Measuring Efficiency of Total Productive Maintenance (TPM) with Newly Developed Performance Measures using Fuzzy Data Envelopment Analysis

E. Turanoglu Bekar, and C. Kahraman

Abstract—**Total Productive Maintenance (TPM) has been widely accepted as a strategic tool for succeeding manufacturing performance and also it has been effectively implemented in many organizations. The evaluation of TPM efficiency can make a great contribution to companies in advancing their operations across a variety of dimensions. This study aims to propose a new framework for evaluation TPM performance. Proposed TPM effectiveness system can be divided into three stages: (i) the design of the new performance measures, (ii) the evaluation of the new performance measures, and (iii) the use of the new performance measures to evaluate TPM effectiveness. Finally, proposed fuzzy DEA method is used to evaluate TPM performance with newly developed performance measures using real manufacturing case. In this study, the fuzzy utility degrees achieved from fuzzy COPRAS are integrated with fuzzy DEA in order to determine efficient and inefficient TPM performance.**

Index Terms—**Fuzzy COPRAS, Fuzzy Data Envelopment Analysis, Total Productive Maintenance (TPM), performance evaluation, performance measures in TPM**

I. Introduction

TPM implementation and applying is a systematic activity throughout the organization. It requires a significant change culturally and will be a lifestyle. Thus, to measure TPM application effectiveness, it should be needed a systematic program based on different factors having impact on TPM affecting the whole organization.

When it comes to performance evaluation in TPM, overall equipment effectiveness (OEE) has commonly been used as a performance measure since TPM aims to maximize equipment effectiveness [1]-[2]. Although OEE has been considered as a standard measure for equipment performance [3], what it captures is only effectiveness of TPM, not efficiency.

In most companies, when evaluating the performance of TPM, only OEE is considered. However, the performance evaluation of TPM should include an objective and comprehensive method based on multiple inputs and outputs.

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Since the evaluation contains multiple inputs and outputs, it can be considered of as a multi-criteria decision making problem. In the literature, a few studies have been made referred to the efficiency measurement in TPM implementation. In these studies, Wang [4] and Jeon et al. [5] were used DEA to measure the efficiency of TPM implementation. Also a number of studies have been conducted to identify important factors in TPM [6]-[11]. Therefore, the motivation for this research is developed new performance measures in TPM and evaluated these performance measures under fuzzy environment and then classified into TPM inputs and outputs. Finally they are performed to measure TPM efficiency using fuzzy DEA.

II. Method

In this study, proposed TPM effectiveness system can be divided into three stages: (i) the design of the new performance measures, (ii) the evaluation of the new performance measures, and (iii) the use of the new performance measures to evaluate TPM effectiveness.

The current results indicate that there should be more use of TPM as a performance development process. Its improvements must be measured, both ***subjectively*** and ***quantitatively*** as supposed in the literature. So there are a large number of tangible and intangible factors, which often are in conflict with each other, that should be considered in development of new performance measure in TPM. In this study, the fuzzy utility degrees achieved from fuzzy COPRAS were integrated with fuzzy DEA in order to determine efficient and inefficient TPM performance. The flow diagram of the integrated fuzzy COPRAS-fuzzy DEA method is shown in Figure 1.

A. Literature Review on Fuzzy DEA Method

In this study, an integrated fuzzy COPRAS- fuzzy DEA method are conducted so we examine some articles that joins different decision making techniques with fuzzy DEA and improves hybrid methods. However, in the literature there are few studies that use fuzzy DEA in multiattribute decision making problems. In one of the most referenced papers Ertay et al. [12] integrate fuzzy DEA with analytic hierarchy process (AHP) for designing of facility layout which can deal with both qualitative and quantitative data.

