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Machine Efficiency Measurement in Industry 4.0 Using Fuzzy Data Envelopment Analysis

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Abstract

Industry 4.0 implementations are competitive tools of recent production systems in which complex computerized systems are employed. Efficiency of these systems is generally measured by Data Envelopment Analysis (DEA) under certainty. However, the required data in modelling the system involve high degree of uncertainty, which necessitates the usage of fuzzy set theory. Fuzzy DEA models can successfully handle this problem and present efficient solutions for Industry 4.0 implementation. In this paper, efficiency of Industry 4.0 applications is measured by classical DEA and fuzzy DEA models, allowing the variables to have different units of measurement and to be independent from analytical production functions. Besides that, fuzzy algorithms for output-oriented DEA are proposed for BBC and CCR models. To the best of our knowledge, this article is the first quantitative academic study to measure the effects of Industry 4.0 applications on productivity. It also shows how fuzzy factors can affect decision-making by comparing fuzzy and classical DEA results. A real application of the models is realized in a company of home appliances manufacturing sector having Industry 4.0 applications. The effect of Industry 4.0 implementation on machine productivity, and superiority of fuzzy DEA over classical DEA are shown through the application.

Keywords: Industry 4.0, Fuzzy data envelopment analysis, Efficiency, Home appliance production.

1 | Introduction

Industry 4.0 concept, which is proposed firstly in 2011 by Kagermann et al. [8] and published as a manifesto in 2013 by ACATECH (German Academy of Science and Engineering), is a collective term that contains contemporary automation systems, data exchange, and production technologies. It describes production systems that accord the consumer requirements instantly and automation systems that stay in touch with each other continuously [17]. Industry 4.0 can be described as in which all units that are directly or indirectly associated with production, are worked each other having digital data, software, and information technologies integration [15]. According to Thames and Schaefer [16], smart systems that have autonomic self-properties will drive manufacturing ecosystems with the implementation of Industry 4.0, which causes an accelerated growth in productivity and unprecedented levels of operational efficiencies. Mrugalska and Wyrwicka [12] determined possible

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benefits of Industry 4.0 implementations as increasing the flexibility of business processes, elimination of failures in the demand chain, decision-making process optimization with instant end-to-end visibility, increased resource productivity, and efficiency, creating value opportunities, and reduction of energy and personal costs. Although there are many studies in the literature that mention the potential benefits of Industry 4.0 applications, no study has been found that examines existing applications and reveals these effects. To fill this gap in the literature, this study aims to perform an efficiency analysis to reveal the effects of current practices of Industry 4.0 applications.

Data Envelopment Analysis (DEA) is an adopted efficiency measurement system that has been researched and used for many years. DEA which can take place in different fields of application can also be used with fuzzy numbers in the application areas where it has unknown cases, obscurity, randomness. Measuring the efficiency of Industry 4.0 implementations involves high uncertainty with its unpredictable rapidly developing manner and its unmeasurable side effects. Industry 4.0 tools are frequently updated, and the gains it brings are constantly changing (increasing) and therefore it becomes difficult to measure these gains. The increase in the gains obtained by the combination of different applications of Industry 4.0 tools can also make measurement difficult and bring uncertainty in the evaluation process. The main aim of fuzzy logic and set theory is to model thinking and decision-making mechanisms in uncertain environments with inaccurate information [20]. Fuzzy sets enable analysts to define linguistic variables that have uncertain and ambiguous information to involve uncertainty in the analysis. Therefore, in this paper, it is decided to carry out a comprehensive study including DEA and fuzzy DEA to measure the efficiency of Industry 4.0 implementations for a real case. To be able to apply fuzzy algorithms for output-oriented DEA, fuzzy output-oriented CCR (Constant Return to Scale model) algorithm and fuzzy output-oriented BCC (Variable Return to Scale model) algorithm are proposed. In addition, the results of DEA and Fuzzy DEA methods are compared to determine the effect of uncertainty for Industry 4.0 implementations.

This paper will make important contributions to the literature by being the first quantitative academic study to measure the effects of Industry 4.0 applications on productivity. In addition, it shows how fuzzy factors can influence decision-making by comparing fuzzy and classical DEA results. The rest of the paper is organized as follows: In Section 2, the methods used in the paper are detailed. In Section 3, the information about the real case and the application details are given. Then the results of the application are discussed in Section 4 and the paper is concluded in Section 5.

