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A data envelopment analysis model with interval data and undesirable output for combined cycle power plant performance assessment

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ABSTRACT

Determining the optimal scale size of a combined cycle power plant is inherently a complex problem often with multiple and conflicting criteria as well as uncertain factors. The complexity of the problem is compounded by the production of undesirable outputs and the presence of natural and managerial disposability. We propose a customized data envelopment analysis (DEA) method for solving the return to scale (RS) problem in the presence of uncertain data and undesirable outputs. A combined cycle power plant is considered a decision making unit (DMU) which consumes fuels to produce electricity and emissions. The uncertainty of the inputs and outputs are modeled with interval data and the emissions are assumed to be undesirable outputs. The proposed DEA method determines the interval efficiency scores of the DMUs and offers a practical benchmark for enhancing the efficiency scores. We demonstrate the applicability of the proposed method and exhibit the efficacy of the procedure with a six-year study of 17 combined cycle power plants in Iran. The main contributions of this paper are six fold: we (1) model the uncertainties in the input and output data using interval data; (2) consider undesirable outputs; (3) determine the efficiency scores of the DMUs as interval values; (4) develop a group of indices to distinguish between the efficient and inefficient DMUs; (5) determine the most economic scale size for the efficient DMUs; and (6) determine practical benchmarks for the inefficient DMUs.

1. Introduction

Energy generation, distribution and consumption play a vital role in the economy. Generation and distribution of clean energy and sustainable development considerations are essential for future generations especially in developing countries. Therefore, energy systems should systematically be assessed and updated in order to improve the performance, to determine the economic scale size and to efficiently utilize resources.

A great deal of research has been devoted to the field of energy system assessment and evaluation during recent years. Azade, Ghaderi, and Maghsoudi (2008) proposed an integrated hierarchical approach based on data envelopment analysis (DEA), principal component analysis and numerical taxonomy to locate solar plants in different regions and cities in Iran. Aguirre, Villalobos, Phelan, and Pacheco (2011) presented a methodology to measure relative industrial energy efficiency across plants within a manufacturing sector through the use of energy-production signatures. They used linear programming, regression, benchmarking and simulation models to study the behavior of a representative manufacturing plant. The methodology was validated using data from the Department of Energy database. Bampatsou, Papadopoulos, and Zervas (2013) used a DEA model to determine the technical efficiency index of EU-15 countries. Salazar-Ordóñez, Pérez-Hernández, and Martín-Lozano (2013) estimated the potential efficiency of the sugar beet crop in Spain using a DEA model. Kagawa, Takezono, Suh, and Kudoh (2013) evaluated the efficiency of an advanced bio-diesel plant in Japan using DEA. Fang, Hu, and Lou (2013) used an input-oriented variable return to scale (VRS) DEA model to compute the pure technical efficiency and energy-saving targets. Fang et al. (2013) utilized a four-stage DEA and studied the effects of industry characteristics on the energy-saving targets.

Chang, Zhang, Danao, and Zhang (2013) proposed a non-radial DEA model with slack-based measures to analyze the environmental

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efficiency of the Chinese transportation sector. Zhou, Xing, Fang, Liang, and Xu (2013) proposed a new non-radial DEA approach by integrating the entropy weight and the slack-based model to evaluate efficiency of the Chinese power industry at the provincial level. Çelen (2013) used stochastic frontier analysis to analyze the efficiency performances of Turkish electricity distribution companies. Çelen (2013) measured "how the efficiency performances of the electricity distribution regions were affected by the merges between distribution regions". Kuosmanen, Saastamoinen, and Sipiläinen (2013) compared the impact of three methods on cost efficiency estimation and analysis. Kuosmanen et al. (2013) validated the performance of their approach using Monte Carlo simulations in a study of the electricity distribution industry in Finland. Vazhayil and Balasubramanian (2013) proposed deterministic and stochastic DEA models to optimize energy planning in the Indian power sector.

Wu, An, Xiong, and Chen (2013) proposed a method that considered undesirable outputs and analyzed congestion of industrial regions in China. Bian, He, and Xu (2013) evaluated regional energy efficiency in China based on a non-radial DEA model. Bian et al. (2013) treated non-fossil energy as a fixed input in order to measure energy savings as well as reduce Carbon dioxide (CO_2) emission for improving efficiency. Zhang, Zhou, and Choi (2013) modeled energy and CO_2 emission performance in electricity generation and proposed a meta-frontier non-radial directional distance function to consider the heterogeneous group of electricity generation, non-radial slacks, and undesirable outputs, simultaneously. Zhang et al. (2013) studied electricity generation in Korea and estimated the CO_2 emissions and the potential reductions in energy usage under different technological assumptions. Riccardi, Oggioni, and Toninelli (2012) estimated the efficiency of high energetic and CO_2 emissions in the cement production process in 21 countries. Riccardi et al. (2012) compared standard DEA models with a directional distance function approach to measure the efficiency in the presence and in the absence of CO_2 emission. Sueyoshi and Goto (2010) reformulated the original non-radial DEA model to handle undesirable (bad) outputs. They applied their method on the operational, environmental and combined efficiency measures of US coal-fired power plants. Wu, Fan, Zhou, and Zhou (2012) measured industrial energy efficiency by constructing both static and dynamic energy efficiency performance indices. Wu et al. (2012) considered undesirable outputs such as CO_2 emissions in their modeling framework. Mandal (2010) evaluated the Indian cement industry in the presence of emissions and undesirable outputs using a DEA model.

Although electricity is considered a form of clean energy, production of electricity using gas, steam, and combined cycle power plants often causes some emissions and pollutions. Therefore, the output of electricity production is often mixed with some unwanted and undesirable outputs. Consequently, it is critical to improve the process of efficiency measurement and the determination of economic scale size of electricity power plants. Moreover, better estimate of emissions and pollutions produced by power plants can enhance the strategic planning of sustainable development.

The problem of performance assessment of electrical power plants is challenging and complex. This problem usually involves multiple and often conflicting criteria and undesirable outputs which are often difficult to assess because of environmental uncertainties. The production of a variety of emissions, pollutions, and other undesirable outputs such as CO_2 causes further complications.

To the best of our knowledge, there is no single method in the literature that can measure the efficiency scores and to determine the most economic scale size of decision making units (DMUs) in the presence of undesirable outputs and uncertain data. In this paper, we propose a DEA method for measuring the performance of combined cycle power plants in the presence of pollution production and data uncertainty. A combined cycle power plant is assumed to be a DMU which consumes fossil fuels to produce electricity as desirable outputs and polluting gases (i.e., CO_2, SO_x and NO_x) as undesirable outputs. Moreover, the uncertainty of inputs and outputs during the planning horizon is modeled using interval data. The proposed approach is used to determine the most economic scale size of power plants and to present practical suggestions for efficiency improvement of inefficient DMUs. The proposed method is customized and applied to a case study of Iranian electrical power plants to illustrate its applicability and efficacy. The theoretical contributions of this paper are six fold: we (1) model the uncertainties in the input and output data using interval data; (2) consider undesirable outputs; (3) determine the efficiency scores of the DMUs as interval values; (4) develop a group of indices to distinguish between the efficient and inefficient DMUs; (5) determine the most economic scale size for the efficient DMUs; and (6) determine practical benchmarks for the inefficient DMUs.

The remainder of this paper is organized as follows. In Section 2, we briefly review the relevant literature on the conventional DEA models, uncertainty in DEA models, undesirable outputs in DEA models, RS in DEA models, and the applications of DEA models in power plants assessment and energy generation. In Section 3, we briefly outline the mathematical basis of the DEA models. In Section 4, we develop the proposed DEA model in the presence of interval data and undesirable outputs. In Section 5, we demonstrate the applicability of the proposed method and exhibit the efficacy of the procedure using a six-year study of 17 combined cycle power plants in Iran. In Section 6, we discuss the managerial implications and in Section 7, we present our conclusion and future research directions.

2. Literature review

DEA is a non-parametric method for evaluating the relative efficiency of DMUs with multiple inputs and multiple outputs (Charnes, Cooper, & Rhodes, 1978). The first DEA model (i.e., the CCR model) was proposed by Charnes et al. (1978) by considering the constant RS assumption. Banker, Charnes, and Cooper (1984) extended the Charnes et al.'s (1978) model by proposing the BCC model and considering the VRS assumption (Cooper, Seiford, & Tone, 2007).

2.1. Uncertainty in DEA models

In general, classical DEA problems are solved under the assumption that the values of parameters are specified precisely in a crisp environment. However, the observed values of the input and output data in real-world problems are often imprecise or vague. Imprecise evaluations is primarily the result of unquantifiable, incomplete and non-obtainable information. The most common form of uncertainty in DEA problems occurs when some or all of the relevant data are not known precisely. This type of uncertainty is called *ambiguity* (Inuiguchi & Ramík, 2000). The ambiguity in data can be modeled using the possibility approach parameterized through fuzzy sets, or the probability approach parameterized through random variables, or interval data. Several optimization methods such as stochastic programming, fuzzy mathematical programming, and interval mathematical programming are proposed to take into account various uncertainties in the optimization process (Liu, Huang, Liu, Fuller, & Zeng, 2003).

Stochastic programming methods model uncertainties with probability distributions derived from historical data (Peidro, Mula, Poler, & Lario, 2009), which may not be available in many real-life problems. Fuzzy set theory (Zadeh, 1978) and possibility theory provide a framework to deal with uncertainties in the form of vagueness and ambiguity (Dubois-Ferriere, Grossglauser, & Vetterli, 2003). Fuzzy mathematical programming usually requires assumptions about membership functions and rough estimation may increase vagueness and ambiguity. Interval programming is often used when the available data are insufficient for accurately estimating distribution functions or membership functions.

