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Selection of Solder Paste Inspection Machines by Multi-Criteria Decision Analysis

İpek DEVECİ KOCAKOÇ
Dokuz Eylül University, Faculty of Economics and Administrative Sciences, Turkey.
www.orcid.org/0000-0001-9155-8269
ipek.deveci@deu.edu.tr

Gökçe BAYSAL TÜRKÖLMEZ
Dokuz Eylül University, Faculty of Economics and Administrative Sciences, Turkey.
www.orcid.org/0000-0001-9185-3356
gokce.baysal@deu.edu.tr

Abstract

One of the most important factors to give an inspection automation decision is the precision of measurements taken by the inspection machine. This paper aims to provide help in the selection of an automatic optical inspection (AOI) machine for a printed circuit board (PCB) assembly line of an electronics manufacturer. Since the visual inspection of soldered surfaces on a PCB is a crucial step, AOI machines bring great speed and accuracy to the inspection process. The main goal is to find the best automatic inspection machine alternative among the three AOI machine offerings according to nine selection criteria by integrating coefficient of variation statistic with TOPSIS and VIKOR, which are well-known multicriteria decision analysis methods. For this purpose, three different brands of AOI machines have been tested for the same PCBs, with 10 different components. After calculation of TOPSIS and VIKOR rank scores, the coefficient of variation of rank scores for all components is obtained and the selection of the AOI machine is finalized.

Keywords: inspection machine selection, PCB assembly line, multi-criteria decision making, TOPSIS, VIKOR, coefficient of variation.

INTRODUCTION

Quality improvement and cost reduction is a must in today's highly competitive electronics industry. Component sizes continue to shrink, and Printed Circuit Boards (PCB's) are becoming increasingly complex, as more functions are crammed into mobile phones, PCs, portable media players, and TVs. In these complex structures, a lot of different kinds of errors and defects occur and they avoid working electronic devices properly. Gunn and Reis (2001) recorded that about 50% of all electronic assembly errors and 65% of SMT-only defects have been correlated with solder paste printing and solder joint details over the past two years. Surface-mount (SMT) technology is often a method of manufacturing electronic circuits where the components are mounted or positioned directly on the computer circuit board surface (PCBs). As it has either smaller leads or no leads at all, an SMT component is typically smaller than its through-hole counterpart. (Wikipedia1). Therefore, inspections are required in various phases in the process of assembling PCBs. These studies have shown that successful and thorough inspection of paste immediately after screen printing is important to ensure high yields, minimize rework/retest and reduce overall scrap costs. (Gunn and Reis, 2001). An inspection procedure is capable of partially identifying the defects created, preventing them from being processed further downstream and, more crucially, from succeeding in customers (Rezaei-Malek, 2018).

A critical phase in the production process is visual verification of soldered surfaces (Ray, R. 1988). Generally, two kinds of inspection methods are used by electronic companies: Traditional Manual Vision Inspection and Automatic Optical Inspection (AOI)/Machine Vision.

Traditional Manual Vision Inspection is a procedure in which human professionals undertake visual inspection and quality control (Malamas et al., 2003). It is a labor-intensive process and humans can make subjective judgments affecting the quality of the product. Traditional manual vision inspection simply cannot achieve the level of quality control and cost reduction required by today's markets. Meanwhile, computer developments in terms of high-speed, massive, low-cost memory have resulted in better and cheaper image processing equipment. There is also a chance to introduce and incorporate an automatic PCB inspection system to eliminate the subjective elements of manual inspection (Dave et al., 2016).

Automatic Optical Inspection (AOI) - Machine Vision consists of capturing an image (a snapshot in time), transforming the image to digital information, and applying processing algorithms to extract helpful image information for pattern recognition, part inspection, or part positioning and orientation requirements. The use of machine vision technologies can increase PCB product quality while lowering production costs (Guo and Guan, 2011).

There are a lot of hidden benefits and costs behind "implementation of AOI":

• Advantage against Manual Vision Inspection: AOI is said to cover more than 95% of faults while MVI has only 60-70% coverage. The machinery works 24H a day 7 days a week consistently, providing high throughput, high speed, and high accuracy.

• Cost Performance: Replacing operators with AOI equipment will reduce the cost of operators, but other hidden costs can be reduced. For instance, the time and cost of operators to be trained cause a loss of profit for the company. As AOI can be used to prevent defects at the earlier stage of production, rework time, and rework costs are reduced. Prevention of field failure contributes to sustained customer reputation and reduction of repair costs.

