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Technology Selection Based on EDAS Cross-Efficiency Evaluation Method

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ABSTRACT Technology selection is an important part of enterprises sustainable development. The best technologies could create significant competitive advantages for an enterprise to realize its profit growth and capability improvement, and then realize its sustainable development. However, due to the complexity of technology selection, decision makers are faced with a difficult task, therefore, to select the best technologies, we introduce the evaluation based on distance from average solution (EDAS) method to aggregate ultimate cross-efficiency scores. By calculating the positive distance from average solution (PDA) and the negative distance from average solution (NDA), we can get the appraisal scores (AS) to rank for each rated decision making unit (DMU). Finally, an example of technology selection is illustrated to examine the validity of the proposed method.

INDEX TERMS Cross-efficiency evaluation, DEA (data envelopment analysis), EDAS (evaluation based on distance from average solution) method, technology selection.

I. INTRODUCTION

Sustainable development refers to the development of the ability to meet the needs of the present without compromising the ability of future generations to meet their needs [1]. With the development of sustainability, people pay more and more attention to sustainability, and sustainable development has penetrated into various fields. The sustainable development of an enterprise means that in the process of pursuing self-survival and sustainable development, the enterprise should not only consider the realization of the business goals, but also improve its market position. It is necessary to maintain a sustained profit growth and capability improvement in the leading competitive areas and future expansion of the business environment [2]. Among this, technology selection as one of the elements of sustainable strategies has received extensive attention. In the past few years, the range of manufacturing technologies available to enterprises has significantly increased, decision makers of a technology such as machine tools, industrial robots, or flexible manufacturing systems are faced with many options, so how to select a best technology is an important part for enterprises. The best technologies could create significant competitive advantages for an enterprise to realize its profit growth and capability improvement, and then realize its sustainable development.

However, technology selection is always a difficult task for decision makers. Technologies have varied strengths and weaknesses which require careful assessment by the purchasers. Technology selection model can help decision-makers choose the best technology between the evolving technologies. Because of the complexity of technology evaluation which includes strategic and operational characteristic, there are many tools that consider a wide range of dimensions have been developed for evaluating these characteristics, which include cost, quality, flexibility, time, etc. Rai *et al.* [3] addressed application of a fuzzy Goal Programming(GP) concept to model the problem of machine-tool selection and operation allocation with explicit considerations given to objectives of minimizing the tool cost of machining operation, material handling and setup. Chan *et al.* [4] presented a fuzzy GP approach to model the machine tool selection and operation allocation problem of flexible manufacturing systems (FMSs). Jaganathan *et al.* [5] proposed an integrated fuzzy analytic hierarchy process (AHP) based approach to facilitate the selection and evaluation of new

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manufacturing technologies in the presence of intangible attributes and uncertainty. Khouja [6] proposed a decision model for technology selection problems using a two-phase procedure. Maghsoodi *et al.* [7] investigated a technology selection problem by proposing a hybrid MADM approach based on the Step-Wise Weight Assessment Ratio Analysis (SWARA) approach with a hierarchical arrangement combined with the Multi-Objective Optimization on the basis of Ratio Analysis plus the full MULTIplicative form (MULTIMOORA). Peng *et al.* [8] applied the fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach to select a proper restoring technology for the crankshaft remanufacturing. Narayanamoorthy *et al.* [9] proposed interval valued intuitionistic hesitant fuzzy entropy based on VlseKriterijumska Optimizacija I Kompromisno Resenje(VIKOR) method for robot selection. Liu *et al.* [10] proposed a novel robot selection model by integrating quality function development (QFD) theory and qualitative flexible multiple criteria method (QUALIFLEX) under interval valued Pythagorean uncertain linguistic context.

Otherwise, many researchers used data envelopment analysis (DEA) to study the problems of technology selection. For example, Baker and Talluri [11] proposed an alternate methodology for technology selection using data envelopment analysis (DEA). Ramanathan [12] introduced the use of DEA for synthesizing the diverse characteristics of energy supply technologies into a single objective efficiency score. Farzipoor [13] proposed an innovative approach, which is based on imprecise data envelopment analysis (IDEA). Talluri *et al.* [14] proposed a framework, which is based on the combined application of DEA and non-parametric statistical procedures, for the selection of FMSs. Seiford and Zhu [15] extended the context-dependent DEA by incorporating value judgment into attractiveness and progress measures. Sarkis and Talluri [16] introduced an application of DEA that considers both cardinal and ordinal data, for the evaluation of alternative FMS. Talluri and Yoon [17] introduced the advanced manufacturing technology selection process. They proposed a combination of a cone-ratio DEA model and a new methodological extension in DEA, while allowing for the incorporation of preference of decision-makers. Shang and Sueyoshi [18] utilized a combination of AHP and DEA for selection of FMS. Braglia and Petroni [19] proposed the use of DEA for selection of industrial robots.