2 | Literature Review

The subject of the efficiency of Industry 4.0 has been investigated by various authors. Most of the studies have been done in recent years and they are focused on the understanding and conceptualization of Industry 4.0. Costa et al. [6] simulated three different Industry 4.0 implementations in a flexible flow shop for production activity control. Liu et al. [10] proposed an industrial blockchain concept that integrates IoT, M2M, and efficient consensus algorithms and illustrated a blockchain-based application between the cooperating partners in four emerging product lifecycle stages. Cicconi and Raffaeli [5] determined Industry 3.0 technologies to support defect analysis for mechanical workpieces and proposed a knowledge-based tool to support the configurations of the quality control chain. Sorkun [15] investigated the Industry 4.0 enabling technologies in logistics operations using the fuzzy-total interpretative structure modeling. Dalmarco et al. [7] examined the challenges and opportunities of adopting Industry 4.0 from the perspective of technology provider companies using a research method based on interviews. Malik and Khan [11] presented an optimized IoT-based Job Shop Scheduler Monitoring System which will improve the efficiency of the whole shop floor. Kumar and Iyer [9] made exploratory research to explore the benefits of IIoT in engineering and manufacturing industries.

When efficiency analysis and Industry 4.0 are investigated together in the literature, it is seen that a limited number of studies have been carried out. Arora et al. [1] analyzed several factors hindering the growth of the agricultural supply chain and several industry 4.0 technologies. They presented a priority

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list that provides a ranking based on the relative efficiency of technologies' advances in addressing barriers. Woo et al. [19] investigated existing smart manufacturing and smart factories in the shipbuilding industry and developed a new framework for smart shipyard maturity level assessment using DEA. Pinheiro and Putnik [14] investigated the effects on the hierarchical structures of organizations to assess the possible benefits for the efficiency of the organizations resulting from the implementation of Industry 4.0.

In the literature review, it is seen that all papers focused on the effects of Industry 4.0 agreed that there will be an improvement in production systems with the utilization of Industry 4.0 tools, but no publication has been identified with efficiency impact analysis by empirical evaluations. Therefore, the main driver of this paper is to measure the effects of Industry 4.0 implementations on the manufacturing systems.

3 | Methodology

Efficiency measurement methods are mostly classified as ratio analysis, parametric techniques, and non-parametric techniques. In this study, DEA and FDEA which are non-parametric techniques, are used to determine the efficiency effect of Industry 4.0 applications.

3.1 | Data Envelopment Analysis

DEA which is one of the nonparametric methods is a structured method based on the principles of linear programming for measuring the relative effectiveness of units (DMUs) that are responsible for converting inputs into outputs. The efficiency of a Decision-Making Unit (DMU) in DEA is obtained by dividing the weighted sum of outputs by the weighted sum of inputs. The DMUs in which the objective function value is calculated to 1, are defined as active DMU, The DMUs in which the objective function value is not equal to 1, are defined as inactive DMU. The best DMUs form the efficiency frontier with the envelope algorithm and the effectiveness of other DMUs is measured according to their distance from this limit. In the envelope algorithm, DMU observations are drawn into an envelope by drawing an effective boundary with the use of algorithms and there is no observation beyond this limit [6] and[19]. Different DEA models are defined according to the way of enveloping and the distance from inactive units to the effective production limit [13].

According to the envelope type, there are two DEA models; Constant Return to Scale (CCR) model which was developed by Charnes et al. [4] in 1978, and Variable Return to Scale model which was developed by Banker et al. [2] (BCC) in 1984. According to the distance of inactive units to the effective production limit, there are two types of algorithms. The input-oriented model investigates how much input composition should be reduced to achieve the same output level most effectively without changing output level and the output-oriented model investigates how much output composition should be increased to achieve the same input level most effectively without changing input level.

3.2 | Fuzzy Data Envelopment Analysis

Data envelopment models are based on linear programming basics. The classical boundaries of DEA models that are created by classical mathematics are not able to overcome uncertain information, which could be clarified with fuzzy set theory, and in this way, the uncertainty could be included in the decision processes. When some of the observations are blurred, the objective function and constraints in the decision process become blurred. As data envelopment models are based on linear programming basics, fuzzy data envelopment problems are based on fuzzy linear programming techniques [21].

DEA methods that are using fuzzy set theory, are generally classified under five headlines in the literature, the tolerance approach, the fuzzy ranking approach, the possibility approach, the α-level-based approach, and Interval DEA (IDEA) approach. In this paper, the IDEA approach is determined as the efficiency measurement method to be used.

A pair of IDEA models are proposed by Wang et al. [18] for dealing with imprecise data such as interval data, ordinal preference information, fuzzy data, and their mixture. In these models, the efficiency scores are obtained as interval numbers and a minimax regret approach is used to rank the interval numbers.

To avoid the use of different efficient frontiers in measuring the effectiveness of different DMUs, the IDEA model is based on interval arithmetic, which is always using the same set of constraints (a unified and fixed efficient frontier), was developed.

As it is mentioned in Secion 2.1, four basic data envelopment model algorithms are input-oriented CCR, output-oriented CCR, input-oriented BCC, and output-oriented BCC. The classical and fuzzy models for these four DEA model algorithms are given below.

