The Implementation of Material Flow Cost Accounting Analysis to Determine the Optimal Sample Size and Lot Size in Serial Multi-stage Processes

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Abstract

Product quality is a crucial factor that significantly affects customer's satisfaction and many organizations emphasize and invest large amounts in designing and assuring quality system to prevent flow of defectives along the process. Surviving in competitive environment many organizations attempt to reorganize their inspection policies in order to satisfy customer's expectations while reducing costs. Inefficient inspection policy can lead to significant wastage of resources. Therefore, the researches on designing efficient inspection strategy have been studied extensively in last few decades. This research applied the Material Flow Cost Accounting (MFCA) technique first to trace material and energy used both in terms of physical quantity and monetary units in order to analyze efficiency of process and then to design the lot size and quality inspection system that maximize ratio of total positive product cost to the total cost obtained from the MFCA concept. In this paper, an artificial bee colony (ABC) algorithm is used as a search algorithm for the optimal inspection sampling size and the lot size under serial multi-stage processes. This studied shows that the best solution obtained from the proposed methodology results in the production and inspection system with higher resource efficiency and greater proportion of the total positive cost.

Keywords
Material flow cost accounting, Optimal sample size, optimal lot size, artificial bee colony, Serial multi-stage process, Inspection strategy

1. Introduction

The quality management strategy is an important key to improve the product's quality while maintaining organization's profitability. Product quality is the key factors that significantly affects customer's satisfaction and many organizations have invested large amounts in quality system. Implementing different inspection strategy will result in different costs. In order to satisfy the customer needs and survive in competitive environment, the organizations have to implement an efficient inspection policy. In the same time, the waste reduction becomes a major concern for many organizations because it affect in organization's finance.

Generally reducing waste in a production means reduce process variation, resources usage and eliminate cause of defects to achieve higher quality and output. In this study, reducing waste means implement an efficient inspection strategy to defect defective items as soon as possible, ensure the required output quantity while minimizing costs. In case of inspection only last stage may cause to non-conforming products, incur penalty costs, losing customer trustworthiness and market share, etc. In the same way, insufficient inspection fraction or sample size will result in non-conforming products reach to next process which is cause of waste resources. On the other hand, more and tighter will lead to a higher product quality, but will result in higher costs of inspection, rework and scrap. Therefore, a cost trade-off is important to select the efficient economic inspection strategy which desired to balance quality with cost effects (Azadeh et al., 2012).

Another interesting factor is lot size impact. During past few decade, inventory management has been important for the most manufacturing industries. Previously, most organizations use economic order quantity (EOQ) model to

identify the optimal lot size considering set up and holding costs. There are many researches extend EOQ model concept for better solution and more suitable for each manufacturing environments. As lot size impact on work in process or inventory level which affect directly on inventory holding costs, the study on optimal lot size will help design an economic order quantity and increase the organization's profitability.

Furthermore, environmental protection has become a priority concern in many organization's issue. MFCA techniques is used to measure and manage the environmental impact. This method measure and trace materials and energy used in terms of physical quantity and monetary units which consist of material, system, energy and waste treatment costs. These costs are distributed to positive or negative product based on the attribution of activities to generation of product and waste. The negative product costs incurred show that current production process operate inefficiently.

This study aims to apply MFCA technique to show waste costs occurred from unidentified detective items being process unnecessarily during manufacturing operations as a result of established inefficient inspection strategy. In addition, this study intend to declare the optimal lot size relatively with inventory and work in process holding costs. Therefore, the proposed of this study is determine the optimal sample size and lot size for serial multi-stage processes under MFCA framework based on ABC algorithm optimization search and compare with present process. The key performance of this study is the ratio of total positive product cost (TPC) to total cost (TC) which calculated by MFCA techniques.

2. Literature review

Sampling techniques on manufacturing industries have been developed in the last few decades. Several sampling strategies exist and can be classified into three categories: static sampling, adaptive sampling and dynamic sampling. Static sampling consists in selecting a fixed number of lots to inspect at each production stages depend on the availability of inspection resources, the maturity of the technology, and the process step criticality. Adaptive sampling consists in adjusting the number of lots selected which can be adjusted throughout production depending on the process state. Statistical Process Control (SPC), the feedback and feed-forward process control techniques, are used to determine adjusting sampling decisions. Dynamic sampling, the selection of lot are done in real time depending on the production state, metrology capacity, and the factory dynamics. This sampling strategy is widely use in semi-conductor manufacturing (Nduhurar-Munga et al., 2013).

Most organizations spend large investment on quality system in each year. Since the quality is important priority factors that significantly affects customer's satisfaction. In order to survive in competitive environment, the organizations have been attempt to improve the effective quality system management and maintain their profit. One of the improvement viewpoints is designing the optimal inspection strategies. In previous studies, it have been applied various solution approaches.