DEA proposed by Charnes *et al.* [20] (CCR model)and developed by Banker *et al.* [21] (BCC model) is an approach for evaluating the efficiencies of a group of homogenous decision making units (DMUs) in which one or multiple inputs are consumed to produce one or multiple outputs. In the traditional DEA models, each DMU selects its own most favorable set of optimal weights to evaluate its efficiency, namely self-evaluation, which may results in the problem that many DMUs are evaluated as DEA efficiency and the efficient DMUs cannot be further distinguished or ranked. To solve this problem, some scholars have extended the traditional DEA and proposed new technologies to improve the discriminative power of DEA. One method is the DEA cross-efficiency evaluation method proposed by Sexton *et al.* [22]. However, because of the optimal weights calculated by the DEA model are generally not unique, cross-efficiency scores may be generated arbitrarily. Doyle and Green [23] introduced the aggressive and benevolent models, which minimize and maximize, respectively, the efficiency of the composite DMU constructed from the other DMUs compared to DMU_0. Wang and Chin [24] suggested a neutral DEA model for cross-efficiency evaluation. Wu *et al.* [25] and Contreras [26] proposed models in which the secondary goal is to optimize the ranking position of the DMU under evaluation. Wu *et al.* [27] proposed a weight-balanced model, which goals are to lessen large differences in weighted data and reduce the number of zero-weights. Liang *et al.* [28] proposed the game cross-efficiency model and an algorithm.

Another problem in the cross-efficiency evaluation is the aggregation of the ultimate cross-efficiency scores. The most extensively used approach is to aggregate cross-efficiency scores with equal weights. Additionally, Wang *et al.* [29] investigated how to determine the weights in cross-efficiency evaluation. Wu *et al.* [30] introduced the Shannon entropy to aggregate the cross-efficiency scores. Yang *et al.* [31] proposed a cross-efficiency aggregation model using the evidential-reasoning approach. Oukil [32] embedded ordered weighted averaging (OWA) under preference ranking for DEA cross-efficiency aggregation. Song *et al.* [33] improved a recently proposed DEA cross-efficiency aggregation method based on the Shannon entropy. The weights for determining cross-efficiency are derived from minimizing the square distance of weighted cross-efficiency and weighted CCR efficiency. In addition, Kao *et al.* [34] implied the ideal of cross evaluation to measure the efficiency of the two basic structures of network systems, series and parallel. Liu *et al.* [35] considered the decision makers' risk attitude and investigated the cross-efficiency based on prospect theory. Fan *et al.* [36] proposed a group decision-making for cross-efficiency based on hesitant fuzzy sets(HFSs).

The evaluation based on distance from average solution (EDAS) method developed by Ghorabaee *et al.* [37] is a novel multiple criteria decision-making method (MCDM) for inventory classification, which is a compromise MCDM method. Peng and Chong [38] extended the EDAS method to neutrosophic soft decision making. Galina *et al.* [39] introducedL_1 metrics in EDAS method for multiple criteria decision-making. Liang *et al.* [40] integrated the EDAS with elimination and choice translating reality (ELECTRE) approaches for assessing the cleaner production of gold mines. Li *et al.* [41] developed an approach that incorporates power aggregation operators with the evaluation based on distance from average solution (EDAS) method under linguistic neutrosophic situations to solve fuzzy multi-criteria group decision-making problems. Stevic *et al.* [42]proposed a model based on fuzzy AHP and fuzzy EDAS for evaluation of suppliers. Feng *et al.* [43]extended the Evaluation Based on Distance from Average Solution (EDAS) method to the extended hesitant fuzzy linguistic environment, which use average solution for appraising alternatives.

At present, the EDAS method is used in MCDM. In this paper, we will introduce the EDAS method to aggregate the ultimate cross-efficiency scores. By calculating the positive distance from average solution (PDA) and the negative distance from average solution (NDA), we can get the appraisal scores (AS) for each Rated DMU, then we can rank for all DMUs according to the AS. Finally, an example of 27 industrial robots is illustrated to examine the method.

The rest of this paper unfolds as follows: Section 2 presents the DEA cross-efficiency evaluation method; Section 3 determines the ultimate cross-efficiency scores using the EDAS method. An example of technology selection is given in section 4 and conclusions are made in section 5.

II. DEA CROSS-EFFICIENCY

We assume that there are a set of n DMUs, and each $DMU_j (j = 1, 2, \ldots, n)$ produce s different outputs using m different inputs which are denoted as $x_{ij} (i = 1, 2, \ldots, m)$ and $y_{rj} (r = 1, 2, \ldots, s)$ respectively.