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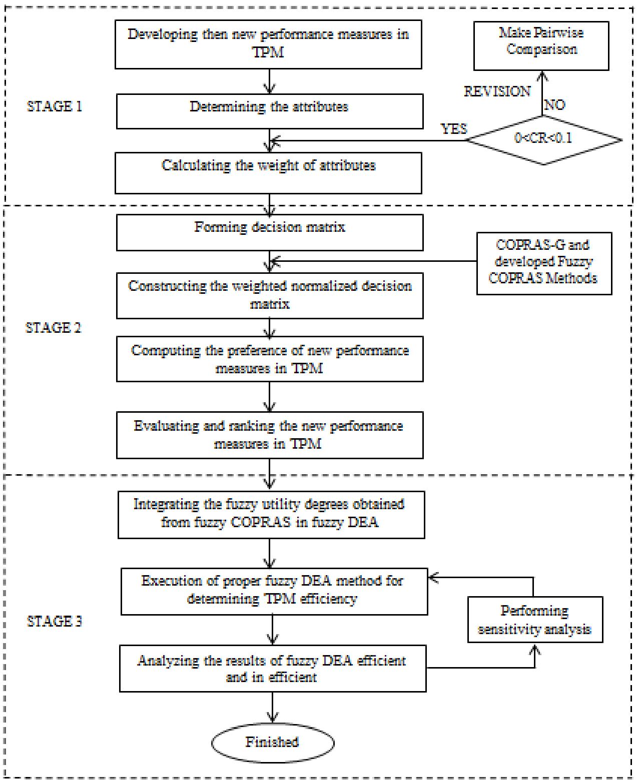

Fig. 1. The flow diagram of the integrated fuzzy COPRAS-fuzzy DEA method.

In a different paper, Liu [13] improves a fuzzy DEA/AR (assurance region) method which can assess the performance of flexible manufacturing system options where the input and output data can be fuzzy as well as crisp values. Wu [14] suggests a combined technique using DEA and fuzzy preference relations to rank decision alternatives. Kuo et al. [15] integrate both fuzzy AHP and fuzzy DEA methods for assisting organizations to select proper supplier. Zhou et al. [16] offered generalized fuzzy DEA model with GFDEA/AR to evaluate the performance of manufacturing enterprises using different cases. Awasthi et al. [17] present a multistep approach based on fuzzy DEA approach for supplier quality evaluation.

According to literature review and the best knowledge of the authors, this is the first study that integrates fuzzy COPRAS-fuzzy DEA method to evaluate performance efficiency of TPM with newly developed performance measures.

B. *Fuzzy DEA Methodology*

We consider that there are n DMUs and each DMU uses differing amounts of m different fuzzy inputs to produce s different fuzzy outputs. Specifically, DMU_j uses amounts $\tilde{x}_{ij}$ of inputs to produce amounts $\tilde{y}_{rj}$ of outputs. In the model formulation, $\tilde{x}_{ip}$ and $\tilde{y}_{rp}$ denote, respectively, the input and output values for the DMU_p. In order to explain the fuzzy BBC (variable returns-to-scale as introduced in Banker et al. [18]) model, Kao and Liu [19] proposed a pair of two-level mathematical models to calculate the lower bound $(w_p)_p^L$ and upper bound $(w_p)_p^U$ of the fuzzy efficiency score for a specific α-level as follows:

$$(w_p)_\alpha^U = \max_{\substack{X_{ij\alpha}^L \le x_{ij} \le X_{ij\alpha}^U \\ Y_{rj\alpha}^L \le y_{rj} \le Y_{rj\alpha}^U \\ \forall r,i,j}} \left\{ \begin{array}{l} \tilde{w}_p = \max \sum_{r=1}^{s} u_r y_{rp} + u_0 \\ s.t. \ \sum_{i=1}^{m} v_i x_{ip} = 1, \\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + u_0 \le 0, \ \forall_j, \\ u_r, v_i \ge 0, \ \forall_{r,i}. \end{array} \right. \quad (1)$$

