Received 29 October 2014
Revised 21 March 2015
21 May 2015
Accepted 1 July 2015

Development of an optimization model to determine sampling levels

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Abstract

Purpose – As the complexity of the multi-component products increases the quality of these products becomes increasingly difficult to control throughout the supply chain. The first step to manufacturing a quality product is to ensure that the product components from suppliers meet specifications. Product quality can be controlled through sampling inspection of the components. The paper aims to discuss these issues.

Design/methodology/approach – The model presented in this paper was developed to determine the optimal sampling levels for incoming lots containing parts for production and assembly of multi-component systems. The main objective of the model is to minimize the expected cost that is associated with a nonconforming item reaching assembly.

Findings – In this research, the results showed that even with limited time available for inspection, performing sampling inspection significantly reduced the expected cost of a nonconforming item reaching assembly. The model, solved by the evolutionary algorithm, was able to provide a meaningful, near optimal solution to the problem.

Originality/value – In this model the time available for inspection is limited, the distribution of defects is assumed to follow the binomial distribution, and the distribution of accepting the lot with defects follows the hypergeometric distribution. In addition, the inspection is considered to be accurate and, if a nonconforming item is found in the inspected sample, the entire lot is rejected. An example is given with real world data and the results are discussed as they relate to supply chain management and quality.

Keywords Supply chain management, Cost optimization, Inspection optimization, Quality engineering, Sampling inspection

Paper type Research paper

1. Introduction

The purpose of this research is to determine the optimal sampling inspection plan of incoming lots. These lots contain a specific number of individual items for the manufacturing and assembly of multi-component systems. These systems are common in the automotive, aerospace, heavy equipment, off highway vehicle, and electronic industry. The complexity and demand for these products have increased dramatically. Therefore, the number of incoming lots and parts used in production has also increased dramatically. Since the quality of the product corresponds to the durability, reliability, and customer's safety and satisfaction, quality controls are necessary to improve the quality through the supply chain and in the final product. Competition in the market and quality appreciation by consumers has driven manufacturers to pay more attention to the quality of their products (Marttinen, 2002; Setijono and Dahlgaard, 2008).

One method to improve the product quality is to perform sampling inspection on the incoming lots from supplier products. Manufacturers also provide sampling results to their suppliers as feedback on the quality of receiving lots, thus promoting healthy

International Journal of Quality & Reliability Management
Vol. 33 No. 4, 2016
pp. 476-487

0265-671X
DOI 10.1108/IJQRM-10-2014-0159

consumer-supplier relationship (Hill, 1960; Robinson and McNicholl, 1990). In order to do this, it is then necessary to determine the appropriate level of inspection. If the company is not inspecting enough, there is a risk of a nonconforming item reaching the assembly line and possibly remaining in the supply chain as a finished product. This would result in a final product that does not meet the customer's specifications and possible penalty costs such as shipping charges, loss of faith in the product and manufacturer, or even lawsuits. Since these costs affect the company, they increase the cost of the final product and reduce the profit from the product. On the other hand, if the company performs 100 percent inspection, the risk of nonconforming items reaching assembly would be minimized. The cost associated with 100 percent inspection (manpower, equipment, etc.) would, again, drive up the production cost of the final product and even possibly delay production (Oppermann *et al.*, 2001). Therefore, an optimal inspection strategy is needed in order to minimize the total cost while providing a certain level of quality. In order to minimize the total cost, an optimal trade-off between the appraisal cost, which is the cost that is generated from performing quality inspection, and the prevention cost, which is the cost that is generated from preventing the defects from reaching the consumer, must be established to lower the failure cost and, therefore, the total cost (Keogh *et al.*, 2000).

Companies typically follow some type of sampling inspection procedure in their facilities. A common practice of companies is to follow the "trust the supplier" ideology where only a few items in the first lot are inspected. If these items meet the specifications, that lot and consecutive lots are sent to the assembly line without further inspection. It should be also noted that some companies do not have the ability to inspect certain features of the items in the lot, which forces them to trust the supplier.

This research considers sampling inspection optimization and provides a model that determines the inspection levels. The research focusses on determining the inspection levels that would minimize the expected total cost of nonconforming items in the time available. The paper is organized as follows. Section 2 covers the literature review. Section 3 proposes and describes the model and the solution approach. Section 4 covers the analysis and the results. Lastly, Section 5 discusses future work and provides conclusions.

