Journal of Air Pollution and Health (Spring 2016); 1(2):83-98

Original Article

Available online at http://japh.tums.ac.ir

JOINT ENVIRONMENTAL AND TECHNICAL EFFICIENCY OF STEAM POWER PLANTS: A CASE STUDY OF IRAN

Foroogh Shadman[1], Khalid Abdul Rahim[2]*

[1] Faculty of Economics and Management, University Putra Malaysia (UPM), Serdang, Selangor, Malaysia,

[2] Professor, Faculty of Economics and Management, University Putra Malaysia (UPM), Serdang, Selangor, Malaysia.

ARTICLE INFORMATION

Article Chronology:

Received 01 January 2016

Revised 30 January 2016

Accepted 14 March 2016

Published 31 May 2016

Keywords:

Environmental efficiency, Data envelopment analysis, Material balanced principle, Electricity generation.

CORRESPONDING AUTHOR:

foroogh.shadman@gmail.com

Tel: (+603) 8947 1096

Fax: (+603) 8943 2611.

ABSTRACT:

Introduction: One of the largest proportions of human-related air pollution is produced by fossil-fuel based electricity generation units. Hence, the environmental performance that complies with technical performance receives increasing attention and seems to be the missing point in environmental impact analysis and energy policy studies. Therefore, empirical analysis which leads to increasing awareness of official policy makers concerning the technical and environmental trade-offs is the objective of the study in the electric generating sector by applying a two-stage Data Envelopment Analysis (DEA).

Materials and Methods: In the first stage the DEA incorporates Materials Balanced Principle (DEA-MBP) to estimate the allocation of gas, mazut and gas oil of steam plants to minimize inputs and SO_2 emissions respectively with the given technology. It is then followed by applying Ordinary Least Squares (OLS) applied in the second stage investigate the other explanatory variables which may influence the efficiency and were not properly considered in the first stage analysis.

Results: The results evident that there is considerable gap between technical and environmental efficiency (76% and 10% respectively) scores. The impact of most important explanatory variables in the second stage clearly demonstrates that plant sizes and fuel type have significant influence while plant age and the year of observation have no statistically significant influence on the technical and also environmental efficiencies of steam power plants.

Conclusions: Advancement in interdisciplinary research helps to increase technical efficiency while reducing emissions by applying analytical methods, which may provide better information for decision making units. Hence, it is the management's responsibility to improve efficiency by modifying regulation and competition performance in this respect.

INTRODUCTION

Energy efficiency should be given more attention to ensure that technically available energy fulfills the needs of economic growth and sustainable development. Efficient energy production seems mandatory for the future generation. Like other developing countries, fossil fuels play an important role as the major energy sources in power generation in Iran [1]. Iran, with an area that is roughly 1,648,000 Km^2, is located in the heart of

Please cite this article as: Shadman F, Abdulrahim Kh. Joint environmental and technical efficiency of stream power plants: A case study of Iran. Journal of Air Pollution and Health. 2016; 1(2): 83-98.

the Middle East and is also the one among the countries with the largest oil and gas reserves in the world. Iran is a member of the Organization of the Petroleum Exporting Countries (OPEC), and ranks among the world's top three holders of both proven oil and natural gas reserves.

Power industry in Iran is owned, operated and administrated by the Ministry of Energy (MOE), Iran. By 2012, Iran with about 67GW installed nominal capacity was ranked first in the Middle East countries and 15th in the world [2]. Most of the power plants in Iran are using non-renewable sources such as natural gas, fuel oil and diesel to generate electricity. In 2006, steam power plants using those fuels have a capacity of 15,598 MW, which is equivalent to 29.5 percent of the overall installed capacity and this amount represents 45.4 percent of the total thermal electricity generation in the country (Ministry of Energy, 2009). Steam power plants also have the largest share of electricity generation (91.1 billion kWh) while the lowest (0.2 billion kWh) comes from diesel power plants (Iran Central Bank, Annual Report, 2007/8).