where $[(X_{ij})_\alpha^L, (X_{ij})_\alpha^U]$ and $[(Y_{rj})_\alpha^L, (Y_{rj})_\alpha^U]$ are α-level form of the fuzzy inputs and the fuzzy outputs respectively. This two-level mathematical model can be clarified to the conventional one-level model as follows:

$$\begin{aligned} (w_p)_\alpha^L = \ & \max \sum_{r=1}^{s} u_r (Y_{rp})_\alpha^L + u_0 \\ s.t. \ & \sum_{r=1}^{s} u_r (Y_{rp})_\alpha^L - \sum_{i=1}^{m} v_i (X_{ip})_\alpha^U + u_0 \le 0, \\ & \sum_{r=1}^{s} u_r (Y_{rj})_\alpha^U - \sum_{i=1}^{m} v_i (X_{ij})_\alpha^L + u_0 \le 0, \quad \forall_j, j \ne p, \\ & \sum_{i=1}^{m} v_i (X_{ip})_\alpha^U = 1, \qquad u_r, v_i \ge 0, \quad \forall_{r,i}. \end{aligned} \quad (2)$$

$$\begin{aligned} (w_p)_\alpha^U = \ & \max \sum_{r=1}^{s} u_r (Y_{rp})_\alpha^U + u_0 \\ s.t. \ & \sum_{r=1}^{s} u_r (Y_{rp})_\alpha^U - \sum_{i=1}^{m} v_i (X_{ip})_\alpha^L + u_0 \le 0, \\ & \sum_{r=1}^{s} u_r (Y_{rj})_\alpha^L - \sum_{i=1}^{m} v_i (X_{ij})_\alpha^U + u_0 \le 0, \quad \forall_j, j \ne p, \\ & \sum_{i=1}^{m} v_i (X_{ip})_\alpha^L = 1, \qquad u_r, v_i \ge 0, \quad \forall_{r,i}. \end{aligned} \quad (3)$$

Next, a membership function is built by solving the lower and upper bounds $[(w_p)_\alpha^L, (w_p)_\alpha^U]$ of the α-levels for each DMU using models (1) and (2).

III. PERFORMANCE EVALUATION OF TPM THROUGH FUZZY DEA: A REAL MANUFACTURING CASE

A. *Definition of Decision Making Units (DMU)*

This study is considered to be implemented in a company operating in the automotive industry in Aegean Free Zone since 2002. 860 Direct and 130 indirect employees work in the company. Along with core operating departments, there are support functions including TPM department. In TPM department, there are 1 lead engineer and 4 supervisors and 28 maintenance technicians. The overall TPM activities of this company are managed by the TPM-office..

In this study, we use the proposed fuzzy DEA model to evaluate the performance efficiency of TPM for four production lines (DMUs) such as “Rail Machining (DMU1)”, “Rail Assembly and HPV (DMU2)”, “NHB Beginning of Line (BOL) (DMU3)”and “NHB End of Line (EOL) (DMU4)”.

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B. Definitions of Inputs and Outputs

The newly developed performance measures that are to be minimized are viewed as inputs, whereas the ones to be maximized are considered as outputs throughout the TPM performance evaluation study. The decision framework involves the evaluation of the relative TPM efficiency of four production lines with respect to seven outputs and ten inputs given as in Table 1. Table 1 also shows the fuzzy weights of inputs and outputs were determined by fuzzy COPRAS.

The inputs "Availability of maintenance personnel", "Operator reliability" and "Refusal of extended hours or overtimes" are evaluated from observations of production line supervisor and team leader using fuzzy linguistic scale such as "very low", "low", "medium", "high" and "very high" and their membership functions are shown as in Figure 2.

