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A HYBRID MEASURE OF ENERGY EFFICIENCY BASED ON FUZZY DEA WITH UNDESIRABLE CONSTRAINTS: AN EMPIRICAL ANALYSIS FOR G20 COUNTRIES

Xiaoling Wang[1], Feng He[1], Junhu Ruan[2] and Olaf Weber[3]

[1]School of Economics and Management
University of Science & Technology Beijing
No. 30, Xueyuan Road, Haidian District, Beijing 100083, P. R. China
xiaolingwang@ustb.edu.cn; hefeng@manage.ustb.edu.cn

[2]College of Economics and Management
Northwest A&F University
No. 3, Taicheng Road, Yangling 712100, P. R. China
ruanjunhu@163.com

[3]School of Environment, Enterprise & Development
University of Waterloo
Waterloo, ON, N2L 3G1, Canada
oweber@uwaterloo.ca

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Abstract. *The Data Envelopment Analysis has been identified as one of the most reliable, convenient, and widely used approaches to evaluate energy efficiencies of a set of decision-making units. To conquer the difficulty of processing imprecise or vague observations in real-world problems, the fuzzy DEA method was promoted and developed as an adjustment and solution to the drawback of conventional DEA models. Drawing on the existing fuzzy models, this study proposes an Undesirable-Hybrid-Fuzzy DEA (UHFDEA) by taking the coexistence of radical and non-radical inputs and/or outputs into account. An application of the suggested approach is further presented in an empirical analysis for the Group 20 countries. The findings indicate that the model is not only significant for assessing energy efficiency on a national level, but also serves as a reliable and applicable tool for relative efficiency evaluation in similar situations.*
Keywords: Hybrid measure, Fuzzy DEA, Energy efficiency, Undesirable output, Group 20

1. **Introduction.** Energy efficiency is expected to play a key role in improving production outputs of the energy system with minimum costs, thereby partly addressing the challenges of a global energy transition through lower energy use. The Data Envelopment Analysis (DEA) initiated by Charnes et al. in 1978 has been considered the most mature and versatile method to evaluate the relative efficiencies for homogeneous Decision-Making Units (DMUs) with multiple heterogeneous inputs and outputs [1]. Moreover, this non-parametric model has been developed with the total factor energy efficiency framework [2]. In accordance with environmental conservation and protection awareness worldwide, especially after the first United Nations conference on environment and development, hazard byproducts and undesirable outputs deriving from energy production and usage have been strongly considered in efficiency measurement [3].

The studies regarding energy efficiency measurement are fruitful on divergent levels, yet few studies have investigated or commented on incorporating imprecise data for evaluation. Fuzzy variables commonly exist and are more informative and realistic in real-world modeling and decision making [4,5]. Government support, policy intervention, and other closely-related subjective in-puts also have impacts on energy utilization level [6]. Despite the outstanding advantages of DEA, such vague observed values are not treatable in the conventional models, resulting in the formation and development of Fuzzy DEA (FDEA).

Fuzzy DEA was first introduced by Sengupta in 1992 [7] based on the fuzzy set theory [8]. Since its appearance, numerous fuzzy approaches have been proposed to deal with the inaccuracy and ambiguity in DEA. For example, Ignatius et al. proposed a DEA-based framework for evaluating carbon efficiency using the fuzzy ranking approach. Two numerical examples were also tested to illustrate the model in which the input-output data are described by fuzzy numbers [9]. Wanke et al. combined bootstrapped regressions with the traditional FDEA models to access the productive efficiency in Nigerian airports. Policy designs for Nigerian airports were then suggested by controlling the fuzziness and randomness [10]. Khalili-Damghani et al. considered undesirable outputs when rating the performance of combined cycle power plants in Iran with interval data. The most economic scale sizes as well as the practical benchmarks for the plants were proposed afterwards [11]. Hsiao et al. introduced the Slack-Based Measure (SBM) into FDEA to observe the performance of 24 commercial banks in Taiwan [12]. Azadeh et al. also developed a series of studies on layout optimization with the help of fuzzy DEA and fuzzy simulation [13].