For any evaluated $DMU_d (d = 1, 2, \ldots, n)$, the efficiency score E_{dd} can be calculated by the following model (1), proposed by Charnes *et al.* [20].

$$\begin{aligned} &\max \sum_{r=1}^{s} \mu_{rd}\, y_{rj} = E_{dd} \\ &s.t. \sum_{i=1}^{m} \omega_{id} x_{ij} - \sum_{r=1}^{s} \mu_{rd}\, y_{rj} \geq 0, \quad j = 1, 2, \ldots, n \\ &\quad\ \sum_{i=1}^{m} \omega_{id} x_{id} = 1 \\ &\quad\ \omega_{id} \geq 0, \quad i = 1, 2, \ldots, m \\ &\quad\ \mu_{rd} \geq 0, \quad r = 1, 2, \ldots, s \end{aligned} \tag{1}$$

By solving the above model (1), we can get a group of optimal weights $\omega_{1d}^*, \ldots, \omega_{md}^*, \mu_{1d}^*, \ldots, \mu_{sd}^*$ for each $DMU_d (d = 1, 2, \ldots, n)$. In the model, each DMU is self-evaluated and termed efficient if and only if the optimal objective function is equal to 1. The traditional cross-efficiency of each DMU_j using the weights of DMU_d, namely E_{dj}, can be calculated as follows:

$$E_{dj} = \frac{\sum_{r=1}^{s} \mu_{rd}^* y_{rj}}{\sum_{i=1}^{m} \omega_{id}^* x_{ij}}, \quad d, j = 1, 2, \ldots, n \tag{2}$$

Then we can obtain the cross-efficiency matrix (CEM) as shown in table1. For each row, E_{dj} is the cross-efficiency score of DMU_j using the weights that $DMU_d (d = 1, 2, \ldots, n)$ has chosen. We can also find that the elements in the diagonal are the special cases that can be seen as self-evaluated.

For each DMU, the average of all E_{dj}, that are listed in the last column of table 1, namely, $\bar{E}_j = \frac{1}{n} \sum_{d=1}^{n} E_{dj} (j = 1, 2, \ldots, n)$ can be treated as a new efficiency measure, that is, the cross-efficiency score for DMU_j.

TABLE 1. Generalized cross-efficiency matrix.

Rated DMU$_j$	Rating DMU$_d$ 1	2	3	...	...	n	Mean
1	E_{11}	E_{21}	E_{31}	...	...	E_{n1}	$\bar{E}_1$
2	E_{12}	E_{22}	E_{32}	...	...	E_{2n}	$\bar{E}_2$
3	E_{13}	E_{23}	E_{33}	...	...	E_{n3}	$\bar{E}_3$
...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...
n	E_{1n}	E_{2n}	E_{3n}	...	...	E_{nn}	$\bar{E}_n$

TABLE 2. Data for 27 industrial robots.

Robots (DMUs)	Inputs: Cost	Inputs: Repeatability	Outputs: Load Capacity	Outputs: Velocity
1	7.2	0.15	60	1.35
2	4.8	0.05	6	1.1
3	5	1.27	45	1.27
4	7.2	0.025	1.5	0.66
5	9.6	0.25	50	0.05
6	1.07	0.1	1	0.3
7	1.76	0.1	5	1
8	3.2	0.1	15	1
9	6.72	0.2	10	1.11
10	2.4	0.05	6	1
11	2.88	0.5	30	0.9
12	6.9	1	13.6	0.15
13	3.2	0.05	10	1.2
14	4	0.05	30	1.2
15	3.68	1	47	1
16	6.88	1	80	1
17	8	2	15	2
18	6.3	0.2	10	1
19	0.94	0.05	10	0.3
20	0.16	2	1.5	0.8
21	2.81	2	27	1.7
22	3.8	0.05	0.9	1
23	1.25	0.1	2.5	0.5
24	1.37	0.1	2.5	0.5
25	3.63	0.2	10	1
26	5.3	1.27	70	1.25
27	4	2.03	205	0.75

III. DETERMINATION OF ULTIMATE CROSS-EFFICIENCY USING EDAS

In this section, we will use the EDAS to aggregate the cross-efficiency. The EDAS method is used for MCDM problems. In this paper, the Rating DMU_d will be seen as criteria, and the Rated DMU_j will be seen as all alternatives in the MCDM.

Step 1: Determine the average solution according to all Rating DMU_d, shown as follows:

$$AV = [AV_d]_{1 \times n} \tag{3}$$

TABLE 3. Cross-efficiency matrix.