Bai and Yun (1996) have been studied the optimal allocation of inspection for serial multi-stage production in which limited number of automatic inspection machines are available. Considering the production rate is constrained by the rate of inspection. This study propose backward dynamic programing (DP) search the combination of inspection location and inspection level which provide the smaller expected total cost per unit. The result show that heuristic algorithm can be provide an optimal or close to optimal solution with less computing time even though the problem are large.

Viswanadham et al. (1996) studied the location of inspection stations problem that resulted in minimum total system cost for multi-stage manufacturing system. This model considers two types of inspection errors: acceptance of defective units and rejection of conforming items. The study proposed two stochastic search algorithms which are simulated annealing (SA) and genetic algorithm (GA). The results show that either SA or GA provide the same set of inspection solutions. Although these two methods provide the same set of solution, the GA takes smaller processing times than the SA for small size problem. In contrast, the SA method perform better for large problem. Van Volsem et al. (2007) are also proposed the GA for solving inspection problem in multi-stage processes. There are three decision variables considered: the number and location of inspection stations, the inspection sample size and the acceptance limits. The study tests various on GA parameters and results that GA is suggested to inspection optimization problem.

Another inspection solution approach, a particle swarm optimization (PSO) algorithm was proposed by Azadeh et al. (2012). This study extend Van Volsem et al. (2007) problem to find the most efficient combination of three decision parameters in previous study minimizing the total inspection cost (TIC). In addition, the experimental investigate in two scenarios: fixed sample size and sample size as decision parameters. The results clearly show that PSO provide the different optimal solution with lower TIC.

Shetwan et al. (2011) have discussed on inspection allocation results in minimum total cost considering two types of inspection errors with Average Outgoing Quality Limit (AOQL) constraint. The study aims to test the performance of heuristic method (HMLS) compared with the complete enumeration method (CEM). The result show that HMLS can derive and acceptable solution and faster than CEM.

Rau and Cho (2009) presented model of inspection allocation results in most profitable for re-entrant manufacturing by using the static sampling concepts. This model considers impact of two type of inspection errors and account in term of non-conforming costs which vary according to the stage where non-conforming products have appeared such as cost of rework, repair, scrap, penalty of shipping nonconforming items. The study proposed GA method for solving inspection allocation problem. The GA method gives the same answer as CEM (Rau and Chu, 2005) which is optimal solution but takes less processing time. It's well known that semi-conductor or re-entrant manufacturing is highly complex production, expensive cost and complicate to inspection. When use static sampling strategy to select lot for inspection, it is possible to identify whether defects were recently added or not since the last operation by inspecting the same wafers at different stages. However, static sampling are less suitable for the dynamics of fabrication process. Rodriguez-Verjan et al. (2015) introduced the dynamic sampling strategy to estimate the defect inspection capacity. By considering the risk on process tools in terms of Waffer at Risk (W@R), which is can be better controlled but the defect inspection capacity will be allocated in real time. A proposed linear programing can be used to justify the defect inspection capacity required in order to satisfy a given set of W@R limits at the different decision levels.

The study on performance of an artificial bee colony (ABC) algorithm (Karaboga and Basturk, 2007) compared with PSO and GA. The study reveal that PSO and ABC algorithm provide solution nearly optimal solution on linear problem, non-linear problem and quadratic problem. However an artificial bee colony (ABC) can solve the problem efficiently, it never been found in previous inspection optimization problem studies. Therefore, this study aims to use ABC algorithm for solve the inspection strategy problem.

From the review of relevant literatures, the study only measures in term of conventional cost incurred such as total cost, inspection cost, rejected cost etc. The previous studies did not consider to the loss of material and resource used. In fact, these loss associated with the product costs, which is likely to increase from unidentified detective items being produced unnecessarily during manufacturing activities. Therefore, this study imply the MFCA technique as a framework to determine an optimal inspection model.

3. Problem statement

The serial multi-stage production system schemes in this study is extended from Bai and Yun (1996) conceptual. Consider a case study production process consist of i processes for $i = 1, 2, \ldots, I$ and the last process is customer as shown in Figure 1. Each process has 2 stages $j = 1, 2$ as shown in Figure 2. The operation station is may followed by an inspection process with three buffers in every process. Buffers are used for inventory i.e. raw material, good quality products and non-conforming products.