Collectively, the research on FDEA is relatively new compared with traditional DEA models; however, it has gained momentum over the past two decades as inaccuracies are inevitable in reality. Research to date has provided a relatively large array of FDEA's applications and solution methods, as well as analytical perspectives. Despite extensive research on the FDEA, few studies have focused on the coexistence of radial and non-radial variables, and none have simultaneously examined the fuzzy models based on such hybrid-featured distance function with undesirable and non-separable data, which also commonly exist in various situations. Therefore, an Undesirable-Hybrid-Fuzzy DEA (UHFDEA) model is proposed in the study to address the problem. The contribution of this paper is two-fold: in terms of analytical perspective, government intervention related to energy systems has been considered in the efficiency evaluation process; in terms of model development, an extended fuzzy DEA has been offered to enrich the existing approaches to further solve certain real-world problems.

The remainder of the paper is organized as follows: Section 2 illustrates the research design and the construction of a generalized UHFDEA model; Section 3 presents the application of the model using empirical data of the G20 countries; Section 4 concludes the paper and illustrates future directions of study.

2. **Research Design and Model Construction.**

2.1. **Research design.** Grounded in total factor productivity conception and optimizing theory, the DEA approach is employed to finish the efficiency evaluation because of the following particular features: it is an effective as well as flexible tool for evaluating the relative efficiency of homogeneous subjects with multiple heterogeneous performance measures; it avoids the shortcoming of subjective estimates when a priori weighting and aggregating for inputs or out-puts are eliminated; and it has a number of specified models that can be used and modified for various purposes [14].

Despite the advantages listed above, the conventional DEA models only deal with variables that are accurate and crisp. Thus, a solution is required to address the ambiguity and uncertainty of certain inputs and/or outputs in real-world problems. Drawing on the fuzzy set theory as well as the research gap identified in Section 1, this paper aims to propose a new efficiency assessment model (i.e., the UHFDEA) by incorporating the hybrid measure of efficiency with undesirable constraints into the basic FDEA. The next step is to identify the fuzzy scores or score intervals by choosing a mathematical approach, followed by a ranking phase to derive a comprehensive efficiency number for each

DMU based on the entropy concept. Finally, a case for specific countries is conducted to demonstrate the applicability and reliability of the model.

2.2. **Model construction.** Suppose we have n DMUs with m input variables and s output variables. Let the observed input and output data matrices be $X \in R^{m\times n}$ and $Y \in R^{s\times n}$, respectively. Then for any DMU_o, a standard basic CCR model is defined as:

$$\rho^*_{ccr} = \min(\theta - \phi) \tag{1}$$

$$\text{Subject to} \quad \theta x_o \geq X\lambda;\ \phi y_o \leq Y\lambda;\ \theta \leq 1,\ \phi \geq 1,\ \lambda \geq 0$$

where λ is a nonnegative vector in R^n. Input and output data in model (1) are fuzzy numbers and represented as $\bar{x}_{ij}$ $(i = 1, 2, \ldots, m)$ and $\tilde{y}_{rj}$ $(r = 1, 2, \ldots, s; j = 1, 2, \ldots, n)$, respectively. The corresponding metrics are denoted as $\widetilde{X}$ and $\widetilde{Y}$, respectively. Thus, the fuzzy CCR model can be formulated as:

$$\rho^*_{f-ccr} = \min(\theta - \phi) \tag{2}$$

$$\text{Subject to} \quad \theta \tilde{x}_o \geq \widetilde{X}\lambda;\ \phi \tilde{y}_o \leq \widetilde{Y}\lambda;\ \theta \leq 1,\ \phi \geq 1,\ \lambda \geq 0$$