Rated DMU	Rating DMU 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	1	0.38	0.48	0.37	1	0.34	0.48	0.8	0.7	0.63	0.78	1	0.41	0.56	0.48	1	0.48	0.7	0.83	0.07	0.48	0.38	0.48	0.48	0.8	0.78	0.18
2	0.17	0.9	0.42	0.85	0.17	0.42	0.6	0.51	0.61	0.64	0.49	0.19	0.81	0.47	0.42	0.19	0.42	0.61	0.44	0.05	0.42	0.9	0.42	0.42	0.51	0.49	0.05
3	0.29	0.04	0.53	0.04	0.31	0.4	0.2	0.44	0.27	0.19	0.47	0.32	0.06	0.05	0.53	0.32	0.53	0.27	0.42	0.08	0.53	0.04	0.53	0.53	0.44	0.47	0.2
4	0.03	1	0.16	1	0.03	0.17	0.26	0.19	0.25	0.28	0.19	0.04	0.57	0.45	0.16	0.04	0.16	0.25	0.16	0.02	0.16	1	0.16	0.16	0.19	0.19	0.01
5	0.59	0.01	0.11	0.02	0.59	0.01	0.04	0.29	0.19	0.13	0.29	0.58	0.02	0.21	0.11	0.58	0.11	0.19	0.35	0.02	0.11	0.01	0.11	0.11	0.29	0.29	0.1
6	0.06	0.13	0.47	0.12	0.06	0.48	0.39	0.41	0.38	0.33	0.41	0.08	0.16	0.06	0.47	0.08	0.47	0.38	0.33	0.06	0.47	0.13	0.47	0.47	0.41	0.41	0.05
7	0.25	0.43	1	0.39	0.25	1	1	1	1	0.9	1	0.29	0.51	0.21	1	0.29	1	1	0.85	0.12	1	0.43	1	1	1	1	0.12
8	0.51	0.42	0.62	0.39	0.51	0.56	0.69	0.78	0.77	0.72	0.77	0.53	0.48	0.32	0.62	0.53	0.62	0.77	0.73	0.08	0.62	0.42	0.62	0.62	0.78	0.77	0.13
9	0.16	0.23	0.31	0.22	0.16	0.3	0.36	0.36	0.38	0.36	0.36	0.18	0.26	0.14	0.31	0.18	0.31	0.38	0.32	0.04	0.31	0.23	0.31	0.31	0.36	0.36	0.05
10	0.31	0.84	0.76	0.78	0.3	0.75	0.99	0.89	1	1	0.87	0.34	0.89	0.44	0.76	0.34	0.76	1	0.78	0.09	0.76	0.84	0.76	0.76	0.89	0.87	0.09
11	0.45	0.08	0.67	0.07	0.48	0.51	0.32	0.64	0.43	0.31	0.67	0.49	0.1	0.09	0.67	0.49	0.67	0.43	0.62	0.1	0.67	0.08	0.67	0.67	0.64	0.67	0.24
12	0.1	0.01	0.07	0.01	0.1	0.04	0.03	0.09	0.05	0.04	0.09	0.1	0.01	0.02	0.07	0.1	0.07	0.05	0.1	0.01	0.07	0.01	0.07	0.07	0.09	0.09	0.04
13	0.41	1	0.7	0.93	0.4	0.68	0.94	0.87	0.98	0.99	0.85	0.43	1	0.59	0.7	0.43	0.7	0.98	0.78	0.09	0.7	1	0.7	0.7	0.87	0.85	0.1
14	1	0.99	0.66	0.96	0.99	0.54	0.8	1	1	0.98	0.97	1	0.95	1	0.66	1	0.66	1	0.99	0.09	0.66	0.99	0.66	0.66	1	0.97	0.18
15	0.39	0.04	0.61	0.04	0.42	0.42	0.21	0.52	0.31	0.21	0.56	0.42	0.06	0.07	0.61	0.42	0.61	0.31	0.52	0.1	0.61	0.04	0.61	0.61	0.52	0.56	0.28
16	0.57	0.04	0.44	0.04	0.6	0.24	0.18	0.55	0.33	0.23	0.58	0.6	0.06	0.1	0.44	0.6	0.44	0.33	0.59	0.07	0.44	0.04	0.44	0.44	0.55	0.58	0.24
17	0.06	0.04	0.4	0.04	0.07	0.39	0.19	0.26	0.19	0.15	0.27	0.07	0.06	0.02	0.4	0.07	0.4	0.19	0.21	0.06	0.4	0.04	0.4	0.4	0.26	0.27	0.06
18	0.17	0.21	0.3	0.2	0.17	0.28	0.34	0.35	0.37	0.34	0.35	0.18	0.24	0.13	0.3	0.18	0.3	0.37	0.32	0.04	0.3	0.21	0.3	0.3	0.35	0.35	0.05
19	0.93	0.26	0.73	0.24	0.95	0.56	0.61	1	0.82	0.68	1	0.96	0.31	0.31	0.73	0.96	0.73	0.82	1	0.1	0.73	0.26	0.73	0.73	1	1	0.24
20	0.01	0.02	1	0.02	0.01	1	0.1	0.15	0.09	0.07	0.17	0.01	0.02	0.01	1	0.01	1	0.09	0.11	1	1	0.02	1	1	0.15	0.17	0.53
21	0.13	0.04	0.85	0.03	0.14	0.75	0.19	0.36	0.22	0.15	0.4	0.15	0.05	0.03	0.85	0.15	0.85	0.22	0.31	0.16	0.85	0.04	0.85	0.85	0.36	0.4	0.25
22	0.04	0.83	0.45	0.77	0.03	0.48	0.67	0.51	0.63	0.67	0.49	0.06	0.79	0.33	0.45	0.06	0.45	0.63	0.42	0.05	0.45	0.83	0.45	0.45	0.51	0.49	0.03
23	0.15	0.21	0.69	0.19	0.15	0.69	0.6	0.64	0.6	0.52	0.65	0.17	0.26	0.11	0.69	0.17	0.69	0.6	0.54	0.09	0.69	0.21	0.69	0.69	0.64	0.65	0.08
24	0.14	0.21	0.64	0.19	0.14	0.64	0.58	0.6	0.58	0.5	0.61	0.16	0.26	0.11	0.64	0.16	0.64	0.58	0.51	0.08	0.64	0.21	0.64	0.64	0.6	0.61	0.08
25	0.24	0.21	0.51	0.2	0.24	0.49	0.5	0.55	0.53	0.47	0.55	0.26	0.26	0.13	0.51	0.26	0.51	0.53	0.49	0.06	0.51	0.21	0.51	0.51	0.55	0.55	0.08
26	0.45	0.04	0.58	0.04	0.48	0.37	0.2	0.55	0.32	0.21	0.58	0.48	0.06	0.07	0.58	0.48	0.58	0.32	0.55	0.1	0.58	0.04	0.58	0.58	0.55	0.58	0.28
27	0.93	0.02	1	0.02	1	0.26	0.12	0.91	0.39	0.22	1	1	0.03	0.11	1	1	1	0.39	1	0.23	1	0.02	1	1	0.91	1	1