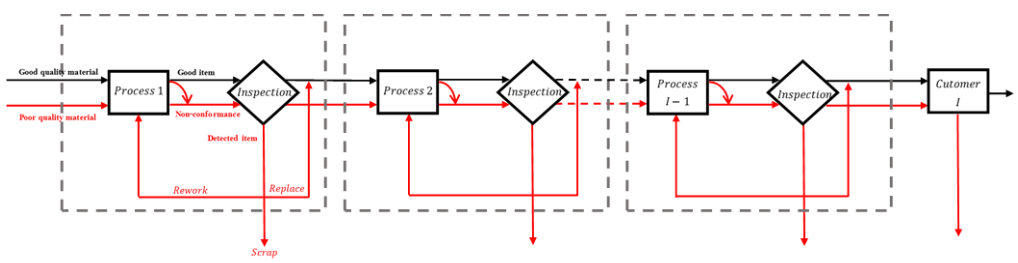

Figure 1. Serial multi-stage process

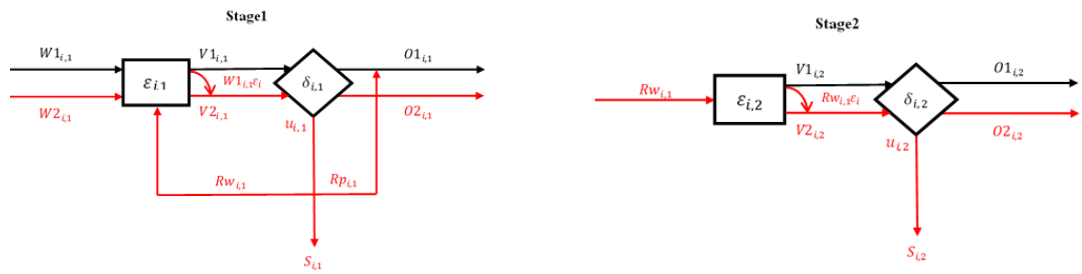

Figure 2. Processing during stage1 and stage2

A lot of material (Q_i) consists of good quality materials ($W1_{i,j}$) and non-conforming materials ($W2_{i,j}$) arrives the process on stage1 for transform tangible inputs in each cycle. At each stage a unit becomes non-conforming items through improper manufacturing operations, and if stage are following by inspection operation can be performed to detect non-conformities occurred at this processing station or at some earlier processes. If any process have inspection allocated, the inspection activities will be performed with constant inspection proportion ($\delta_{i,j}$). In fact, an item consist of many identical component characteristics which are simultaneously operated through the production system. In this case, items are considered as non-conforming items if any component is not meet the requirement of each characteristic. Those inspected items are identified as good quality products and non-conforming products. Non-conforming products are classified three categories: replaceable items, rework able items and reject items with constant proportion $f1_{i,j}$, $f2_{i,j}$ and $f3_{i,j}$ respectively. Note that the summation of proportion classified non-conforming products must be equal to 1. Then, rework able items reach into stage2 for rework process as shown in Figure 2. Reworked items are also released for inspection with the same proportion in stage1. Every process has the same operation cycle except the last process which is customer. Customer section has no any operation but penalty cost occurred in case non-conforming products are delivered to customer. There are following assumptions on this study:

1. Shortage are not allowed
2. Demand are pre-determined
3. Production is performed lot by lot
4. Non-conforming products are produced with constant proportion in each process
5. Each process has constant inspection proportion and both stages are equal
6. Non-conforming products are classified into three categories with constant proportion
7. There is no type of inspection error
8. Rework operation is done one time only (non-conforming detected by stage2 inspection are all rejected). In other word, proportion of replaceable and rework able items in stage2 are equal to 0

To detect non-conforming items, inspection of total production lot is desirable. But this may be time-consuming and affect to the production rate and costs. Therefore, Appling an appropriate inspection policy is quite good alternative for the organizations.

4. Modeling

4.1 Serial multi-stage production model

From the serial multi-stage process model, suppose that each item must go through i processes and each of process has 2 stages. Then mass balance are calculated as follows:

Stage $j=1$

(a) Amount of non-conforming products produced from process i stage $j=1$

$$V2_{i,1} = W2_{i,1} + W1_{i,1}(\varepsilon_{i,1})$$

(b) Amount of good quality products produced from process i stage $j=1$

$$V1_{i,1} = W1_{i,1}(1-\varepsilon_{i,1})$$

(c) Amount of non-conforming products detected from process i stage $j=1$

$$u_{i,1} = \delta_{i,1}(V2_{i,1})$$

(d) Amount of replaceable items from process i stage $j=1$
$Rp_{i,1} = u_{i,1}(f1_{i,1})$

(e) Amount of rework able items from process i stage $j=1$
$Rw_{i,1} = u_{i,1}(f2_{i,1})$

(f) Amount of reject items from process i stage $j=1$
$S_{i,1} = u_{i,1}(f3_{i,1})$

(g) Total good quality outcomes from i stage $j=1$
$O1_{i,1} = V1_{i,1} + Rp_{i,1}$