• SPC and Traceability: AOI generates various statistical data of each defect, which can then be analyzed to improve production quality. By understanding current process trends in real-time, the process can be controlled before faults are produced. SPC data of all boards can be stored as an insurance measure for quality issues.

Overall, implementing AOI will achieve yield improvement, cost reduction, and improved quality assurance and control.

Because of the high rate of defects, solder paste inspection is examined in this study. A leading electronics company wants to select a Solder Paste Inspection (SPI) machine for inspecting assembled PCBs among 3 major suppliers. They are analyzed according to their measuring performances and tests performed for bending, repeatability, rotation, and r-pass rate. Because of the structure of the problem, the multi-criteria approach to help the company choose the best machine is utilized in this study.

PCB ASSEMBLY LINE AND INSPECTION OF PCBS

Electronic soldering joins two metallic wires/ connectors/ pins of a circuit. The soldering happens when a metallic alloy, called solder, is melted down on the joint due to soldering iron's heat, and bonds the target conductors together when the solder cools down and solidifies. Machine soldering happens by driving component-populated printed circuit board (PCB) through molten solder (drag and wave soldering), or by applying solder paste to the contacts and melt the paste by heat (reflow soldering). A machine soldering needs the industrial process and it is for mass production. There are different methods for PCB inspection and AOI is one of them. AOI is used to examine solder quality as well as pad and trace connections (Tempoautomation, 2018).

As stated by Anderson (2018), "AOI finds defects in both bare PC boards and assemblies. With small components, these defects are often invisible to the eye. The AOI process finds uneven soldering, tombstones, missing components, and misaligned parts within the PCB assembly process. The AOI machine takes a series of high-resolution photos and stitches them together using the software."

2D inspection detects lands, silk points, via holes, and traces to recognize precise solder height. Also, it measures the solder's deposition shape. It then calculates the solder area, height, and volume by 3D Phase shape inspection. For a detailed literature review on AOI for PCBs, Wang et al. (2017) can be referred to.

There exist three kinds of inspection points in a PCB production line. These are "Solder Paste Inspection", "Pre Reflow Inspection" and "Post Reflow Inspection" (Figure 1). AOI appliances have a unique name in each location. Solder Paste Inspection (SPI, also known as Post-Printing Inspection), Automatic Placement Inspection (API, also known as Post-Placement Inspection), and Post-Soldering Inspection (PSI) are three of them. Universal AOI systems (UAOI) are AOI systems that can check each production sequence (Janóczki et al., 2013).

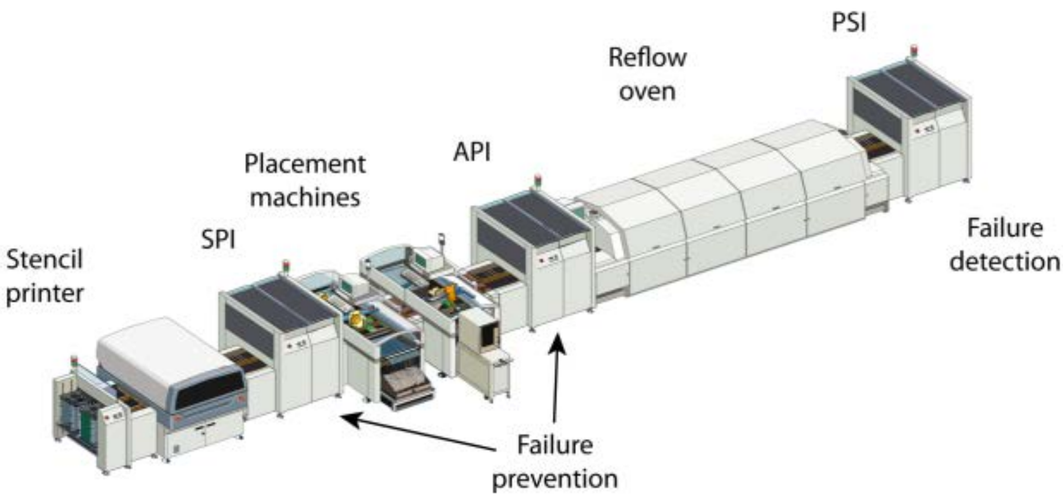

Figure 1. Possibilities for AOI placement in an SMT line (Janóczki et al., 2013).

There are not enough studies on the "automatic optical inspection system" selection problem in the literature. Since AOI is a part of the automatization process, AOI systems can be considered similar to robots, so we based our literature review on robot selection problems. Parameshwaran et al. (2015) composed a very detailed literature review on robot selection up to 2014. They presented tables listing the techniques used and selection criteria. In the following table, we extend this literature review including articles from 2015 to 2019.