By referencing [15], the input matrix can be decomposed into a radial part as $\widetilde{X}^R \in R^{m1\times n}$ and a non-radial part as $\widetilde{X}^{NR} \in R^{m2\times n}$ with $m = m1 + m2$. Analogously, the output matrix can be decomposed into a radial part as $\widetilde{Y}^R \in R^{s1\times n}$ and a non-radial part as $\widetilde{Y}^{NR} \in R^{s2\times n}$ with $s = s1 + s2$. Then a Hybrid-Fuzzy-DEA model will be described as:

$$\begin{aligned}\rho^*_{hf} = {} & \left[1 - \frac{m1}{m}(1-\theta) - \frac{1}{m}\sum_{i=1}^{m2} s_i^{NR-} \Big/ \tilde{x}_{io}^{NR}\right] \tilde{x}_{io}^{NR} \Big/ \left[1 + \frac{s1}{s}(\phi - 1)\right. \\ & \left. + \frac{1}{s}\sum_{r=1}^{s2} S_r^{NR} \Big/ \tilde{y}_{ro}^{NR}\right]\end{aligned} \tag{3}$$

$$\text{Subject to} \quad \begin{array}{l} \theta \tilde{x}_o^R = \widetilde{X}^R\lambda + s^{R-};\ \tilde{x}_o^{NR} = \widetilde{X}^{NR}\lambda + s^{NR-}; \\ \phi \tilde{y}_o^R = \widetilde{Y}^R\lambda - s^{R+};\ \tilde{y}_o^{NR} = \widetilde{Y}^{NR}\lambda - s^{NR+}; \\ \theta \leq 1,\ \phi \geq 1,\ \lambda \geq 0,\ s^{R-} \geq 0,\ s^{NR-} \geq 0, \\ s^{R+} \geq 0,\ s^{NR+} \geq 0 \end{array}$$

Based on model (3), undesirable outputs are considered when certain yields are non-separable from a production process, and are radial in most cases. Accordingly, the output matrix will be re-decomposed into the desirable radial part, undesirable radial part, desirable non-radial part, and undesirable non-radial part as $\widetilde{Y}^{Rg} \in R^{s1\times n}$, $\widetilde{Y}^{Rb} \in R^{s2\times n}$, $\widetilde{Y}^{NRg} \in R^{s3\times n}$, and $\widetilde{Y}^{NRb} \in R^{s4\times n}$, respectively [16].

The Undesirable-Hybrid-Fuzzy-DEA model can be described as:

$$\begin{aligned}\rho^*_{uhf} = {} & 1 - \frac{m1}{m}(1-\theta) - \frac{1}{m}\sum_{i=1}^{m2} \frac{s_i^{NR-}}{\tilde{x}_{io}^{NR}} \Big/ 1 + \frac{s1}{s}(\phi - 1) + \frac{s2}{s}(\varphi - 1) \\ & + \frac{1}{s}\sum_{r=1}^{s3} \frac{S_r^{NRg+}}{\tilde{y}_{ro}^{NRg}} + \frac{1}{s}\sum_{j=1}^{s4} \frac{S_j^{NRb+}}{\tilde{y}_{jo}^{NRb}}\end{aligned} \tag{4}$$

$$\text{Subject to} \quad \begin{array}{l} \theta \tilde{x}_o^R = \widetilde{X}^R\lambda + s^{R-};\ \tilde{x}_o^{NR} = \widetilde{X}^{NR}\lambda + s^{NR-};\ \phi \tilde{y}_o^{Rg} = \widetilde{Y}^{Rg}\lambda - s^{Rg+}; \\ \varphi \tilde{y}_o^{Rb} = \widetilde{Y}^{Rb}\lambda - s^{Rb+};\ \tilde{y}_o^{NRg} = \widetilde{Y}^{NRg}\lambda - s^{NRg+};\ \tilde{y}_o^{NRb} = \widetilde{Y}^{NRb}\lambda - s^{NRb+}; \\ \theta \leq 1,\ \phi \geq 1,\ \lambda \geq 0,\ s^{Rg+} \geq 0,\ s^{Rg-} \geq 0,\ s^{Rb+} \geq 0,\ s^{Rb-} \geq 0,\ s^{NR-} \geq 0, \\ s^{NRg+} \geq 0,\ s^{NRg-} \geq 0,\ s^{NRb+} \geq 0,\ s^{NRb-} \geq 0;\ s = s1 + s2 + s3 + s4 \end{array}$$

The tolerance approach, the α-level based approach, the fuzzy ranking approach, and the possibility approach are available to solve program (4). The α-level based approach is selected in the paper due to its popularity and maturity [17].