where

$$AV_d = \frac{\sum_{j=1}^{n} E_{dj}}{n} \tag{4}$$

In this step, the Rating DMU_d will be seen as criteria in the MCDM. We can obtain the average scores for every Rating DMU_d by calculating equation (3) and (4).

Step 2: Calculate the positive distance from average solution (PDA) and the negative distance from average solution (NDA) matrices, shown as follows:

$$PDA = [PDA_{dj}]_{n\times n} \tag{5}$$
$$NDA = [NDA_{dj}]_{n\times n} \tag{6}$$
$$PDA_{dj} = \frac{\max(0, (E_{dj} - AV_d))}{AV_d} \tag{7}$$
$$NDA_{dj} = \frac{\max(0, (AV_d - E_{dj}))}{AV_d} \tag{8}$$

where PDA_{dj} and NDA_{dj} denote the positive and the negative distance of jth Rated DMU_j from average solution in terms of dth Rating DMU_d, respectively.

Step 3: Aggregate PDA and NDA for all Rated DMU_j, shown as follows:

$$SP_j = \frac{1}{n}\sum_{d=1}^{n} PDA_{dj} \tag{9}$$

$$SN_j = \frac{1}{n}\sum_{d=1}^{n} NDA_{dj} \tag{10}$$

Step 4: Normalize the values of SP and SN for all Rated DMU_j, shown as follows:

$$NSP_j = \frac{SP_j}{\max_j(SP_j)} \tag{11}$$
$$NSN_j = 1 - \frac{SN_j}{\max_j(SN_j)} \tag{12}$$

Step 5: Calculate the appraisal scores (AS) for all Rated DMU_j, shown as follows:

$$AS_j = \frac{1}{2}(NSP_j + NSN_j) \tag{13}$$

where $0 \le AS_j \le 1$.

In this step, we aggregate the NSP_j and NSN_j to get the ultimate AS.

Step 6: Rank the Rated DMU_j according to the decreasing values of appraisal scores(AS). The higher AS, the better the Rated DMU_j.

IV. APPLICATION TO TECHNOLOGY SELECTION

Many advanced manufacturers use robots extensively to perform repetitious, difficult, and hazardous tasks with precision. Robots improve quality and productivity if deployed

TABLE 4. The results of the EDAS.

Rated DMU	SP_j	NSP_j	NP_j	NNP_j	AS_j
1	0.4749	0.4613	0.0526	0.9391	0.7002
2	0.3456	0.3357	0.2027	0.7655	0.5506
3	0.0052	0.0050	0.3171	0.6332	0.3191
4	0.3078	0.2991	0.5700	0.3407	0.3199
5	0.0892	0.0866	0.5947	0.3120	0.1993
6	0.0006	0.0005	0.3931	0.5452	0.2729
7	0.5734	0.5570	0.0534	0.9383	0.7476
8	0.3150	0.3060	0.0205	0.9763	0.6412
9	0.0000	0.0000	0.3912	0.5474	0.2737
10	0.6491	0.6305	0.0432	0.9501	0.7903
11	0.1341	0.1303	0.1666	0.8073	0.4688
12	0.0000	0.0000	0.8644	0.0000	0.0000
13	0.7201	0.6995	0.0236	0.9727	0.8361
14	1.0294	1.0000	0.0076	0.9912	0.9956
15	0.0603	0.0586	0.2351	0.7280	0.3933
16	0.1111	0.1080	0.2903	0.6642	0.3861
17	0.0000	0.0000	0.5825	0.3262	0.1631
18	0.0000	0.0000	0.4133	0.5219	0.2609
19	0.5676	0.5514	0.0272	0.9685	0.7600
20	0.5794	0.5628	0.5742	0.3358	0.4493
21	0.1668	0.1621	0.4026	0.5342	0.3482
22	0.3066	0.2978	0.2458	0.7157	0.5068
23	0.1258	0.1222	0.1766	0.7958	0.4590
24	0.0844	0.0820	0.1852	0.7858	0.4339
25	0.0149	0.0145	0.1696	0.8038	0.4092
26	0.0754	0.0733	0.2324	0.7311	0.4022
27	0.7699	0.7479	0.2345	0.7287	0.7383

properly, so the selection of robots is an important part for enterprises. The best robots can create profits for enterprises and enhance their capabilities, so that enterprises can achieve sustainable development. In this section, the proposed method is used for robot selection. There are 27 industrial robots that need to be evaluated and selected, the inputs include cost (in $10,000), repeatability (in millimeters), and the outputs include load capacity (in kilograms) and velocity (in meters per second). The data for the 27 robots are listed in Table 2.