Table 1. Extension of literature review

Techniques/tools used	Authors	Publication year	Selection criteria
Fuzzy Delphi Method (FDM), Fuzzy Analytical Hierarchical Process (FAHP), Fuzzy modified TOPSIS, Fuzzy VIKOR and Brown–Gibson model	Parameshwaran et al.	2015	22 criteria including both objective (i.e. Equipment cost, load capacity, repeatability) and subjective (i.e.stability, compliance, stability) factors.
PROMETHEE II	Sen et al.	2015	Load capacity, repeatability, velocity, cost
MCDM- interval type-2 fuzzy sets	Ghorabaee	2016	Inconsistency with infrastructure, Man-machine interface, Programming flexibility, Vendor's service contract, Supporting channel partner's performance, Compliance, Stability
Interval-Valued Hesitant Fuzzy-Distance-Based Group Decision (IVHF-DBGD)	Gitinavard et al.	2016	Man-machine interface, Programming flexibility, Vendor's service contract, Load capacity, Positioning accuracy, Purchase cost
integrated model based on hesitant 2-tuple linguistic term sets and an extended QUALIFLEX approach	Xue et al.	2016	Man-machine interface, Programming flexibility, Vendor's service contract, Purchase cost, Load capacity, Positioning accuracy.
Fuzzy PROMETHEE	Sen et al.	2016b	Load capacity, repeatability, maximum tip speed, memory capacity, manipulator reach, man-machine interface, programming flexibility, vendor's service contract, positioning accuracy, safety, environmental performance, reliability, maintainability
Iterative MCDM- TODIM	Sen et al.	2016a	load capacity, repeatability, maximum tip speed, memory capacity, manipulator reach
Fuzzy VIKOR	Bahadır and Büyüközkan	2016	Total Cost, Velocity, Load Capacity, Operating Time, Functionality
Weighted sum method (WSM), weighted product method (WPM),	Karande et al.	2016	Load capacity, maximum tip speed, repeatability, memory capacity, manipulator reach; cost, handling

weighted aggregated sum product assessment (WASPAS) method, multi-objective optimization based on ratio analysis and reference point approach (MOORA) method, and multiplicative form of MOORA method (MULTIMOORA)			coefficient, load capacity, repeatability, velocity
Weighted aggregated sum product assessment method (WASPAS)	Mathew et al.	2017	Load capacity, maximum tip speed, repeatability, memory capacity, manipulator reach
AHP	Breaz et al.	2017	Load capacity, reach, weight, repeatability, power consumption, dexterity, service
Fuzzy extended VIKOR	Zhou et al.	2018	Total ownership of cost, Velocity or speed of travel, Load capacity, Repeatability, Positioning accuracy, Programming flexibility, Man-machine interface

THEORETICAL BACKGROUND FOR METHODS

Robot selection may be viewed as a dynamic set of decision-making challenges that necessitate the consideration of various alternative providers with multiple quantitative and qualitative criteria (You, 2015). Indeed, selecting an appropriate robot in pursuit of a certain sector of operation is a demanding task that, if failed, can have a negative impact on an organization's competitiveness (in terms of productivity) (Sen, 2016a).

There are more than two possibilities and more than one decision criterion in this study to determine the suitable AOI system. Multi-criteria decision-making procedures are appropriate for the problem's structure. As a result, we applied two multi-criteria decision-making methodologies, TOPSIS and VIKOR, in an innovative way to analyze AOI systems. Both methods rely on an aggregating concept that indicates closeness to the reference location (s). They presume that there is an output matrix created by assessing all possibilities in terms of each criterion. In solution, both strategies provide a ranking list.

TOPSIS Method

TOPSIS (Technique for order preference by similarity to an ideal solution), created by Hwang and Yoon in 1981, gives a ranking list based on choice problem criteria. This technique provides two reference points in the solution algorithm: ideal and negative-ideal solutions. The primary notion is that the chosen option should be the furthest away from the perfect solution and the furthest away from the negative ideal solution. The distance is an n-dimensional Euclidean distance (Opricovic and Tzeng, 2004). TOPSIS employs vector normalization, and the normalized value may represent distinct evaluation units of a certain criteria. The highest-ranked alternative by TOPSIS is the best in terms of the ranking index, but this does not always imply that it is the closest to the optimal solution (Tzeng et al. 2005).