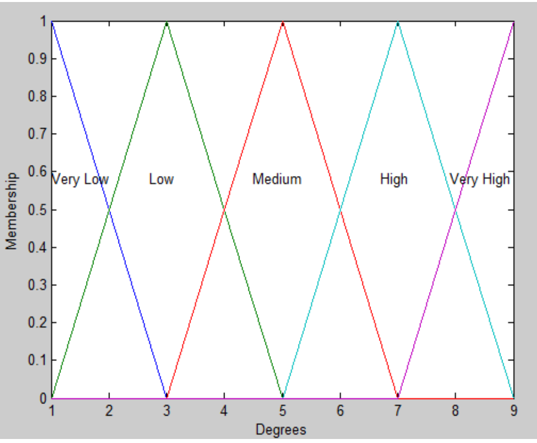

Fig. 2. The Membership functions of the inputs "Availability of Maintenance Personnel", "Operator Reliability" and "Refusal of extended hours or overtimes".

TABLE 1
THE FUZZY WEIGHTS OF INPUTS AND OUTPUTS OBTAINED BY FUZZY COPRAS

	Category	***Outputs***	***Fuzzy Weights***
NEWLY DEVELOPED PERFORMANCE MEASURES	Operational Related	Mean Time to Repair (MTTR)	(0.536, 0.573, 0.611)
		Mean Time Between Failure (MTBF)	(0.512, 0.547, 0.584)
		Number of unplanned maintenance	(0.554, 0.593, 0.634)
		Reduced speed	(0.555, 0.589, 0.624)
		Reduced yield	(0.575, 0.606, 0.639)
		Quality defects	(0.552, 0.586, 0.622)
	Environmental, Health & Safety Problems	Number of safety, health and environment incidents	(0.474, 0.526, 0.582)
		Inputs	
	Direct Human Factor	Availability of maintenance personnel	(0.448, 0.507, 0.567)
		Competence of maintenance personnel	(0.473, 0.517, 0.562)
		Experience of operators in production line	(0.473, 0.517, 0.562)
		Operator reliability	(0.473, 0.517, 0.562)
		Training and continuing education	(0.473, 0.517, 0.562)

	Indirect Human Factor	Motivational Management	New ideas generated and implemented	(0.473, 0.517, 0.562)
		Work environment	Level of 5S	(0.473, 0.517, 0.562)
	Business Related	Organization problems & labour unrest (Employee satisfaction)	Employee absentees	(0.415, 0.464, 0.514)
			Employee turn-over rate	(0.415, 0.464, 0.514)
			Refusal of extended hours or overtimes	(0.415, 0.464, 0.514)

According to the objective function of DEA, it is essential to convert the output indicants into fractional numbers as large as possible and the input indicants as small as possible.

C. Data Description and Normalization

All input and output data regarding the four production lines (DMUs) are defined approximate values, crisp data or linguistic terms. Then the inputs and outputs data determined by crisp and approximate values and linguistic terms are transformed triangular fuzzy numbers. Table 2 lists fuzzy values for all inputs and outputs.

In order to refine the problems because of the important differences in the magnitude of inputs and outputs, the linear scale transformation is performed to the different inputs and outputs scales into a comparable scale. Therefore, we can get the normalized fuzzy values of inputs and outputs denoted by $\tilde{R} = \left[\tilde{r}_{ij}\right]$,the triangular fuzzy numbers(TFN) $\tilde{x}_{ij}=(a_{ij},b_{ij},c_{ij})$, B and C are the set of benefit inputs and outputs and cost inputs and outputs, respectively, and

$$\tilde{r} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right),\ j \in B; \qquad (4)$$

$$\tilde{r} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right),\ j \in C; \qquad (5)$$

$$c_j^* = \max_i c_{ij} \ \ if \ \ j \in B; \qquad (6)$$

$$a_j^- = \min_i a_{ij} \ \ if \ \ j \in C; \qquad (7)$$

The normalization method noted above is to protect the property that the ranges of normalized triangular fuzzy numbers belong to [0; 1].