(h) Total good non-conforming outcomes from i stage $j=1$
$O2_{i,1} = V2_{i,1} - u_{i,1}$

Stage $j=2$

(a) Amount of non-conforming products produced from process i stage $j=2$
$V2_{i,2} = Rw_{i,1}(\varepsilon_{i,2})$

(b) Amount of good quality products produced from process i stage $j=2$
$V1_{i,2} = Rw_{i,1}(1-\varepsilon_{i,2})$

(c) Amount of non-conformance products detected from process i stage $j=2$
$u_{i,2} = \delta_{i,2}(V2_{i,2})$

(d) Amount of replaceable items from process i stage $j=2$
$Rp_{i,2} = u_{i,2}(f1_{i,2})$

(e) Amount of rework able items from process i stage $j=2$
$Rw_{i,2} = u_{i,2}(f2_{i,2})$

(f) Amount of reject items from process i stage $j=2$
$S_{i,2} = u_{i,2}(f3_{i,2})$

(g) Total good quality outcomes from i stage $j=2$
$O1_{i,2} = V1_{i,2} + Rp_{i,2}$

(h) Total good non-conforming outcomes from i stage $j=2$
$O2_{i,2} = V2_{i,2} - u_{i,2}$

Therefore, the total outcomes reach into next process where $W1_{i+1,1} = O1_{i,1} + O1_{i,2}$ and $W2_{i+1,1} = O2_{i,1} + O2_{i,2}$. Reject items are waste $Scrap_i = S_{i,1} + S_{i,2}$

4.2 Modeling of cost calculation

Notations

w_i	input item weight through process i (kg/unit)
Mat_i	input main material cost per unit of process i ($/kg)
Aux_i^k	cost per unit of auxiliary material type k ($/unit)
P_{mc_i}	machine power of process i (kW)
P_{insp_i}	inspection machine power of process i (kW
$treat_i$	treatment cost per unit ($/g)
Pn	penalty cost per unit ($/unit)
t_{c_i}	cycle time (year/lot)
t_{p_i}	total processing time of process i (hr/lot)
t_{s_i}	setup time of process i (hr/lot)
t_{m_i}	manufacturing time of process i (min/unit)
t_{insp_i}	inspection time of process i (min/unit)
t_{rw_i}	rework time of process i (min/unit)
$\bar{t}_i$	average production time of process i (hr/unit)
G_i	average storage inventory level of process i (unit/lot)
$\overline{W}_i$	average WIP inventory monetary value of process i ($/lot)
OP_i	number of operator in process i
IP_i	number of inspection operator in process i

The cost calculation model of this problem is extended the GTOQIRR conceptual models and mathematical equations for single-stage process (Ullah and Kang, 2014) towards to cost calculation for serial multi-stage processes. Overall considered details and cost calculation of the model are described below:

Since the production must be satisfied customer demand (d) therefore lot size (Q) is defined to keep customer demand. As production undergoing imperfection environment, results in poor quality products are rejected at the end of each process. Therefore, cycle time (t_c) must be related with the last process output which are delivered to customer ($i = I$) as following

$$Q_I = dt_c$$

$$t_c = \frac{Q_{i+1}}{d} \tag{1}$$

In production system, each process has manufacturing (t_{m_i}), rework (t_{rw_i}) and inspection time (t_{insp_i}) consumed individually. The total processing time of each process is

$$t_{p_i} = t_{s_i} + \frac{t_{m_i} Q_i + t_{insp_i}\left(Q_i \delta_{i,1}\right) + t_{rw_i} Rw_{i,1} + t_{insp_i}\left(Rw_{i,1}\delta_{i,2}\right)}{60} \tag{2}$$

Therefore average processing time is

$$\overline{t_i} = \frac{t_{p_i}}{Q_i} \tag{3}$$

Eq.(4) and (5) are rate charge per unit of production time (M_i) and inspection time ($Insp_i$) respectively

$$M_i = \frac{LC\left(OP_i\right)}{h} \tag{4}$$

$$Insp_i = \frac{LC\left(IP_i\right)}{h} \tag{5}$$

Where LC and h are represent labor cost per hour and work hours respectively.

Therefore average production system cost per unit is

$$c_i = Mat_i w_i + M_i \overline{t_i} \tag{6}$$

All these cost equations below are calculated from considering associated components in this study based on cycle time.

1. Main material cost (\$/year)

$$C_i^{MainMat} = \frac{Mat_i}{t_c}\left(Q_i \times w_i\right) \tag{7}$$

2. Auxiliary material cost (\$/year)

$$C_i^{AuxMat} = \frac{\sum_{k=1}^{K} Aux_i^k \left(q_{i,1}^k \times Q_i\right)}{t_c} \tag{8}$$

Where q_i^k amount of auxiliary material type k used.