TOPSIS has the following steps (Jahanshahloo et al., 2006):

1. Make a decision matrix that is normalized. The normalized value n_{ij} is computed as follows:
   $n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, i = 1, \ldots, m, \; j = 1, \ldots, n.$
2. v_{ij} is the weighted normalized decision matrix.:
   $v_{ij} = w_j n_{ij}, \; i = 1, \ldots, m, \; j = 1, \ldots, n$, where w_j is the weight of the ith criterion, and $\sum_{j=1}^{n} w_j = 1$.
3. Identify the positive and negative ideal solutions.
   $A^+ = \{v_1^+, \ldots, v_n^+\} = \left\{\left(\max_j v_{ij} \mid i \in I\right), \left(\min_j v_{ij} \mid i \in J\right)\right\},$
   $A^- = \{v_1^-, \ldots, v_n^-\} = \left\{\left(\min_j v_{ij} \mid i \in I\right), \left(\max_j v_{ij} \mid i \in J\right)\right\},$

   where I is associated with benefit criteria, and J is associated with cost criteria.

4. Using the n-dimensional Euclidean distance, compute the separation measures. The distance between each alternative and the optimal answer is denoted as
   $d_i^+ = \left\{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2\right\}^{1/2}, i = 1, \ldots, m,$

   Similarly, the separation from the negative ideal solution is given as

   $d_i^- = \left\{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2\right\}^{1/2}, \; i = 1, \ldots, m,$
5. Calculate the relative closeness to the ideal solution. The relative closeness of the alternative A_i with respect to A^+ is defined as $R_i = d_i^- / (d_i^+ + d_i^-)$, $i = 1, \ldots, m$. Since $d_i^- \geq 0$ and $d_i^+ \geq 0$, then, clearly, $R_i \in [0,1]$.

6. Sort your preferences in descending order. We may use this index to rank options in decreasing order.

VIKOR Method

VIKOR (Vise Kriterijumska Optimizacija I Kompromisno Resenje) calculates the compromise ranking-list, compromise solution, and weight stability intervals for preference stability of the compromise solution achieved with the initial (provided) weights. In the context of competing criteria, this strategy focuses on ranking and selecting among a group of possibilities (Opricovic and Tzeng, 2004). As the ideal solution, there is just one reference point. The Multicriteria ranking index is based on a specific measure of proximity to the ideal solution, and this technique suggests a compromise alternative with a rate of benefit. Linear normalization is used, and the normalized value is independent of the criterion's evaluation unit. It adds an aggregating function that represents the distance from the optimal answer. This rating index is an amalgamation of all criteria, their relative significance, and a balance of overall and individual happiness. (2010) (Sanayei et al.) The option with the greatest VIKOR rating is the closest to the perfect solution. The Lp-metric, which is employed in the compromise programming approach, is used to build the multi-criteria merit for compromise ranking (Zeleny, 1982).

$$L_{pj} = \left\{\sum_{i=1}^{n}\left[w_i (f_i^* - f_{ij}) / (f_i^* - f_i^-)\right]^p\right\}^{1/p}, \; 1 \leq p \leq \infty; j = 1,2, \ldots, J.$$

The following stages constitute the compromise ranking algorithm VIKOR (Opricovic and Tzeng, 2007):

1. Determine the best f_i^* and the worst f_i^- values for all criterion functions, i=1,2,…,n.
2. Compute the values S_j and R_j, $j = 1,2, \dots, J$, by the relations
$S_j = \sum_{i=1}^{n} w_i (f_i^* - f_{ij})/(f_i^* - f_i^-)$
$R_j = \max_i [w_i (f_i^* - f_{ij})/(f_i^* - f_i^-)]$

where w_i , i=1,2,…,n are the weights of criteria according to their relative importance.

3. Calculate values $Q_j, j = 1,2, \dots, J$ by the relation
$Q_j = \frac{v(S_j - S^*)}{S^- - S^*} + \frac{(1-v)(R_j - R^*)}{R^- - R^*}$

where $S^* = \min_j S_j$, $S^- = \max_j S_j$, $R^* = \min_j R_j$, $R^- = \max_j R_j$, and v is introduced as the weight of strategy of the majority of criteria.