2. Literature review

2.1 Sampling inspection of lots

Research and publications on sampling inspection of lots increased during and after Second World War. Demand for military products increased greatly and tolerance for faulty equipment was low during this period. Since production increased dramatically, unit-by-unit, or 100 percent, inspection was not practical. Therefore, quality control shifted from unit-to-unit inspection to statistically controlled sampling inspection. Various military standards schemes were created in order to control the quality of the incoming lots (Champernowne, 1953; Barnard, 1954). Military standards first inspect a large sample size to determine the distribution of defects. If the lots are found to meet the specifications, the inspection on the consecutive lots is then relaxed.

Li *et al.* (2011) examined Military Standard MIL-STD-1916. This standard works under "zero accept one reject" premises; meaning that if there is a nonconformance in the sample of the population then the entire population is rejected. Lie *et al.* revised MIL-STD-1916 by expanding the current standard from 11 to 18 groups of inspection in order to separate the sampling plans from 100 percent inspection. Li *et al.* acknowledged that just because there are no nonconforming items in the sample it does not mean that the population meets conformance requirements, meaning that the lots can still carry a risk of a defect reaching the final product.

The research of Champernowne (1953) focussed on the economic success of the problem by using sampling inspection as a tool in the process. For the purpose of the study Champernowne assumed that several variables in the problem are known:

> (i) the average quality of the batches to be tested and the variation between batches of quality about that average, (ii) the cost of inspection and its dependence on the amount of inspection undertaken, and (iii) the cost involved by deciding wrongly to accept or wrongly to reject a batch, and the way this cost depends on the quality of the batch.

Using this information, Champernowne developed an economical boundaries model that uses sampling inspection results (number of effective and defective items) to determine whether the lot should be accepted or rejected. Champernowne mainly focussed on satisfying the economical aspect of the problem, meaning that as long as the result is within the economical boundaries the lot would be accepted even if defects were found in the sample. On the other hand, Barnard (1954) argued that the information, which Champernowne assumes are given, are not readily available in the real world. Barnard argued that assigning a distribution for defects is needed in order to solve the problem. Barnard also argued that a considerable amount of information for each lot is needed to make an optimal decision for the problem.

Hamaker (1958) described three different approaches to sampling inspection: sampling tables, collecting data, and constructing inspection plans. Hamaker also modeled a plan using economic theories where the research concluded that it might be more economical not to inspect the lots with a small probability of nonconforming items. While all the methods have been implemented in the real world, Hamaker warned that the data collection and sampling tables might lead to over sampling while using economic theories might not always be possible because certain factors might not be obtainable. Hamaker then suggested that a sampling plan should be selected and monitored for its performance and then later adjusted for the new data if needed.

2.2 Sampling inspection in multi-stage process systems (MSPS)

Research performed in this field has mainly focussed on the allocation of inspection stations within MSPS. These inspection stations are supposed to catch the possible defects that might be experienced during production. The solutions have mainly been developed using dynamic programing or heuristic methods. The published research has commonly considered the economical aspect of the problem, trading off the risk, and cost of inspection.

Dynamic programming has widely been considered while searching for the problem solution. It managed to break down the multi-stage problem into smaller, more manageable problems, which are then easier to solve (Bellman, 1952, 1953, 1956; Bellman *et al.*, 1953). Other researchers have expanded the problem considering among others that only no inspection or 100 percent inspection is available (White, 1969), imperfect inspection where inspection stations may label a nonconforming item conforming and vice versa (Hurst, 1973; Eppen and Hurst, 1974), and statistically controlled inspection (Oppermann *et al.*, 2001, 2003). Dynamic programming was able to determine an optimal solution to the problem and it was very effective for MSPS with a small number of stations. An increase in the number of stations in the MSPS dynamic programming took longer than desired to find a solution. New methods, such as heuristic methods, have been found for calculating solutions for the problem.

Heuristic methods such as evolutionary algorithms are popular methods in finding the solution to the inspection stations allocation problem. Researchers have, again, considered imperfect inspection (Taneja and Viswanadham, 1994), and economical trade-offs (Van Volsem *et al.*, 2007; Van Volsem, 2010). While providing a fairly quick solution, heuristic methods are not guaranteeing optimal, but rather a close to optimal solution.

