A Cost-Based Allocation of Inspection Efforts in Quality Control of a Multistage Assembly Line: A Case Study of an Electronics Assembly Line

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Abstract: Electronic Manufacturing Service (EMS) providers often face a high-volume high-mix product manufacturing industry. This study presents a cost-based allocation of inspection efforts in quality control of a sequential multi-stage electronic assembly line, considering all relevant costs and proposes the optimum inspection strategy. A dynamic sampling plan is incorporated in the model to maintain the desired quality levels. Monte-Carlo simulation is used to obtain the solution of this complex model. The model is created based on an actual electronics packaging company. This approach provides the ability to minimize the costs and does not sacrifice the quality of the products. The input factors that significantly affect the costs are identified so that they can be optimized for performance improvement and decision-making.

Keywords: Electronics Assembly, SMT line, Quality Control, Cost based optimization of inspection effort

1. Introduction

The Electronic Manufacturing Service (EMS) provider renders service by providing electronic assemblies for Original Equipment Manufacturers (OEMs). The high demand in the market has made the OEMs realize that they should concentrate on their core competency by researching product design and marketing it to the end users. This has resulted in reducing costs by avoiding outsourcing. The importance of EMS or Contract Manufacturers (CMs) has become more dominant and, thus, EMS providers have gone out of their way to coalesce their own product development teams. As a result of these factors, they have started to become more akin to all-around service providers with products of their own. EMS providers have realized the significance of planning and utilizing their resources now more than ever. As competition increases and costs must be brought down, they must be critical in breaking down the costs of each workstation in an assembly line. This has been a driving force for the development of a decision support system in the inspection strategies across the entire manufacturing plant. This study endeavors to optimize the costs that are specific to the EMS provider's inspection resource allocation.

1.1 Problem Statement

Surface Mount Technology (SMT) assembly line have different features and many possible inspection strategies. The following is a list of problems that are addressed in this study:

1. The varying yields of different stations.
2. The inspection stations after various work stations effect the product quality characteristics.
3. The interaction of inspection stations is not considered to affect the output quality.
4. The above concerns are not dealt with by considering the cost factors involved.
5. Each inspection station can have its own sampling plan or inspection strategy.

All the above listed concerns are represented in a mathematical model and the costs are optimized to maximize profit. The optimal inspection strategy is thus determined.

1.2 Objective

The objective of this study is to develop a mathematical model for optimizing the allocation of inspection stations and the inspection strategies along a serial production line; in this case, an SMT assembly line. The case study will be specific to the electronics industry depending on the probabilities of workstation performances and other relevant criteria. The optimal solution will be presented based on the minimum cost and maximum profit considerations while fulfilling all the applicable constraints.

1.3 Allocation of Quality Control Stations

An example of the Allocation of Quality Control Stations **(**AQCS) system is shown in Figure 1. This is the generic flow of materials at each station A decision is made after the workstation to either inspect the product or not. If an inspection is required, the product will go to the conformance decision stage. If no inspection is required, the product will directly advance to the next station. The nonconforming products will be scrapped or reworked and the conforming products will continue to the consequent station.

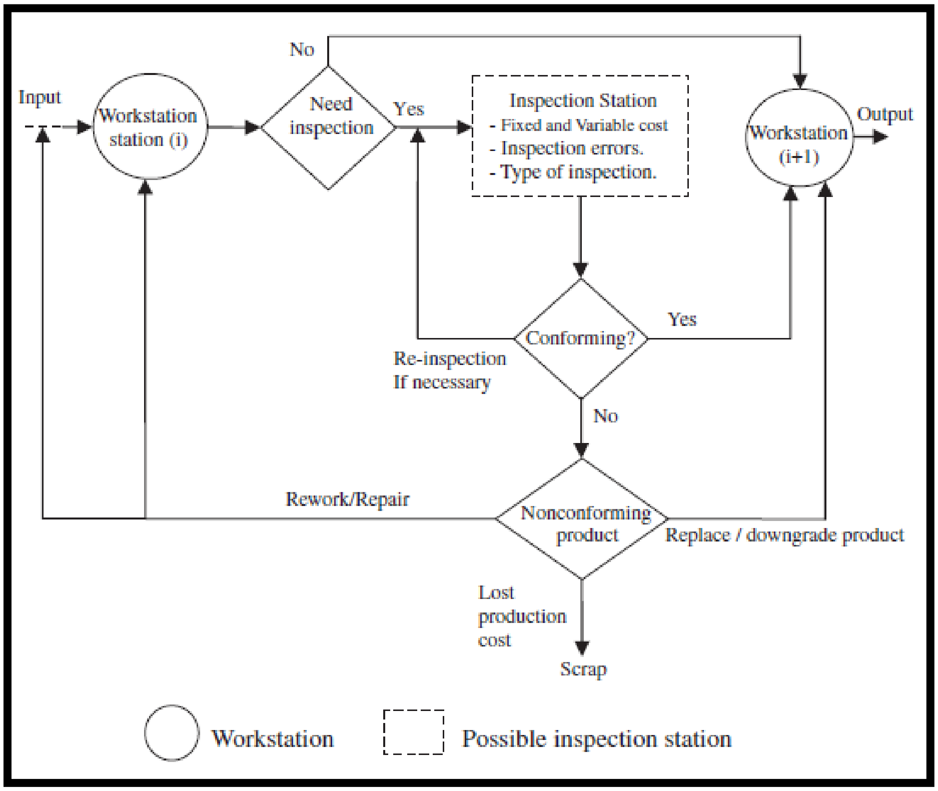

Figure 1. AQCS example (Shetwan et al., 2011)

2. Literature Review

2.1 Allocation of Quality Control Stations (AQCS)

A multistage production system has the potential to add a quality control (QC) station after every work station. Figure 2 depicts the basic concept of a multistage production system with possible inspection stations.The QC station checks the quality of the products after the process. It is cost and time prohibitive to assign a QC station after each production stage, considering the cost and time constraints. An optimum allocation of QC stations is required that maintains the desired quality levels and minimizes the costs (Van Volsem et al., 2007).
The line structure is also important because it directly affects the occurrence of defects. An assembly line that merges into one line from multiple lines makes it more difficult to account for the defects. Figure 3 shows the flow of material and the costs assigned to them. A product is deemed defective if the damage is irreparable and it can be scrapped. Products are reworked if the damage is repairable and returned to the main product flow of the assembly line. Another conforming product might be added to the assembly line to compensate for the defective one. The defective product can also be included in another substandard product line if acceptable. A product is disposed as a defective if its quality characteristics are not acceptable as per the standards. There are specification limits that define the acceptability. It is known that the cost of reworking and scrapping the products will be at a minimum if there are inspection stations after every work-station. This cost

has to be weighed against the cost of inspection stations and all their associated costs. The balance between these costs will be used to minimize the total cost (Shetwan et al., 2011).