4. Sort the alternatives in decreasing order by the values S, R, and Q.
5. Propose the alternative (a') that is ranked the best by the measure Q (minimum) as a compromise solution if the following two requirements are met:

C1: “Acceptable advantage”

$DQ = 1/(J-1)$; J is the number of alternatives
a'' is the alternative with the second position in the ranking list by Q.

$$Q(a'') - Q(a') \geq DQ$$

C2: “Acceptable stability in decision making”. Alternative a' must likewise be ranked highest by S or/and R. This compromise solution is stable inside a decision-making process, such as "vote by majority rule" (where v>0.5 is required), "by consensus" (v≈0.5), or "with veto" (v<0.5). In this case, v represents the weight of the decision-making method "the majority of criteria" (or "the largest group utility").

If one of the requirements is not met, a set of compromise options consisting one of the following two is provided:

Alternatives a' and a'' if only conditions C2 is not satisfied, or

Alternatives a', a'',…, $a^{(M)}$ if condition C1 is not satisfied; and $a^{(M)}$ is determined by the relation $Q(a^{(M)}) - Q(a') < DQ$ for maximum M (the positions of these alternatives are “in closeness”).

The best option, as rated by Q, is the one with the lowest Q value. The compromise ranking list of alternatives, as well as the compromise solution with the "advantage rate," are the primary ranking results.

PROPOSED SELECTION APPROACH AND CASE STUDY

In this study, three AOI systems for solder paste inspection are tested for the same ten components on one type of assembled PCBs. The reason for analyzing components on the same type of PCBs is to measure inspection accuracy in detail for these three systems. This selection will affect the whole PCB assembly process. Therefore, the measuring sensitivity of AOI systems on components has crucial importance for the electronics company.
Criteria for selecting the most accurate AOI system for the company are PCB Bending for original, 850 mic and 1600 mic, repeatability, rotation for 0, 90, 180 and 270 degrees, and r-pass rates. The means of test results for ten experiments are presented in Tables 2, 3, and 4.

Table 2. Test results for AOI-1

AOI 1	PCB BENDING				ROTATION				
	orjinal	850 mik	1600 mik	REPEATABILITY	0	90	180	270	R-PASS
U163_1	109.37	108.72	108.46	132.84	52.41	65.07	53.50	50.45	0.92
U163_2	83.63	86.33	89.92	117.42	49.68	53.79	57.31	67.60	0.89
U164_1	87.31	83.84	84.59	106.63	41.62	51.41	53.09	55.38	0.80
U164_2	130.34	125.92	128.70	98.88	57.70	47.37	43.25	56.56	0.81
U157_1	78.35	79.69	78.01	74.87	74.30	79.53	74.95	76.79	0.76
U157_2	65.27	64.63	64.23	53.70	78.56	80.69	75.30	75.31	0.76
CN707_1	86.16	86.94	86.50	84.00	83.98	85.21	88.02	86.82	0.38
CN707_2	89.15	88.74	87.16	77.85	89.91	88.34	80.69	80.89	0.39
CN708_1	82.96	81.77	81.95	77.39	78.08	80.51	85.74	84.46	0.72
CN708_2	77.53	76.68	78.51	72.15	81.99	83.12	81.87	80.41	0.71
Std. Dev.	17.34	16.34	16.97	22.69	15.99	14.76	15.20	12.47	0.18
Mean	89.01	88.33	88.80	89.57	68.82	71.50	69.37	71.47	0.71
CV	19.49	18.50	19.11	25.33	23.24	20.64	21.91	17.44	24.69

Table 3. Test results for AOI-2

AOI 2	PCB BENDING				ROTATION				
	orjinal	850 mik	1600 mik	REPEATABILITY	0	90	180	270	R-PASS
U163_1	76.56	75.44	74.26	75.33	69.21	63.95	65.87	69.40	0.90
U163_2	73.75	73.95	73.03	65.61	85.10	78.49	85.56	79.93	0.91
U164_1	71.52	71.14	70.20	111.20	86.21	84.13	88.10	85.54	0.75
U164_2	82.59	82.95	82.75	80.88	77.38	82.30	83.01	81.85	0.74
U157_1	122.23	122.66	120.85	117.50	140.81	132.99	131.62	133.71	0.78
U157_2	141.68	140.24	141.23	151.92	144.11	144.54	150.93	149.60	0.78
CN707_1	125.26	126.82	126.67	107.10	119.11	108.11	121.63	100.40	0.40
CN707_2	123.11	124.33	124.60	110.26	116.90	105.95	120.27	111.55	0.41
CN708_1	116.32	116.62	118.91	112.43	123.63	114.73	120.70	103.20	0.69
CN708_2	126.01	127.52	129.63	119.33	114.44	99.40	116.26	106.86	0.70
Std. Dev.	25.20	25.50	26.22	23.88	25.12	23.87	25.03	23.70	0.17
Mean	105.90	106.17	106.21	105.16	107.69	101.46	108.40	102.20	0.71
CV	23.80	24.02	24.69	22.71	23.32	23.52	23.09	23.19	23.48