Based on the two-level mathematical model suggested by Kao and Liu [18], the fuzzy model can be converted into a pair of parametric programs to find the lower and upper bounds of a set of efficiency scores under different confidence intervals (i.e., α-level). Thus, the lower bound $(w_p)^L_\alpha$ and the upper bound $(w_p)^U_\alpha$ of the undesirable fuzzy efficiency score in model (4) can be solved for a given α ($\alpha \in [0, 1]$) as follows:

$$
\begin{aligned}
(w_p)^L_\alpha &= \min_{\substack{(X_{ij})^L_\alpha \le x_{ij} \le (X_{ij})^U_\alpha \\ (Y_{rj})^L_\alpha \le y_{rj} \le (Y_{rj})^U_\alpha \\ \forall r,i,j}} \left\{ \tilde{w}_p = \rho^*_{uhf} = \frac{1 - \dfrac{m1}{m}(1-\theta) - \dfrac{1}{m}\sum_{i=1}^{m2} \dfrac{s_i^{NR-}}{\tilde{x}_{io}^{NR}}}{1 + \dfrac{s1}{s}(\phi - 1) + \dfrac{s2}{s}(\varphi - 1) + \dfrac{1}{s}\sum_{r=1}^{s3} \dfrac{S_r^{NRg+}}{y_{ro}^{NRg}} + \dfrac{1}{s}\sum_{j=1}^{s4} \dfrac{S_j^{NRb+}}{y_{jo}^{NRb}}} \right\} \\
(w_p)^U_\alpha &= \max_{\substack{(X_{ij})^L_\alpha \le x_{ij} \le (X_{ij})^U_\alpha \\ (Y_{rj})^L_\alpha \le y_{rj} \le (Y_{rj})^U_\alpha \\ \forall r,i,j}} \left\{ \tilde{w}_p = \rho^*_{uhf} = \frac{1 - \dfrac{m1}{m}(1-\theta) - \dfrac{1}{m}\sum_{i=1}^{m2} \dfrac{s_i^{NR-}}{\tilde{x}_{io}^{NR}}}{1 + \dfrac{s1}{s}(\phi - 1) + \dfrac{s2}{s}(\varphi - 1) + \dfrac{1}{s}\sum_{r=1}^{s3} \dfrac{S_r^{NRg+}}{y_{ro}^{NRg}} + \dfrac{1}{s}\sum_{j=1}^{s4} \dfrac{S_j^{NRb+}}{y_{jo}^{NRb}}} \right\}
\end{aligned}
\tag{5}
$$

where $\left[(X_{ij})^L_\alpha, (X_{ij})^U_\alpha\right]$ and $\left[(Y_{rj})^L_\alpha, (Y_{rj})^U_\alpha\right]$ are α-level form of the fuzzy inputs and outputs, respectively. Further, an entropy-based technique is utilized to combine the efficiency scores and convert them into comprehensive and sortable final efficiency indexes using the formulas listed below [19]:

$$e_l = (\ln n)^{-1} \sum_{i=1}^{n} E^*_{il} \ln E^*_{il} \tag{6}$$

$$w_l = (1 - e_l) \Big/ \sum_{l=1}^{k} (1 - e_l) \tag{7}$$

$$EE_i = \sum_{l}^{k} w_l E_{il} \tag{8}$$

where EE_i is the final comprehensive efficiency score for DMU_i ($i = 1, 2, \ldots, n$); EE_{il} ($l = 1, 2, \ldots k$) are a set of efficiency numbers of DMU_i derived from the l-th model; EE^*_{il} are the normalized version of EE_{il}; e_l and w_l are the entropy value and the weight of the l-th model, respectively.

3. **Empirical Analysis.**

3.1. **Sample.** To observe "efficiency gaps" among divergent nations, especially the ones with distinct features, the newly founded international group – the Group 20 (G20) – is selected as the research sample to finish the empirical test.