Despotis and Smirlis (2002) proposed a method to deal with imprecise data in DEA models. They proposed appropriate variable exchanges to achieve the solutions to the linear programs. Saati, Memariani, and Jahanshahloo (2002) proposed a fuzzy version of the CCR model first proposed by Charnes et al. (1978) for ranking the DMUs with asymmetrical triangular fuzzy numbers. They transformed the fuzzy CCR model into a crisp linear programming problem by applying an alternative alpha-cut approach. Wang, Greatbanks, and Yang (2005) proposed a method for measuring the lower and upper-bounds of efficiency scores of DMUs. This method is capable of incorporating decision makers' preferences for the input and output weights. Kao (2006) applied a two-level non-linear mathematical programming technique to derive the lower- and upper-bounds of efficiency scores of DMU in the presence of impreciseness. Emrouznejad, Rostamy-Malkhalifeh, Hatami-Marbini, and Tavana (2012) proposed two new DEA models for evaluating the relative efficiencies of DMUs with interval input and output data. Hatami-Marbini, Emrouznejad, and Tavana (2011) has classified the fuzzy DEA approaches into four classes of the tolerance approach, the α-level based approach, the fuzzy ranking approach and the possibility approach.

Other types of uncertainties often observed in real-life problems include probability, robustness, and interval data. Li (1998) proposed a stochastic DEA model by assuming random disturbances to represent the variations in the input–output data structure. Li (1998) defined the stochastic efficiency measure of the DMUs using joint probabilistic comparisons of the inputs and outputs with the other DMUs. Li (1998) proposed a chance-constrained programming problem to solve the stochastic DEA model and derived the deterministic equivalents for the cases of multivariate symmetric random disturbances and a single random factor in the production relationships.

Lahdelma and Salminen (2006) introduced a DEA method to handle uncertain or imprecise data in the form of stochastic efficiency measures called the stochastic multi-criteria acceptability analysis DEA method. Kao and Liu (2009) used a simulation method to obtain the efficiency distribution of the DMUS in DEA. Kao and Liu (2009) used the conventional method of average data to represent stochastic variables. This resulted in efficiency scores which were different from the mean efficiencies of the distributions estimated from the simulation method. They also applied the interval-data approach and concluded that the intervals were too wide to provide valuable information. Finally, they showed that, in the presence of multiple observations for each DMU, the stochastic-data approach produced more reliable and informative results than the average-data and interval-data approaches.

Tavana, Shiraz, Hatami-Marbini, Agrell, and Khalil (2012) proposed three fuzzy DEA models with respect to probability–possibility, probability–necessity and probability–credibility constraints. They also considered the probability constraints and presented a very comprehensive case study for a military base realignment and closure decision process at the U.S. Department of Defense to illustrate the features and the applicability of the proposed models. Sadjadi and Omrani (2008) proposed a DEA method based on robust optimization to deal with imprecise data in the Iranian electricity distribution companies. Sadjadi and Omrani (2008) proposed a new DEA method with uncertain output parameters based on the robust optimization approaches. They compared the results with stochastic frontier analysis using data from a group of electricity distribution companies and showed the effects of the data uncertainties on the performance of DEA outputs. The results indicated that the robust DEA approach was a relatively more reliable method for efficiency estimation and the ranking of strategies.

Sadjadi, Omrani, Abdollahzadeh, Alinaghian, and Mohammadi (2011), Sadjadi, Omrani, Makui, and Shahanaghi (2011) developed a new method which incorporated the robust counterpart of super-efficiency DEA. The perturbation and uncertainty in data was assumed as an ellipsoidal set and the robust super-efficiency DEA model was extended. In this method, a target setting was implemented with the uncertain data and the decision maker could search the envelop frontier and find the targets based on his/her preferences. In order to search the envelop frontier, they combined DEA with a multi-objective linear programming method. The combined method was capable of handling uncertainty in the data and finding the target values according to the decision makers' preferences. The results indicated that their combined model was suitable for target setting and for cases of uncertain data.

Abtahi and Khalili-Damghani (2011) proposed a mathematical formulation for measuring the performance of agility in supply chains using a single-stage fuzzy DEA. Khalili-Damghani, Taghavifard, Olfat, and Feizi (2011) applied the proposed formulation of Abtahi and Khalili-Damghani (2011) to measure the efficiency of agility in supply chains and used simulation to rank the interval efficiency scores. Khalili-Damghani and Abtahi (2011) measured the efficiency of just in time productions systems using a fuzzy DEA approach. Khalili-Damghani and Taghavifard (2012) proposed a fuzzy two-stage DEA approach for performance measurement in supply chains.

Khalili-Damghani, Taghavifard, Olfat, and Feizi (2012) used ordinal data in a new two-stage DEA approach for agility performance and illustrated the efficacy of their approach in a supply chain. Khalili-Damghani and Taghavifard (2013) performed sensitivity and stability analysis in two-stage DEA models with fuzzy data. They proposed several models for calculating the stability radius in DEA problems with considerable input and output variations and uncertainties. Khalili-Damghani and Tavana (2013) proposed a new network DEA model for measuring the performance of agility in supply chains. The uncertainty of the input and output data were modeled with linguistic terms and the proposed model was used to measure the performance of agility in a real-life case study of the dairy industry.

2.2. Undesirable inputs/outputs in DEA models

A DMU is usually called efficient if it can produce maximum outputs using minimum inputs. In this case, the associated DMU is situated on the efficient frontier and its efficiency score will be equal to unity (Banker et al., 1984; Charnes et al., 1978). Occasionally, a DMU may be efficient if the value of some outputs are as low as possible. These types of outputs are called undesirable and several studies have been proposed to model such outputs (Chung, Färe, & Grosskopf, 1997; Färe, Grosskopf, Lovell, & Pasurka, 1989; Jahanshahloo, Lotfi, Shoja, Tohidi, & Razavyan, 2005; Pathomsiri, Haghani, Dresner, & Windle, 2008; Seiford & Zhu, 2002). Pathomsiri et al. (2008) assessed the productivity of US airports, and the joint production of both desirable and undesirable output, i.e. delays of flight. There are several methods can deal with undesirable factors in efficiency evaluation. One of them is to treat the undesirable outputs as inputs (Wang, Wei, & Zhang, 2012). Another method is to use a non-linear programming approach to deal with undesirable outputs and utilize the complementary of the undesirable outputs in the standard DEA model (Färe et al., 1989). Other approaches include methods that are designed to increase the desirable outputs and reduce the undesirable outputs by simultaneous application of the directional distance function (Chung et al., 1997; Pathomsiri et al., 2008).

2.3. Return to scale in DEA models

The RS specifically seeks the most productive scale size for each DMU in the production possibility set. Banker et al. (1984) first proposed the concept of the most productive scale size using DEA. Banker, Bardhan, and Cooper (1996) discussed equivalence and implementation of alternative methods for determining the RS in DEA. Golany and Yu (1997) proposed a new algorithm to estimate RS in DEA based on a slack-based method.

2.4. Applications of DEA models in energy systems

Sueyoshi and Goto (2012a) proposed a DEA method and discriminant analysis to determine the efficiency-based ranking of energy firms. The proposed approach was applied to examine the performance of the Japanese electric power industry. They proposed two types of output unification (i.e., natural disposability, and managerial disposability) for DEA environmental assessment by using a non-radial model. Sueyoshi and Goto (2012b) explored how to measure RS under natural disposability and DS under managerial disposability. They used their method to compare the performance of national oil firms with international oil companies.

Sueyoshi and Goto (2012c) measured unified efficiency under natural and managerial disposability in radial DEA models. They applied their method to compare the performance of US coal-fired power plants under the Independent System Operators/Regional Transmission Organizations with independent power plants. Sueyoshi and Goto (2012d) reviewed the disposability concepts and replaced two traditional economic concepts on disposability with natural and managerial disposability. They studied the conceptual and methodological differences of weak/strong disposability and natural/managerial disposability, focusing upon the concept of congestion and technological innovation. They used their method to compare Japanese electric power firms with manufacturing firms. They showed that the manufacturing firms outperformed the electric power firms under natural disposability, whereas the opposite resulted under managerial disposability.

Sueyoshi and Goto (2012e) suggested a broader focus for DEA environmental assessment by measuring the marginal rate of transformation and the rate of substitution between desirable and undesirable outputs. They used their method to evaluate the performance of US coal-fired power plants and concluded that the regulation policy on NO_x and SO_2 had been effective on their emission controls under the US Clean Air Act. They also showed that the regulation of CO_2, a major source of the global warming and climate change, was still insufficient in the United States. Sueyoshi and Goto (2012f) proposed a method for measuring RS under natural disposability and DS under managerial disposability using DEA. The measurement of RS and DS was formulated by incorporating "strong complementary slackness conditions". Multiple reference sets and multiple projections in the RS/DS measurement were proposed. Sueyoshi and Goto (2012f) showed that such analytical capabilities is essential but they have not been previously explored in DEA environmental assessment for energy industries.

Sueyoshi and Goto (2012g) proposed a non-radial DEA approach for measuring the operational and environmental performance of DMUs. Environmental performance was calculated based on the undesirable outputs of the production process while operational performance was measured based on the normal outputs of the system. They applied their method to US coal fired power plants and compared methodological strengths and drawbacks of the radial and non-radial models used for DEA environmental assessments. Sueyoshi and Goto (2012h) proposed a DEA method based on radial and non-radial projection. They considered a production process which produced not only desirable (good) but also undesirable (bad) outputs. To unify these two types of outputs, Sueyoshi and Goto (2012h) used two types of disposability, natural disposability and managerial disposability. They discussed how to measure RS under natural disposability and DS under managerial disposability. They applied their method to US fossil fuel power plants and suggested a policy implication for introducing new technology for environmental protection. They also argued for the necessity of developing a methodological basis for energy studies.