Table 4: Test results for AOI-3

AOI 3	PCB BENDING				ROTATION				
	orjinal	850 mik	1600 mik	REPEATABILITY	0	90	180	270	R-PASS
U163_1	42.56	41.53	40.72	46.15	59.55	54.86	62.33	56.90	0.94
U163_2	45.49	42.47	40.68	45.39	39.75	39.40	36.42	31.25	0.93
U164_1	71.32	68.80	68.88	61.60	29.08	31.60	31.62	28.98	0.79
U164_2	66.72	60.65	58.83	44.08	38.15	39.13	33.98	31.29	0.79
U157_1	89.61	84.94	84.44	98.37	87.74	99.88	83.47	91.64	0.75
U157_2	81.41	81.47	86.82	91.98	94.08	94.87	86.52	104.46	0.75
CN707_1	127.61	126.69	126.64	125.23	120.56	113.38	110.22	107.25	0.41
CN707_2	109.55	109.57	112.49	112.62	117.71	99.39	106.69	104.12	0.43
CN708_1	116.42	115.02	115.01	124.43	118.45	115.92	117.74	111.61	0.71
CN708_2	126.60	123.89	124.46	114.08	118.39	106.41	113.32	103.34	0.70
Std. Dev.	29.97	30.53	31.33	32.08	35.50	32.23	32.94	33.77	0.17
Mean	87.73	85.50	85.90	86.39	82.35	79.48	78.23	77.08	0.72
CV	34.16	35.70	36.47	37.13	43.12	40.54	42.11	43.81	23.44

Since we aim to select the AOI with the highest precision, we need to evaluate them based on their results on different components. Although we know the means and standard deviations of the test results, they do not give us enough information for the selection. Since we do not know the real values of the test criteria, we cannot decide which AOI is the best one. Here, our novel selection approach comes into the stage.

When we examine the means and standard deviations, we can see that different AOIs have different means and standard deviations for components. The scales of the tests are also different, so it will not be statistically possible to compare the mean of the means for all components. Only the coefficient of variation (CV) statistic, which is defined as the ratio of the standard deviation to the mean or its absolute value, may be compared in this situation. The mean CV statistics for AOIs are 21.15, 23.54, and 37.39, respectively. By looking at this piece of information, the selection of AOI-1 is a reasonable decision since it has the smallest mean CV across all components and all test criteria. However, we need a two-way evaluation; both component-wise and criteria-wise.

Our proposed approach is an effort to make a more information-based decision by also investigating the rankings of component test scores. The stages of the proposed approach are as follows:

1. Test scores are recorded for all components.
2. Standard deviation, mean, and CV of the test scores are calculated for each component.
3. Test scores are evaluated by TOPSIS and VIKOR and component rankings are obtained.
4. Standard deviation, mean, and CV of the rankings are calculated for each component.
5. Since we aim to select the best AOI across components and the test criteria, rankings that are closer to each other (smaller CV) should be preferred.

The ranking of components, tested by AOI-1, AOI-2, and AOI-3, are calculated by TOPSIS and VIKOR (Table 5).

Table 5. TOPSIS and VIKOR results for AOI systems.

	TOPSIS (Ci*)			VIKOR (Qj)		
	AOI-1	AOI-2	AOI-3	AOI-1	AOI-2	AOI-3
CN707_1	0.62	0.65	0.96	0.00	0.32	0.00
CN707_2	0.61	0.66	0.85	0.05	0.22	0.13
CN708_1	0.46	0.55	0.79	0.38	0.54	0.42
CN708_2	0.43	0.55	0.79	0.43	0.53	0.42
U157_1	0.39	0.63	0.58	0.55	0.47	0.60
U157_2	0.34	0.73	0.59	0.88	0.37	0.60
U163_1	0.47	0.05	0.21	0.78	1.00	0.94
U163_2	0.36	0.13	0.06	0.87	0.94	1.00
U164_1	0.31	0.24	0.19	1.00	0.90	0.94
U164_2	0.49	0.18	0.15	0.75	0.82	0.96
Std. Dev.	0.10	0.24	0.32	0.33	0.27	0.34
Mean	0.45	0.44	0.52	0.57	0.61	0.60
CV	22.01	55.84	61.75	58.61	43.47	56.66