Then we can obtain the cross-efficiency matrix by model (2), it was shown in Table 3. After getting the cross-efficiency matrix (CEM), we can use the method proposed in section III to obtain the ultimate cross-efficiency scores. The results are shown in Table4.

After getting the SP, NP, NSP, NNP, then we can obtain the ultimate AS for each Rated DMU_j that are listed in the last column of table 4. From table 4, we can see that DMU14 get the highest AS,0.9956, however DMU12 get the worst AS,0, so DMU14 is the best selection and its use will could create significant competitive advantages for an enterprise to realize its profit growth and capability improvement, and then realize its sustainable development.

TABLE 5. Evaluation results of 27 industrial robots.

DMU	CCR efficiency	Rank	Wu	Rank	AS	Rank
1	1.0000	1	0.6175	8	0.7002	7
2	0.9038	10	0.4656	18	0.5506	9
3	0.5289	22	0.4027	20	0.3191	21
4	1.0000	1	0.2139	25	0.3199	20
5	0.5924	19	0.1964	26	0.1993	25
6	0.4824	23	0.3741	21	0.2729	23
7	1.0000	1	0.8732	1	0.7476	5
8	0.7825	13	0.6436	7	0.6412	8
9	0.3814	25	0.3080	22	0.2737	22
10	1.0000	1	0.7735	5	0.7903	3
11	0.6713	15	0.5531	10	0.4688	11
12	0.1027	27	0.0692	27	0.0000	27
13	1.0000	1	0.7598	6	0.8361	2
14	1.0000	1	0.8268	2	0.9956	1
15	0.6125	17	0.4747	14	0.3933	17
16	0.6035	18	0.4270	19	0.3861	18
17	0.4045	24	0.2733	24	0.1631	26
18	0.3652	26	0.2984	23	0.2609	24
19	1.0000	1	0.7798	4	0.7600	4
20	1.0000	1	0.4794	13	0.4493	13
21	0.8515	11	0.4938	12	0.3482	19
22	0.8289	12	0.4690	16	0.5068	10
23	0.6943	14	0.5718	9	0.4590	12
24	0.6361	16	0.5324	11	0.4339	14
25	0.5533	21	0.4687	17	0.4092	15
26	0.581	20	0.4716	15	0.4022	16
27	1.0000	1	0.7931	3	0.7383	6

Table 5 shows the results of the traditional CCR efficiency scores, the efficiency scores of Wu'method [30], and the AS calculated by the EDAS. The CCR efficiency scores show that nine DMUs are identified as efficient DMUs, which cannot be discriminated any further. Wu'method [30] use the Shannon entropy to aggregate the cross-efficiency and the rankings are listed in the fifth column of table 5. The sixth column of the table 5 lists the results of the EDAS. The rankings of the 27 industrial robots obtained by the Wu'method [30] and the EDAS are not significantly different based on a Spearman rank correlation coefficient test, with the statistic of

$r_s = 0.913$ and the corresponding p-value of $p < 0.01$, so this method is feasible.

V. CONCLUSIONS

In the sustainable development of enterprises, more and more attention has been paid to the technology selection. In this paper, we introduce the EDAS to aggregate ultimate cross-efficiency scores. In this method, we introduce the PDA, NDA, and AS to rank for all DMUs. Finally, our method is applied to an example of technology selection. Compared with Wu'method [30], this method does not need to generate a set of weights for aggregating and determining the ultimate cross-efficiency scores, it only needs to calculate the AS for each Rated DMU, so it is more simple. Otherwise, the Spearman Rank correlation coefficient shows that the rankings obtained by the Wu'method [30] and the EDAS are not significantly different, so this method is feasible.

In this paper, we discussed the problem of the selection of industrial robots based on EDAS cross-efficiency evaluation method. However, we don't consider the non-uniqueness of the weights, so we can take it into consideration in the future. In addition, we can use this method to discuss other decision making problems, and the EDAS method can be used in network data envelopment analysis (NDEA) with other methods to solve the more complex problems.

REFERENCES

[1] Brundtland. (1987). *Our Common Future*. [Online]. Available: https://www.iisd.org/topic/sustainable-development

[2] L. G. Liu, "Research on sustainable development model of enterprises," *J. Liaoning Univ.*, vol. 28, no. 3, pp. 12–15, 2000.