Sueyoshi and Goto (2013a) compared fossil fuel power plants in Pennsylvania–New Jersey–Maryland and California with respect to operational and environmental performance using DEA methodology. They incorporated strategic concepts such as natural and managerial disposability into the computational process and presented a method to measure RS under natural disposability and to measure DS under managerial disposability. They showed that California outperformed Pennsylvania–New Jersey–Maryland in terms of the three unified efficiency measures. The result implied that strict regulation on undesirable outputs, as found in California, was important in enhancing the performance of US fossil fuel power plants. Sueyoshi and Goto (2013b) proposed a DEA method by using the Malmquist index to examine the degree of a frontier shift among multiple periods. The frontier shift indicated a technological progress and/or managerial innovation during an observed period. They utilized the proposed approach in an empirical application and identified the relationship between fuel mix, electricity and CO_2 among ten industrial nations.

Sueyoshi, Goto, and Sugiyama (2013) proposed a new use for window analysis in DEA environmental assessment. They incorporated the concept of natural and managerial disposability into the computational framework of DEA and extended the two disposability concepts. They used the DEA window analysis on a data set for the US coal-fired power plants. Their study showed that the coal-fired power plants had gradually adhered to the environmental protections under the Clean Air Act and the performance with respect to managerial disposability had increased.

Zhang and Choi (2013) proposed a meta-frontier non-radial Malmquist CO_2 emission performance index (MCPI) for measuring dynamic changes in total-factor CO_2 emission performance over time. The meta-frontier non-radial MCPI method took into account the incorporation of group heterogeneity and non-radial slack into the previously introduced MCPI. Zhang and Choi (2013) examined the dynamic changes in CO_2 emission performance and its decomposition of fossil fuel power plants in China. The empirical results represented an increase in total-factor CO_2 emission performance as a whole and a U-shaped meta-frontier non-radial MCPI curve for the sample period.

Chen (2013) reexamined non-additive environmental efficiency models with weakly-disposable undesirable outputs that were published in the energy economics literature. He presented a taxonomy of efficiency models found in the energy economics literature and illustrated some limitations and discussed implications of monotonicity from a practical viewpoint. He also formulated a variable returns-to-scale technology with weakly-disposable undesirable outputs to evaluate the energy efficiencies of 23 European Union states.

2.5. Motivation and contribution

This paper is motivated by the need to develop a comprehensive performance evaluation model for combined cycle power plants where the model could concurrently consider uncertainty (interval data) and undesirable factors (outputs) and determine (1) the relative efficiencies and inefficiencies of the power plants (DMUs); (2) the most economic scale size for the efficient DMUs; and (3) practical benchmarks and reference sets for all the inefficient DMUs. Unfortunately, the models developed in the literature have specific restrictions and limitations that prevented their application to our problem. Therefore, the model proposed in this study was developed to fill this research gap.

In order to demonstrate our contribution to the literature in DEA, we compared the method proposed in this study with the methods proposed in 39 papers from the literature based on the following nine unique features including: (1) consideration of uncertainty (i.e., (1-a) fuzzy, (1-b) probabilistic/stochastic, (1-c) robust, and (1-d) interval); (2) consideration of undesirable outputs (i.e., (2-a) transfer function, (2-b) treatment of inputs, and (2-c) Inverse output); (3) determination of the efficiency scores of the DMUs as interval values; (4) development of a group of indices to distinguish the efficient and inefficient DMUs; (5) determination of the most economic scale size for the efficient DMUs; (6) determination of practical benchmarks for the inefficient DMUs; (7) orientation of a projection toward the efficient frontier (i.e., (7-a) input, (7-b) output, and (7-c) mixed); (8) application in the field of energy; and (9) classical DEA modeling. The results are presented in Table 1.

As shown in Table 1, the method proposed in this study has several unique features. We use interval data to model the uncertainties, treat the undesirable outputs as inputs during the mathematical modeling phase, achieve interval efficiency scores for the DMUs, provide classification to rank the DMUs, rank the DMUs using a multi-attribute decision making method, determine the most economic scale size for the efficient DMUs, and determine the projection and practical benchmarks for the inefficient DMUs based on the projection toward the efficient frontier. Although, these features have been separately reported in the DEA literature, to the best of our knowledge, no one has reported a simultaneous treatment of these features in one model. The combination of these unique and attractive features make the model proposed in this study robust and applicable to real-life performance measurement problems.

3. Background

Let us consider $n(j = 1, 2, \ldots, n)$ DMUs under evaluation. Each DMU_j is assumed to produce $s(r = 1, 2, \ldots, s)$ outputs represented

Table 1
Research contributions.

Research paper	Research contribution*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Aguirre et al. (2011)				✓		✓	(7-a)	✓	✓
Azade et al. (2008)				✓		✓	(7-a)	✓	✓
Bampatsou et al. (2013)				✓		✓	(7-a)		✓
Banker et al. (1984)				✓	✓	✓	(7-a)		✓
Bian et al. (2013)		(2-b)		✓			(7-a)	✓	✓
Charnes et al. (1978)				✓		✓	(7-a)		✓
Chung et al. (1997)		(2-a)		✓			(7-a)		✓
Despotis and Smirlis (2002)	(1-a)		✓	✓			(7-a)		
Emrouznejad et al. (2012)	(1-d)		✓	✓			(7-a)		✓
Fang et al. (2013)				✓		✓	(7-a)	✓	✓
Färe et al. (1989)		(2-c)		✓			(7-a)		✓
Golany and Yu (1997)				✓	✓	✓	(7-a)		✓
Hatami-Marbini et al. (2011)	(1-a)		✓	✓			(7-a),(7-b),(7-c)		✓
Kagawa et al. (2013)				✓		✓	(7-a)	✓	✓
Kao (2006)	(1-a)		✓	✓			(7-a)		
Kao and Liu (2009)	(1-b),(1-d)		✓	✓			(7-a)		
Khalili-Damghani and Tavana (2013)	(1-a)	(2-c)	✓	✓		✓	(7-a)		
Lahdelma and Salminen (2006)	(1-b)			✓		✓	(7-a)		
Lee (2009)				✓	✓	✓	(7-a)		
Li (1998)	(1-b)			✓		✓	(7-a)		
Liou and Wu (2011)				✓	✓	✓	(7-a)	✓	
Lozano (2011)				✓	✓	✓	(7-a)	✓	
Mandal (2010)		(2-b)		✓		✓	(7-a)	✓	
Pathomsiri et al. (2008)		(2-a)		✓			(7-a)		✓
Puri and Yadav (2013)	(1-a)	(2-b)	✓	✓			(7-a)		✓
Puri and Yadav (2014)	(1-a)	(2-b)	✓	✓			(7-a)		✓
Riccardi et al. (2012)		(2-a)		✓		✓	(7-a)	✓	✓
Saati et al. (2002)	(1-a)		✓	✓			(7-a)		✓
Sadjadi and Omrani (2008)	(1-c)		✓	✓		✓	(7-a)	✓	
Sadjadi, Omrani, Abdollahzadeh et al. (2011), Sadjadi, Omrani, Makui, et al. (2011b)	(1-c)		✓	✓		✓	(7-a)	✓	
Salazar-Ordóñez et al. (2013)				✓			(7-a)		✓
Sueyoshi and Goto (2010)		(2-b)		✓		✓	(7-a)	✓	
Tavana et al. (2012)	(1-a),(1-b)		✓	✓			(7-a)		
Vazhayil and Balasubramanian (2013)	(1-b)			✓		✓	(7-a)	✓	✓
Wang et al. (2005)	(1-a)		✓	✓			(7-a)		
Wu et al. (2012)				✓			(7-a)	✓	
Wu et al. (2013)		(2-b)		✓			(7-a)		✓
Zhang et al. (2013)		(2-a)		✓			(7-a)	✓	
Zhou et al. (2013)				✓		✓	(7-a)	✓	
Method proposed in this study	(1-d)	(2-b)	✓	✓	✓	✓	(7-a)	✓	✓

* Note on research contributions: (1) Consideration of uncertainty: (1-a) fuzzy, (1-b) probabilistic/stochastic, (1-c) robust, (1-d) interval. (2) Consideration of undesirable outputs: (2-a) transfer function, (2-b) treatment of inputs, (2-c) Inverse output. (3) Determination of the efficiency scores of the DMUs as interval values. (4) Development of group of indices to distinguish between the efficient and inefficient DMUs. (5) Determination of the most economic scale size for the efficient DMUs. (6) Determination of practical benchmarks for the inefficient DMUs. (7) Orientation of the projection toward the efficient frontier: (7-a) input, (7-b) output, (7-c) mixed. (8) Application in the field of energy. (9) Classical DEA modeling.

by $Y_j = (y_{1j}, y_{2j}, \ldots, y_{mj})$ and to consume $m(i = 1, 2, \ldots, m)$ inputs represented by $X_j = (x_{1j}, x_{2j}, \ldots, x_{mj})$. All inputs and outputs for all the DMUs are non-negative and each DMU has at least one strictly positive input and output. The CCR production possibility set proposed by Charnes et al. (1978) is estimated by (1).

$$T_{CCR} = \left\{ (X,Y) | X \geqslant \sum_{j=1}^{n} \lambda_j X_j,\ Y \leqslant \sum_{j=1}^{n} \lambda_j Y_j \geqslant 0,\ \lambda_j \geqslant 0, j = 1, \ldots, n \right\} \quad (1)$$

The BCC production possibility set proposed by Banker et al. (1984) is estimated by (2).