D. Integrating Fuzzy COPRAS with Fuzzy DEA

This study integrates both fuzzy COPRAS and fuzzy DEA methods to evaluate TPM performance in the company. As noted earlier, we can use fuzzy COPRAS to obtain the range of weights for inputs and outputs. After performing these weights into fuzzy DEA model developed by Kao and Liu (2000) whose mathematical representations were given in Eqs. 1-3. Firstly we have obtained the α-cut sets of inputs and outputs for the each production line (DMU) given as in Table 3. Then, for the lower and upper bounds of each DMU we have established mathematical models in order to analyze the performance efficiency of TPM.

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TABLE 2
FUZZY VALUES OF ALL INPUTS AND OUTPUTS FOR FOUR PRODUCTION LINES

	PRODUCTION LINES (DMUS)				UNITS
INPUTS	**DMU1**	**DMU2**	**DMU3**	**DMU4**	
Availability of maintenance personnel (v_1)	(3, 5, 7)	(1, 3, 5)	(3 ,5, 7)	(5, 7, 9)	Linguistics Scale
Competence of maintenance personnel (v_2)	(80, 82, 84)	(83, 85, 87)	(65, 67, 69)	(76, 78, 80)	Point Scoring System (0 To 100)
Experience of operators in production line (v_3)	(7.0, 7.2, 7.4)	(6.2, 6.4, 6.6)	(4.3, 4.5, 4.7)	(3.8, 4.0, 4.2)	Years
Operator reliability (v_4)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	Linguistics Scale
Training and continuing education (v_5)	(10, 14, 18)	(13, 17, 21)	(11, 15, 19)	(12, 16, 20)	Hours per Year
New ideas generated and implemented (v_6)	(16, 18, 20)	(8, 10, 12)	(4, 6, 8)	(6, 8, 10)	Avg. Points Gained/Employee)
Level of 5S (v_7)	(3.21, 3.71, 4.21)	(3.33, 3.83, 4.33)	(3.50, 4.00, 4.50)	(3.33, 3.83, 4.33)	Point Scoring System (1 To 5)
Employee absentees (v_8)	(1.09, 1.39, 1.69)	(1.50, 1.80, 2.10)	(1.79, 2.09, 2.39)	(1.07, 1.37, 1.67)	%
Employee turn-over rate (v_9)	(0.1, 0.3, 0.5)	(0.4, 0.6, 0.8)	(1.0, 1.2, 1.4)	(0.5, 0.7, 0.9)	%
Refusal of extended hours or overtimes (v_{10})	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	Linguistics Scale
OUTPUTS					
MTTR (u_1)	(0.76, 1.59, 2.42)	(0.99, 1.24, 1.49)	(0.49, 1.80, 3.11)	(0.68, 1.11, 1.79)	Minute (Mean-Standard Deviation)
MTBF (u_2)	(85.67, 120.99, 156.31)	(55.94, 78.66, 101.38	(105.21, 134.46, 163.71)	(27.52, 63.43, 99.34)	Minute (Mean-Standard Deviation)
Number of Unplanned Maintenance (u_3)	(59.31, 76.19, 93.07)	(80.45, 104.51, 128.57)	(137.69, 178.68, 219.67)	(41.63, 114.11, 186.59)	Number (Mean-Standard Deviation)
Number of safety, health and environment incidents (u_4)	(0.75, 0.77, 0.79)	(1.78, 1.80, 1.82)	(1.01, 1.03, 1.05)	(1.53, 1.55, 1.57)	Incident per Man Hour
Reduced speed (u_5)	(2413, 2473, 2533)	(1696, 1756, 1816)	(2010, 2070, 2130)	(1774, 1834, 1894)	Minute
Reduced yield (u_6)	(94.05, 99.00, 103.95)	(88.35, 93.00, 97.65)	(92.15, 97.00, 101.85)	(90.25, 95.00, 99.75)	%
Quality defects (u_7)	(0.95, 1.00, 1.05)	(6.65, 7.00, 7.35)	(2.85, 3.00, 3.15)	(4.75, 5.00, 5.25)	%

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TABLE 3
THE α -CUT SETS OF INPUTS AND OUTPUTS

