solution. The analysis shows that (1) no inspection policy is suggested for $0 \le p_0 < 1.75\%$ and $p_0 \ge 2.75\%$, and (2) sampling inspection policy with $c = 23$ and $n = 677$ is suggested for $1.75\% \le p_0 < 2.75\%$. An analysis on the effect of the change in the lot size N results in the following conclusion, for $N < 5000$, no inspection policy is suggested and for $N \ge 5000$, sampling inspection with $c = 23$ and $n = 677$ is suggested. The selected sampling inspection has an $AOQL = 2.39\%$ implying that the worst quality level received by the consumer is 2.39%.

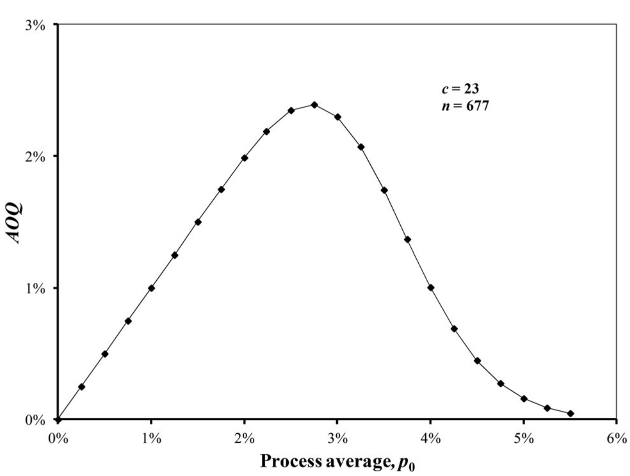

Figure 7. *AOQ* of the sampling plan as a function of process average, p_0.

Moreover, we have shown that the proposed model has a better performance than the methods that are widely used to develop a single sampling plan. The comparison that has been performed shows that the single sampling plan produced by the model does not exceed the stipulated producers' and consumers' risks. The reduced and normal inspections sampling plan obtained using MIL-STD-105E exceeds the stipulated consumer's risk at $LTPD$. For the tightened inspection, it exceeds the stipulated producer's risk at AQL. Moreover, they have a higher expected total cost and environmental impact too. The $AOQL$ based model has a lower economic and ecological impact but exceeds the stipulated producer's risk.

Besides its advantages, the proposed model has limitations. Its first limitation is that the economic impacts considered in the proposed model are the partial effects of the type I and II errors. When lots of products rejected by the consumer, there may be other impacts faced by the producer, such as loss of future sales. Second, the model assumes that the 100 percent inspection is 100 percent effective. This assumption is not always valid. Third, the model does not consider inspector errors in judging the quality of the products.

We suggest the use of the proposed model is integrated with the implementation of the company's sustainability initiative. Since sustainability initiative requires life cycle inventory data, see ISO 14040, the integration can aid the industries in collecting data requested by the model. The inventory includes all flows (input and output) for a product system, including materials, energy, costs, and pollutants.

Table 6. Results of comparison with methods widely used.

Method	c	n	α at AQL = 1% (%)	β at LTPD = 4.5% (%)	Expected total cost $\varphi_{s,ec}$ (US$)	Expected total environmental impact, $\varphi_{s,ev}$ (kg CO2)
Proposed model	23	677	2.17E-05	10.00	12.79	103.33
MIL-STD-105E, General Inspection Level II, Reduced Inspection	2	80	4.74	30.27	33.04	270.43
MIL-STD-105E, General Inspection Level II, Normal Inspection	5	200	1.66	11.57	37.02	303.08
MIL-STD-105E, General Inspection Level II, Tightened Inspection	3	200	14.29	2.12	77.12	629.38
AOQL based sampling plan	12	321	3.21E-03	31.61	9.55	82.94

Conclusions

The main contribution of this research to science is the method proposed to determine the best inspection option based on the quality, economic and environmental considerations. The model assumes that 100 percent inspection is 100 percent effective and there is no inspection error. Since most research in this area only considered the economic and quality parameters, the inclusion of the ecological parameters in the models in determining the best inspection option is the novelty offered by this paper.

To determine the best inspection option, an algorithm is designed. In the algorithm, acceptance number c and sample size n for the sampling inspection option are determined such that they meet consumer's risk β at *LTPD* and producer's risk α at *AQL*. The developed models and algorithm have also been applied to a real case study.

According to the results of the case study, a single sampling plan with $c = 23$ and $n = 677$ is suggested by the model. This plan produces a better level of protection for the producer and consumer than a single sampling plan obtained from the MIL-STD-10E and *AOQL* based sampling plan. The suggested plan also has a better economic and environmental performance than the plan derived from the MIL-STD-10E. Although the *AOQL* based single sampling plan results in a lower expected total cost and environmental impact, its consumer's risk at *LTPD* is higher than the stipulated consumer's risk.

Recommendations for future research

Based on the limitations of the model, we formulate two types of recommendations for future research. The suggestions are for the theoretical and practical aspects of the method.

For the theoretical element, we recommend future research to consider that 100 percent inspection is not always 100 percent effective, and the inspector may make errors in judging the quality of the products. Furthermore, we also suggest future research to include other economic impacts that may occur when the lot is rejected by the consumer, such as loss of future sales. From a practical perspective, we recommend that a computer program supports the implementation of the model. With the computer's help, the process of finding the solution becomes faster and improves the applicability of the model in the industries.

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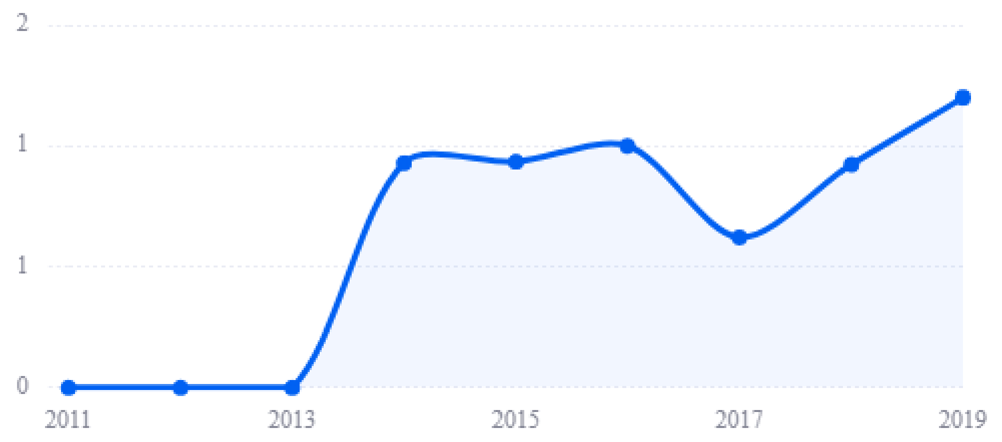

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Quality Management Journal

The 2019-2020 Journal Impact IF of **Quality Management Journal** is **1.2**, which is just updated in 2020.

— *Quality Management Journal Journal Impact IF*

Quality Management Journal Impact Factor

Highest IF
1.2
Key Factor Analysis

Lowest IF
0.621
Key Factor Analysis

Total Growth Rate
29.2%
Key Factor Analysis

Annual Growth Rate
4.9%
Key Factor Analysis

Journal Impact IF Ranking

Subcategory	Quartile	Rank	Percentile
General Business,Management and Accounting	Q2	79/221	General Business,Management and Accounting 64%

Key Factor Analysis

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