TOPSIS and VIKOR results rate alternatives based on how near they are to the ideal solution. The best alternative in TOPSIS is the one with the highest ranking. The solution method of VIKOR, on the other hand, calculates the highest-ranked alternative around zero. The dispersion of results between ideal and negative ideal solution supports us to determine the sensitivity of the three AOI systems. If the best alternatives for TOPSIS and VIKOR according to three suppliers are examined, it is obvious that they are approximately similar. In other words, both methods produce approximately the same orders of alternatives. We are interested in the inspection accuracy of these machines. So, we need to know which machine's measurements are more reliable than others. Since a small range of the results is required, a smaller standard deviation is better, however from a statistical point of view, evaluating CVs is better. When CVs of all results for each AOI system are calculated, it's obvious that according to the TOPSIS method AOI-1's measurements are more sensitive than others. Since VIKOR transforms results in the range of 0-1, it changes their structure and it induces them to fluctuate. However, VIKOR also gives the same result as TOPSIS, AOI-1 has smaller dispersion.

Test results of AOI-1 aren't close to the ideal point. It provides average values for inspection accuracy. Test results of AOI-2 and AOI-3 are closer to the ideal point, but they also provide results that are close to the negative-ideal point. According to the mean and the standard deviation values of these results, the TOPSIS method produces a smaller CV for AOI-1 than other AOIs. It means that the inspection accuracy of AOI-1 is more stable than those of other machines. In this manner, the CVs of other machines are higher than AOI-1. It means that they could have sensitive measures, but also, they could get measures close to the negative-ideal point. We cannot be sure of the inspection accuracy of their results. According to these results, the preference ordering of these three suppliers should be: AOI-1 > AOI-3 > AOI-3. Therefore, we can recommend the company to choose AOI-1.

CONCLUSIONS

Our problem was that the selection should be made based on two dimensions instead of only one. When the results are examined, multi-criteria decision-making methods reduce the multidimensional and complex structure of the problem to a single ordered list for decision-makers. The coefficient of variation of the rank list shows how the results spread around the mean. The CV of the ordered list provides important information to the decision-maker regarding the accuracy and precision of the machines from which the data is obtained. Multi-criteria decision-making methods are useful tools for the decision-makers not only by sorting results and selecting the best one but also by descriptive statistics of the ordered list.

REFERENCES

Breaz, R. E., Bologa, O. and Racz, S. G. (2017). Selecting industrial robots for milling applications using AHP. *Procedia computer science*, *122*, 346-353.

Huang, C. Y., Lin, Y. H., Ying, K. C. and Ku, C. L. (2011). The solder paste printing process: critical parameters, defect scenarios, specifications, and cost reduction. *Soldering & surface mount technology*.

Dave, N., Tambade, V., Pandhare, B. and Saurav, S. (2016). PCB defect detection using image processing and embedded system. *International Research Journal of Engineering and Technology (IRJET)*, *3*(5), 1897-1901.

Deng, H., Yeh, C. H. and Willis, R. J. (2000). Inter-company comparison using modified TOPSIS with objective weights. *Computers & Operations Research*, *27*(10), 963-973.

Gunn, R. and Ries, B. (2001, January). Selecting and implementing solder paste inspection for SMT process control. In *IPC SMEMA Council APEX* (pp. 31-38).

Ghorabaee, M. K. (2016). Developing an MCDM method for robot selection with interval type-2 fuzzy sets. *Robotics and Computer-Integrated Manufacturing*, *37*, 221-232.

Gitinavard, H., Mousavi, S. M., Vahdani, B. and Siadat, A. (2016). A new distance-based decision model in interval-valued hesitant fuzzy setting for industrial selection problems. *Scientia Iranica*, *23*(4), 1928-1940.

Guo, F. and Guan, S. A. (2011, August). Research of the machine vision based PCB defect inspection system. In *2011 International Conference on Intelligence Science and Information Engineering* (pp. 472-475). IEEE.

Hwang, C. L. and Yoon, K. (1981). Multiple criteria decision making. *Lecture Notes in Economics and Mathematical Systems*, *186*, 58-191.

Jahan, A., Mustapha, F., Ismail, M. Y., Sapuan, S. M. and Bahraminasab, M. (2011). A comprehensive VIKOR method for material selection. *Materials & Design*, *32*(3), 1215-1221.

Jahanshahloo, G. R., Lotfi, F. H. and Izadikhah, M. (2006). Extension of the TOPSIS method for decision-making problems with fuzzy data. *Applied Mathematics and computation*, *181*(2), 1544-1551.