$$T_{BCC} = \left\{ (X,Y) | X \geqslant \sum_{j=1}^{n} \lambda_j X_j,\ Y \leqslant \sum_{j=1}^{n} \lambda_j Y_j \geqslant 0, \right.$$
$$\left. \sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \geqslant 0,\ j = 1, \ldots, n \right\} \quad (2)$$

The CCR and BCC efficiency scores can be obtained by using the envelopment input-oriented Models (3) and (4), respectively where x_{io} and y_{ro} represent the ith input and the rth output vector of DMU$_o$ under evaluation in both Models (3) and (4). A DMU is called CCR-efficient if its objective value in Model (3) is equal to unity.

$$\begin{aligned} \min \quad & \theta_{(CCR)} \\ s.t. \quad & \\ & \sum_{j=1}^{n} \lambda_j x_{ij} \leqslant \theta_{(CCR)} \times x_{io}, \quad i = 1, \ldots, m \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \geqslant y_{ro}, \quad r = 1, \ldots, s \\ & \lambda_j \geqslant 0, \quad j = 1, \ldots, n. \end{aligned} \quad (3)$$

$$\begin{aligned} \min & \theta_{(BCC)} \\ s.t. \quad & \\ & \sum_{j=1}^{n} \lambda_j x_{ij} \leqslant \theta_{(BCC)} \times x_{io}, \quad i = 1, \ldots, m \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \geqslant y_{ro}, \quad r = 1, \ldots, s \\ & \sum_{j=1}^{n} \lambda_j = 1 \\ & \lambda_j \geqslant 0, \quad j = 1, \ldots, n. \end{aligned} \quad (4)$$

A DMU is called BCC-efficient if its objective value in Model (4) is equal to unity.

4. Proposed DEA models considering interval data and undesirable output

In this section, DEA models in the presence of interval data and undesirable outputs are proposed to measure the RS. The method proposed by Guo and Wu (2013) is customized to handle undesirable outputs. Moreover, the method proposed by Despotis and Smirlis (2002) is adapted to handle interval inputs and outputs.

4.1. Efficiency scores in the presence of interval data and undesirable output

Consider n DMUs which consume m inputs to produce s outputs. Let us further assume that x_{ij} represents the level of the ith input for DMU$_j$; y^d_{rj}represents the level of the rth desirable output for DMU$_j$; and $y^u_{r'j}$represents the level of the rth undesirable output for DMU$_j$ The undesirable outputs should be decreased to improve the performance of a DMU.

The uncertainty of the inputs and outputs are considered by the positive interval data of $x_{ij} \in \left[x^L_{ij}, x^U_{ij}\right]$, $y^d_{rj} \in \left[y^{Ld}_{rj}, y^{Ud}_{rj}\right]$, and $y^u_{r'j} \in \left[y^{Lu}_{r'j}, y^{Uu}_{r'j}\right]$. Moreover, the undesirable outputs are considered as inputs. Model (5) is proposed in the presence of interval data and undesirable outputs.

$$\begin{aligned} \min \quad & \theta_{(CCR)} \\ s.t. \quad & \\ & \sum_{j=1}^{n} \lambda_j \left[x^L_{ij}, x^U_{ij}\right] \leqslant \theta_{(CCR)} \times \left[x^L_{io}, x^U_{io}\right], \quad i = 1, \ldots, m \\ & \sum_{j=1}^{n} \lambda_j \left[y^{Ld}_{rj}, y^{Ud}_{rj}\right] \geqslant \left[y^{Ld}_{ro}, y^{Ud}_{ro}\right], \quad r = 1, \ldots, s \\ & \sum_{j=1}^{n} \lambda_j \left[y^{Lu}_{r'j}, y^{Uu}_{r'j}\right] \leqslant \theta_{(CCR)} \times \left[y^{Lu}_{r'o}, y^{Uu}_{r'o}\right], \quad r' = 1, \ldots, s' \\ & \lambda_j \geqslant 0, \quad j = 1, 2, \ldots, n \end{aligned} \quad (5)$$

Model (5) cannot be solved in its current form. We used the optimistic and pessimistic cases in order to calculate the upper and lower-bounds of the efficiency score for each DMU (Despotis & Smirlis, 2002; Seiford & Zhu 2002; Wang et al., 2005). We consider the pessimistic scenario where the DMU under evaluation is set to its worst situation and all the remaining DMUs are set to their best situations and propose Model (6) to calculate the lower-bound of the efficiency score for each DMU in the presence of interval data and undesirable outputs.

$$\begin{aligned} \min \quad & \theta_{(CCR)_l} \\ s.t. \quad & \\ & \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j x^L_{ij} + \lambda_o x^U_{io} \leqslant \theta_{(CCR)_l} \times x^U_{io}, \quad i = 1, 2, \ldots, m \\ & \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j y^{Ud}_{rj} + \lambda_o y^{Ld}_{ro} \geqslant y^{Ld}_{ro}, \quad r = 1, 2, \ldots, S \\ & \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j y^{Lu}_{r'j} + \lambda_o y^{Uu}_{r'o} \leqslant \theta_{(CCR)_l} \times y^{Uu}_{r'o}, \quad r' = 1, 2, \ldots, S' \\ & \lambda_j \geqslant 0, \quad j = 1, 2, \ldots, n. \end{aligned} \quad (6)$$

Next, we consider the optimistic scenario where the DMU under evaluation is set to its best situation and all the remaining DMUs are set to their worst situations and propose Model (7) to calculate the upper-bound of the efficiency score for each DMU in the presence of interval data and undesirable outputs.

$$\begin{aligned} \min \quad & \theta_{(CCR)_u} \\ s.t. \quad & \\ & \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j x^U_{ij} + \lambda_o x^L_{io} \leqslant \theta_{(CCR)_u} \times x^L_{io}, \quad i = 1, 2, \ldots, m \\ & \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j y^{Ld}_{rj} + \lambda_o y^{Ud}_{ro} \geqslant y^{Ud}_{ro}, \quad r = 1, 2, \ldots, S \\ & \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j y^{Uu}_{r'j} + \lambda_o y^{Lu}_{r'o} \leqslant \theta_{(CCR)_u} \times y^{Uu}_{r'o}, \quad r' = 1, 2, \ldots, S' \\ & \lambda_j \geqslant 0, \quad \forall j = 1, 2, \ldots, n. \end{aligned} \quad (7)$$

Solving models (6) and (7) for all DMUs will result in the interval efficiency score of $\left[\theta^*_{(CCR)_l}, \theta^*_{(CCR)_u}\right]$ for each DMU.

4.1.1. Properties of the proposed models

Theorem #1. *Model (6) is always feasible and bounded. Its optimal objective function is equal to unity.*

Proof. Consider the following solution for Model (6):

$$\lambda_j = 0, \quad j = 1,2,\ldots,n,j^1o$$

$$\lambda_o = 1$$

$$\theta_{(CCR)_l} = 1$$

It is obvious that the solution to Model (6) is always feasible. Therefore, independent of inputs and outputs values, there always exists at least one feasible solution for Model (6). Since the above solution is feasible and the objective function of Model (6) is minimization, the optimum value of the objective function in Model (6) is definitely less than or equal to unity (i.e., $\theta*_{(CCR)_l} \leqslant 1$). Consequently, we can conclude that Model (6) is always bounded. This completes the proof. □

Theorem #2. *Model (7) is always feasible and bounded. Its optimal objective function is equal to unity.*

Proof. Consider a solution for Model (7) as follows:

$$\lambda_j = 0, \quad j = 1,2,\ldots,n, \ j \neq o$$

$$\lambda_o = 1$$

$$\theta_{(CCR)_u} = 1$$

It is obvious that the solution to Model (7) is always feasible. Therefore, independent of inputs and outputs values, there always exists at least one feasible solution for Model (7). Since the above solution is feasible and the objective function of Model (7) is minimization, the optimum value of the objective function in Model (7) is definitely less than or equal to unit (i.e, $\theta*_{(CCR)_u} \leqslant 1$). Consequently, it can be concluded that the Model (7) is always bounded. This completes the proof. □

Corollary #1. The BCC models constructed by adding $\sum_{j=1}^{n}\lambda_j = 1$ to Models (6) and (7) are also always feasible and bounded.

Corollary #2. The BCC–CCR models constructed by adding $\sum_{j=1}^{n}\lambda_j \geqslant 1$ to Models (6) and (7) are also always feasible and bounded.

Corollary #3. The CCR–BCC models constructed by adding $\sum_{j=1}^{n}\lambda_j \leqslant 1$ to Models (6) and (7) are also always feasible and bounded.

4.2. Determining the RS in the presence of interval data and undesirable outputs

In order to determine the RS for each DMU in the presence of interval data and undesirable outputs, the efficiency scores are calculated by considering the assumptions of VRS, Decreasing Return to Scale (DRS), and Increasing Return to Scale (IRS). For the VRS situation, the constraint $\sum_{j=1}^{n}\lambda_j = 1$ is added to Models (6) and (7) to calculate the lower-bound and upper-bound of the efficiency scores for the DMUs represented by the interval $[\theta^*_{(BCC)_l}, \theta^*_{(BCC)_u}]$. For the DRS situation, the constraint $\sum_{j=1}^{n}\lambda_j \leqslant 1$ is added to Models (6) and (7) to calculate the lower-bound and upper-bound of the efficiency scores for the DMUs represented by the interval $\left[\theta^*_{(CCR-BCC)_l}, \theta^*_{(CCR-BCC)_u}\right]$. For the IRS situation, the constraint $\sum_{j=1}^{n}\lambda_j \geqslant 1$ is added to Models (6) and (7) to calculate the lower-bound and upper-bound of the efficiency scores for the DMUs represented by the interval $\left[\theta^*_{(BCC-CCR)_l}, \theta^*_{(BCC-CCR)_u}\right]$. As the procedure is clear, the associated models are not presented here for the sake of brevity.