Established in 1999, the G20 is composed of 20 major economies in the world, including nine major developed/advanced countries (i.e., Australia, Canada, France, Germany, Italy, Japan, South Korea, the United Kingdom and the United States); the five biggest emerging markets – the BRICS – Brazil, China, India, Russia, and South Africa; and five important developing countries (i.e., Argentina, Indonesia, Mexico, Saudi Arabia, and Turkey), along with the European Union (EU). Despite the countries' divergent backgrounds, the G20 exerts great influences on international energy, economy, and environment. The group accounts for two thirds, 90%, and 80% of the world's total population, GDP, and CO_2 emissions, respectively [20]. The countries are also the major players in the global energy market. All this has made the group very attractive for observation in the realm of national energy efficiency comparison.

The members of the BRICS are identified as the five "stars" with much faster growth rates and larger emissions than the rest. Therefore, the paper separates the BRICS from other developing countries in the G20. Considering that the EU members keep changing over time and some indicators cannot simply be added up to reflect the union's status, this study replaces the EU with Spain to form a new "Group 20" by referencing Lee's study [21]. Data for the countries in year 2012 are selected in the next section.

3.2. **Variable and data source.** Drawing on the existing literature on measuring economy-wide energy efficiency [3,22], this study identifies the following variables as the inputs and outputs:

Real GDP: Real GDP in the study, which is also the "good" one in the model, is collected directly from the World Bank Database (WB Database) denoted with market exchange rate chained in year 2005 (in US dollars).

CO_2 emissions: Carbon dioxide is emitted from fossil fuels use and is considered as the bad yet non-separable by-product of energy consumption. CO_2 emissions data are collected directly from the British Petroleum database.

Labor employment: Labor, along with capital, has always been the critical input for almost all production activities, not just energy generation. The labor data are calculated using working-age population and employment rates data from the WB Database.

Capital stock: Capital stock numbers are calculated using the perpetual inventory method with the base year of 1990 [23]. The depreciation rates for advanced economies, BRICS and developing countries are set as 7%, 5% and 4%, respectively [24]. The result is also denoted in chained U.S. dollars in the year 2005.

Energy consumption: Total primary energy use is also critical for efficiency evaluation. The data are derived directly from the British Petroleum database.

Governance input: To provide a comprehensive and reliable description of government intervention, this paper constructs a linguistic set of triangular fuzzy numbers [25] based on the qualitative descriptions from the World Energy Council (WEC). The WEC evaluates a nation's energy governance level by observing whether a country has "energy efficiency law", "energy law with energy efficiency targets", "national energy agency" and "ministry department for energy efficiency" [26].

The statistical description of the input and output variables is listed in Table 1.

Table 1. Statistical description of variable

Variable	Average	Std.	Min	Max	Unit	Arribute
Capital	5743.71	7466.39	716.89	33023.00	Billion	Non-radial crisp input
Labor	100.09	182.52	9.74	753.02	Million	Non-radial crisp input
Energy	482.14	703.54	82.15	2735.16	Mtoe	Radial crisp input
Governance	0.625	0.25	0.00	1.00	–	Non-radial fuzzy input
GDP	2203.90	3098.66	3076.50	14231.58	Billion	Non-radial crisp output
CO_2	1362.11	2216.27	190.48	9208.05	Mtoe	Undesirable radial crisp output

3.3. **Empirical test of the G20.** Based on the UHFDEA model proposed in Section 2, empirical tests are conducted using the data fuzzy numbers prepared in Section 3.2. The final efficiency scores for the 20 countries archived from the proposed UHFDEA with various α levels are listed in Table 2.

As can be seen in Table 2, the United States, United Kingdom, and France reached the efficiency frontier and were the most efficient countries in the G20, whereas India, Indonesia, and Russia were the most inefficient economies compared to the others. Moreover, remarkable efficiency gaps also appeared among the three groups where the advanced economies usually ranked better than developing countries in general terms.