3. The model

Consider an assembly line that has M different parts coming in. These parts have different lot sizes, defect rates, and repair costs if a defective item enters the assembly line. They also have a specific time interval needed to inspect a single item. Incoming inspection is performed on these parts in order to control the quality of the final product. The problem facing management is to determine the appropriate inspection sample size for each part considering the variability of risks associated with the M parts and the limited resource of labor hours the assembly line can spend on inspection. The problem can be modeled as a Nonlinear Integer Programming problem as follows:

Index sets:
$I = \{1, 2, \ldots, M\}$ = index set for parts considered by inspections.

Parameters:
T = total labor hours available for inspection
t_i = time needed to inspect a single item of part i
N_i = total number of items in the lot for part i (lot size)
d_i = probability of a defective item in the lot for part i (defect rate)
C_i = cost of a nonconforming item reaching assembly for part i

Variables:
D_i = total number of defective items in lot i
n_i = number of items to be inspected for part i

Minimize:

$$\sum_{i=1}^{M}\sum_{D_i=0}^{N_i} P(D_i) D_i C_i P(0|N_i, D_i, n_i) \tag{1}$$

Subject to:

$$P(D_i) = \binom{N_i}{D_i} d_i^{D_i} (1-d_i)^{N_i-D_i} \tag{2}$$

$$P(0|N_i, D_i, n_i) = \frac{\binom{N_i-D_i}{n_i}}{\binom{N_i}{n_i}} \tag{3}$$

$$\sum_{i=1}^{M} t_i n_i \leqslant T \tag{4}$$

$$0 \leqslant n_i \leqslant N_i, n_i\text{'s are integers} \tag{5}$$

It is assumed that the parts that are in the lot can either pass (conforming items) or fail inspection (nonconforming items). Since there are only two possible outcomes (pass, fail), it is assumed that the probability of having D_i number of defects of part i in the lot follows the binomial distribution. Therefore, calculating the probability of having an exact number of nonconforming items ($P(D_i)$) in the lot is possible as long as the defect rate and the lot size for part i are available. The cost of the exact number of nonconforming items reaching assembly is calculated by multiplying the number of defects in the lot with the cost of a nonconforming item reaching assembly for part i (C_i). Using this cost and the probability of having a specific number of defects is multiplied to obtain an expected cost of nonconformance for the specific number of defects. In order to cover all the possible values of D_i ($0 \leqslant D_i \leqslant N_i$) and to calculate the total expected cost of nonconforming items in the lot for part i, all possible outcomes are summarized $\left(\sum_{D_i=0}^{N_i} P(D_i)D_i\, C_i\right)$. This also represents the total expected cost of nonconformance for part i if there is no inspection performed and the lot is sent directly to the assembly line.

With the inspection of a certain number of items (n_i), it is expected that the probability of a nonconforming item reaching assembly for that particular part number will be reduced. The number of defects found in the sample size that would be tolerated is zero, meaning that if a nonconformance is found in the sample size the entire lot is rejected. It is assumed that the inspection is performed without replacement. Since two mutually exclusive categories (pass/fail) are considered, it is assumed that the probability of accepting the lot with a defect follows the hypergeometric distribution shown in Equation (3).

The sample size n_i can be any number between zero and lot size N_i (Equation (5)). Also, n_i must be an integer (Equation (5)). If the sample size is zero, then no inspection performed. This means that the risk of accepting the lot with D_i defects is large. However, if the sample size is N_i, then 100 percent inspection is performed and the risk of accepting the lot with D_i defects is zero; however, the inspection cost would be high. The decision variable is, therefore, the sample size, n_i. With the increase of the sample size, the probability of accepting the lot with D_i defects decreases. Therefore, the bigger the sample size n, the smaller the expected cost of a nonconforming item reaching assembly for a specific number of defects D_i:

$$P(D_i)\, D_i\, C_i\, P\left(0 \middle| N_i, D_i, n_i\right) \tag{6}$$

In order to find the total expected cost for the specific part with all possible values of D_i, the summation of these equations is needed:

$$\sum_{D_i=0}^{N_i} P(D_i)D_i\, C_i\, P\left(0 \middle| N_i, D_i, n_i\right) \tag{7}$$

Finally, the research goal is to minimize the expected total cost of the nonconforming items for all the parts M in the system as shown in the Equation (1).