3. Setup cost (\$/year)

$$C_i^{set} = \frac{M_i t_{s_i}}{t_c} \tag{9}$$

4. Processing cost (\$/year)

$$C_i^{processing} = \frac{Q_i t_{m_i} M_i}{t_c \times 60} \tag{10}$$

5. Inspection cost (\$/year)

$$C_i^{insp} = \frac{t_{insp_i} Insp_i}{t_c \times 60}\left(\delta_{i,1} Q_i + \delta_{i,2} Rw_{i,1}\right) \tag{11}$$

6. Rework cost (\$/year)

$$C_i^{rework} = \frac{M_i t_{rw_i} Rw_{i,1}}{t_c \times 60} \tag{12}$$

7. Energy cost (\$/year)

$$C_i^{Energy} = \frac{En}{t_c}\left[\begin{array}{l} P_{mc_i}\left(t_{s_i} + \dfrac{t_{m_i} Q_i + t_{rw_i} Rw_{i,1}}{60}\right) \\ + P_{insp_i}\left(\dfrac{t_{insp_i}\left(Q_i \delta_{i,1}\right) + t_{insp_i}\left(Rw_{i,1}\delta_{i,2}\right)}{60}\right) \end{array}\right] \tag{13}$$

Where En is electrical rates (\$/kWh)

8. Inventory holding cost (\$/year)

$$C_i^{IH} = a c_i G_i \tag{14}$$

where $G_i = \frac{\frac{1}{2} Q_{i+1}}{t_c}$ and a is percentage inventory holding costs

9. Work-in-process cost (\$/year)

$$C_i^{WIP} = a\overline{W_i} \tag{15}$$

where $\overline{W_i} = \frac{1}{2t_c}\left(Mat_i Q_i w_i + Scrap_i c_i\right)$

10. Waste treatment cost (\$/year)

$$C_i^{treat} = \frac{\left(treat_i\right)\left(q_i^k\right)}{t_c} \tag{16}$$

Note that this study main material waste can be sold as steel scrap. Therefore, there is only auxiliary materials need to be scraped.

11. Penalty cost (\$/year)

$$C_I^{penalty} = \frac{\left(W2_{I,1}\right)\left(Pn\right)}{t_c} \tag{17}$$

4.3 Modeling of MFCA analysis

MFCA technique was proposed to trace all material used and calculate all activities in monetary term. There are four types of costs i.e. material cost, system cost, energy cost and waste treatment cost. These costs are distributed into positive and negative product cost based on the attribution of activities to generation of product and waste. Schmidt, Götze and Sygulla (2015) have proposed MFAC analysis procedures as follows:

1. Drawing the material flow diagram and identify the quantity center (QC). Then, specify material types used through process. Materials used can be classified into three categories:
   1) Main Material is the main raw materials used in the product.
   2) Sub Material is the raw materials used as a component of the product.
   3) Auxiliary Material is supplement materials used for help to produce such as chemicals, coolants, auxiliary equipment, etc.
2. The quantification of flows: Quantify input and output of each work center. Integrating mass balance technique to calculate the difference of materials lost from the process.
3. Evaluate flow in terms of cost which are consist of material cost (MC), cost of production (SC), energy cost (EC), and waste management cost (WC) are the costs. These costs had calculated by the previous mathematical equations. The details are as follows:
   1) Material cost of process i: cost of all raw material types used in the production process.
   $$MC_i = C_i^{MainMat} \tag{18}$$
   2) System cost of process i: including of setup cost, production cost, inspection cost, rework cost, inventory cost and WIP cost.
   $$SC_i = C_i^{set} + C_i^{processing} + C_i^{Q} + C_i^{IH} + C_i^{WIP} \tag{19}$$
   3) Energy cost of process i: cost of the electrical energy used in production and inspection.
   $$EC_i = C_i^{Energy} \tag{20}$$
   4) Waste treatment cost of process i: for production WC is including of waste displacement costs, waste transportation costs, waste storage costs, wastewater treatment costs, etc. On the other hand, the customer section waste displacement refers to penalty due to non-conforming products delivered to customer.
   $$WC_i = C_i^{treat} \quad \text{or} \quad WC_I = C_I^{penalty} \tag{21}$$
   5) Finally, these costs are distributed as positive product costs and negative product costs. Cost allocation can be calculated by ratio of the entire entering material weight process to the forward material weight into next process. This will determine the amount of loss proportion ($p0_i$), proportion of products ($p1_i$) and $p0_i + p1_i = 1$, so the classified costs have shown in Table 1.