3.2.1 | Input oriented model – CCR input algorithm

In the crisp case, the model is given in *Eq. (1)* where E_0 represents the efficiency of oth DMU, n represents the number of DMUs, m and s represent the number of inputs and outputs, respectively, u_r represents r^{th} output's weight value of oth DMU, $v_i$represents i^{th} input's weight value of oth DMU, x_{io} represents i^{th} input quantity of oth DMU, y_{ro} represents r^{th} output quantity of oth DMU:

$$
\begin{aligned}
& E_0 = \max \sum_{r=1}^{s} u_r y_{ro}, \\
& \text{s.t.} \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1,2,\dots,n \\
& \sum_{i=1}^{m} v_i x_{io} = 1. \\
& v_i, u_r \ge 0 \qquad r = 1,2,\dots,s \qquad i = 1,2,\dots,m
\end{aligned}
\tag{1}
$$

In the fuzzy case of the model, the efficiency of oth DMU is determined by an interval fuzzy number $\tilde{E}_o = [E_o^L, E_o^U]$ where E_o^L and E_o^U represent lower and upper levels of the efficiency of oth DMU, respectively. The upper level of efficiency is calculated using *Eq. (2)* [18]:

$$
\begin{aligned}
& \max E_o^U = \frac{\sum_{r=1}^{s} u_r y_{ro}^U}{\sum_{i=1}^{m} v_i x_{io}^L}, \\
& \text{s.t.} \\
& E_j^U = \sum_{r=1}^{s} u_r y_{rj}^U - \sum_{i=1}^{m} v_i x_{ij}^L \le 0. \qquad j = 1,\dots,n \\
& u_r, v_i \ge \varepsilon \quad \forall\, r, i
\end{aligned}
\tag{2}
$$

where y_{ro}^U represents the upper bound of rth output quantity of oth DMU, x_{io}^L represents the lower bound of ith input quantity of oth DMU. The lower level of efficiency is calculated using *Eq. (3)* [18]:

$$
\begin{aligned}
& \max E_o^L = \frac{\sum_{r=1}^{s} u_r y_{ro}^L}{\sum_{i=1}^{m} v_i x_{io}^U}, \\
& \text{s.t.} \\
& E_j^U = \sum_{r=1}^{s} u_r y_{rj}^U - \sum_{i=1}^{m} v_i x_{ij}^L \le 0. \qquad j = 1,\dots,n \\
& u_r, v_i \ge \varepsilon \quad \forall\, r, I
\end{aligned}
\tag{3}
$$

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where y_{ro}^{L} represents the lower bound of rth output quantity of oth DMU, x_{io}^{U} represents the upper bound of ith input quantity of oth DMU. As it is stated and proved in [19] using the same constraint for *Eq. (2)* and *Eq. (3)* determines a fixed production frontier for all the DMUs with fuzzy inputs and outputs.

3.2.2 | Output oriented model–CCR output algorithm

In the crisp case, the output-oriented CCR algorithm is given as in *Eq. (4)* as follows:

$$\begin{aligned} & E_0 = \min \frac{\sum_{i=1}^{m} v_i x_{io}}{\sum_{r=1}^{s} u_r y_{ro}}, \\ & \text{s.t.} \\ & \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0. \qquad j = 1,2,\dots,n \\ & v_i, u_r \geq \varepsilon. \qquad r = 1,2,\dots,s \qquad i = 1,2,\dots,m \end{aligned} \tag{4}$$

In the literature review, it is seen that there is not any proposed algorithm for IDEA approach for output oriented CCR algorithm. Thus, the algorithms that are given in *Eq. (5)* and *Eq. (6)* are proposed for the output-oriented fuzzy CCR using the same assumptions of [18]. In the fuzzy case of the output-oriented CCR algorithm, the upper level of the efficiency of oth DMU can be calculated using *Eq. (5)*:

$$\begin{aligned} & \min E_o^U = \frac{\sum_{r=1}^{s} v_i x_{io}^U}{\sum_{i=1}^{m} u_r y_{ro}^L}, \\ & \text{s.t.} \\ & E_j^U = \sum_{r=1}^{s} v_i x_{ij}^U - \sum_{i=1}^{m} u_r y_{rj}^L \leq 0. \qquad j = 1,\dots,n \\ & u_r, v_i \geq \mathcal{E} \qquad \forall\ r, i \end{aligned} \tag{5}$$

The lower level of the efficiency of oth DMU in fuzzy case of output-oriented CCR algorithm can be calculated using *Eq. (6)*:

$$\begin{aligned} & \min E_o^L = \frac{\sum_{r=1}^{s} v_i x_{io}^L}{\sum_{i=1}^{m} u_r y_{ro}^U}, \\ & \text{s.t.} \\ & E_j^U = \sum_{r=1}^{s} v_i x_{ij}^U - \sum_{i=1}^{m} u_r y_{rj}^L \leq 0\,. \qquad j = 1,\dots,n \\ & u_r, v_i \geq \mathcal{E} \qquad \forall\ r, i \end{aligned} \tag{6}$$

In *Eq. (5)* and *Eq. (6)*, the same constraint is used to determine a fixed upper bound for the inputs.