Improving energy efficiency is the most important concern in most developing countries all around the world and there are ample studies on this subject regarding technically efficient implementation of energy production, economically viable and environmentally efficient in terms of pollution reduction. In general, huge amount of air pollutants are produced by thermal power plants operated using fossil fuels. The problem arises where during cold seasons in Iran when the residential usage of natural gas is maximized, the national gas pipeline pressure drops, power plants have to switch their fuel type from one to other types of fuels such as fuel oil and diesel. However, sulfur dioxide (SO_2) is one of the major air pollutants from these heavy fuels and coal in the electricity generation industry. High proportion of SO_2 has significant impact on human health(United States Environmental Protection Agency) and harmful effects on the environment and thus, to increase the ecological efficiency, particular measures should be taken [3] and one of the most important pollutants in the electric industry. However, it could not be the sole measure of environmental performance. In 1998, it has indicated that the definition of environmental performance includes a wide scope and therefore, selecting a single performance indicator or even the entire ones would be an insufficient measure for a plant's environmental performance [4]. The assessment of environmental performance and waste management study suggested that one way to measure environmental performance is to assess the relevance of actions adopted, which results in improvements of the interest gauged [5]. Based on this insight and mainly due to its most important air pollutions from heavy fuels in steam plants reducing pollution from production system seems necessary. Therefore, in the electricity generation industry an efficiency analysis which considers the SO_2 content of different fuel inputs can help identify appropriate technical and environmental trade-offs. Though based on several national agreements to reduce emissions have considered SO_2 as an appropriate proxy for environmental performance, as being carried out in this study and is recognized as one of the main pollutants emerging from the power sector that justifies the pressure for its reduction, and it is necessary for a power plant to find an effective solution to achieve it [6]. Hence, consciousness of this air pollutant from different fuel input per unit of electricity generation consider necessary to assess the possible environmental tradeoffs in selecting the best policy for the future.

The potential deterioration of ecosystems and the harmful impact on human health caused by sulfur dioxide have brought a serious and increasing concern of the government and especially for the energy sector to formulate incentive plans for the generating plants in order to reduce the pollutants. In Iran, several national agreements to reduce air pollutions have been established and many rules and regulations were passed in the third and fourth national development plans such as Article 15 of air pollution prevention law(Air Pollution Prevention Law, for emission standards of factories and workshops passed in the year 2003) which prescribed the maximum amount of allowable SO_2 emissions by the power plants, and also Article 121 (2000) which was validated and extended in the fourth national development plan in the third 5-year national development plan. Executive by-laws for paragraph (c) of article 104 and article 134 of the law of the third economic, social and cultural development plans of Iran was also ratified by the Department of the Environment (October 2001), which determined the monthly fines for extra discharge of pollutants into the environment. Moreover, Article 20 (2004) emphasized the emission reduction out of fuel consumption by all possible means.

Based on the above discussions, this study embarks on considering and estimating the technical and environmental efficiency analysis of the steam power plants which are using different fuel mixtures, mostly heavy fuels, especially in winters and autumns when the polluted air is trapped under the cold weather and cause serious environmental and social problems.

This study also provides an insight for energy policy making at micro and macro levels (individual plants and public policy makers) analyzing the technical and environmental trade-offs applying DEA-MBP methodology [7, 8], which was applied for the United States steam plants to illustrate whether the procedure is applicable to specific decisions for individual plants [9]. Our analysis takes a step further by applying Ordinary Least Square (OLS) in the second stage for the first time to investigate the degree to which various factors influence the technical and environmental efficiency levels. This study follows by using the two-stage DEA estimation methods and then applying OLS in the second stage of the analysis and discussion [10]. Our study uses seasonal data for the last three years leading to the removal of fuel subsidies in Iran aiming at developing a study of technical and environmental efficiency of steam electricity utilities in Iran to highlight the role of the most important factors.

The rest of the paper is as follows: Section 2 is designed to address the Data Envelopment Analyses (DEA), Materials Balance Principle (MBP) and the extended DEA-MBP theory followed by the use of least square method in second stage of DEA analysis. In addition, this section concisely explains the most recent studies on incorporation of certain explanatory variables such as plant age, size, and fuel types to elaborate the impact of explanatory variables on the efficiency level. Section 3 presents the methodology undertaken in the study. Descriptive statistics and the results of the technical and environmental efficiency analysis are discussed in this section followed by the findings in section 4. Finally, we draw some concluding remarks and policy insights in Section 5.

MATERIALS AND METHODS

This study aims to estimate allocations of gas, fuel oil and mazut to minimize SO_2 emissions applying Data Envelopment Analysis which incorporates the material balance principle. Finding also would point out significant information to specify appropriate policy to consider new incentive systems in power generation industry of Iran. As indicated in the previous section, the main methodology of this research is a two-stage DEA-MBP application. Here, we briefly address the advantages and the literature related to this methodology.

Overview of DEA-MBP theory and methodology

Data envelopment analysis

DEA is fundamentally based on the work done by Farrell [11] and extended by Charnes, Cooper [12] and Banker et al. [13]. Based on the basic concept of efficiency revealed by Fare et al. [14], an efficiency measures how well a firm succeeds in transforming inputs into outputs according to the plant's behavioral objective. The efficiency of each Decision Making Unit (DMU) is measured as the maximum of the ratio of weighted outputs to weighted inputs [12]. DEA provides benchmark indices for a given industry or subunits in a firm to evaluate the relative productive efficiency of its DMUs [15]. However, researchers have realized the need to modify the traditional methods of productivity and efficiency analyses in order to allow for better monitoring and evaluation performances of firms and their production processes and also to integrate environmental concerns into the standard technical efficiency measures [7, 16-22]. Thus, DEA has been widely used in performing empirical efficiency (or productivity) analyses to construct composite indictors for benchmarking and policy evaluation especially when the units (DMUs) applied multiple inputs to produce multiple outputs [23-25]. DEA methodology is also applied to examine the relationship between technical and environmental efficiency [26]. DEA was also implemented to measure the environmental efficiency and total factor productivity applying Malmquist productivity index [27].