Since the time for inspection (T) is limited and there are a large number of different parts (M) with various lot sizes, 100 percent inspection is time consuming, expensive, and unpractical. Each part i has a specific time interval (t_i) it takes the operator to inspect one item of part i. Therefore, the time it takes to inspect sample size n_i, for all parts M, must be less than or equal to the total time available for the inspection, which is the constraint show in Equation (4).

It is known from the problem statement and the objective that the purpose of the model is to find an optimal sampling inspection plan that would minimize the expected cost of a nonconforming item reaching the assembly line in the limited time available. If the sample size n_i is equal to zero then the probability of a lot with defectives being accepted would be equal to one. This would then result in the maximum expected cost of the nonconforming item. However, if inspection is performed and the sample size increases then the probability of accepting the lot with D_i defects decreases. The model, therefore, provides a sample size n_i for all parts M in the system.

4. Analysis and results

Since the time to calculate these inspection plans is limited and the size of the problem is usually large, it was decided to use an evolutionary algorithm (Ashlock, 2006) to solve the problem. Industry is typically interested in a better solution than the one they currently have and not the optimal solution, particularly if the solution is fast and easy to obtain. In the testing phase Excel was used to program the model. The model was built using the Solver program and it is solved using the evolutionary algorithm built in Solver. The advantage of this algorithm is that it gives a fast solution. However, the disadvantage of the algorithm is that the generated solution might not be the optimal solution, but rather a near optimal solution. Another disadvantage of the evolutionary algorithm is that it may show some inconsistencies in generating the solutions.

The model was initially tested for two parts. The data used for the two-part problem was provided by the automotive industry. The two parts in question are a tube and a harness. The tube has a historic defect rate of 1.93 percent, lot size of 125, inspection time of 30 minutes, and cost of nonconformance of \$17. The harness has a historic defect rate of 3.13 percent, lot size of 300, inspection time of five minutes, and cost of nonconformance of \$235. The time available is one workday of eight hours or 480 minutes and the wage for the inspectors was set to \$40.

The small problem analysis was set up for the user to input following data: lot size (N_i) for each part, defect rate (d_i) for each part, time needed to inspect (t_i) for each part, cost of nonconformance reaching assembly (C_i) for each part, time available for inspection (T), and employee's salary (C_S). All of the constraints were set up as the model suggests and the program was set to determine the solution using the evolutionary algorithm. While using an evolutionary algorithm it is expected to see some inconsistencies in the results.

The results that were found were promising for the real world application. In the two-part example, the expected cost of nonconformance was decreased by 83 percent and the total cost was decreased by 63 percent as shown in Table I. In addition, the defect rate was reduced with inspection as shown in Figure 1. The expected cost of

Table I. Comparison of costs with and without inspection for a two-part problem

	No inspection (\$)	With inspection (\$)	Change in cost (\$)	% change in cost
Cost of work force	320.00	320.00	0.00	0
Expected cost of N-C	1,019.03	172.34	846.69	83
Total cost	1,339.03	492.34	846.69	63

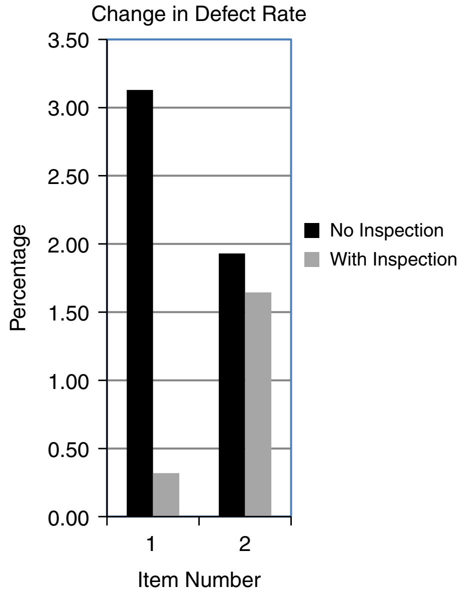

Figure 1.
Change in defect rate for the two-part problem

nonconformance also was reduced with inspection as shown in Figure 2. The cost of the work force represents the cost of labor hours. For this research, the inspectors are paid at a pre-specified rate regardless of whether they are inspecting incoming material or they are idle. Therefore, it is a sunk cost and it does not affect the decision. The model determines that the optimal sample size for the harness is 56 (44.8 percent of the lot size) and that for the tube is six (2 percent of the lot size). After inspection is performed the defect rate of the lot is 0.29 percent for the harness and 1.68 percent for the tube.