That is, the least efficient countries always belong to lower or middle income groups. This finding is consistent with the single factor efficiency (i.e., energy intensity) and the majority of observations from similar studies [3,22,23]. The performance of the BRICS in general was lower than the other five emerging markets, which is slightly unexpected yet reasonable. The BRICS has seen striking and continuous economic growth for years,

Table 2. Energy efficiency derived from UHFDEA for G20

Country	**Efficiency**	**Rank**	**Country**	**Efficiency**	**Rank**
United States	1.000	1	Argentina	0.744	12
United Kingdom	1.000	1	Turkey	0.721	13
France	1.000	1	Mexico	0.688	15
Spain	0.981	4	Saudi Aribia	0.676	16
Japan	0.958	5	Indonesia	0.591	19
Italy	0.952	6	***Average mean***	***0.703***	–
Germany	0.916	7	China	0.771	10
Australia	0.812	8	Brazil	0.769	11
Canada	0.772	9	South Africa	0.659	17
South Korea	0.695	14	India	0.638	18
Average mean	***0.909***	–	Russia	0.578	20
–	–	–	***Average mean***	***0.684***	–

especially during the first decade in the 21st century. Nevertheless, environmental deterioration and rapid-growing CO_2 emissions have been the undesirable outcomes along with the "grey" growth pattern in these countries, which in turn consumed the fruits of the efficiency gains associated with income improvement, especially when China, India, and Russia became the top four emitters along with the United States. Specifically, Russia was the most inefficient country in the G20 and the BRICS as well; this result is also consistent with [27][1], indicating the reliability and validity of the proposed model.

4. **Conclusions.** Energy efficiency on a country level is consistently at the forefront of today's economic, political, and environmental concerns worldwide. Extensive studies have been done to observe the efficiency gaps and augmentation capacity. The literature mentioning fuzzy DEA focuses either on radial measures represented by the CCR or non-radial approaches expressed by the SBM. However, differences that exist in real-world variables are far from simple. This study thus proposes a generalized hybrid model to comprehensively incorporate the dispensable, non-separable, fuzzy, and undesirable features of inputs and/or outputs. Further mathematical solutions and concepts are suggested to support the model as well. An empirical analysis of the G20 countries was conducted to demonstrate the applicability and validity of the UHFDEA in this paper.

With its extensive influence on the global economy, energy market, and climate change, the G20 is a suitable sample for the study to observe efficiency gaps between countries with divergent backgrounds and income levels. For the model settings, GDP and CO_2 emissions are identified as non-radial good performance and undesirable radial output, respectively. Meanwhile, labor force and capital stock are set as non-radial normal crisp input variable, whereas energy consumption and government support are selected as non-separable crisp input and fuzzy input, respectively. The results derived from the proposed UHFDEA reveal that advanced economies still outweighed their counterparts of less developed countries in terms of energy efficiency. In particular the United States, the United Kingdom, and France were UHFDEA efficient, while Canada and South Korea performed unsatisfactorily in the sub-group. For the lower performing countries, the five emerging markets – Argentina, Saudi Arabia, Mexico, Turkey, and Indonesia – excelled the former five fastest-growing stars (i.e., BRICS), reflecting severe environmental constraints facing the BRICS in general.

[1] In [27], the authors evaluated the total factor energy efficiencies of the BRICS countries with capital stock, labor use, primary energy consumption, and number of patents as inputs and real GDP as output. The results indicate that Russia ranked as the least-inefficient country in the BRICS during 2003-2010.

This paper proposes a hybrid measure of efficiency based on fuzzy DEA with undesirable constraints. The UFHDEA is an extension of the existing fuzzy DEA models and can be applied to other cases with similar concerns. The empirical test and analysis for the G20 countries also present the validity and reliability of the suggested approach, showing that the approach could serve as a useful tool to deal with real-world problems. Future studies are expected to expand the sample into panel data with more diversified nations to observe the dynamic change in energy efficiencies with undesirable and fuzzy numbers. In addition, the model can be converted into output-oriented or non-oriented versions with VRS (Variable Return to Scale) hypotheses.

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