Janóczki, M., Becker, Á., Jakab, L., Gróf, R. and Takács, T. (2013). Automatic optical inspection of soldering. *Materials Science-Advanced Topics*.

Karande, P., Zavadskas, E. and Chakraborty, S. (2016). A study on the ranking performance of some MCDM methods for industrial robot selection problems. *International Journal of Industrial Engineering Computations*, *7*(3), 399-422.

Malamas, E. N., Petrakis, E. G., Zervakis, M., Petit, L. and Legat, J. D. (2003). A survey on industrial vision systems, applications and tools. *Image and vision computing*, *21*(2), 171-188.

Mathew, M., Sahu, S. and Upadhyay, A. K. (2017). Effect of normalization techniques in robot selection using weighted aggregated sum product assessment. *Int. J. Innov. Res. Adv. Stud*, *4*(2), 59-63.

Opricovic, S. and Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European journal of operational research*, *156*(2), 445-455.

Opricovic, S. and Tzeng, G. H. (2007). Extended VIKOR method in comparison with outranking methods. *European journal of operational research*, *178*(2), 514-529.

Opricovic, S. (1998). *Multicriteria optimization of civil engineering systems*. Faculty of Civil Engineering, *Belgrade*, *2*(1), 5-21.

Parameshwaran, R., Kumar, S. P. and Saravanakumar, K. (2015). An integrated fuzzy MCDM based approach for robot selection considering objective and subjective criteria. *Applied Soft Computing*, *26*, 31-41.

Ray, R. (1988). Automated visual inspection of solder bumps. *AT&T technical journal*, *67*(2), 47-60.

Rezaei-Malek, M., Mohammadi, M., Dantan, J. Y., Siadat, A. and Tavakkoli-Moghaddam, R. (2019). A review on optimisation of part quality inspection planning in a multi-stage manufacturing system. *International Journal of Production Research*, *57*(15-16), 4880-4897.

Sanayei, A., Mousavi, S. F. and Yazdankhah, A. (2010). Group decision making process for supplier selection with VIKOR under fuzzy environment. *Expert Systems with Applications*, *37*(1), 24-30.

Sayadi, M. K., Heydari, M. and Shahanaghi, K. (2009). Extension of VIKOR method for decision making problem with interval numbers. *Applied Mathematical Modelling*, *33*(5), 2257-2262.

Sen, D. K., Datta, S. and Mahapatra, S. S. (2016). Application of TODIM (Tomada de Decisión Inerativa Multicritero) for industrial robot selection. *Benchmarking: An International Journal*.

Sen, D. K., Datta, S. and Mahapatra, S. S. (2016). Extension of PROMETHEE for robot selection decision making. *Benchmarking: An International Journal*.

Tempoautomation, (May 2018). *Circuit Board Testing Methods for PCB Manufacturing*, https://www.tempoautomation.com/blog/circuit-board-testing-methods-for-pcb-manufacturing/(Last Access: 28.06.2020)

Triantaphyllou, E. (2000). Multi-criteria decision making methods. In *Multi-criteria decision making methods: A comparative study* (pp. 5-21). Springer, Boston, MA.

Tzeng, G. H., Lin, C. W. and Opricovic, S. (2005). Multi-criteria analysis of alternative-fuel buses for public transportation. *Energy Policy*, *33*(11), 1373-1383.

Wang, W. C., Chen, S. L., Chen, L. B. and Chang, W. J. (2016). A machine vision based automatic optical inspection system for measuring drilling quality of printed circuit boards. *IEEE Access*, *5*, 10817-10833.

Wikipedia, https://en.m.wikipedia.org/wiki/Surface-mount_technology. (Last Access: 28.06.2020)

Xue, Y. X., You, J. X., Zhao, X. and Liu, H. C. (2016). An integrated linguistic MCDM approach for robot evaluation and selection with incomplete weight information. *International Journal of Production Research*, *54*(18), 5452-5467.

You, X. Y., You, J. X., Liu, H. C. and Zhen, L. (2015). Group multi-criteria supplier selection using an extended VIKOR method with interval 2-tuple linguistic information. *Expert Systems with Applications*, *42*(4), 1906-1916.

Zeleny, M. (1982). Multiple Criteria Decision Making, McGraw-Hill, Company.

Zhou, F., Wang, X. and Goh, M. (2018). Fuzzy extended VIKOR-based mobile robot selection model for hospital pharmacy. *International Journal of Advanced Robotic Systems*, *15*(4), 1729881418787315.