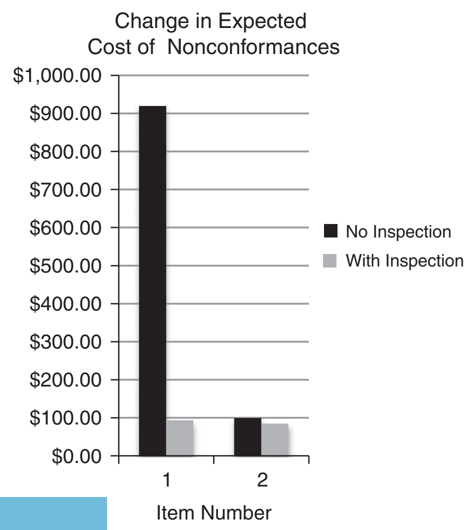

Figure 2.
Change in expected cost for the two-part problem

The model was then tested for a 20-part problem. The data were randomly generated where the defect rate had a range from 1 to 10 percent, lot size had a range from 10 to 500, time needed to inspect certain item ranged from 1 to 30 minutes, and the cost of a nonconforming item ranged from \$10 to \$300 as shown in Table II. In order to compare the 20-part problem to the two-part problem the time to inspect remained the same at 480 minutes.

Table III shows the output provided by the program. It calculates the defect rate after inspection in order to see what type of risk the lot is still carrying as we calculated the cost of nonconformance with and without inspection. It also provides the sample size for inspection.

After running the program, the model came to a solution where the expected cost of nonconformance decreased by 18 percent and the total cost (the expected cost of nonconformance and the cost of labor) decreased by 18 percent as shown in Table IV.

As shown in Table IV, the expected cost of nonconformance reduced by the optimal inspection is significantly greater than the cost of work force; therefore, performing sampling inspection on the incoming lots is very cost-effective.

To demonstrate the affect of having greater inspection capacity, we examine the 20-part numerical example again, but with 2,400 minutes of inspection time. The model lowered the total expected cost of nonconformance by 68 percent and the total cost by 65 percent (Table V). The changes in the defect rate and the expected

		Inputs		
Total time available (min)	2,400			
Hourly wage =	\$40.00			
Part number	Inspection time per piece *i* (min) t_i	Defect cost per piece *i* (\$) C_i	Lot size *i* N_i	Defect rate for part *i* (%) d_i
1	10	\$86.00	450	8.00
2	5	\$129.00	35	3.00
3	11	\$121.00	165	7.00
4	3	\$182.00	425	10.00
5	20	\$60.00	100	8.00
6	10	\$61.00	175	10.00
7	18	\$40.00	350	2.00
8	3	\$76.00	15	7.00
9	20	\$111.00	60	1.00
10	16	\$74.00	90	9.00
11	19	\$182.00	120	4.00
12	23	\$189.00	500	5.00
13	20	\$28.00	100	7.00
14	3	\$69.00	300	4.00
15	17	\$67.00	465	5.00
16	8	\$104.00	160	4.00
17	20	\$45.00	120	6.00
18	3	\$129.00	455	6.00
19	2	\$82.00	255	10.00
20	17	\$49.00	190	3.00

Table II. Inputs for the 20-part problem

Table III. Outputs for a 20-part problem with available time of 2,400 minutes

Defect rate after inspection (%)	Change in defect rate (%)	Expected cost of nonconformance without inspection ($)	Expected cost of nonconformance with inspection ($)	Change in expected cost of nonconformance (%)	Inspection size (n_i)
2.41	5.59	3,096.00	933.48	70	14
2.83	0.17	135.45	127.63	6	1
1.83	5.17	1,397.55	365.05	74	17
0.21	9.79	7,735.00	159.50	98	36
6.04	1.96	480.00	362.56	24	3
2.35	7.65	1,067.50	251.19	76	13
1.45	0.55	280.00	202.58	28	14
6.08	0.92	79.80	69.27	13	1
0.92	0.08	66.60	61.39	8	3
5.90	3.10	599.40	392.77	34	4
3.45	0.55	873.60	753.58	14	3
2.25	2.75	4,725.00	2,123.38	55	15
5.03	1.97	196.00	140.75	28	4
2.46	1.54	828.00	509.09	39	11
1.31	3.69	1,557.75	408.87	74	26
2.27	1.73	665.60	377.23	43	12
4.22	1.78	324.00	227.88	30	5
2.45	3.55	3,521.70	1,435.39	59	14
2.16	7.84	2,091.00	452.09	78	14
2.51	0.49	279.30	233.53	16	5
		Expected total cost of no inspection	Expected total cost of a nonconforming		
		29,999.25	9,587.21		