Returns-to-scale is another property that can be handled by DEA. Constant returns-to-scale (CRS) assumption demonstrates that there is no significant relationship between the scale of operations and efficiency pre-supposed by the CCR (Charnes, Cooper and Rhodes) model, which delivers the overall technical efficiency (OTE) [12]. However, firms or DMUs in practice might face either economies or diseconomies of scale [28]. In essence, CCR would be the main model deployed in this study.

Materials balance principle (MBP)

This section addresses a new principle recently added to DEA literature. During the last decade, when preservation of environment gradually became one of the main humankind concerns, undesirable products such as pollutants out of a system, analysis of the relevant issue has become a new entry towards every performance measurement methods. According to the law of conservation of mass which dated back to 1789 by Antoine Lavoisier's, mass is neither created nor destroyed in chemical reactions [29]. However, to embrace the comprehensiveness of an efficiency measurement study, it is necessary to include some variables which cannot be included in a DEA kind of measurement system but are useful to explain dark angles of the analysis.

Therefore, incorporating pollutant as an outcome of the production process in the materials balance recognized as preferable approach for an environmental activity analysis. Using the term "outcome" refers both to the balancing item acquired through applying the MBP and to the more general concept of environmental outcome.

Later on, an environmentally optimal allocation of inputs investigated by Reinhard [30] is continued debating on input-oriented approach instead of a materials balance concept of production efficiency models [31]. In 2007, a study which applied the Lauwers et al. (1999) suggested the analytic similarity method in achieving the environmental and economic objectives, which were derived from an analogous model as for the economic efficiency measurement [8]. Then, the Materials flow coefficients concept has been extended towards eco-efficiency [21]. Finally, it was clearly demonstrated that viability problems would not be properly tackled without applying the material balance condition [7, 8].

DEA-MBP approach

As the environmental side effects have become the central part of public and political discussions during the past two decades, researchers have realized the need to modify traditional methods of productivity and efficiency analysis to integrate environmental concerns into the standard technical and economic efficiency measures [7]. All physical systems would be identified in the material balance flow. Material flows recognized by accounting for material entering and leaving of the system. Thus, engineering and also environmental analysis widely rely on the mass balance concept and mathematical models remains incompatible especially when undesirable output taking into account. Hence, DEA researches efforts have begun to develop new methods that would represent promising new avenues for considering the material flows. Finally, in 2005, Coelli successfully employed the analysis of both economic and environmental inputs and outputs in DEA-Materials Balance Principle model (DEA–MBP) [9]. Coelli (2005) mentioned that by considering fixed output vector (y), surplus or undesirable output will be minimized when the aggregate surplus (pollutant) content of the inputs is minimized. This would be in contrast with previous studies which indicated a reduction in pollution can only occur by increasing in one or more traditional inputs or reduction in one or more traditional output. Based on the new environmental efficiency measures defined by Coelli [7], environmental efficiency (EE) of a firm is equal to the ratio of technically possible minimum pollution over the observed pollution whereas TE refers to the minimum input needed to produce one unit of output . This efficiency can be scaled between zero and one, with a value of one indicating full environmental efficiency. This modeling pollution is mathematically consistent with the materials balance condition and allows for technical and environmental trade-offs inherent in energy production as well.

DEA- application in the electricity generation

In 1994, Golany and Roll were the first who consider pollution variable in DEA methodology [32]. Since then many such studies have been carried out and incorporated in their literature survey on DEA with respect to energy and environment [33]. Integrating MBP environmental considerations into economic and energy policy sector represents a major objective of electricity generation utility companies throughout the world. In 2009, DEA-MBP methodology was first applied by Welch et al. in US electricity generation companies demonstrating the economic and environmental tradeoffs among the different types of fuels which are applied by these plants [34]. The study indicated that both cost and carbon efficiency of many plants on the production frontier could be improved by changing their mixture of fossil-fuel inputs. Following that, Färe, Grosskopf [35] applied a network technology approach to incorporate MBP into directional distance function models to measure U.S. coal-fired power plants eco-efficiency. A similar study was conducted over a 10-year period from 1985 to 1995 on 92 U.S. coal-fired power plants by introducing new approach which rectified the shortcomings of the past models [36].

The least squares method in the second stage of DEA efficiency analysis is discussed in the next section.