3.2.3 | Input oriented model–BCC input algorithm

In the crisp case, input-oriented BCC algorithm is given in *Eq. (7)* where u_o represents unrestricted variable of oth DMU.

$$\begin{aligned} & E_0 = \max \frac{\sum_{r=1}^{s} u_r y_{ro} - u_o}{\sum_{i=1}^{m} v_i x_{io}}, \\ & \text{s.t.} \\ & \sum_{r=1}^{s} u_r y_{rj} - u_o - \sum_{i=1}^{m} v_i x_{ij} \leq 0. \qquad j = 1,2,\dots,n \\ & v_i, u_r \geq \varepsilon \qquad r = 1,2,\dots,s \qquad i = 1,2,\dots,m \end{aligned} \tag{7}$$

In the fuzzy case, same as previously determined algorithms first lower and upper levels of the efficiency of oth DMU are calculated using *Eq. (8)* and *Eq. (9)*, respectively:

$$\max E_o^U = \frac{\sum_{r=1}^{s} u_r y_{ro}^U - u_o}{\sum_{i=1}^{m} v_i x_{io}^L},$$
$$\text{s.t.} \tag{8}$$
$$E_j^U = \sum_{r=1}^{s} u_r y_{rj}^U - u_o - \sum_{i=1}^{m} v_i x_{ij}^L \le 0. \qquad j = 1, \dots, n$$
$$u_r, v_i \ge \mathcal{E} \quad \forall\, r, i$$

$$\max E_o^L = \frac{\sum_{r=1}^{s} u_r y_{ro}^L - u_o}{\sum_{i=1}^{m} v_i x_{io}^U},$$
$$\text{s.t.} \tag{9}$$
$$E_j^U = \sum_{r=1}^{s} u_r y_{rj}^U - u_o - \sum_{i=1}^{m} v_i x_{ij}^L \le 0. \qquad j = 1, \dots, n$$
$$u_r, v_i \ge \mathcal{E} \quad \forall\, r, i$$

3.2.4 | Output oriented model – BCC output algorithm

In the crisp case, output-oriented BCC algorithm is given in *Eq. (10)* where v_o represents unrestricted variable of oth DMU.

$$E_0 = \min \frac{\sum_{i=1}^{m} v_i x_{io} - v_o}{\sum_{r=1}^{s} u_r y_{ro}},$$
$$\text{s.t.} \tag{10}$$
$$\sum_{i=1}^{m} v_i x_{ij} - v_o - \sum_{r=1}^{s} u_r y_{rj} \ge 0. \qquad j = 1,2, \dots, n$$
$$v_i, u_r \ge \varepsilon \qquad r = 1,2, \dots, s \qquad i = 1,2, \dots, m$$

To the best of our knowledge, there is not any paper that proposed algorithms for output oriented fuzzy BCC algorithms in the literature. The upper level of the efficiency of oth DMU in the fuzzy case of output-oriented BCC algorithm can be calculated using *Eq. (11)*.

$$\min E_o^U = \frac{\sum_{r=1}^{s} v_i x_{io}^U - v_o}{\sum_{i=1}^{m} u_r y_{ro}^L},$$
$$\text{s.t.} \tag{11}$$
$$E_j^U = \sum_{r=1}^{s} v_i x_{ij}^U - v_o - \sum_{i=1}^{m} u_r y_{rj}^L \le 0. \quad j = 1, \dots, n$$
$$u_r, v_i \ge \mathcal{E} \quad \forall\, r, i$$

Eq. (12) shows the calculation of the lower level of the efficiency of oth DMU in the fuzzy case of output-oriented BCC algorithm.

$$\min E_o^L = \frac{\sum_{r=1}^{s} v_i x_{io}^L - v_o}{\sum_{i=1}^{m} u_r y_{ro}^U},$$
$$\text{s.t.} \tag{12}$$
$$E_j^U = \sum_{r=1}^{s} v_i x_{ij}^U - v_o - \sum_{i=1}^{m} u_r y_{rj}^L \le 0. \quad j = 1, \dots, n$$
$$u_r, v_i \ge \mathcal{E}. \quad \forall\, r, i$$

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In the evaluation of the efficiency of the interval data, in which the final efficiency scores for each DMU are defined by an interval, a minimax regret-based approach that is proposed by Wang et al. [18] is used to sort and compare the effectiveness of the different DMUs.