Table IV. Comparison between without and with sampling inspections (480 minutes)

	No inspection ($)	With inspection ($)	Change in cost ($)	% change in cost
Cost of work force	320.00	320.00	0.00	0
Expected cost of N-C	29,999.25	24,490.07	5,509.18	18
Total cost	30,319.25	24,810.07	5,509.18	18

Note: Comparison of costs with and without inspection for a 20-part problem with available time of 480 minutes

Table V. Comparison between without and with sampling inspections (2,400 minutes)

	No inspection ($)	With inspection ($)	Change in cost ($)	% Change in cost
Cost of work force	1,600.00	1,600.00	0.00	0
Expected cost of N-C	29,999.25	9,587.21	20,412.04	68
Total cost	31,599.25	11,187.21	20,412.04	65

Note: Comparison of costs with and without inspection for a 20-part problem with available time of 2,400 minutes

cost of nonconformance without inspection and after suggested inspection are also shown in Figures 3 and 4, respectively. A comparison between Tables IV and V shows that greater cost savings would be expected if the assembly adds additional inspection capacity.

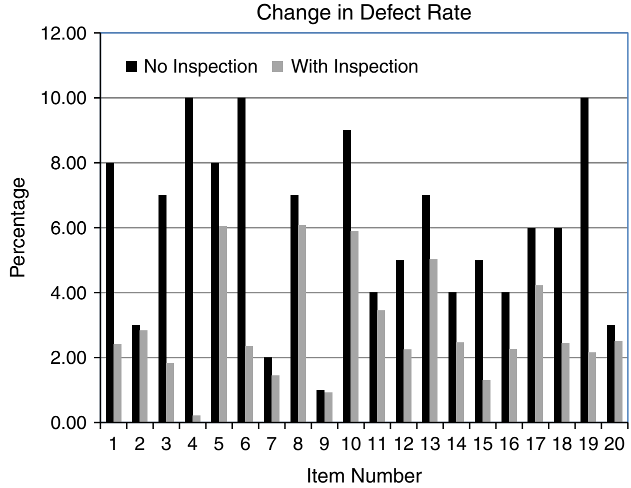

Figure 3.
Change in defect rate for the 20-part problem with available time of 2,400 minutes

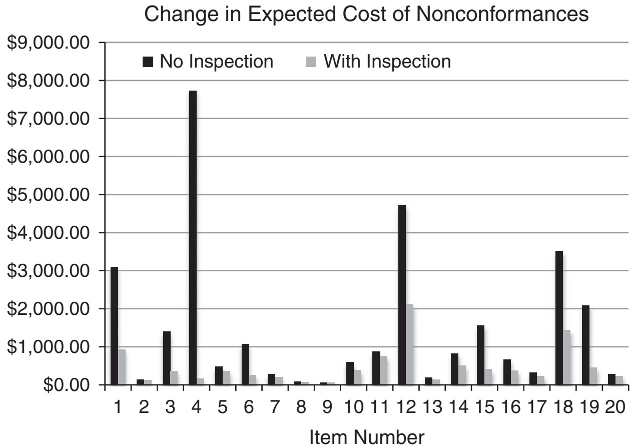

Figure 4.
Change in expected cost of nonconformance for the 20-part with available time of 2,400 minutes

5. Conclusions and future work

The proposed model has a potential of solving the problem if the necessary inputs are available. In this research, the results showed that even with limited time available for inspection, performing sampling inspection significantly reduced the expected cost of a nonconforming item reaching assembly. The model was able to provide a meaningful solution to the problem although not necessarily an optimal solution as expected from using the evolutionary algorithm given that the algorithm provides a near optimal solution. Programming the model in a different programming language might provide a more consistent and more accurate solutions.

Future work includes developing a model that would not just address the number of items that need to be inspected but also the specific characteristic of the item that is proven to have a possible issue. This would increase the efficiency of inspection, which means that operators could inspect more items if they know which particular characteristic needs more attention.

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