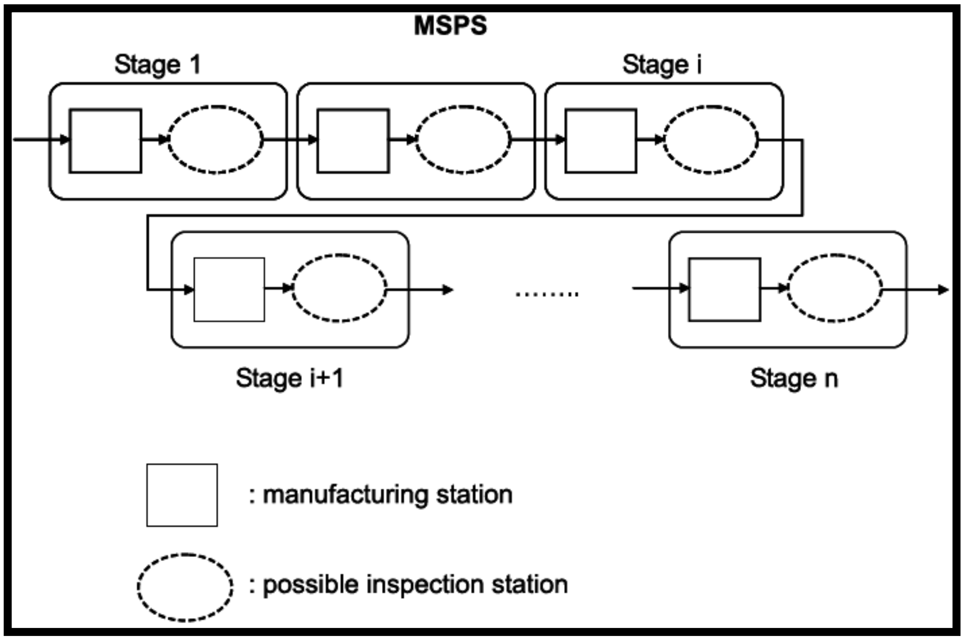

Figure 2. A multistage production system with potential inspection stations (Van Volsem et al., 2007)

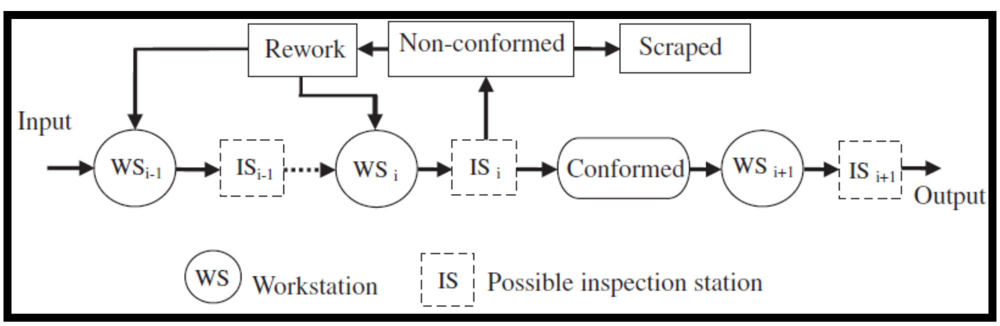

Figure 3. Costs at Inspection Station (Shetwan et al., 2011)

Another study (Penn & Raviv, 2008) addresses the inspection stations that separate all the defective products and remove them from the main material flow in the production line. One station can only produce one product at a time and one product can only be located in one station at a time. There is no limit on the number of products that can wait before entering a workstation. “Production rate” is the pace at which products enter the assembly line. The inspection stations are responsible for reducing the rate of outgoing products because they take time to identify some products as defective and remove them from the main assembly line flow.

AQCS is especially relevant in the electronics packaging industry where surface mount technology is in use. There are many automatic inspection stations available, not only the inspection stations but also the lines. For example, solder paste has to be deposited on a PCB to mount electronic components on the board. This process is critical to the quality of the final electronic assembly. An optical inspection machine is available for solder paste inspection. Using this type of machine or other automated inspection machines on the line is not practical. This model of Kakade et al., 2004. optimizes the allocation of such inspection stations on the multistage assembly line. The company has limited resources as to the number of inspection stations it can allocate on the assembly line. The optimal locations of these stations can be determined using the

AQCS model. The study considered focused on the sampling inspection, its effect on quality, and, eventually, profitability. A percentage level for sampling inspection was optimized

2.2 Objectives of AQCS

The main objective of the AQCS model is to obtain the best strategy that will minimize the cost components while maintaining the desired quality levels (Shetwan et al., 2011). Another approach is to maximize profit for each unit (Penn & Raviv, 2008). The two main objectives are to decide the location of the inspection station and to decide which inspection station should be chosen. The options for solutions increase drastically as the problem becomes more complicated. A system that manufactured a variety of part types was considered and each part variety had its own sequence of workstations it went through. The inspection stations could be allotted after the given production stations to check the quality of the products manufactured. The constraints in this situation are the time constraint for inspection and the inspection capability constraint. The time constraint addresses the total time taken to inspect the products, whereas the capability constraint is based on the accuracy and precision of the inspection (Lee & Unnikrishnan, 2010). The accuracy and precision of inspection can be qualified by calibration methods and Gage R & R studies.

Adjusting certain processes, like those in which products are built in batches and the setup has to be changed before every new variety of a product, can have a high cost. In such cases, efforts are made to identify the point in the production timeline after which the products failed to conform to specifications. After this point is established, all the products thereafter are labeled as defective, which may mean that either a Type I or a Type II error has occurred, akin to hypothesis testing. A Type I error would be if the parts produced before the point of defect identification are non-defective and are rejected. A Type II error would take place if the defective parts are accepted that were produced after the point of defect identification. These concerns must be attended because a 100% inspection strategy is not feasible all the time. The optimization of batch size becomes an important part of addressing this problem (Raz et al., 2007).

The objective of another study was to solve an inspection allocation problem while considering the inspection cost along with the costs of false calls. A heuristic solution approach was used with a dynamic algorithm. The optimal inspection policy was done along with no inspection policy to account for all combinations of the inspection strategies along the production line. The computational complexity of the algorithm was low and thus it was easy to solve. A sensitivity analysis was performed to check for different values of the probabilities and costs considered. The primary objective of this study was to assist managers in making decisions for an offline inspection system (Finkelshtein et al., 2004).

2.3 Inspection Stations

The SMT production line is depicted in Figure 4. It starts with the board loader that manually receives a stack of bare boards, which are typically green colored and are made of FR4 material. These boards have traces and copper pads on them for electrical connections and are ready for components to get mounted on them.