Using the aforementioned procedure, four efficiency scores are calculated for each DMU for the optimistic scenario and four efficiency scores are calculated for each DMU for the pessimistic scenario. Fig. 1 depicts the efficient frontier (considering one input and one output) for the CCR, BCC, BCC–CCR, and CCR–BCC models. It is notable that these frontiers are estimated for both the optimistic and pessimistic scenarios, respectively.

We then propose the following procedure to determine the RS for each DMU. First, we classify each DMU based on its associated interval efficiency score as follows: if the lower and the upper-bounds of the DMU are both equal to unity, the DMU is classified as E^{++}; if the lower-bound of the efficiency score for the DMU is less than unity and the upper-bound of the efficiency score for the DMU is equal to unity, the DMU is classified as E^{+}; and if the lower and the upper-bounds of the efficiency scores of the DMU are both less than unity, the DMU is classified as E^{-}. For the DMUs classified in the E^{++} group, the cross-efficiency method is used to make a full ranking and sequentially determine the RS (see Table 2).

Table 1 is also used to determine the RS for the DMUs classified in the E^{+} group. The comparisons in the E^{+} group are simply accomplished by using the lower-bound of the efficiency score given in Table 2. For the DMUs classified in the E^{-} group, the following steps are proposed:

Step 1. We calculate the *range* and the *mean value* of the interval efficiency score for each DMU for the CCR, BCC, BCC–CCR, and CCR–BCC models using both the optimistic and the pessimistic scenarios, respectively.

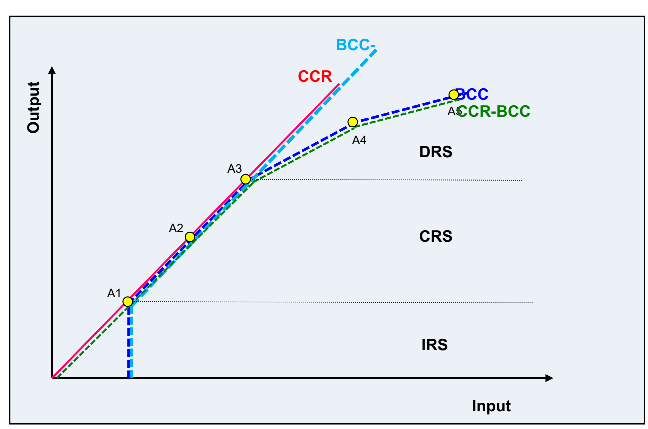

Fig. 1. Areas for different RS assumptions.

Table 2
Efficiency score relations used in determining the RS.

DRS	CRS	IRS
BCC–CCR > CCR–BCC CCR–BCC = BCC BCC–CCR = CCR	BCC = CCR	BCC–CCR < CCR–BCC CCR–BCC = BCC BCC–CCR = CCR

Step 2. We use the calculated *ranges* and *means* and run the TOPSIS algorithm proposed by Hwang and Yoon (1981) and Shih, Shyur, and Lee (2007) for all 4 models based on both the optimistic and the pessimistic scenarios to assign a ranking score to each DMU.

The TOPSIS algorithm is based on the distances between the DMUs and two dummy DMUs (i.e., the ideal DMU and the anti-ideal DMU). The DMU which is far from the anti-ideal DMU and near the ideal-DMU, simultaneously, is the best choice. The DMU which is far from the ideal DMU and near the anti-ideal DMU, simultaneously, is the worst choice. The ideal DMU and the anti-ideal DMU are identified by using (8) and (9), respectively.

$$A+ = \{X_{A+} = Max\ Mean\ value, Y_{A+} = Min\ Range\} \quad (8)$$

$$A- = \{X_{A-} = Min\ Mean\ value, Y_{A-} = Max\ Range\} \quad (9)$$

The distance between each DMU and the ideal DMU and the distance between each DMU and the anti-ideal DMU is calculated using (10) and (11), respectively.

$$d_j(A+) = \sqrt{(Mean_j - X_{A+})^2 + (Range_j - Y_{A+})^2} \quad j = 1, 2, \ldots, n \quad (10)$$

$$d_j(A-) = \sqrt{(Mean_j - X_{A-})^2 + (Range_j - Y_{A-})^2} \quad j = 1, 2, \ldots, n \quad (11)$$

Eq. (12) is used next to calculate a closeness coefficient (CC) index for each DMU under consideration

$$CC_j = \frac{d_j(A-)}{(d_j(A+) + d_j(A-))} \quad \forall j = 1, 2, \ldots, n \quad (12)$$

Finally, the DMUs are ranked based on the decreasing order of their CCs. As a result, four primary ranks, associated with the CCR, BCC, CCR–BCC, and BCC–CCR, are assigned to each DMU. Table 1 can be used next to determine the RS based on these rankings.

4.3. Final ranking of the DMUs

After determining the RS, decision makers may be interested in assigning a unique ranking to each DMU (considering the four different rankings). We customize the method proposed by Soleimani-Damaneh and Zarepisheh (2009) (based on Shannon's entropy) to determine a final unique ranking for each DMU in presence of the interval data, undesirable outputs and several RS assumptions.

The decision making matrix contains the ordinal values of the DMUs' rankings achieved based on the proposed TOPSIS method described in the previous section. We had assumed that n DMUs have been evaluated by a DEA model under k criteria ($k = 1, 2, \ldots, K$). The efficiency results are listed in the matrix $E_{n\times k}$. Each row of the E matrix corresponds to a DMU and each column corresponds to a ranking. The following steps are proposed to assign a unique rank for each DMU:

Step 1. We use Eq. (13) and normalize the rankings in the decision matrix.

$$\bar{R}_{jk} = \frac{R_{jk}}{\sum_{j=1}^{n} R_{jk}}, \quad j = 1, 2, \ldots, n, \quad k = 1, 2, \ldots, K \quad (13)$$

where R_{jk} is the ranking order of DMU$_j$ in RS$_k$.
Step 2. We use Eq. (14) and compute the entropy value (e_k).

$$e_k = -e_0 \sum_{j=1}^{n} \bar{E}_{jk} \ln \bar{E}_{jk}, \quad k = 1, 2, \ldots, K \quad (14)$$

where e_0 is the entropy constant and is equal to $e_0 = (\ln n)^{-1}$
Step 3. We set $d_k = 1 - e_k$ as the degree of diversification for $k = 1, 2, \ldots, K$.
Step 4. We then use Eq. (15) to normalize d_k.

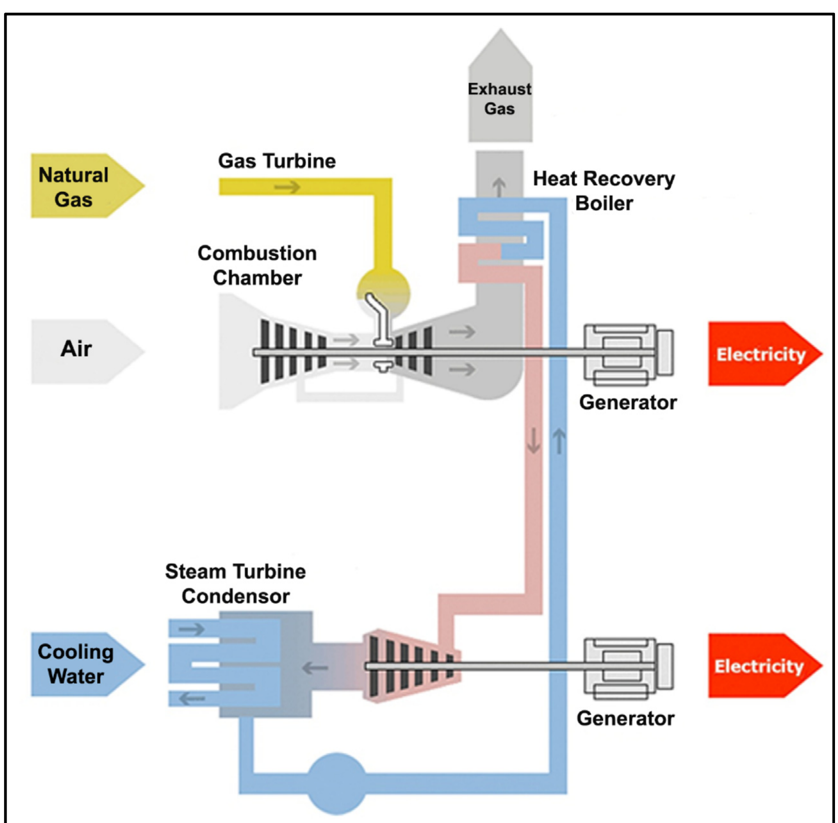

Fig. 2. Combined cycle power plant.

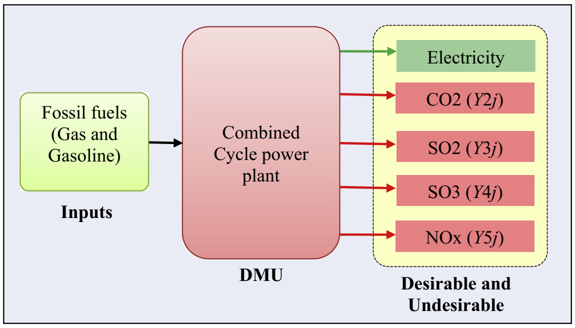

Fig. 3. A power plant as a DMU.

$$w_k = \frac{d_k}{\sum_{k=1}^{K} d_k}, \quad k = 1, 2, \ldots, K \tag{15}$$

where w_k represents the relative importance of the ranking achieved by the RS of type k.