Table 1. MFCA cost evaluation

		Quantity center : Process i			
		$i=1$	$i=2$	$\cdots$	$i=I$
Cost of Prev. Process	Material Cost PMC_{i-1}	PMC_0	PMC_1		PMC_{I-1}
	System Cost PSC_{i-1}	PSC_0	PSC_1	$\cdots$	PSC_{I-1}
	Energy Cost PEC_{i-1}	PEC_0	PEC_1		PEC_{I-1}
Newly Input	Material Cost MC_i	MC_1	MC_2		MC_I
	System Cost SC_i	SC_1	SC_2	$\cdots$	SC_I
	Energy Cost EC_i	EC_1	EC_2		EC_I
Process Total Cost	Material Cost TMC_i	$TMC_1 = PMC_0 + MC_1$	$TMC_2 = PMC_1 + MC_2$		$TMC_I = PMC_{I-1} + MC_I$
	System Cost TSC_i	$TSC_1 = PSC_0 + SC_1$	$TSC_2 = PSC_1 + SC_2$	$\cdots$	$TSC_I = PSC_{I-1} + SC_I$
	Energy Cost TEC_i	$TEC_1 = PEC_0 + EC_1$	$TEC_2 = PEC_1 + EC_2$		$TEC_I = PEC_{I-1} + EC_I$
Positive Product Cost	Material Cost PMC_i	$PMC_1 = p1_1(TMC_1)$	$PMC_2 = p1_2(TMC_2)$		$PMC_I = p1_I(TMC_I)$
	System Cost PSC_i	$PSC_1 = p1_1(TSC_1)$	$PSC_2 = p1_2(TSC_2)$	$\cdots$	$PSC_I = p1_I(TSC_I)$
	Energy Cost PEC_i	$PEC_1 = p1_1(TEC_1)$	$PEC_2 = p1_2(TEC_2)$		$PEC_I = p1_I(TEC_I)$
Negative Product Cost	Material Cost NMC_i	$NMC_1 = p0_1(TMC_1)$	$NMC_2 = p0_2(TMC_2)$		$NMC_I = p0_I(TMC_I)$
	System Cost NSC_i	$NSC_1 = p0_1(TSC_1)$	$NSC_2 = p0_2(TSC_2)$		$NSC_I = p0_I(TSC_I)$
	Energy Cost NEC_i	$NEC_1 = p0_1(TEC_1)$	$NEC_2 = p0_2(TEC_2)$	$\cdots$	$NEC_I = p0_I(TEC_I)$
	Waste Treatment Cost WC_i	WC_1	WC_2		WC_I
Total Loss	Material Cost		$\sum_{i=1}^{I} NMC_i$		
	System Cost		$\sum_{i=1}^{I} NSC_i$		
	Energy Cost		$\sum_{i=1}^{I} NEC_i$		
	Waste Treatment Cost		$\sum_{i=1}^{I} WC_i$		
Total Cost	Material Cost		$TCMC = PMC_I + \sum_{i=1}^{I} NMC_i$		
	System Cost		$TCSC = PSC_I + \sum_{i=1}^{I} NSC_i$		
	Energy Cost		$TCEC = PEC_I + \sum_{i=1}^{I} NEC_i$		
	Waste Treatment Cost		$TCWC = \sum_{i=1}^{I} WC_i$		

Therefore, concluding overall production system:

Total cost $$TC = \sum_{i=1}^{I} TC_i \tag{22}$$

Total positive product cost $$TPC = PMC_I + PSC_I + PEC_I \tag{23}$$

Total negative product cost $$TNC = \sum_{i=1}^{I} NMC_i + \sum_{i=1}^{I} NSC_i + \sum_{i=1}^{I} NEC_i + \sum_{i=1}^{I} WC_i \tag{24}$$

5. Artificial bee colony algorithm approach

5.1 ABC optimization

In multi-stage manufacturing systems, the higher processing cost added is the more important to decide inspection strategy for screening previous process. The inspection sample size should be considered in order to avoid the unnecessary production costs added from unidentified non-conforming items being processes during manufacturing operations. Furthermore, lot size are also considered because it is effect on inventory cost during process storage. This study is focusing on artificial bee colony algorithm search for the optimal solution. The following steps show the ABC algorithm procedure (Karaboga and Basturk, 2007):

Step1 Generates a randomly distributed initial population X_i of SN solutions (food source positions). Each solution consists of member x_{ij} $i \in \{1,2,\ldots,SN\}$ where SN denotes the size of population and $j \in \{1,2,\ldots,D\}$ which are $\{Q_1, \delta_{1,1}, \delta_{1,2}, \delta_{2,1}, \ldots, \delta_{I,1}, \delta_{I,2}\}$. Initial population can be calculated by the following expression:

$$x_{ij} = x^j_{\min} + rand(0,1)\left(x^j_{\max} - x^j_{\min}\right) \tag{25}$$

Step2 Evaluate the nectar amount (fitness value; $fit_i(V_i)$) of the each source.