 ISSN (Online): 2329-0188

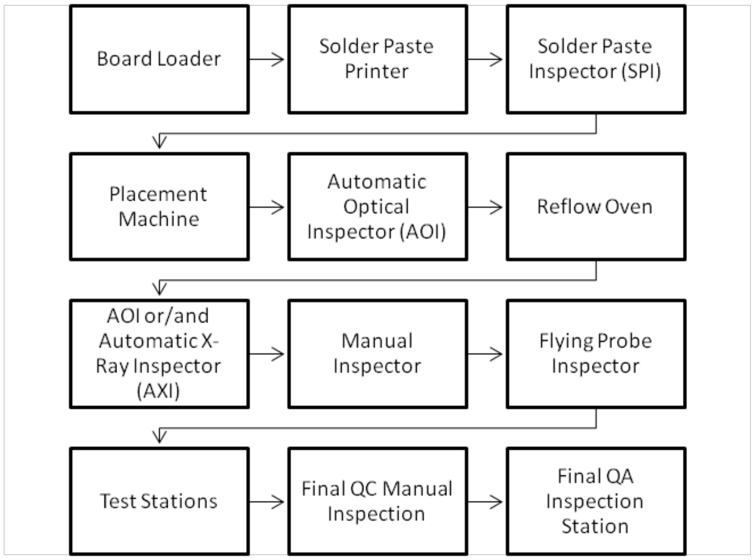

Figure 4. Typical SMT production line

The Surface Mount Technology (SMT) production line is depicted in Figure 4. It starts with the board loader that manually receives a stack of bare boards, which are typically green colored and are made of FR4 material. These boards have traces and copper pads on them for electrical connections and are ready for components to get mounted on them.

The board loader has a vacuum system that consists of nozzles that pick up one board at a time. This board is then passed on to the solder paste printer via a conveyer belt. The board can also be directly fed into the solder paste printer if the board loader is not available or practical in the facility. The printer checks the board for alignment in the fixture using an optical fiducial recognizing mechanism. This is a part of the computer program of the board's detailed drawing. The board has copper pads mapped on it that are sites for the placements of the components to be mounted on them. The copper pads need to be covered with solder paste. The solder paste acts as a bonding material that holds the component in place. The printed solder paste also provides electrical connections along with many other qualities. The solder paste is printed when a stencil is placed over the board and a layer of solder paste is manually placed over it. The paste can also be automatically squeezed out of a paste tube mechanism. The stencil has apertures or holes in it at the exact same locations mapped as the board. A squeegee blade passes over the stencil and squeezes the paste through the stencil apertures onto the bare board. The board gets the solder paste printed on its surface according to the dimensional requirements. The process of solder paste printing is in the following steps. Step 1 presents that the solder paste is ready to spread onto the stencil with the squeegee. In the next step, the aperture is coincided with the pads on the bare board. The paste gets printed on the pad and the stencil is lifted up after the squeegee has completely passed.

The printed board is then transported by the conveyer system to the next station. The solder paste inspection station uses an automatic optical inspection system to inspect the solder paste. The camera uses phase shift interferometry for solder paste inspection. This inspection station is effective in controlling the quality of the products because solder paste printing is considered to be the most critical process step in SMT assembly line. About 60% of solder related defects are mainly caused by solder paste printing issues (Buttars, 1993), (Huang, 2010). The machine then accepts or rejects a board based on the solder paste dimensions, location, and the specifications set by the users. The machine has the ability to override its decision and the operator can decide if they want to pass or fail a board. All these settings can be configured by the user as per the requirements.

After the solder paste inspection is performed, the board is passed by the conveyer to the next station in line, which has the placement machines. These machines have reels of components of different types, such as Integrated Circuit (IC) chips, capacitors, resistors, and other active and passive components. These reels are loaded in the feeders, which are then loaded in the machines. The robotic head picks the components using a vacuum nozzle system and places them on the board at their respective pad and solder paste deposit location. These heads are capable of picking up and placing multiple components at very high speeds. This is achieved because the machines follow complex algorithms to place the components on the boards. A pick and place machine that has feeders at the bottom that are loaded with reels. The components are picked from the feeders and placed inside the machine on the boards as explained earlier (Direct Industry, 2014).

After the placements are carried out, the machine advances to an AOI station that inspects the placements made. The optical device looks for missing placements, misalignments, and inverted placements of the components. It can also read the text on the components, which helps it to verify the electrical value, date code, and supplier name. A go, no-go system is used to pass the board to the subsequent station just like the solder paste inspection machine does.

The board is transported to a reflow oven by conveyers or manually and undergoes the reflow stages. The board is continuously moved by the conveyer through the reflow oven. During this motion, it goes through four main temperature zones. They are the preheat zone, the thermal soak zone, the reflow zone and the cooling zone. There are heating and cooling apparatus inside the reflow oven that attain the specified temperatures. These thermal transformations affect the solder joint and ideally lead to a proper joint formation between the board and the components (Tummala, 2004). The AOI equipment can also be placed after this reflow oven to inspect for the solder joint quality by observing the placement accuracy. It will check for the same attributes as the earlier AOI machine, but will be implemental in including the solder joint reliability after reflow. During reflow, the changes that occur in the solder joint can cause the device to get misaligned or jump off. The root cause behind this is the solder paste printed, because a bad solder print will eventually keep causing problems even until after reflow.

The three pieces of inspection equipment work on the common principles of optics. These machines also have the ability to communicate with each other and use this information to make process adjustments and help in proactively improving the quality. The SPI can detect the defects and feedback information to the printer to make process parameter adjustments. For example, if the solder paste printed is seen as offset from the specification, the printer is commanded to make an offset in the position of the board in the equal and opposite direction, thus eliminating similar defects in the future runs. The SPI can also mark the pads that have close to a defective print and communicate this information to the downstream AOI equipment. The AOI equipment will double-check those particular pads in addition to its regular inspection.

In addition to the AOI, AXI (Automatic X-ray Inspection) machines can also be used to observe some features, like solder balls, for defects. AXI has an advantage over AOIs, which is that it can see through components for the hidden solder joints. BGAs and stacked devices, both of which have solder balls, can be inspected using AXIs. AXI machines are also good for detecting voids in the solder balls, which are small pockets of air or the absence of solder within the solder mass. A manual visual inspection is also an established form of inspection and is prevalent in the SMT industry. Another test equipment is the flying probe, which is used to measure the electrical connections for the components across the board using probes that physically contact the solder joints or pads for testing. Various types of probes are available based on the applications. A typical probe angle is 5-6 degrees. A bill of material verification can be done for all the components of an assembly.

The assembled products then go through a series of software or electrically configured tests. All these tests have a pass or fail result module, which helps in inspecting the products. If any of the products fail, they are sent to a rework station for diagnosing their failure and then they are sent back to the work flow after being repaired. The tests are the last step of production. A manual inspection is done after the test stations. This is called the final Quality Control (QC) station, which follows a set of guidelines that are standards for inspecting the assemblies. A Quality Assurance (QA) station is located at the end of all the stations for validating the products exiting the facility.

2.4 Relevant Models

During the assembly, there may come a point in the process in which products are manufactured serially in a batch (size=N), the products start to non-conform as per the specification. For a specific example, consider product ‘j’ (transition unit), which is in the middle of a serially arranged lot. All the units produced after ‘j’ are non-conforming and the ones before ‘j’ are conforming (Raz et al., 2007). The above scenario accounts for two different possibilities: inspection versus non-inspection. They considered situations in each of the above approaches where the quality of the last product is either known or unknown, to develop the mathematical model. The total minimum cost was minimized by summing all the costs in the objective function. A zero defects policy and the policy of perfect information were considered as an alternate to the main model: optimal inspection/disposition policy. The policy of perfect information made sure that all the products were determined to be either defective or not. On the other hand, the zero defects policy was only concerned that the products that reach customers be conforming. The three policies were compared and a sensitivity analysis was done along with changing the combinations of inspection costs and the penalty costs for false calls. The optimal batch size was obtained easily by using the complete enumeration method.