Step 5. We finally use Eq. (16) and calculate the following efficiency index.

$$\beta_j = \sum_{k=1}^{K} w_k E_{jk} \quad , \quad j = 1, 2, \ldots, n \tag{16}$$

where β_j is the final ranking of DMU$_j$, and E_{jk} is the efficiency score of DMU$_j$ considering the RS of type k. All DMUs are ranked based on a decreasing order of β_j.

5. Case study and results

A combined power plant works with gas and steam turbines. The gas turbine uses natural gas or gasoline fuels to generate electricity and the steam turbine uses the waste heat from the gas turbine to generate electricity. The process is very efficient since exhaust heat (that would otherwise be lost through the exhaust stack) is re-used throughout the system. A gas turbine compresses the air and mixes it with the fuel. The fuel is burned and the resultant hot air expands and spins the turbine blades. The spinning turbine blades drives a generator and the generator converts the spinning motion into electricity power. The exhaust heat generated in the gas turbine is sent to a heat recovery steam generator. This generator uses the gas turbine exhaust heat to produce steam and delivers it to the steam turbine. The steam produces additional energy in the steam turbine and the steam turbine delivers this energy to the generator drive shaft. The generator converts this energy into electricity. The process of generating electricity in a combined cycle power plant is briefly shown in Fig. 2.

The method proposed in this study was used by the Iranian Power Generation, Transmission, and Distribution Management Company (TAVANIR) to evaluate 17 combined cycle power plants in Iran during a six year period. TAVANIR is responsible for electricity generation, transmission and distribution in Iran. Six variables were chosen as the inputs and outputs to estimate the efficiency scores of the 17 combined cycle power plants units. Fossil fuel is the primary input in the combined cycle power plants managed by TAVANIR. The desirable output is the units of produced energy and the undesirable outputs are gases such as CO_2, SO_2, SO_3, and NO_x. Each power plant consumes some combination of fuels to produce units of electricity energy, emissions, and pollutions. Fig. 3 represents the schematic view of a DMU as a power plant.

The measurement unit used for the desirable outputs is thousand kilo-watts per hour and the measurement unit used for the inputs is liters or m^3. The measurement unit used for the undesirable outputs is ton. Table 3 presents the input and output data used in this study.

Considering the optimistic and pessimistic scenarios, four interval efficiency scores were calculated based on different RS assumptions for each combined cycle power plant (i.e., CCR, BCC, CCR–BCC, and BCC–CCR). The interval efficiency scores are presented in Table 4.

The combined cycle power plants (DMUs) are classified according to the lower and upper-bounds of their efficiency scores to determine the RS. Given that all the DMUs in all the models have an upper-bound efficiency score of 1 and a lower-bound efficiency score less than 1, we use Table 1 to classify all the DMUs in the E^+ group. The RS values associated with the DMUs are also summarized in Table 4. Fig. 4 represents the efficiency scores of the DMUs for all the RS assumptions under both optimistic and pessimistic scenarios.

The proposed TOPSIS method was used to fully rank the DMUs. The computational results of the TOPSIS method are presented in Table 5 for all the RS assumptions. The final ranking of the DMUs

Table 3
Interval inputs and outputs of the power plants during the six-year study.

DMU	Input		Desirable output		Undesirable output (GAS/Ton)							
	Fuel (M^3)		Electricity power (1000KW/Hr.)		No$_x$		SO_2		CO_2		SO_3	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
1	1,002,243	1,534,381	4,663,820	5,948,123	3.6	5	1.8	6.6	2338	3015	0	0.1
2	971,509	1,298,112	4,821,296	5,657,392	3.7	4.4	2.1	4.7	2367	2727	0	0.1
3	1,331,457	1,831,098	7,220,851	7,699,512	5.3	5.8	2.8	6.7	3478	3631	0	0.1
4	766,658	1,117,322	3,781,843	4,628,520	2.8	3.7	1.7	4.8	1779	2250	0	0.1
5	24,213	1,060,942	356,963	3,184,631	0.6	3.2	0.4	2.2	318	2119	0	0
6	1,045,455	1,283,541	5,339,780	5,975,686	3.8	4.4	1.3	3	2545	2806	0	0
7	412,442	758,142	1,925,856	2,631,210	1.7	2.3	0.1	1.1	1052	1557	0	0
8	446,094	1,017,339	1,836,793	4,289,004	1.8	3.6	1.1	4.2	1089	2229	0	0.1
9	1,244,520	1,820,737	4,222,796	7,935,571	4.3	8	0.2	12.5	2806	4788	0	0.2
10	1,056,182	1,410,680	5,126,256	6,213,138	3.4	4.4	0.2	3	2262	2802	0	0
11	311,239	635,257	1,820,209	2,106,015	1.6	1.9	1	3.3	979	1091	0	0.1
12	204	796,605	515	2,128,410	0	2.6	0	5	1	1595	0	0.1
13	1,234,922	2,303,468	4,500,169	9,886,102	5.2	8.3	4.1	11.4	3209	4993	0.1	0.2
14	422,191	905,874	1,770,332	2,761,553	1.9	2.9	0.4	2.4	1222	1848	0	0
15	147,683	2,769,634	5,008,772	1,030,008	5.5	8.5	3	9.2	3546	5535	0	0.1
16	161,614	928,637	1,258,570	2,678,996	1.9	4.5	1.4	7.7	985	2661	0	0.1
17	1,298,688	1,961,314	4,785,753	5,898,717	5.3	5.7	0.5	4	3382	3828	0	0.1

Table 4
Efficiency results for different DEA models.

DMU*	Class	BCC		CCR-BCC		CCR		BCC-CCR		RS of DMU
		Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	
1	E^+	0.323068	1	0.000727	1	0.000727	1	0.323068	1	IRS
2	E^+	0.391690	1	0.000831	1	0.000831	1	0.391690	1	IRS
3	E^+	0.581180	1	0.000934	1	0.000934	1	0.581180	1	IRS
4	E^+	0.272956	1	0.000790	1	0.000790	1	0.272956	1	IRS
5	E^+	0.000472	1	0.000472	1	0.000079	1	0.000079	1	DRS
6	E^+	0.473665	1	0.000894	1	0.000894	1	0.473665	1	IRS
7	E^+	0.000642	1	0.000642	1	0.000581	1	0.000581	1	DRS
8	E^+	0.000449	1	0.000449	1	0.000387	1	0.000387	1	DRS
9	E^+	0.164077	1	0.000414	1	0.000414	1	0.164077	1	IRS
10	E^+	0.440247	1	0.000860	1	0.000860	1	0.440247	1	IRS
11	E^+	0.000917	1	0.000917	1	0.000784	1	0.000784	1	DRS
12	E^+	0.230769	1	0.230769	1	0.000037	1	0.000037	1	DRS
13	E^+	0.183218	1	0.000423	1	0.000423	1	0.183218	1	IRS
14	E^+	0.000541	1	0.000541	1	0.000450	1	0.000450	1	DRS
15	E^+	0.221583	1	0.000425	1	0.000425	1	0.221583	1	IRS
16	E^+	0.000376	1	0.000376	1	0.000222	1	0.000222	1	DRS
17	E^+	0.298267	1	0.000587	1	0.000587	1	0.298267	1	IRS

* The name of the power plants are intentionally omitted to protect their anonymity.

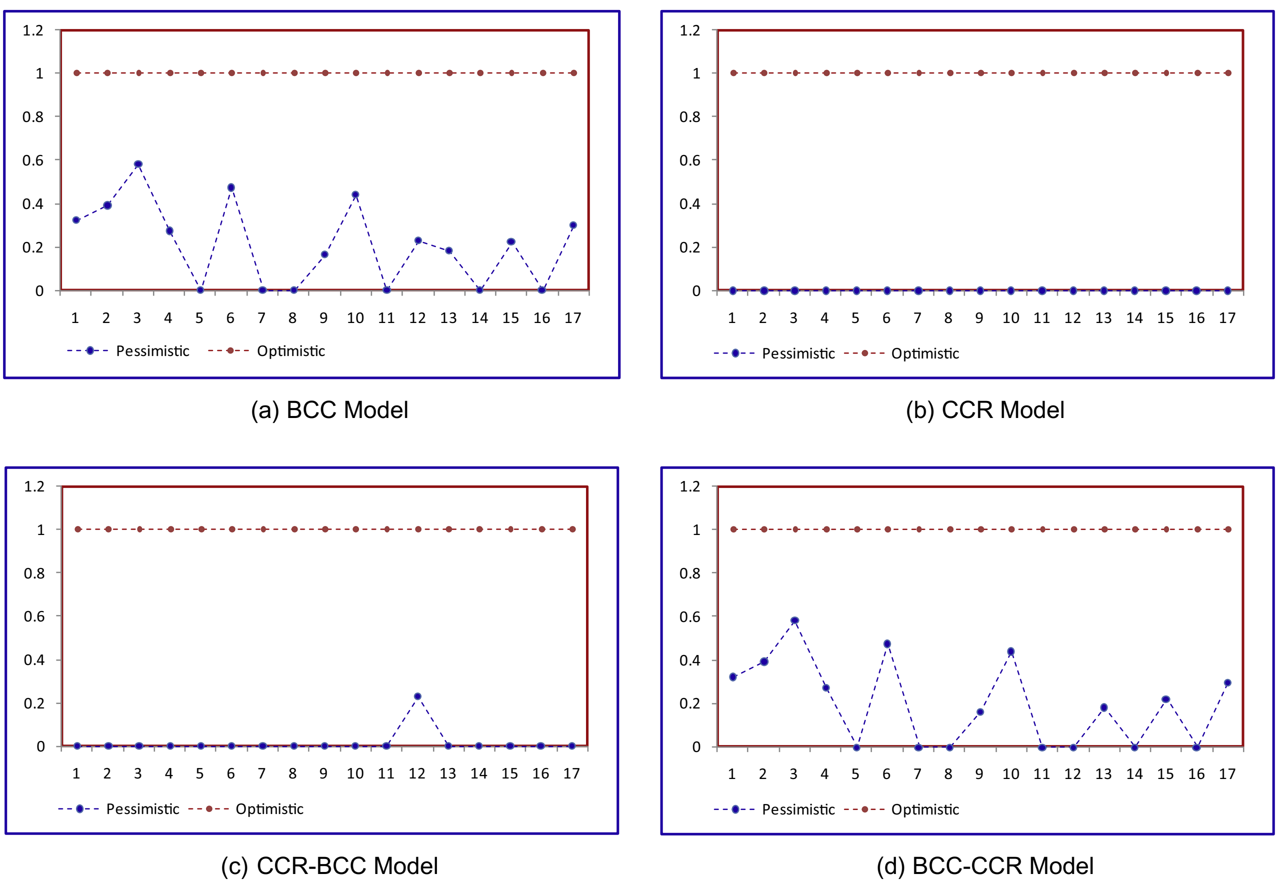

Fig. 4. Optimistic and pessimistic efficiency scores of the DMUs.