Step3 Specify the maximum cycle number (MCN)

Step4 Employed bees produce a modification on the position (υ_{ij}) by the following expression:

$$\upsilon_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{26}$$

Where ϕ_{ij} is a random number between [-1, 1]. Then, tests the nectar amount (fitness value) of the new source (new solution). Provided that the nectar amount of the new one is higher than the previous one, the bee memorizes the new position and forgets the old one. Otherwise it keeps the previous one.

Step5 Onlooker bee chooses a food source depending on the probability value associated with that food source, p_i , calculated by the following expression:

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \tag{27}$$

Step6 Onlooker bees choose a food source with a probability related to its nectar amount and produce a modification on the position (υ_{ij}) by Eq. (26). Then, tests the nectar amount (fitness value) of the new source (new solution). Provided that the nectar amount of the new one is higher than the previous one, the bee memorizes the new position and forgets the old one. Otherwise it keeps the previous one.

Step7 Providing that a position cannot be improved further through a predetermined number of cycles (*limit*), then that food source is assumed to be abandoned. The food source of which the nectar is abandoned is replaced with a new food source as Eq. (25) by the scout bees.

Step8 Memorize the best solution achieved so far.

Step9 repeat step 4-8.

Step10 until cycle = MCN

5.2 Mathematical model

For i processes, decision variables for each of process are inspection proportions ($\delta_{i,j}$). Additional decision variables are amount of good quality materials ($W1_{1,1}$) and non-conforming materials ($W2_{1,1}$) feed into the first process. Thus, the mathematical models can be constructed determine the optimal lot size and inspection proportions relatively with cost as described below:

Decision variables

$W1_{1,1} \in [200, 3000]$	Amount of good quality materials feed into process $i=1$
$W2_{1,1} \in [0, 200]$	Amount of poor quality materials feed into process $i=1$
$\delta_{i,j} \in [0,1]$	Inspection proportion of process i stage j

Objective function

$$Maximize \frac{TPC}{TC} \tag{28}$$

Subject to

$$\frac{W1_{I,1} + W2_{I,1}}{t_c} \geq d \tag{29}$$

Where Eq. (29) is the total products delivered to customer constraint. Note that the limited inspection resource constraint i.e. inspection persons, inspection time are not mentioned in this study.

5.3 Design of ABC parameters

In the ABC method, there are four control parameters used: The number of food sources which is equal to the number of employed and onlooker bees (*SN*), the value of abandonment limit (*limit*) and the maximum cycle number (*MCN*). ABC parameters setting in this study are shown in Table 2.

Table 2. ABC parameters used in this study

Parameter	**Value**
Population size (*SN*)	20
Abandonment limit (*limit*)	1
Maximum cycle number (*MCN*)	25

As table shown, colony size ($2*SN$) is 40 and the maximum cycle number (*MCN*) is 25. Thus, the total objective function evaluation number is 1000.

6. Experimental results

The experimental data tests and results will be described in this section. The developed model from previous section have been coded in MATLAB R2014a and performed on a laptop computer Core i5 CPU @2.2 GHz and 4 GB RAM to implement the ABC algorithm which generate the optimal inspection and lot size solution.

6.1 Experimental design

In this study, the experimental data was obtained from the case study manufacturer. Since the present production has no replacement and rework process ($f1_{i,1}$ and $f2_{i,1}$ = 0), the detected items in stage1 will categorized as reject or scrap. The production parameters used in the mass balance calculation are shown in Table 3. All material costs are kept confidential. Assuming that the customer demand (d) = 15000 units per year, the penalty (Pn) = \$18 per unit, percentage inventory holding costs (a) = 30%, electrical rate (En) = \$0.11 per kWh, operating person each process = 1, inspection person (in case inspection) = 1, labor cost (LC) = \$12 per day and labor hour (h) = 8 hours per day.

Table 3. Production data

Para-meter	Process i														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$\varepsilon_{i,1}$	0.00%	0.18%	0.02%	0.00%	0.00%	2.50%	0.00%	6.60%	1.20%	0.18%	0.24%	0.14%	1.73%	0.00%	-
$\delta_{i,1} = \delta_{i,2}$	2.50%	2.50%	0.00%	0.00%	0.00%	0.00%	0.00%	2.50%	0.00%	0.00%	0.00%	0.00%	0.00%	2.50%	-
$f3_{i,1} = f3_{i,2}$	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	-
$\varepsilon_{i,2}$	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	-
t_{s_i}	4.00	8.00	0.00	0.25	0.00	0.25	0.50	4.00	0.50	1.00	1.00	0.00	0.00	0.00	-
t_{m_i}	2.30	8.22	10.70	2.00	0.00	0.63	4.00	3.89	1.71	1.00	2.63	11.47	0.00	0.00	-
t_{insp_i}	42.00	42.00	0.00	0.00	0.00	0.00	0.00	42.00	0.00	0.00	0.00	0.00	0.00	42.00	-