Input oriented. The maximum efficiency loss of all DMUs is calculated using *Eq. (13)*. Relative lowest efficient DMU with the highest efficiency loss is obtained with DMU removal iterations of lowest efficiency loss.

$$\begin{aligned} R(\text{i. DMU}) = \max\Big[&\max\Big(\text{Other DMUs' upper level efficiency}\big(\Theta_k^U\big)\Big) \\ &- \text{i. DMU's lower level efficiency}(\Theta_k^L), 0\Big]. \end{aligned} \tag{13}$$

Output oriented. The maximum efficiency loss of all DMUs is calculated using *Eq. (14)*. Relative highest efficient DMU with the highest efficiency loss is obtained with DMU removal iterations of lowest efficiency loss.

$$\begin{aligned} (\text{i. DMU}) = \max\Big[&\max\Big(\text{Other DMUs' lower level efficiency}\big(\Theta_k^L\big)\Big) \\ &- \text{i. DMU's upper level efficiency}(\Theta_k^U), 0\Big]. \end{aligned} \tag{14}$$

4 | Application in Home Appliances Sector

In this study, 44 machines of a company that is the leader of the sector according to many indicators including market share are examined. The factory to be examined within the scope of the research belongs to a group of companies, which supplies innovative white goods in 43 factories to consumers through 80 companies in 48 countries.

From the end of 2018, the company has started to implement the Industry 4.0 applications for the machines that were identified as bottlenecks (production capacity constraint). The company has decided to invest in the "Instantaneous System Condition Monitoring" and "Personnel Warning Systems" for the Preventive Maintenance Activity of the 3 of 44 machines that have the production capacity constraint. For a single machine 52 analog pressure sensors, 10 analog temperature sensors, 5 pieces of oil level sensors, 16 pcs laser distance sensors and 1 optical sensor are added. The working conditions of the machines are monitored instantaneously with the advanced precision measurement systems and the algorithms that are created specifically for the machine are provided to warn the machine without any downtimes (within the scope of the algorithm) by foreseeing the possible causes of stopping. In this study, machines (DMUs) that have Industry 4.0 applications are analyzed and denoted as M5, M12, and M26.

To avoid the effects of pandemics and to find out the real effect of Industry 4.0 implementations in the manufacturing process, data of 2018 and 2019 are used for the analysis.

4.1 | Definition of Variables

In the literature, a mathematical study on measuring the effects of Industry 4.0 applications could not be determined, however, Turanoglu Bekar and Kahraman [3] examined total productive maintenance by FDEA. The variables used in this literature (denoted with "*" in the tableau) is expanded and final input and output variables are determined in *Table 1* as follows:

Table 1. Input and output variables.

Inputs Variable No.	Variable Description	Unit
X1	Average Machine Operator Quantity	Unit
X2	Workpiece Technical Complexity Value	Between 1-10
X3	Workpiece Managerial Complexity Value	Between 1-10
X4	Machine Operator absenteeism Rate *	(%) Percent
X5	Machine Operator Turn-Over Rate *	(%) Percent
X6	1 / Machine Operator Working Year *	1/Year
X7	100 – Operator New Ideas Generated and Implemented *	Between 1-100
X8	100 – Level of 5S Point *	Between 1-100
X9	Availability of Maintenance Personnel *	Between 1-100
X10	Competence of Maintenance Personnel *	Between 1-100
Outputs **Variable No.**	**Variable Description**	**Unit**
Y1	Machine Available Working Time	Hour/Month
Y2	Machine OEE(Overall Equipment Effectiveness) Rate	(%) Percent
Y3	Workpiece Quantity Per Hour	Piece/Hour
Y4	Machine Autonomous Maintenance Level	Between 1-100
Y5	100 – Machine Work Accident Quantity *	100-Unit
Y6	100 / Machine Average Breakdown Quantity *	100/Unit
Y7	100 – Machine Mean Time to Repair (MTTR) *	100-Minute
Y8	Mean Time Between Failure (MTBF) *	Hour

In DEA, unit differences are eliminated by using weights according to the minimization of inputs and maximization of outputs. By this information, the variables to be used in the study were selected and their units were scaled.

Data control. In the study, Cronbach Alpha reliability analysis is performed in terms of internal consistency of statistical attitude scale. Reliability in terms of internal consistency is made to determine whether a single measurement tool measures the psychological conceptual structure in a consistent way by making a single application [22]. For the 2018 data set, Cronbach's alpha is found as 0.790, Cronbach's alpha based on standardized items is found as 0.895 for 18 items. In the 2019 data set, Cronbach's alpha is found as 0.744, Cronbach's alpha based on standardized items is found as 0.745 for 18 items.

4.2 | Classical Data Envelopment Analysis

In this subsection, four basic classical DEA algorithms are applied to data. The results of M5, M12, and M26 which are the Industry 4.0 machines are detailed to point out the effect of Industry 4.0 implementations.

4.2.1 | Classical data envelopment analysis: CCR–input

CCR-input-oriented classical DEA results and efficiency variations of the machines for 2018 and 2019 are given in *Table 2*.

Table 2. CCR – input-oriented classical DEA results and efficiency variations.

2018 - CCR-I Model Classical DEA Result		2019 - CCR-I Model Classical DEA Result		Classical DEA CCR-I Model 2018 - 2019 Efficiency Variation	
DMU	Efficiency rate	DMU	Efficiency rate	DMU	Efficiency rate
M5	62,9%	M5	100%	M5	37,1%
M12	66,4%	M12	92,4%	M12	26,0%
M26	77,1%	M26	100,0%	M26	22,9%
All machines average	92,4%	All machines average	97,8%	All machines average variation	5,4%

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According to the results, in 2019 the average relative efficiency of 44 machines increased by 5.4%. Machines M5, M12, and M26 are Industry 4.0 machines, their relative efficiency increased by 37.1%, 26%, and 22.9% respectively, and in 2019, M5 and M26 passed to the active border.