were then calculated using Shannon's entropy method. The primary ranking of TOPSIS method and the final ranking measure of Shannon's entropy method are presented in Table 5. As shown in Table 6, the best DMU is DMU No. 3 and the worst DMU is DMU No. 16.

As shown in Table 3, some power plants should be expanded (i.e., those under the IRS scenario) since they have achieved their most productive scale size. Some other power plants should be condensed (i.e., those under the DRS scenario) so that they can achieve their most productive scale size. The reference sets of the CCR, BCC, BCC–CCR, and CCR–BCC models are summarized in Table 7.

Considering return to scale assumptions, and using the linear combination of the inputs and outputs of the reference set of a DMU, the DMU can be projected towards the efficient frontier (i.e., most productive scale size). It should be noted that since the proposed models in this paper are input-oriented, the projection is accomplished based on the input values.

For example, DMU_6 can be projected towards the efficient frontier using its reference set provided in Table 7. Given the fact that

Table 5
TOPSIS results for the primary rankings.

DMU	BCC			CCR–BCC			CCR			BCC–CCR		
	dj(A+)	dj(A−)	CCj	dj(A+)	dj(A−)	CCj	dj(A+)	dj(A−)	CCj	dj(A+)	dj(A−)	CCj
1	0.28857	0.36078	0.55559	0.25719	0.00039	0.00152	0.00023	0.00077	0.76860	0.288578	0.36115	0.55585
2	0.21185	0.43750	0.67374	0.25707	0.00050	0.00197	0.00011	0.00088	0.88441	0.211857	0.43788	0.67393
3	0	0.64935	1	0.25696	0.00062	0.00242	0	0.00100	1	0	0.64973	1
4	0.34460	0.30475	0.46931	0.25712	0.00046	0.00179	0.00016	0.00084	0.83875	0.344605	0.30513	0.46962
5	0.64925	0.00010	0.00016	0.25748	0.00010	0.00041	0.00095	4.6E−05	0.04663	0.6496	4.7E−05	7.2E−05
6	0.12020	0.52915	0.81488	0.25700	0.00057	0.00225	4.5E−05	0.00095	0.95512	0.12020	0.52953	0.81499
7	0.64906	0.00029	0.00045	0.25729	0.00029	0.00115	0.00039	0.00060	0.60624	0.64912	0.00060	0.00093
8	0.64927	8.1E−05	0.00012	0.25750	8.1E−05	0.00031	0.00061	0.00039	0.39000	0.64934	0.00039	0.00060
9	0.46633	0.18302	0.28185	0.25754	4.3E−05	0.00016	0.00058	0.00042	0.42033	0.46633	0.18340	0.2822
10	0.15756	0.49179	0.75734	0.25704	0.00054	0.0021	8.3E−05	0.00091	0.91663	0.15756	0.49216	0.75748
11	0.64875	0.00060	0.00093	0.25698	0.00060	0.00234	0.00016	0.00083	0.83224	0.64890	0.00083	0.00128
12	0.39177	0.25758	0.39668	0	0.25758	1	0.00100	0	0	0.64973	0	0
13	0.44493	0.20442	0.31480	0.25753	5.3E−05	0.00020	0.00057	0.00043	0.43046	0.44493	0.20480	0.31520
14	0.64917	0.00018	0.00028	0.25740	0.00015	0.00071	0.00054	0.00046	0.46015	0.64927	0.00046	0.00071
15	0.40204	0.24731	0.38086	0.25753	5.52E−0	0.00021	0.00056	0.00043	0.4323	0.40204	0.24769	0.38122
16	0.64935	0	0	0.25758	0	0	0.00079	0.00020	0.20612	0.64953	0.00020	0.00031
17	0.31630	0.33305	0.51289	0.25735	0.00023	0.00091	0.00038	0.00061	0.61321	0.31630	0.33343	0.51317

Table 6
TOPSIS (primary rankings) and Shannon's entropy (final rankings).

DMU	Primary Ranks				Shannon's Entropy Score	Final Rank
	BCC	CCR-BCC	CCR	BCC-CCR		
1	5	8	7	5	6.25	5
2	4	6	4	4	4.5	4
3	1	2	1	1	1.25	1
4	7	7	5	7	6.5	6
5	15	12	16	16	14.75	16
6	2	4	2	2	2.5	2
7	13	9	9	12	10.75	10
8	16	13	14	14	14.25	15
9	11	16	13	10	12.5	14
10	3	5	3	3	3.5	3
11	12	3	6	11	8	8
12	8	1	17	17	10.75	10
13	10	15	12	9	11.5	12
14	14	11	10	13	12	13
15	9	14	11	8	10.5	9
16	17	17	15	15	16	17
17	6	10	8	6	7.5	7

DMU_6 is classified as an IRS DMU (check the efficiency scores of DMU_6 in Table 3 and use the categories in Table 1), it can be projected towards the efficient frontier using a linear combination of DMU_5 and DMU_{15} (i.e., the members of reference set for DMU_6 in the BCC–CCR column). Since the inputs and outputs of the reference set are also interval values, a practical solution is required to project the DMUs toward the efficient frontier. This projection should reduce the inputs and undesirable outputs for DMU_6 based on its interval efficiency score and the combination of the associated decision variables of the reference set for DMU_6.

The following strategies are proposed to project the inefficient DMUs towards the efficient frontier in the presence of undesirable outputs and interval data:

Optimistic Scenario: This scenario considers a risk-seeking decision maker. Therefore, we assume that the upper-bound of the efficiency score is achieved and the inputs and outputs have achieved their best levels. In other words, the DMU under assessment can achieve the upper-bound of the efficiency score while consuming the lower-bound of the inputs and producing the upper-bound of the desirable outputs and the lower-bound of the undesirable outputs.

Pessimistic Scenario: This scenario considers a risk-averse decision maker. Therefore, we assume that the lower-bound of efficiency score is achieved and the inputs and outputs have achieved their worst levels. In other words, the DMU under assessment can achieve the lower-bound of the efficiency score while consuming the upper-bound of the inputs and producing the lower-bound of the desirable outputs and the upper-bound of undesirable outputs. Table 8 presents the parameters of a given DMU under the optimistic and pessimistic scenarios.

For example, DMU_6 has the following parameters under the optimistic scenario: $X_{16} = 1{,}045{,}455$, $Y_{16} = 5{,}975{,}686$, $Y_{1'6} = 3.8$, $Y_{2'6} = 1.3$, $Y_{3'6} = 2545$, $Y_{4'6} = 0$.

The RS for DMU_6 is classified in the IRS group based on the results provided in Table 3. In the optimistic scenario, the efficiency score of DMU_6 is 1 based on the results provided in Table 4.

Table 7
DMU reference sets and decision variables.