[3] R. Rai, S. Kameshwaran, and M. K. Tiwari, "Machine-tool selection and operation allocation in FMS: Solving a fuzzy goal-programming model using a genetic algorithm," *Int. J. Prod. Res.*, vol. 40, no. 3, pp. 641–665, Nov. 2002.

[4] F. T. S. Chan, R. Swarnkar, and M. K. Tiwari, "Fuzzy goal-programming model with an artificial immune system (AIS) approach for a machine tool selection and operation allocation problem in a flexible manufacturing system," *Int. J. Prod. Res.*, vol. 43, no. 19, pp. 4147–4163, Feb. 2005.

[5] S. Jaganathan, J. J. Erinjeri, and J. I. Ker, "Fuzzy analytic hierarchy process based group decision support system to select and evaluate new manufacturing technologies," *Int. J. Adv. Manuf. Technol.*, vol. 32, nos. 11–12, pp. 1253–1262, May 2007.

[6] M. Khouja, "The use of data envelopment analysis for technology selection," *Comput. Ind. Eng.*, vol. 28, no. 1, pp. 123–132, Jan. 1995.

[7] A. I. Maghsoodi, A. Mosavi, T. Rabczuk, and E. Zavadskas, "Renewable energy technology selection problem using integrated H-SWARA-MULTIMOORA approach," *Sustainability*, vol. 10, no. 12, p. 4481, Dec. 2018.

[8] S. Peng *et al.*, "An integrated decision model of restoring technologies selection for engine remanufacturing practice," *J. Cleaner Prod.*, vol. 206, pp. 598–610, Jan. 2019.

[9] S. Narayanamoorthya, S. Geethaa, R. Rakkiyappana, and Y. H. Joob, "Interval-valued intuitionistic hesitant fuzzy entropy based VIKOR method for industrial robots selection," *Expert Syst. Appl.*, vol. 121, pp. 28–37, may 2019.

[10] H.-C. Liu, M.-Y. Quan, H. Shi, and C. Guo, "An integrated MCDM method for robot selection under interval-valued Pythagorean uncertain linguistic environment," *Int. J. Intell. Syst.*, vol. 34, no. 2, pp. 188–214, Feb. 2019.

[11] R. C. Baker and S. Talluri, "A closer look at the use of data envelopment analysis for technology selection," *Comput. Ind. Eng.*, vol. 32, no. 1, pp. 101–108, Jan. 1997.

[12] R. Ramanathan, "Comparative Risk Assessment of energy supply technologies: A data envelopment analysis approach," *Energy*, vol. 26, no. 2, pp. 197–203, Feb. 2001.

[13] R. F. Saen, "A decision model for technology selection in the existence of both cardinal and ordinal data," *Appl. Math. Comput.*, vol. 181, no. 2, pp. 1600–1608, Oct. 2006.

[14] S. Talluri, M. M. Whiteside, and S. J. Seipel, "A nonparametric stochastic procedure for FMS evaluation," *Eur. J. Oper. Res.*, vol. 124, no. 3, pp. 529–538, Aug. 2000.

[15] L. M. Seiford and J. Zhu, "Context-dependent data envelopment analysis—Measuring attractiveness and progress," *Omega*, vol. 31, no. 5, pp. 397–408, Oct. 2003.

[16] J. Sarkis and S. Talluri, "A decision model for evaluation of flexible manufacturing systems in the presence of both cardinal and ordinal factors," *Int. J. Prod. Res.*, vol. 37, no. 13, pp. 2927–2938, Nov. 1999.

[17] S. Talluri and K. P. Yoon, "A cone-ratio DEA approach for AMT justification," *Int. J. Prod. Econ.*, vol. 66, no. 2, pp. 119–129, Jun. 2000.

[18] J. Shang and T. Sueyoshi, "A unified framework for the selection of a flexible manufacturing system," *Eur. J. Oper. Res.*, vol. 85, no. 2, pp. 297–315, Sep. 1995.

[19] M. Braglia and A. Petroni, "Evaluating and selecting investments in industrial robots," *Int. J. Prod. Res.*, vol. 37, no. 18, pp. 4157–4178, Dec. 1999.

[20] A. Charnes, W. W. Cooper, and E. Rhodes, "Measuring the efficiency of decision making units," *Eur. J. Oper. Res.*, vol. 2, no. 6, pp. 429–444, Nov. 1978.

[21] R. D. Banker, A. Charnes, and W. W. Cooper, "Some models for estimating technical and scale inefficiencies in data envelopment analysis," *Manage. Sci.*, vol. 30, no. 9, pp. 1078–1092, Sep. 1984.

[22] T. R. Sexton, R. H. Silkman, and A. J. Hogan, "Data envelopment analysis: Critique and extensions," *New Directions Program Eval.*, vol. 1986, no. 32, pp. 73–105, Dec. 1986.

[23] J. Doyle and R. Green, "Efficiency and Cross-efficiency in DEA: Derivations, meanings and uses," *J. Oper. Res. Soc.*, vol. 45, no. 5, pp. 567–578, May 1994.

[24] Y.-M. Wang and K.-S. Chin, "A neutral DEA model for cross-efficiency evaluation and its extension," *Expert Syst. Appl.*, vol. 37, no. 5, pp. 3666–3675, May 2010.