t_{rw_i}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-
P_{mc_i}	25.00	40.00	0.75	5.60	0.00	15.00	5.60	30.00	1.50	1.50	1.50	0.75	0.00	0.00	-
P_{insp_i}	2.00	2.00	0.00	0.00	0.00	0.00	0.00	2.00	0.00	0.00	0.00	0.00	0.10	2.00	-
w_i	0.4344	0.0910	0.0412	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401	0.0401	0.0400	0.0400	0.0400

From table 3, it shows that there are only 4 inspection stations with fixed-inspection proportion = 0.25 of total production lot the current production. In optimal search we assume that if inspection should be performed after that process stage, it will take inspection time equal to 42 min/unit and require 1 inspection person.

6.2 Cost analysis of current production environment

MFCA analysis data of current manufacturing operation is shown in Table 4. Before establish the optimal inspection sample size and lot size, the total cost were $360,098 per year. Table 4 shows that the present operation has ratio of total positive product cost to total cost only 6.80%. The result shows this manufacturing operate inefficiently due to unappropriated inspection strategy. Inefficient sample size are causes of non-conforming items being processes and adding resources unnecessarily during manufacturing activities.

Table 4. MFCA analysis of a present case study manufacturing

	MC	SC	EC	WC	TC
Positive cost ($/year)	2064	12072	10359	0	24495
Negative cost ($/year)	280062	13277	10410	31854	335603
Total cost ($/year)	282126	25349	20769	31854	360098

6.3 Computational results

Considering inspection proportion and lot size as decision variables, the experimental were repeated 5 runs each starting from a different random seed. The computational results are shown in Table 5.

Table 5. Inspection plan and production lot size obtained by ABC algorithm

Run	W1	W2	d														Positive Cost	Total Cost	Ratio
			1	2	3	4	5	6	7	8	9	10	11	12	13	14			
1	3000	200	0.455	0.722	0.000	0.050	0.792	0.446	0.024	1.000	0.036	0.680	0.438	0.731	1.000	1.000	9.32E+04	4.55E+05	0.2047
2	2146	79	0.000	0.440	0.000	0.348	0.141	0.878	0.608	1.000	0.303	0.987	1.000	1.000	0.852	0.987	8.63E+04	4.15E+05	0.2081
3	3000	59	0.395	0.869	0.000	0.274	0.663	0.320	0.248	1.000	0.719	0.454	0.396	1.000	1.000	0.822	9.28E+04	4.51E+05	0.2058
4	2038	86	0.622	1.000	0.208	0.898	0.000	0.000	1.000	1.000	0.917	1.000	1.000	0.729	0.861	0.983	9.98E+04	4.73E+05	0.2112
5	556	12	0.247	0.352	0.584	0.000	1.000	0.632	0.428	0.728	0.802	0.414	0.775	0.528	1.000	1.000	8.26E+04	4.15E+05	0.1988

According to the results, no inspection is the optimal decision for the third process. In contrast, full inspection is suggest plan for the eighth process. Considering the inspection proportion as a decision variable to be optimize increase the average ratio of objective function (TPC/TC) to 0.2057. It is clearly that the ABC method provide the better inspection plan than present manufacturing operated.

7. Conclusions and suggestions for further research

Efficient inspection system requires valuable resources that incurs the high operation cost to the firm. It is important to seek the efficient inspection strategy while reduce cost. An efficient inspection strategy are cost trade-off between inspection cost and penalty. Besides, it will help to prevent the unnecessary processing cost added and wastage of resources in the next processes. In addition, the production lot size was considered as decision variable since it impact on inventory and WIP holding cost structure.

Considering, MFCA technique to show waste costs occurred from unidentified detective items being processes unnecessarily during manufacturing operations as a result of established inefficient inspection strategy. The

objective of optimization problem are the maximum ratio of positive product cost to total cost (TPC/TC). In other words, the study attempt to increase the positive cost while reduce total cost by implement the optimal inspection strategy and production lot size. This study a solution algorithm based on ABC has been develop to solve the optimal inspection strategy and lot size in a serial multi-stage process. In conclusion, the proposed approach is helpful for production and inspection sections especially in serial production process environment.

Since there is no sensitivity analysis of the ABC parameters, the further research suggest to test the effect of changing of parameters. Moreover, benchmarking the solution and performance of ABC algorithm with other optimization techniques is optional in the further research.

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