DMU	Reference sets				Decision variable (λ_j)			
	BCC–CCR	CCR	CCR–BCC	BCC	BCC–CCR	CCR	CCR–BCC	BCC
1	13, 5	12	12	13, 5	λ_5 = 0.77920, λ_{13} = 0.2207	λ_{12} = 2.1912	λ_{12} = 2.1912	λ_5 = 0.7792, λ_{13} = 0.2207
2	13, 5	12	12	13, 5	λ_5 = 0.7557, λ_{13} = 0.2442	λ_{12} = 2.2652	λ_{12} = 2.2652	λ_5 = 0.7557, λ_{13} = 0.2442
3	15,13, 5	12	12	15,13, 5	λ_5 = 0.3989, λ_{13} = 0.5811, λ_{15} = 0.1988E−01	λ_{12} = 3.3926	λ_{12} = 3.3926	λ_5 = 0.3989, λ_{13} = 0.5811, λ_{15} = 0.1988E−01
4	13, 5	12	12	13, 5	λ_5 = 0.9108, λ_{13} = 0.8911E−01	λ_{12} = 1.7768	λ_{12} = 1.7768	λ_5 = 0.9108, λ_{13} = 0.8911E−01
5	12	12	12	12	λ_{12} = 0.1677	λ_{12} = 0.1677	λ_{12} = 1	λ_{12} = 1
6	15, 5	12	12	15, 5	λ_5 = 0.6971, λ_{15} = 0.3028	λ_{12} = 2.5082	λ_{12} = 2.5088	λ_5 = 0.6971, λ_{15} = 0.3028
7	12	12	12	12	λ_{12} = 0.9048	λ_{12} = 0.9048	λ_{12} = 1	λ_{12} = 1
8	12	12	12	12	λ_{12} = 0.8629	λ_{12} = 0.8629	λ_{12} = 1	λ_{12} = 1
9	13, 5	12	12	13, 5	λ_5 = 0.8450, λ_{13} = 0.15491	λ_{12} = 1.9840	λ_{12} = 1.9840	λ_5 = 0.8450, λ_{13} = 0.1549
10	15, 5	12	12	15, 5	λ_5 = 0.7271, λ_{15} = 0.2728	λ_{12} = 2.4084	λ_{12} = 2.40849	λ_5 = 0.7271, λ_{15} = 0.2728
11	12	12	12	12	λ_{12} = 0.8551,	λ_{12} = 0.8551	λ_{12} = 1	λ_{12} = 1
12	5	5	5	5	λ_5 = 0.1617E−03	λ_5 = 0.1617E−03	λ_5 = 1	λ_5 = 1
13	15, 5	12	12	15, 5	λ_5 = 0.8151 , λ_{15} = 0.1848	λ_{12} = 2.114	λ_{12} = 2.1143	λ_5 = 0.8151, λ_{15} = 0.1848
14	12	12	12	12	λ_{12} = 0.8317	λ_{12} = 0.8317	λ_{12}=	λ_{12} = 1
15	13, 9 , 5	12	12	13, 9 , 5	λ_5 = 0.7070 , λ_9 = 0.7139E−01, λ_{13} = 0.2215	λ_{12}=2.3532	λ_{12} = 2.3532	λ_5 = 0.7070, λ_9 = 0.7139E−01, λ_{13} = 0.2215
16	12	12	12	12	λ_{12} = 0.5913	λ_{12} = 0.5913	λ_{12} = 1	λ_{12} = 1
17	15, 13, 5	12	12	15, 13, 5	λ_5 = 0.7653, λ_{13} = 0.1662, λ_{15} = 0.6845E−01	λ_{12} = 2.2485	λ_{12} = 2.2485	λ_5 = 0.7653, λ_{13} = 0.1662, λ_{15} = 0.6845E−01

The reference set for DMU_6 are DMU_5 and DMU_{15}. The associated decision variables are λ_5 = 0.6971170 and λ_{15} = 0.3028830.

In the optimistic scenario, all other DMUs, including the reference set of DMU_6 (i.e., DMU_5 and DMU_{15}), are assumed to be in their worst situations. We have:

X_{15} = 1,060,942, Y_{15} = 356,963, $Y_{1'5}$ = 3.2, $Y_{2'5}$ = 2.2, $Y_{3'5}$ = 2129, $Y_{4'5}$ = 0.

$X_{1,15}$ = 2,769,634, $Y_{1,15}$ = 5,008,772, $Y_{1',15}$ = 8.5, $Y_{2',15}$ = 9.2, $Y_{3',15}$ = 5535, $Y_{4',15}$ = 0.1.

The projection of DMU_6 on the efficient frontier is calculated as a linear combination of the inputs and the outputs of the reference set using λ_5 = 0.6971170 and λ_{15} = 0.3028830 as follows:

X_{16} = 61609.96, Y_{16} = 5,339,780, $Y_{1'6}$ = 2.084127, $Y_{2'6}$ = 1.187496, $Y_{3'6}$ = 1295.706, $Y_{4'6}$ = 0.

As shown here, this practical benchmark, in the optimistic scenario, consumes fewer inputs and produces fewer undesirable outputs in comparison with DMU_6. The remaining DMUs can be described similarly based on the optimistic or the pessimistic viewpoints.

Table 8
Parameters of a DMU under the optimistic and pessimistic scenarios.

CCR	CCR–BCC	BCC	BCC–CCR
Optimistic Scenario			
$\theta^*_{CCR} = \theta^*_{CCR_L}$	$\theta^*_{CCR-BCC} = \theta^*_{CCR-BCC_L}$	$\theta^*_{BCC} = \theta^*_{BCC_L}$	$\theta^*_{BCC-CCR} = \theta^*_{BCC-CCR_L}$
$x_{ij} = x^L_{ij}, \quad \forall i,j$	$x_{ij} = x^L_{ij}, \quad \forall i,j$	$x_{ij} = x^L_{ij}, \quad \forall i,j$	$x_{ij} = x^L_{ij}, \quad \forall i,j$
$y^d_{rj} = y^{Ud}_{rj}, \quad \forall r,j$	$y^d_{rj} = y^{Ud}_{rj}, \quad \forall r,j$	$y^d_{rj} = y^{Ud}_{rj}, \quad \forall r,j$	$y^d_{rj} = y^{Ud}_{rj}, \quad \forall r,j$
$y^u_{rj} = y^{Ld}_{rj}, \quad \forall r,j$	$y^u_{rj} = y^{Ld}_{rj}, \quad \forall r,j$	$y^u_{rj} = y^{Ld}_{rj}, \quad \forall r,j$	$y^u_{rj} = y^{Ld}_{rj}, \quad \forall r,j$
Pessimistic Scenario			
$\theta^*_{CCR} = \theta^*_{CCR_U}$	$\theta^*_{CCR-BCC} = \theta^*_{CCR-BCC_U}$	$\theta^*_{BCC} = \theta^*_{BCC_U}$	$\theta^*_{BCC-CCR} = \theta^*_{BCC-CCR_U}$
$x_{ij} = x^U_{ij}, \quad \forall i,j$	$x_{ij} = x^U_{ij}, \quad \forall i,j$	$x_{ij} = x^U_{ij}, \quad \forall i,j$	$x_{ij} = x^U_{ij}, \quad \forall i,j$
$y^d_{rj} = y^{Ld}_{rj}, \quad \forall r,j$	$y^d_{rj} = y^{Ld}_{rj}, \quad \forall r,j$	$y^d_{rj} = y^{Ld}_{rj}, \quad \forall r,j$	$y^d_{rj} = y^{Ld}_{rj}, \quad \forall r,j$
$y^u_{rj} = y^{Ud}_{rj}, \quad \forall r,j$	$y^u_{rj} = y^{Ud}_{rj}, \quad \forall r,j$	$y^u_{rj} = y^{Ud}_{rj}, \quad \forall r,j$	$y^u_{rj} = y^{Ud}_{rj}, \quad \forall r,j$

6. Managerial implications

In this paper, we developed a performance assessment system based on DEA and used the proposed system to measure the performance of combined cycle power plants (DMUs) with interval data and undesirable outputs. We demonstrated the applicability of the proposed method and exhibited the efficacy of the procedure using interval data and undesirable outputs with a six-year study of 17 combined cycle power plants in Iran. A power plant consumes fossil fuels and produces electricity as a desirable output and polluting gases as undesirable outputs. It is imperative to improve the process of efficiency measurement and economic scale size in combined cycle power plants since a good estimate of emissions and pollutions produced by the power plant can result in practical strategies for sustainable development.

7. Conclusion and future research directions

A good estimate of emissions and pollutions produced by combined cycle power plants can help develop practical strategies for further sustainable progress. Performance assessment of an electricity power plant and determining its economic scale is challenging and complex. This assessment usually requires a careful consideration of multiple and often conflicting factors. The performance assessment process often becomes more complicated because: (1) the data associated with some of these factors are represented with interval values; and (2) these power plants routinely produce emissions which are considered undesirable outputs.

In this paper we developed a performance assessment system based on DEA and used the proposed system to measure the performance of combined cycle power plants (DMUs) with interval data and undesirable outputs. We showed that the proposed approach is able to handle undesirable outputs. Moreover, the uncertainty of data during was modeled using interval data. Several RS assumptions were tested to determine the best economic size for a combined cycle power plant in the presence of interval data and undesirable outputs. The proposed method suggests practical recommendations for re-sizing the combined cycle power plants and improving their overall efficiency.

We presented a comprehensive performance evaluation framework for combined cycle power plants. We needed to concurrently consider interval data and undesirable outputs and determine: the relative efficiencies and inefficiencies of the power plants, the most economic scale size for the efficient power plants, and practical benchmarks and reference sets for all inefficient power plants. Unfortunately, the models developed in the literature could not be used to satisfy the specific requirements in this problems. Consequently, we developed the performance evaluation framework proposed in this study to: (1) model the uncertainties in the input and output data through interval data; (2) consider undesirable outputs; (3) determine the efficiency scores of the DMUs as interval values; (4) develop a group of indices to distinguish the efficient and inefficient DMUs; (5) determine the most economic scale size for the efficient DMUs; and (6) determine practical benchmarks for the inefficient DMUs.

We demonstrated the applicability of the proposed method and exhibited the efficacy of the procedure using interval data and undesirable outputs with a six-year study of 17 combined cycle power plants in Iran. A power plant, represented as a DMU, consumes fossil fuels and produces electricity as a desirable output and polluting gases as undesirable outputs. The efficiency scores were calculated for each power plant during the planning period. The economic scale size, assessment, ranking, and practical suggestion for improvement were suggested for each power plant. The proposed approach had promising results and its implementation was straightforward. The benefits of our model might be still nascent but the potentials could be significant. The method proposed in this study lend itself to many real-life performance measurement problems with interval data and undesirable outputs.

We encourage researchers to use the approach proposed in this study in other applications (e.g., banking, supply chain network performance measurement and re-scaling, healthcare systems evaluation, flexible manufacturing system assessment, transportation system evaluation, etc.). We modeled the uncertainties in the input and output data with interval data in this study. An interesting stream of research is to model these uncertainties with fuzzy data, probabilistic data, and/or grey data. Finally, we determined an interval efficiency score for each DMU and identified the efficient and inefficient DMUs based on these interval efficiency scores. Another interesting stream of research is to conduct sensitivity analysis on the stability of these interval efficiency scores or test the reliability of grouping DMUs as efficient or inefficient.

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