Penn and Raviv (2008) studied a serial production line that has known failure probabilities of all the stations. The research aimed to identify the location of the proposed QC stations with the production rate in mind. This would help in optimizing the profit per unit time during production. Two types of optimizing models were presented:

1. Optimizing the Allocation of QC Stations with minimizing the costs at a predefined production rate

2. Optimizing the Allocation of QC Stations with maximizing the profits and defining the production rate

The probability of a conforming product leaving M_i, that will also be conforming after leaving M_j is as follows:

$$q_{ij} \equiv \prod_{k=i+1}^{j} p_k$$

It will be the product of all the probabilities of success of the individual stations in the range of i to j (Penn and Raviv, 2008).

2.5 Approaches to Solve AQCS

Van Volsem et al. (2007) used discrete event simulation to apportion the cost in the multistage system. The allocation problem was solved with the help of an evolutionary algorithm to obtain the optimal strategy for inspecting the products. The approach was successful in optimizing the sample size and acceptance limits, although the authors felt the need to test the proposed solution as a part of the future work. Inspection cost and the cost of damaged products was minimized using the research. Other research studies were done using heuristic approaches to solve the AQCS problem, and then compared it with Complete Enumeration (CEM). The heuristic methods were much more efficient than CEM and did not significantly affect the objective function cost (Lee and Unnikrishnan, 1998) (Shiau, 2002). A limited number of inspection stations are available based on the constraints that the stations are unavailable during their calibration or when they are being used by another job. Inspection errors might be included after inspection in the form of false calls. These errors in inspection can also be due to the errors from earlier inspection stations or if different quality characteristics are measured at the same station. There are different types of products that result in different specifications for products. These variations contribute to the errors getting induced at the quality control stations. Thus, the model must consider the errors of inspection for its formulation (Shiau, 2002).

CEM can provide the optimum solution, but the solution is produced at the cost of efficiency. Shetwan et al. (2011) proved this when they had compared it with a heuristic method with a local search. Their method greatly increases the performance of the model and yields close to optimum results. The heuristic methods follow a certain flow or rules that allow the search to begin with any solution. The search mechanism then moves onto a solution that is better than the one already selected. A local search only looks around the selected solution for the better solution and keeps moving on in its vicinity.
Evolutionary algorithms have been used widely in manufacturing environments. A Genetic Algorithm (GA) is one such stochastic search model that strives to find the acceptable solution in the scenario where obtaining the optimum solution is not feasible. GA is relevant to problems with constraints due to preceding stations and can be easily implemented. Extensive search spaces can be attended to by using a GA and will be a necessity in this case considering the complex nature of the problem (Sadegheih, 2007).

Heredia-Langner (2010) assumed that the lot size ‘N’ is much bigger than the sample size ‘n’ selected for inspection. The inspection station has a predefined number for the sampling plan, which is the upper limit of the acceptable rejects found in the sample as per the sampling plan. After an inspection of the sample, if the defects are more than the aforementioned predefined upper limit, the lot is considered for rejection. All the products of the lot are scrutinized and the nonconforming ones are sent to the rework station or are scrapped. This decision is governed by the procedure of the company. The assumption enables the use of the binomial distribution for obtaining the probability of accepting a lot that goes through the inspection station. The following formula predicts the probability mentioned above. The limit of acceptable defects in the lot is ‘d’, and ‘c’ is the number of defects observed after checking the sample.

$$Pa = P(d \leq c) = \sum_{d=0}^{c} \frac{n!}{d!(n-d)!} \cdot p^d (1-p)^{n-d}$$

A Markovian approach was used to estimate the optimum process target for each process step in a multi-stage production system. An inspection station is deployed at the end of each stage to collect the data regarding the quality of the products exiting the process step. A model was used to develop a system for evaluating a single stage production process. This model was then applied to predict the process targets for multi-stage processes. A general model for a specific number of steps was designed. Expected profit equation was developed based on the revenue and costs associated with the products. The sensitivity analysis demonstrated the effects of these costs and process parameters like mean and standard deviation on the optimum process targets at each of the multi-stage process (Bowling et al., 2004).

3. Development of the Model

Consider that a multistage production line has stations with different known probabilities of producing a conforming product. An inspection station can be located after every workstation. All the units that are deemed as nonconforming units by the inspection station are sent to the rework station. Here, a decision is taken to either rework or scrap a unit based on the severity of the defect observed. If the unit is reworked, it is then sent directly to the next station, i.e., i+1, as seen in Figure 5.

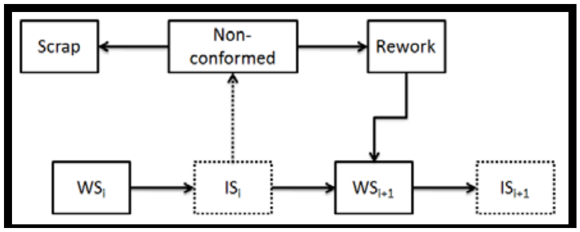

Figure 5. General flow of material

Three types of inspections can be done after every workstation, namely, no inspection, sampling inspection, or full inspection. Each of the 10 workstations can have one of the three inspections performed after them. The sampling station could potentially have different types of sampling plans as options to select the best one. Thus, the objective is to determine which of the workstations will have what type of inspection strategy out of the three options available.

If a sampling inspection is done, a sample (fraction of the lot size) will be inspected. If the sample has s number of nonconforming products that is more than or equal to the acceptance number, then the entire lot is inspected. All the nonconforming products are either scrapped or reworked. If the sample has a number of nonconforming products that is less than the acceptance number, then the entire lot is accepted. All the nonconforming products are either scrapped or reworked. If a full inspection is done, then all the nonconforming products will be either reworked or scrapped based on the decision made by the model. On the other hand, no inspection will simply lead to the products progressing to the consecutive stations.

Nomenclature:

i Workstation number
n_i Number of input products in station i
n_{si} Number of units scrapped at workstation i
p_i Probability of producing a conforming product from workstation i
p_{Fai} Probability of falsely accepting a nonconforming product as a conforming product after inspection
$(n_{i-1}(1-p_{i-1})p_{FAi-1})$ is the number of false accepts that left the inspection station
T_i Time taken to process a unit through ith workstation
c_p Cost of production per unit time. It is assumed to be constant at all workstations.
p_{si} Probability of a unit being scrapped when it is given that it is a nonconforming product after passing through the ith station
c_{si} Cost per unit of scrapping a nonconforming product after it passed through the ith station
d_i Number of defective products in sample
d_{ri} Number of defective products in the lot excluding the sampled units
n_{ni} Number of nonconforming products after passing through inspection station
$= d_i$, if the lot is accepted
$= d_i + d_{ri}$, if the lot is rejected
c_{mi} Cost of the material required for reworking a nonconforming product after it passed through the ith station
c_{ri} Cost of reworking per unit time a nonconforming product after it passed through the ith station
T_{ri} Time required reworking a nonconforming product after it passed through the ith station
n_{ri} Number of units being reworked at station i
c_{rp} Unit replacement cost if a customer returns a product
n_{Ii} Number of units being inspected
f_i Sample size as a fraction of n_i for inspection
Sample size=
n_i if the lot is accepted
$n_i f_i$ if the lot in rejected
c_{Ii} Cost (labor/ machine) for inspecting one product
Following is a recursion equation for the number of units entering a station, for i> 1:

$$n_i = n_{i-1} - n_{s(i-1)}$$

For i = 1,
$n_i =$ n
When a sample out of the lot is inspected, the number of defects is generated randomly following the binomial distribution.
P_a Probability of acceptance
$P\{d \leq t_i\} = \sum ((n_i f_i)! / (d! (n_i f_i - d)!)) (1 - p_i)^d (p_i)^{nifi-d}$
Summation ranges from d=0 to t_i
The above formula gives the number of defects. The parameters used will be sample size ($n_i f_i$) and p_i to generate a random number d.
This random number d will be used to check against t_i, the acceptance number.
If $d_i <= t_i$, Accept the lot
If $d_i > t_i$, Reject the lot (Montgomery, 2009)

Five types of costs are considered in the model viz. production cost, scrap cost, rework cost, cost of false acceptance (replacement cost after customer returns the product) and inspection cost.

Production cost $= \sum n_i T_i c_p$
Scrap cost $= \sum n_{si} c_{si}$
Rework cost $= n_{ri} c_{mi} + [n_{ri} c_{ri} T_{ri}]$
Cost of false acceptance $= (n_i p_{FA} c_{rp})$
Following (Van Volsem et al., 2007), the cost of inspection strategy is considered:
Inspection cost $= c_{Ii}\ n_{Ii}$

During inspection, a false rejection scenario can never occur. This is because the rework operators identify it and send the conforming product back into the production flow. There will be some delay in production if the false rejects are sent to the rework station. This cost will be negligible. If the false rejects are sent to the rework station with other real defective products, then there will be an even lower cost associated with the false rejects. This is because the rework operator will take very little time to decide that the reject was a false one. In addition, the false rejection rate at the inspection station is very low.

There are a few more costs to be addressed. The production system has a batch flow. No buffer inventory levels are maintained between stations. This justifies the exclusion of the cost of inventory levels. The process of manufacturing overheads is very costly. Material handling costs are a part of this cost, so they do not have to make a separate contribution towards the objective function. The overtime costs are assumed to be negligible. When the customer returns a product because of a field failure, one of the following two scenarios can occur. The product can either get scrapped and replaced, which is associated with the replacement cost, or the product can be repaired, if possible, after returning to the company. Both these costs are considered under the same umbrella of the cost of false acceptance. This cost is determined by considering the cost of a product as the same as that of replacement.

Objective Function:

Minimize Σ cost

The total cost is then subtracted from total revenue of the lot to get the net profit. Thus, the constraints for minimum revenue and minimum number of finished goods are not violated. This approach ensures that the model does not give a 0 total cost as the optimum solution, which is unrealistic.

4. Case Study

The stations (with known average probabilities of producing conforming products) are as seen in Table 1.

Table 1. Stations in assembly line

Workstation #	Station Name	Inspection Type
1	Solder paste printer	Solder paste inspector
2	Placement machine	Automated optical inspection
3	Reflow ovens	Automated optical inspection/ Automated X-Ray inspection/ manual visual inspection
4	Labeling and routing	Optical measurement equipment
5	Test 1	Automatic tester
6	Test 2	Automatic tester

7	System Test	Automatic tester
8	SPD Check	Automatic tester
9	QC	Manual & visual inspection
10	Final QA	Manual & visual inspection

When a sample out of the lot is inspected, the number of defects is randomly generated following the binomial distribution.

As seen in Figure 6, the product flows through the above stations. The board loader loads a single board on the conveyer belt to send it to the solder paste printer. After printing, its goes to an optical inspection machine (SPI). After this inspection it goes to the placement machine for loading of the active and passive components. An optical inspection machine can be used to observe the alignment of the components. Reflow oven secures the components to the board and an inspection can be done after that too. Flying probe is another inspection machine used before it goes to the test stations and eventually to final inspection.

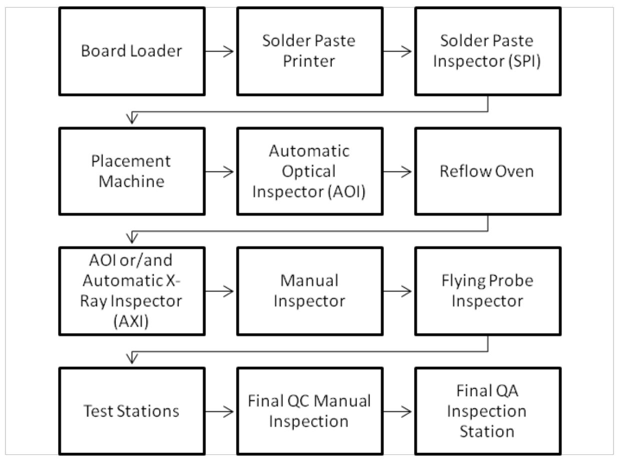

Figure 6. Machines involved in the product flow

P_a = Probability of acceptance

$P\{d \le t_i\} = \sum ((n_i f_i)! / (d! \, (n_i f_i - d)!)) \, (1 - p_i)^d (p_i)^{nifi-d}$

Summation ranges from d=0 to t_i

The above formula gives the number of defects. The parameters used will be sample size ($n_i f_i$) and p_i to generate a random number d.

This random number d will be used to check against t_i, the acceptance number.

If $d_i <= t_i$, Accept the lot

If $d_i > t_i$, Reject the lot (Montgomery, 2009)

Five costs are considered in the model viz. production cost, scrap cost, rework cost, cost of false acceptance (replacement cost after customer returns the product) and inspection cost.

Production cost $= \sum n_i T_i c_p$

The Ti is calculated as shown below. It is a random number as a function of a uniform distribution. A new random number will be obtained in each simulation run. Thus, multiple unique simulation runs will be obtained. Random numbers generated for the following uniform probability distribution function:

$= \frac{1}{b-a} \, for \; x \; \varepsilon \; [a, b]$

$= 0$ otherwise

The parameters are as seen in Table A1 in the Appendix.

Scrap cost$= \sum n_{si} c_{si}$

The parameters p_i and p_{si} are calculated as shown below. They are random numbers as a function of different normal distributions with different parameters. A new random number will be obtained in each simulation run. Thus, multiple unique simulation runs will be obtained. Random numbers (normally distributed) are generated for each workstation (with different parameters) to calculate p_i. The parameters are as seen in Table A2 in the Appendix.

Random numbers (normally distributed) are generated for each workstation (with different parameters) to calculate p_{si}. The parameters are as seen in Table A3 of the Appendix.

Rework cost $= n_{ri}c_{mi} + [n_{ri}c_{ri}T_{ri}]$

Cost of false acceptance $= (n_i p_{FA} c_{rp})$

The parameter p_{FA}, which is a random normal variate, is calculated as shown below. The parameters are as shown in Table A4 in the Appendix. Random numbers (normally distributed) are generated for each workstation (with different parameters).