4.2.2 | Classical data envelopment analysis: CCR–output

CCR–output-oriented classical DEA results and efficiency variations of the machines for 2018 and 2019 are given in *Table 3*.

Table 3. CCR – output-oriented classical DEA results and efficiency variations.

2018 - CCR-O Model Classical DEA Result		2019 - CCR-O Model Classical DEA Result		Classical DEA CCR-O Model 2018 - 2019 Efficiency Variation	
DMU	Efficiency rate	DMU	Efficiency rate	DMU	Efficiency rate
M5	159,1%	M5	100,0%	M5	59,1%
M12	150,7%	M12	108,2%	M12	42,5%
M26	129,7%	M26	100,0%	M26	29,7%
All machines average	109,6%	All machines average	102,4%	All machines average variation	7,2%

According to these results in 2019, the average relative efficiency of 44 machines increased by 7.2%. Machines M5, M12, and M26 are Industry 4.0 applied machines and their relative efficiency increased by 59.1%, 42.5%, and 29.7% respectively. In 2019, M5 and M26 passed to the active border.

4.2.3 | Classical data envelopment analysis: BCC–input

BCC – input-oriented classical DEA results and efficiency variations of the machines for 2018 and 2019 are given in *Table 4*.

Table 4. CCR – input-oriented classical DEA results and efficiency variations.

2018 - BCC-I Model Classical DEA Result		2019 BCC-I Model Classical DEA Result		Classical DEA BCC-I Model 2018 - 2019 Efficiency Variation	
DMU	Efficiency rate	DMU	Efficiency rate	DMU	Efficiency rate
M5	64,8%	M5	100,0%	M5	35,2%
M12	66,4%	M12	92,4%	M12	26,0%
M26	78,1%	M26	100,0%	M26	21,9%
All machines average	94,1%	All machines average	98,3%	All machines average variation	4,2%

According to these results in 2019, the average relative efficiency of 44 machines increased by 4.2%. Machines M5, M12, and M26 are Industry 4.0 machines and their relative efficiency increased by 35.2%, 26%, and 21.9% respectively. In 2019, M5 and M26 passed to the active border.

4.2.4 | Classical data envelopment analysis: BCC–output

BCC–output-oriented classical DEA results and efficiency variations of the machines for 2018 and 2019 are given in *Table 5*.

According to these results in 2019, the average relative efficiency of 44 machines increased by 0.2%. Machines M5, M12, and M26 are machines with Industry 4.0 applications. According to the 2018 BCC-O model, the efficiency of the inactive M5 increased by 3.1% in 2019 and passed to the active border.

Table 5. BCC – output-oriented classical DEA results and efficiency variations.

2018 - BCC-O Model Classical DEA Result		2019 - BCC-O Model Classical DEA Result		Classical DEA BCC-O Model 2018 - 2019 Efficiency Variation	
DMU	Efficiency rate	DMU	Efficiency rate	DMU	Efficiency rate
M5	103,1%	M5	100,0%	M5	3,1%
M12	100,0%	M12	100,0%	M12	0,0%
M26	100,0%	M26	100,0%	M26	0,0%
All machines average	100,3%	All machines average	100,1%	All machines average variation	0,2%

4.3 | Fuzzy Data Envelopment Analysis

In this subsection, four basic fuzzy IDEA algorithms are applied to data. To fuzzify the crisp data, for quantitative variables (X1, X4, X5, X6, X7, Y1, Y2, Y3, Y5, Y6, Y7, and Y8) one standard deviation is subtracted and added to DMU value and for qualitative data (X2, X3, X8, X9, X10, and Y4) 10% of average is subtracted and added to DMU value to determine lower and upper boundary data, respectively. To measure the efficiency with IDEA type, upper and lower limit data must be adapted to the defined equations. For this purpose, the upper limit values of the output data and the lower limit values of the input data are used for the upper boundary activity equation. When measuring the lower limit activity values, the lower limit values of the output data and the upper limit values of the input data are used.

4.3.1 | Fuzzy data envelopment analysis: CCR–input oriented analysis results

CCR–input-oriented FDEA results and relative efficiency changes for 2018 and 2019 are given in *Table 6*.

Table 6. CCR – input-oriented FDEA results and efficiency changes.