	DMUs			
Inputs	**1**	**2**	**3**	**4**
v_1	$(0.333+0.222\alpha, 0.778-0.222\alpha)$	$(0.111+0.222\alpha, 0.556-0.222\alpha)$	$(0.333+0.222\alpha, 0.7778-0.222\alpha)$	$(0.556+0.222\alpha, 1.000-0.222\alpha)$
v_2	$(0.919+0.027\alpha, 0.965-0.027\alpha)$	$(0.954+0.023\alpha, 1.000-0.023\alpha)$	$(0.747+0.023\alpha, 0.7931-0.023\alpha)$	$(0.874+0.023\alpha, 0.919-0.023\alpha)$
v_3	$(0.946+0.027\alpha, 1.000-0.027\alpha)$	$(0.838+0.027\alpha, 0.892-0.027\alpha)$	$(0.581+0.027\alpha, 0.6351-0.027\alpha)$	$(0.513+0.027\alpha, 0.568-0.027\alpha)$
v_4	$(0.556+0.222\alpha, 1.000-0.222\alpha)$	$(0.111+0.222\alpha, 0.556-0.222\alpha)$	$(0.333+0222\alpha, 0.7778-0.222\alpha)$	$(0.444+0.222\alpha, 1.000-0.222\alpha)$
v_5	$(0.476+0.191\alpha, 0.857-0.191\alpha)$	$(0.619+0.190\alpha, 1.000-0.190\alpha)$	$(0.524+0.190\alpha, 0.9048-0.190\alpha)$	$(0.571+0.190\alpha, 0.952-0.190\alpha)$
v_6	$(0.800+0.100\alpha, 1.000-0.100\alpha)$	$(0.400+0.100\alpha, 0.600-0.100\alpha)$	$(0.200+0.100\alpha, 0.4000-0.100\alpha)$	$(0.300+0.100\alpha, 0.500-0.100\alpha)$
v_7	$(0.713+0.111\alpha, 0.936-0.111\alpha)$	$(0.740+0.111\alpha, 0.962-0.111\alpha)$	$(0.778+0.111\alpha, 1.000-0.111\alpha)$	$(0.740+0.111\alpha, 0.962-0.111\alpha)$
v_8	$(0.633+0.137\alpha, 0.982-0.212\alpha)$	$(0.509+0.085\alpha, 0.713-0.119\alpha)$	$(0.448+0.064\alpha, 0.5978-0.086\alpha)$	$(0.641+0.140\alpha, 1.000-0.219\alpha)$
v_9	$(0.200+0.133\alpha, 1.000-0.667\alpha)$	$(0.125+0.042\alpha, 0.250-0.083\alpha)$	$(0.071+0.012\alpha, 0.1000-0.017\alpha)$	$(0.111+0.032\alpha, 0.200-0.057\alpha)$
v_{10}	$(0.200+0.133\alpha, 1.000-0.667\alpha)$	$(0.143+0.057\alpha, 0.333-0.133\alpha)$	$(0.111+0.032\alpha, 0.2000-0.057\alpha)$	$(0.143+0.057\alpha, 0.333-0.133\alpha)$
Outputs	**1**	**2**	**3**	**4**
u_1	$(0.202+0.106\alpha, 0.645-0.336\alpha)$	$(0.329+0.066\alpha, 0.4949-0.098\alpha)$	$(0.158+0.115\alpha, 1.000-0.728\alpha)$	$(0.274+0.168\alpha, 0.721-0.279\alpha)$
u_2	$(0.523+0.216\alpha, 0.959-0.216\alpha)$	$(0.342+0.139\alpha, 0.6193-0.139\alpha)$	$(0.643+0.178\alpha, 1.000-0.178\alpha)$	$(0.168+0.219\alpha, 0.607-0.219\alpha)$
u_3	$(0.447+0.099\alpha, 0.702-0.155\alpha)$	$(0.324+0.074\alpha, 0.5175-0.119\alpha)$	$(0.189+0.043\alpha, 0.302-0.069\alpha)$	$(0.223+0.142\alpha, 1.000-0.635\alpha)$
u_4	$(0.949+0.025\alpha, 1.000-0.026\alpha)$	$(0.414+0.001\alpha, 0.4213-0.001\alpha)$	$(0.714+0.014\alpha, 0.743-0.014\alpha)$	$(0.478+0.001\alpha, 0.490-0.001\alpha)$
u_5	$(0.670+0.016\alpha, 0.703-0.017\alpha)$	$(0.934+0.032\alpha, 1.0000-0.034\alpha)$	$(0.796+0.024\alpha, 0.849-0.052\alpha)$	$(0.900+0.029\alpha, 0.956-0.031\alpha)$
u_6	$(0.850+0.042\alpha, 0.939-0.047\alpha)$	$(0.909+0.045\alpha, 1.0000-0.050\alpha)$	$(0.867+0.043\alpha, 0.959-0.048\alpha)$	$(0.886+0.044\alpha, 0.979-0.049\alpha)$
u_7	$(0.905+0.045\alpha, 1.000-0.050\alpha)$	$(0.129+0.001\alpha, 0.1429-0.001\alpha)$	$(0.302+0015\alpha, 0.333-0.017\alpha)$	$(0.181+0.001\alpha, 0.200-0.010\alpha)$