The four random numbers mentioned earlier will be configured with different parameters for each station, as in Table 2.

Table 2. Example of random values for various parameters

Work station number i	1	2	3	4	5	6	7	8	9	10
Random Numbers: Probability of producing a conforming product from workstation i, (pi)	0.99375	0.98263	0.98711	0.99374	0.98793	0.99082	0.98523	0.99425	0.97708	0.98887
Random Numbers: Probability of a unit being scrapped when it is deemed as nonconforming after passing through the ith station, (psi)	0.41853	0.46736	0.47105	0.45610	0.44587	0.40042	0.46763	0.46391	0.47822	0.53268
Random Numbers: Probability of false acceptance after inspection, (pFA)	0.00473	0.00553	0.00624	0.00544	0.00569	0.00424	0.00360	0.00565	0.00462	0.00243
Random Numbers: Time taken to process a unit through ith workstation, Ti (minutes)	2.75798	2.25923	2.33963	2.64145	2.30008	2.94105	2.18818	2.34595	2.66231	2.43194

In addition to the above 40 variables, there are 10 more variables (d_i) for the 10 stations.

d_i is the number of defective items found in the sample after the inspection is performed.

The parameters for the binomial distribution function used to generate the random numbers are shown in TableA5. These are specific to the sampling strategy scenario (S1). The sample size will vary as the strategy or scenario varies.

The cost of inspection strategy is considered as formulated below (Van Volsem et al., 2007)

Inspection cost $= c_{Ii}\, n_{Ii}$

There are 50 input variables in this model, which are categorized into 5 groups, namely, d_i, p_i, p_{si}, p_{FAi} and T_i. Each of these categories has ten variables for each of the 10 stations. There are six output variables as observed from the expressions earlier, namely, scrap cost, cost of false acceptance, rework cost, inspection cost, production cost and total cost.

The model is run for various numbers of iterations ranging from 10 to 1200 in an increasing trend. The output, variable total cost, is monitored for each of the simulation runs. It is observed, as shown in Figure 7, that after the simulation run of 900 iterations, the results appear to stabilize. The total cost value is seen to be constant after the scenario with 900 iterations at $41,600.

The simulation is executed for 1000 runs, i.e., 1000 sets of the 50 variables are generated and 1000 sets of results are obtained. These results are summarized to give a concise understanding of this scenario.

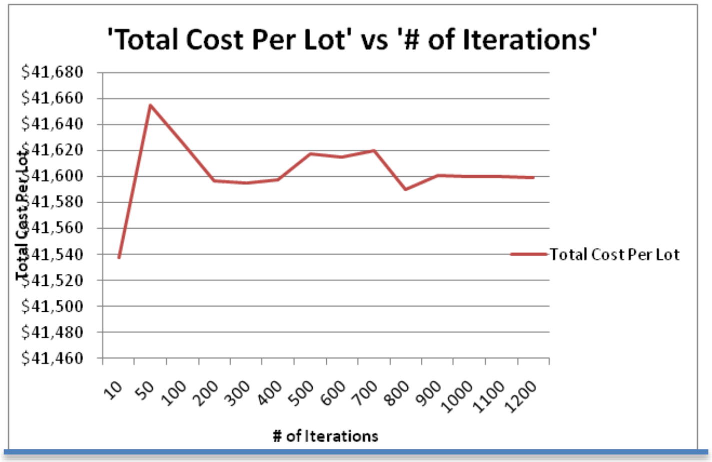

Figure 7. Selection of 1000 iterations

Nine scenarios are considered with the above assumptions. The scenarios are given in Table 3.

Table 3. Scenarios considered

Scenario	Inspection Strategy	All stations: Sample size as a fraction of lot size	Comments
0	No inspection	0.0	
S1	Sampling Inspection	0.1	
S2	Sampling Inspection	0.2	
S3	Sampling Inspection	0.3	
S4	Sampling Inspection	0.4	
S5	Sampling Inspection	0.5	
S6	Sampling Inspection	0.6	
1	Current inspection	Varying	Sample sizes as a fraction of lot sizes for the 10 stations are as follows: 0.5, 1.0, 1.0, 0.2, 0.3, 0.3, 0.3, 0.1, 0.1, 0.0
2	Full inspection	1.0	

The first scenario has no inspection done for the products as shown in Table 8. The scenarios S1 to S6 are all the scenarios where sampling inspection is performed. All the stations have the same sample size in any scenario as shown in Table 8. Scenario 1 is the current or baseline model that is considered. Each of the inspection stations have different sampling fractions assigned. This is the inspection strategy which is typically followed in the electronics manufacturing setting as seen in Table 8. Scenario 2 is where all the items are inspected at all stations.

The data for p_i is taken from the actual electronics manufacturing plant yields data. The 10 weeks of yield data is considered to decide the process means or p_i. The data is averaged separately for the 10 stations to give a mean p_i value for each station. This helped in assuming the p_i values for each of the 10 stations.

5. Analysis and Results

Analyses are performed to first test the input variables for their validity of probability distribution functions and the respective parameters. The model is then run to study the effects of input variables on the output variables. The scenarios are run to choose the best one.

The input variables are validated to confirm their probability distributions. Figures A1 and A2 in the Appendix show a sample of the validation tests for two of the input variables. Other input variables are also observed to be following the defined distributions. It is observed that the variables depict the probability distributions to be a normal distribution and a binomial distribution. The Akaike Information Criterion (AIC) is the test statistic used to validate the probability density function.

The parameters observed in Figure 8 have the mean set as 0.977 and the standard deviation set as 0.0097, which are both very close to the input parameters of 0.978 and 0.009. Figure 9 shows a binomial distribution with 99 and 0.0232 as the parameters, which are almost the same as the input parameters of 100 and 0.022.

The detailed results for scenario S1 are shown from Figure 8 to Figure 10. Figure 9 shows that the input variables do not have a significant effect on the scrap cost.

The summary tables of all results are listed from Table 4 to Table 6 and Table A6.

Nomenclature used for the Figures

di	# of defectives
pi	Probability of conforming products
p_{FAi}	Probability of false acceptance
p_{si}	Probability of scrap
T_i	Time for production
B	Station 1
C	Station 2
D	Station 3
E	Station 4
F	Station 5
G	Station 6
H	Station 7
I	Station 8
J	Station 9
K	Station 10

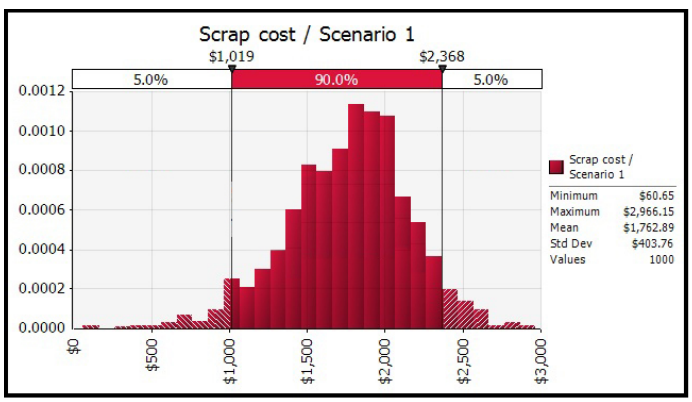

Figure 8. Probability density function for scrap cost (Scenario S1)