	2018 - FDEA CCR-I Results		2019 - FDEA CCR-I Results		FDEA CCR-I 2018 - 2019 Efficiency Variation		
DMU	Lower bound technical efficiency rate	Upper bound technical efficiency rate	Lower bound technical efficiency rate	Upper bound technical efficiency rate	Lower bound technical efficiency variation	Upper bound technical efficiency variation	Min. variation
M5	66.3%	59.2%	99.8%	99.8%	33.6%	40.6%	33.6%
M12	69.8%	62.0%	93.0%	91.8%	23.2%	29.7%	23.2%
M26	79.4%	73.9%	100.0%	100.0%	20.6%	26.1%	20.6%
All machines average	93.9%	89.9%	98.3%	96.6%	4.4%	6.7%	4.4%

In 2018, the machines with the lowest relative activity of 44 machines are respectively; M5, M12, M39 and M26. As mentioned at the beginning of the study, M5, M12, and M26 are also the machines that are applied to Industry 4.0 applications as of 2019.

In 2019, the machines with the lowest relative efficiency of 44 machines are M3 and M39. M5, M12, and M26 were removed from the list of the lowest efficient machines. Even, M26 which was one of the lowest efficiency machines is at the effective boundary according to the FDEA CCR-I model as of 2019. As can be seen in M5 and M12 machines, efficiency improvement is 33.6% and 23.2% respectively.

4.3.2 | Fuzzy data envelopment analysis: CCR-output oriented analysis results

CCR–output-oriented FDEA results and relative efficiency changes for 2018 and 2019 are given in *Table 7*.

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Table 7. CCR – input oriented classical DEA results and efficiency variations.

	2018 - FDEA CCR-I Results		2019 - FDEA CCR-I Results		FDEA CCR-I 2018 - 2019 Efficiency Variation		
DMU	Lower bound technical efficiency rate	Upper bound technical efficiency rate	Lower bound technical efficiency rate	Upper bound technical efficiency rate	Lower bound technical efficiency variation	Upper bound technical efficiency variation	Min. variation
M5	150.9%	168.9%	100.2%	100.2%	50.7%	68.7%	50.7%
M12	143.3%	161.2%	107.5%	109.0%	35.7%	52.2%	35.7%
M26	125.9%	135.2%	100.0%	100.0%	25.9%	35.2%	25.9%
All machines average	107.6%	113.4%	101.9%	103.8%	5.7%	9.6%	5.7%

In 2018, the machines with the lowest relative activity of 44 machines are respectively; M5, M12, M39, and M26.

In 2019, the machines with the lowest relative efficiency of 44 machines are M3 and M39. M5, M12, and M26 were removed from the list of the lowest efficient machines. Even, M26 which is one of the lowest efficiency machines in 2018, is at the effective boundary according to the FDEA CCR-O model as of 2019. As can be seen in M5 and M12 machines, efficiency improvement is 50.7% and 35.7%, respectively.

4.3.3 | Fuzzy data envelopment analysis: BCC-input oriented analysis results

BCC-input oriented FDEA results and relative efficiency changes for 2018 and 2019 are given in *Table 8*.

Table 8. BCC-input oriented FDEA results and efficiency changes.

	2018 FDEA BCC-I Results		2019 FDEA BCC-I Results		Relative Efficiency Variation		
DMU	Lower bound technical efficiency rate	Upper bound technical efficiency rate	Lower bound technical efficiency rate	Upper bound technical efficiency rate	Lower bound technical efficiency variation	Upper bound technical efficiency variation	Min. variation
M5	68.3%	60.4%	99.8%	99.8%	31.5%	39.4%	31.5%
M12	69.8%	62.0%	93.0%	91.8%	23.2%	29.7%	23.2%
M26	80.3%	75.7%	100.0%	100.0%	19.7%	24.3%	19.7%
All machines average	95.1%	91.5%	98.5%	97.9%	3.4%	6.4%	3.4%

In 2018, the machines with the lowest relative activity of 44 machines are respectively; M5, M12, M39, and M26.

In 2019, the machines with the lowest relative efficiency of 44 machines are M3 and M25. M5, M12, and M26 were removed from the list of the lowest efficient machines. Even, M26 which is one of the lowest efficiency machines in 2018, is at the effective boundary according to the FDEA BCC-I model as of 2019. As can be seen in M5 and M12 machines, efficiency improvement is 31.5% and 23.2% respectively.

4.3.4 | Fuzzy data envelopment analysis: BCC-output oriented analysis results

BCC – output-oriented FDEA results and relative efficiency changes for 2018 and 2019 are given in *Table 9*.

Table 9. BCC – output-oriented classical DEA results and efficiency variations.

	2018 FDEA BCC-O Results		2019 FDEA BCC-O Results		Relative Efficiency Variation		
DMU	Lower bound technical efficiency rate	Upper bound technical efficiency rate	Lower bound technical efficiency rate	Upper bound technical efficiency rate	Lower bound technical efficiency variation	Upper bound technical efficiency variation	Min. variation
M5	103.1%	102.0%	100.0%	100.0%	3.1%	2.02%	2.02%
M12	100.0%	100.0%	100.0%	100.0%	0.0%	0.00%	0.00%
M26	100.0%	100.0%	100.0%	100.0%	0.0%	0.00%	0.00%
All machines average	100.3%	100.1%	100.1%	100.0%	0.2%	0.04%	0.04%

In 2018, the machines with the lowest relative activity of 44 machines are respectively; M5, M34, and M39.