[25] J. Wu, L. Liang, Y. Zha, and F. Yang, "Determination of cross-efficiency under the principle of rank priority in cross-evaluation," *Expert Syst. Appl.*, vol. 36, no. 3, pp. 4826–4829, Apr. 2009.

[26] I. Contreras, "Optimizing the rank position of the DMU as secondary goal in DEA cross-evaluation," *Appl. Math. Model.*, vol. 36, no. 6, pp. 2642–2648, Jun. 2012.

[27] J. Wu, J. Sun, and L. Liang, "Cross efficiency evaluation method based on weight-balanced data envelopment analysis model," *Comput. Ind. Eng.*, vol. 63, no. 2, pp. 513–519, Sep. 2012.

[28] L. Liang, J. Wu, W. D. Cook, and J. Zhu, "The DEA game cross-efficiency model and its Nash equilibrium," *Oper. Res.*, vol. 56, no. 5, pp. 1278–1288, Mar. 2008.

[29] Y.-M. Wang, K.-S. Chin, and P. Jiang, "Weight determination in the cross-efficiency evaluation," *Comput. Ind. Eng.*, vol. 61, no. 3, pp. 497–502, Oct. 2011.

[30] J. Wu, J. Sun, and L. Liang, "DEA cross-efficiency aggregation method based upon Shannon entropy," *Int. J. Prod. Res.*, vol. 50, no. 23, pp. 6726–6736, Oct. 2012.

[31] G.-L. Yang, J.-B. Yang, W.-B. Lin, and X.-X. Li, "Cross-efficiency aggregation in DEA models using the evidential-reasoning approach," *Eur. J. Oper. Res.*, vol. 231, no. 2, pp. 393–404, Dec. 2013.

[32] A. Oukil, "Embedding OWA under preference ranking for DEA cross-efficiency aggregation: Issues and procedures," *Int. J. Intell. Syst.*, vol. 34, no. 5, pp. 947–965, May 2019.

[33] L. Song and F. Liu, "An improvement in DEA cross-efficiency aggregation based on the Shannon entropy," *Int. Trans. Oper. Res.*, vol. 25, no. 2, pp. 705–717, Mar. 2018.

[34] C. Kao and S.-T. Liu, "Cross efficiency measurement and decomposition in two basic network systems," *Omega*, vol. 83, pp. 70–79, Mar. 2019.

[35] H.-H. Liu, Y.-Y. Song, and G.-L. Yang, "Cross-efficiency evaluation in data envelopment analysis based on prospect theory," *Eur. J. Oper. Res.*, vol. 273, no. 1, pp. 364–375, Feb. 2019.

[36] J. Fan, J. Lan, J. Zhang, Z. Wang, and M. Wu, "A novel cross-efficiency evaluation method under hesitant fuzzy environment," *J. Intell. Fuzzy Syst.*, vol. 36, no. 1, pp. 371–383, Feb. 2019.

[37] M. K. Ghorabaee, E. K. Zavadskas, L. Olfat, and Z. Turskis, "Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS)," *Informatica*, vol. 26, no. 3, pp. 435–451, Mar. 2015.

[38] X. Peng and L. Chong, "Algorithms for neutrosophic soft decision making based on EDAS, new similarity measure and level soft set," *J. Intell. Fuzzy Syst.*, vol. 32, no. 1, pp. 955–968, Jan. 2017.

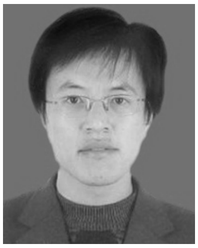
[39] G. Ilieva, T. Yankova, and S. Klisarova-Belcheva, "Decision analysis with classic and fuzzy EDAS modifications," *Comput. Appl. Math.*, vol. 37, no. 5, pp. 5650–5680, Nov. 2018.

[40] W.-Z. Liang, G.-Y. Zhao, and S.-Z. Luo, "An integrated EDAS-ELECTRE method with picture fuzzy information for cleaner production evaluation in gold mines," *IEEE Access*, vol. 6, pp. 65747–65759, 2018.

[41] Y.-Y. Li, J.-Q. W. Wang, and T. L. Wang, "A linguistic neutrosophic multi-criteria group decision-making approach with EDAS method," *Arabian J. Sci. Eng.*, vol. 44, no. 3, pp. 2737–2749, Mar. 2019.

[42] Ž. Stevic, M. Vasiljevic, A. PuÅąka, I. Tanackov, R. Junevicius, and S. Veskovic, "Evaluation of suppliers under uncertainty: A multiphase approach based on fuzzy AHP and fuzzy EDAS," *Transport*, vol. 34, no. 1, pp. 52–66, Jan. 2019.

[43] X. Feng, C. Wei, and Q. Liu, "EDAS method for extended hesitant fuzzy linguistic multi-criteria decision making," *Int. J. Fuzzy Syst.*, vol. 20, no. 8, pp. 2470–2483, Dec. 2018.



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