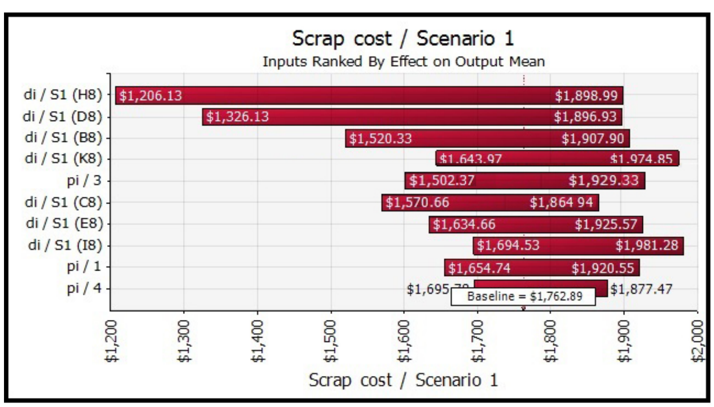

Figure 9. Change in output mean for scrap cost (Scenario S1)

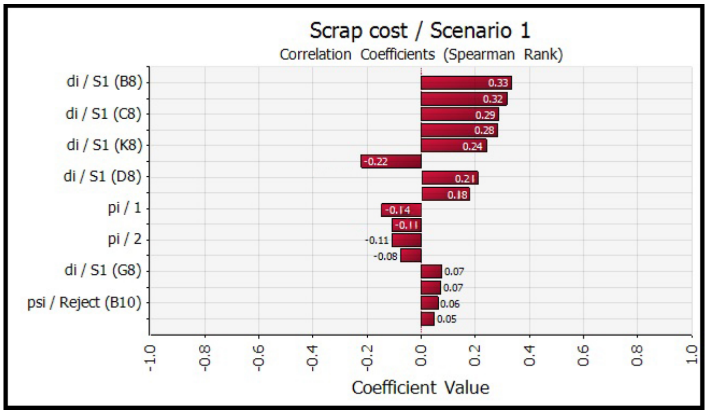

Figure 10. Correlation coefficients for scrap cost (Scenario S1)

The results were analyzed for all of the 9 scenarios and the mean costs are summarized in Table 4. The sampling strategy S1 results in the least total cost. The no inspection strategy 0 results in high costs because of the falsely accepted products. The full inspection strategy 2 also turned out to be very expensive because it increases the inspection cost drastically. The baseline strategy 1 is not the most expensive one, but it can be improved by experimenting with different inspection scenarios. The scenarios S1 to S6 only have the sample size increased from 0.1 fraction of the lot size to 0.6 fraction of the lot size. The total cost is observed to be increasing as the sample size is increased.

Table 5 clearly shows that in order to minimize the costs, the practical constraint of keeping the desired number of finished goods is not violated. If this constraint is not satisfied, the model will give 0 as the number of finished goods to effectively end up with the minimum cost. This is because there is no constraint on final output. This could make the solution to attain a very small value because the production cost is also considered.

Table 4. Comparison of Costs

Scenario	Scrap Cost Per Lot	Rework Cost Per Lot	Cost of False Acceptance Per Lot	Inspection Cost Per Lot	Production Cost Per Lot	Total Cost Per Lot
0	$0	$0	$24901	$0	$25000	**$49901**
S1	$1770	$878	$487	$9533	$24340	**$37007**
S2	$1595	$793	$976	$10655	$24407	$38427
S3	$1432	$715	$1468	$11792	$24469	$39876
S4	$1270	$635	$1962	$12932	$24531	$41330
S5	$1104	$554	$2459	$14083	$24593	$42792
S6	$936	$473	$2959	$15237	$24656	$44260
1	$956	$543	$1889	$11476	$24745	**$39609**
2	$260	$141	$4982	$19928	$24910	**$50220**

Table 5. Comparison of Number of finished goods

Scenario	Total Finished Goods Per Lot
0	1000
S1	965
S2	964
S3	969
S4	988
S5	977
S6	971
1	980
2	993

Table 6 demonstrates the differences in the revenue and profit between the different scenarios. These results agree with the ones seen above for minimizing costs. The maximum profit and revenue is observed to be from scenario S1.

Table 6. Comparison of revenue and profit

Scenario	Total Cost Per Lot	Total Finished Goods Per Lot	Revenue Per Lot at Selling Price of $60 per unit	Profit Per Lot	% Profit Per Lot
0	**$49901**	1000	$60,000	$10099	**17%**
S1	**$37007**	965	$57,900	$20,893	**36%**
S2	$38427	964	$57,840	$19,413	34%
S3	$39876	969	$58,140	$18,264	31%
S4	$41330	988	$59,280	$17,950	30%
S5	$42792	977	$58,620	$15,828	27%
S6	$44260	971	$58,260	$14,000	24%
1	**$39609**	980	$58,800	$19,191	**33%**
2	**$50220**	993	$59,580	$9,360	**16%**

The input variables that affect the corresponding output variables are summarized in Table A6. They are identified using the correlation coefficients values greater than 0.4. Table A7 in the Appendix shows the results of sensitivity analysis done for the output variables of costs with respect to the input variable p_1. The cost values are insensitive to p_1 in scenario S1 unlike in scenario 0. In scenario 0 the cost of false acceptance values decrease as p_i increases. Table A8 shows similar results for sensitivity analysis for p_{10}. The costs in S1 scenario are not affected by p_{10} but they are affected in the scenario 0. The same relation is observed with p_1.

These scenarios give a realistic view of how the model can be manipulated and different simulations can be run. The most significant input variables can be worked upon by using quality improvement tools to affect the output as desired. The complex model can be experimented with and the results can be analyzed to make decisions for inspection strategies.

6. Conclusions and Extensions

The aim of this study is to allocate inspection stations on an electronics assembly line along with the respective inspection strategies. The three major scenarios, namely, no inspection, sampling inspection and full inspection, were modeled and studied using Monte-Carlo simulation. The complex model yields results to assist managers in decision making when the process is designing. The different costs can be compared between different scenarios to make the best choice of inspection strategy. The sampling inspection is the most cost-effective as observed in the analysis. A sensitivity analysis is performed for two variables, namely, p_1 and p_{10} to observe the effects on the output variable total cost. The fraction of lot to be sampled can be varied to get the best result. The model is also flexible with changing the sample sizes at an individual station level. The different inspection equipment types used in the electronics assembly industry have different inspection strategies that are favorable for use. The input variables that have significant effects on the costs are identified in this study. These input variables can be studied in detail to improve the process using lean and six sigma tools. The Monte-Carlo simulation model is flexible to very easily accommodate different scenarios. Changes can be made to the number of stations, variables and probability distributions. The model is easy to understand, operate and interpret the results.