In 2019, the machines with the lowest relative efficiency of 44 machines are M3, M7, and M34. As of 2019, the M5 which has the lowest relative efficiency in 2018, is at the effective boundary according to the FDEA BCC-O model. M5 has a 2.02% efficiency improvement.

In addition, the sensitivity analysis is performed. It is seen that any of the input parameters and output parameters do not change the lowest efficient DMU for all of the algorithms used in the study when a single variable is removed.

5 | Discussions

In determining the efficiency measurement method of this study, there are three basic parting of the ways: efficiency analysis method, logic type selection (crisp, fuzzy), and working algorithm selection.

Method selection; has been carried out comprehensively because it contains unknowns and it has not been specialized in both theoretical and practical studies yet. As a result of the method search, it is decided to work with Interval type FDEA studies. To reveal the effect of the unknown, classical DEA studies are conducted and it is found appropriate to compare these two methods. Thus, it is aimed to reveal the exact efficiency effect.

Classical DEA results. According to the classical DEA results of 2018 and 2019, the efficiency of 44 machines shows an average improvement of at least 4.2% for all machines (The output-oriented BCC algorithm can be excluded because it cannot clearly show the relative separation of machine-specific relative to data). There are inherent differences in input-output-oriented or CRR-BCC enveloping algorithms. In the Classical DEA, the M5 and M26 machines have moved to the efficient frontier, regardless of the model.

Relative productivity of M12 is increased minimum of 26%. From 2018 to 2019, the efficiency increase for these three machines is between 21.9% and 59.1%.

FDEA results. According to the FDEA results of 2018 and 2019, the efficiency of 44 machines shows an average improvement of at least 3.4% for all machines (The output-oriented BCC algorithm can be excluded because it cannot clearly show the relative separation of machine-specific relative to data). There are inherent differences in input-output-oriented or CRR-BCC enveloping algorithms. In the FDEA, the M26 has moved to the efficient frontier, regardless of the model.

Relative productivity of M5 and M12 is increased minimum of 31.5% and 23.2% respectively. From 2018 to 2019, the efficiency increase for these three machines is between 19.7% and 50.7%.

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Classical DEA-FDEA comparison-the uncertainty factor. According to the results of FDEA and Classic DEA, M5, M12, and M26 machines which have been applied to Industry 4.0 applications have a minimum 19.7% increase in 2019, regardless of the DEA model.

According to the data of 2018, the relative lowest efficiencies are M5, M12, M39, M26, respectively, regardless of the Classic, FDEA, or model.

According to 2019 data, the lowest relative efficiency is in the M3, M39, M25 machines, although they differ according to the Classic, FDEA models.

According to Classical DEA of 2019, the M5 and M26 which have Industry 4.0 applications, are among the most efficient machines with the highest efficiency in the efficient frontier with the highest efficiency. This situation applies only to M26 in FDEA. M5 and M12 are not within the active boundary (efficient frontier) even if their efficiency increased minimum of 23.2%. The fact that the full event status of any machine is different in FDEA and Classic DEA is expected in terms of application. Similar differences can be observed in M23, M24, M32, M33. These differences are occurred due to the uncertainty factor. Because classical DEA does not contain uncertainty, it has worked with crisp sets. However, FDEA (IDEA) works with interval data so it contains limited uncertainty that is converting qualitative comments to quantitative.

6 | Conclusion

Industry 4.0 studies require costly investments. This factor is also the basis of the lack of implementation. For this reason, companies want to make a detailed feasibility analysis and especially to see the effects of pilot applications before implementation. In this study, an application road map for efficiency impact analysis of Industry 4.0 applications is presented in the home appliance manufacturing sector, which can be used to find out the real effect of the applications.

As stated at the beginning of the study, Industry 4.0 applications contain high uncertainty. It is also understood that the uncertainty factor is critical to have successful implementations of new technologies. In the case of analysis involving uncertainties, the decision to conclude with the classical DEA will result in an effective interpretation of an inactive (M5) DMU as in practice. In this paper, it is shown that FDEA studies have more clear results in the areas of uncertainty and categorical evaluations.

The other objective of this study is to compare input and output-oriented DEA algorithms. The paper shows that these algorithms have similar results, but the order of the DMUs may differ. The limitation of the study is that the effects of constantly changing/developing industry 4.0 applications are measured with discrete data. Despite this, DEA can show the positive effect of these practices on productivity. For further research, it is suggested to analyze the results of Industry 4.0 implementations from a broader perspective including the effects on demand, cost of production, and customer satisfaction. It is clear how Industry 4.0 practices will affect our use of resources. The research can also be expanded by working with different sectors and machine groups.

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Conflicts of Interest

The authors state no conflict of interest.

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