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By solving mathematical models for the lower and upper bounds for each of the DMU using LINGO 14.0 respectively, we get fuzzy efficiencies for every DMU. Table 4 lists the fuzzy efficiencies of each DMU (production line) under the α-cut levels as 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1.0.

TABLE 4
THE FUZZY EFFICIENCIES ACCORDING TO α -CUT LEVELS

α	DMUs 1		DMUs 2	
	L	U	L	U
0.0	1	1	0.75	0.80
0.1	1	1	0.75	0.79
0.2	1	1	0.75	0.79
0.3	1	1	0.76	0.79
0.4	1	1	0.76	0.78
0.5	1	1	0.76	0.78
0.6	1	1	0.76	0.78
0.7	1	1	0.76	0.78
0.8	1	1	0.77	0.77
0.9	1	1	0.77	0.77
1	1	1	0.77	0.77

α	DMUs 3		DMUs 4	
	L	U	L	U
0.0	0.81	0.91	0.97	0.98
0.1	0.91	0.98	0.97	0.98
0.2	0.92	0.97	0.97	0.98
0.3	0.92	0.97	0.98	0.98
0.4	0.93	0.97	0.98	0.98
0.5	0.93	0.96	0.97	0.98
0.6	0.93	0.96	0.97	0.98
0.7	0.94	0.96	0.97	0.98
0.8	0.94	0.95	0.97	0.98
0.9	0.94	0.95	0.97	0.97
1	0.95	0.95	0.97	0.97

Table 4 reveals that only DMU1 has the highest TPM performance value. The other third DMUs' performance values are all smaller than 1. The DMU2 has the lowest TPM performance value. From the lower bounds and upper bounds of efficiency values, it is observed that production lines DMU1, DMU4 and DMU3 together define an efficient frontier and DMU4 is the production line with the best performance followed by production line DMU1 according to TPM performance.

IV. CONCLUSION

In this study, a new framework is suggested to measure TPM efficiency using fuzzy DEA. Fuzzy DEA is applied for evaluation of TPM performance with newly developed performance measures using real manufacturing case. Also fuzzy COPRAS with fuzzy values are presented to describe the inputs and outputs weights. This method is able to adapt easily to all industries. A case study on a globally automotive company indicated that the proposed method actually has the above-mentioned advantage. By the results produced by the suggested method, this company can make some revisions for its production lines in order to achieve more interesting outcomes. For the future research, other fuzzy DEA methods based on fuzzy ranking approach, the possibility approach and type-2 fuzzy sets will be employed to measure TPM efficiency. Also it will be added another real manufacturing case for a company operating in a different sector.

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