As an extension, the complexity of the model can be increased by adding more probabilistic input variables. The number of input variables can also be increased to study the effect of all the factors involved in defining the costs. This will help in creating a model that represents the randomness in the real world. The cost of false acceptance can also become memory driven by identifying the products that are nonconforming but are deemed conforming. Currently, the model has limitations to achieve this. If the products can be marked as falsely accepted in the model, they can be appropriately dealt with in the consequent stations. These products can be tracked as they progress through the assembly line.

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Appendix

Table A1. Parameters for T_i

Workstation	Distribution parameter: a	Distribution parameter: b
1	2	3
2	2	3
3	2	3
4	2	3
5	2	3
6	2	3
7	2	3
8	2	3
9	2	3
10	2	3

Table A2. Parameters for p_i

Workstation	Distribution parameter: Mean (μ)	Distribution parameter: Std Dev (σ)
1	0.978	0.009
2	0.977	0.008
3	0.961	0.008
4	0.986	0.007
5	0.998	0.001
6	0.994	0.001
7	0.964	0.002
8	0.99	0.001
9	0.999	0.0001
10	0.987	0.001

Table A3.Parameters for p_{si}

Workstation	Distribution parameter: Mean (μ)	Distribution parameter: Std Dev (σ)
1	0.4	0.01
2	0.45	0.03
3	0.455	0.02
4	0.46	0.01
5	0.5	0.04
6	0.49	0.01
7	0.52	0.02
8	0.43	0.03
9	0.45	0.01
10	0.43	0.02

Table A4. Parameters for p_{FA}

Workstation	**Distribution parameter: Mean (μ)**	**Distribution parameter: Std Dev (σ)**
1	0.005	0.001
2	0.02	0.003
3	0.01	0.002
4	0..008	0.001
5	0.001	0.004
6	0.01	0.001
7	0.015	0.002
8	0.005	0.003
9	0.025	0.001
10	0.012	0.002

Table A5. Parameters for d_i

Workstation	**Distribution parameter: Sample size ($n_i f_i$)**	**Distribution parameter: (1 - p_i)**
1	100	0.022
2	100	0.023
3	100	0.039
4	100	0.014
5	100	0.002
6	100	0.006
7	100	0.036
8	100	0.01
9	100	0.001
10	100	0.013

 ISSN (Online): 2329-0188

Table A6. Significant input variables

Scenario	Scrap Cost	Rework Cost	Cost of False Acceptance	Inspection Cost	Production Cost	Total Cost
0	-	-	p_i at station 1, 2, 3 and 4	-	T_i at station 2	p_i at 1 and 3
S1	-	d_i at station 10.	-	-	-	-
S2	-	d_i at station 7, 10.	-	-	-	-
S3	-	d_i at station 10.	-	-	-	-
S4	-	d_i at station 10.	-	d_i at station 10.	-	-
S5	-	d_i at station 10.	-	d_i at station 10.	-	-
S6	d_i at station 7.	d_i at station 7.	-	-	-	-
1	d_i at station 7, 10.	d_i at station 7, 10.	p_{FAi} at station 2.	d_i at station 10.	-	d_i at station 10.
2	d_i at station 7.	d_i at station 7, 10.	-	d_i at station 2, 3. (negatively)	-	-

Table A7. Sensitivity analysis for p_1

Scenario	p_1 Values	Scrap Cost Per Lot	Rework Cost Per Lot	Cost of False Acceptance Per Lot	Inspection Cost Per Lot	Production Cost Per Lot	Total Cost Per Lot
S1	0.9	$2326	$1026	$479	$9378	$23940	$37148
S1	0.95	$1960	$928	$484	$9479	$24202	$37052
S1	0.978	$1770	$878	$487	$9533	$24340	$37007
S1	0.99	$1676	$851	$488	$9552	$24406	$36973
0	**0.9**	-	-	$24400	-	$25000	**$49400**
0	**0.95**	-	-	$19398	-	$25000	**$44398**
0	**0.978**	-	-	$16600	-	$25000	**$41600**
0	**0.99**	-	-	$15399	-	$25000	**$40399**

 ISSN (Online): 2329-0188

Table A8. Sensitivity analysis for p_{10}

Scenario	p_{10} Values	Scrap Cost Per Lot	Rework Cost Per Lot	Cost of False Acceptance Per Lot	Inspection Cost Per Lot	Production Cost Per Lot	Total Cost Per Lot
S1	0.9	$2325	$1278	$487	$9534	$24343	$37966
S1	0.95	$2003	$1047	$487	$9526	$24343	$37406
S1	0.987	$1770	$878	$487	$9533	$24340	$37007
S1	0.99	$1741	$861	$487	$9530	$24345	$36963
0	**0.9**	-	-	$25300	-	$25000	**$50300**
0	**0.95**	-	-	$20301	-	$25000	**$45301**
0	**0.987**	-	-	$16600	-	$25000	**$41600**
0	**0.99**	-	-	$16300	-	$25000	**$41300**

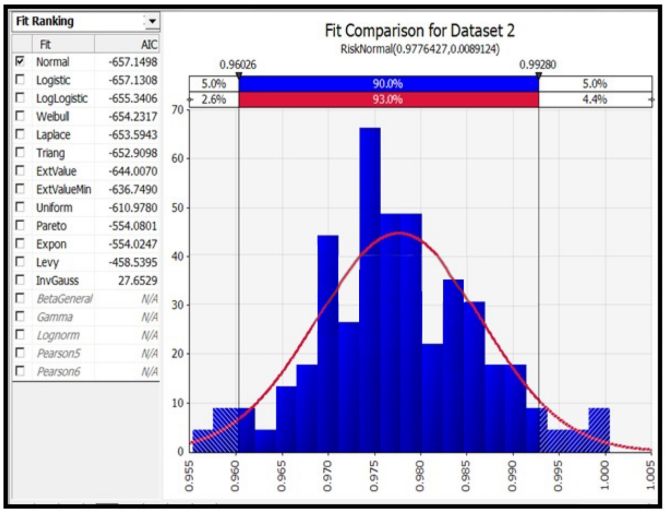

Figure A1. Normal Distribution for p_i at 1st station

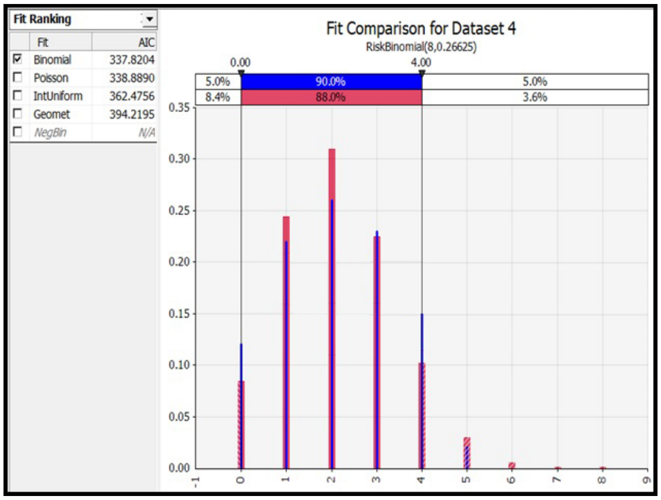

Figure A2. Binomial distribution for d_i