Least squares DEA for efficiency analyses

It is common to analyze efficiency in two stages to investigate the degree that various factors influence efficiency levels, i.e. DEA can be used to estimate efficiency in the first stage and regression analysis in the second stage to study the factors which might influence efficiency scores.

Some procedures have been developed, which have taken into account the relevant factors that influence efficiency during DEA analysis in the second stage [37-39]. The two-stage procedure in terms of simplicity and the way it is interpreted seems appealing. Then, another study showed that the efficiency score are fractional data and hence neither censored nor corner solutions; the generating process can be better described as a normalization process [40]. Hoff [41] in his particular example has compared the within-sample prediction performance (or fit) of two-Limit Tobit (2LT), OLS, a Quasi-Maximum Likelihood Estimation (QMLE) by using Papke and Wooldridge [42] model and also the unit-inflated bet model of Cook et al. [43] which came to the conclusion that OLS performance is at least the same as other applicable methods.

Banker and Natarajan [44] built on the path-breaking paper of Banker [45] in which Banker provided a formal statistical basis for two-stage analysis. The paper also represented a considerable advance by applying DEA linear programming in the first stage and OLS in the second stage for DEA efficiency analysis [44]. Finally, it has argued that DEA efficiency scores are a particular kind of fractional or proportional data and found that OLS can provide an unbiased, consistent estimator, and, can be undertaken as a valid method if heteroskedasticity is allowed for hypothesis testing [10]. Thus, a careful OLS analysis will often be sufficient and merits to be used in familiar and easy to compute methods. Important factors affecting technical and environmental efficiency are presented and discussed in the following section.

Factors influencing power plant efficiency

A number of authors have examined the power plants' technical inefficiency determinants (plant ownership, plant age, plant size, fuel type, plant type and also changes through time or time trend) since the early 1970s by mostly concentrating on the ownership but less emphasis on plant age and size and also fuel type in past studies due to their objective which was to maximize profits instead of public and environmental services [46-58].

Hence, our study took a further step to examine the most important explanatory variables which influence the environmental efficiency in electricity generation facilities. Environmental policy debates are often more contentious and hence the key to making a good policy decision is a clear understanding of the evidence which is linked to efficiency regulation, to competitiveness, and environmental outcomes. Therefore, since the majority of power plants in Iran are produced under direct governmental supervision and ownership, our study does not aim to consider ownership characteristics here.

Two stage DEA-MBP analyses

The main methodology of this study is an application of a two stage DEA-MBP analyses. This methodology is chosen in order to analyze both technical and environmental efficiencies in allocative manner for steam power plants installed in Iran. Here, technical efficiency refers to minimum input required to produce of one unit output over the observed input usage and the environmental efficiency which is regarded as the ratio of potentially minimum amount of pollution generation out of a type of fuel input over the observed amount pollution. Both take the values within zero and one. The main pollutant that comes out as a byproduct from steam power plants using heavy fuels is SO_2. The combined DEA-MPB method with constant return-to-scale assumption based on the actual input-output observations in the sample is implemented to examine the technical and environmental trade-offs among different fuel types used by the plants.

The procedure is as follows: firstly, estimation is done on technical efficiency (TE) and secondly, the estimation is done using SO_2 content per Btu of inputs for each fuel type to obtain the environmental efficiency (EE) scores. Thus, technical and environmental efficiencies are estimated in the conventional way, as the ratio of minimum feasible inputs over the observed one. Finally as addressed in Section 3.1, OLS is employed to evaluate the impact of a number of factors (age, size, fuel type and year of observation) which are supposed to be efficacious but are not included in the DEA-MBP models for estimating the technical and environmental efficiencies in the first stage.

DEA-MBP approach in the first stage analysis

In the first stage, a production frontier with a single output (electricity generated), three conventional inputs (natural gas, fuel oil and gas oil) were used to estimate the technical efficiency, and a single environmentally detrimental input (sulfur dioxide surplus) was specified to estimate environmental efficiency scores. The study incorporates all 17 Iranian public owned steam power plants' seasonal data (204 observations) that produce 45.4 percent of the total thermal electricity in the country. Our data consists of 204 observations obtained for the three years seasonal data (winter of 2007 to autumn 2009). This analysis takes advantage of the available Iranian electricity production and fuel consumption datasets (seasonal dataset, statistics and information office), power generation transmission and distribution management company (*TAVANIR*) under the ministry of energy, Iran. sulfur fuel amount of fuels (MBtu and calculated in g/ GJ of sulfur) were obtained from the department of environment (DOE)[1] of Iran.

[1] According to the result of the comprehensive plan on tehran air pollution control , 1997, by JICA and municipality of tehran

Fuel, labor and capital are complements and are not substitutes in electricity generation industry. So, one reliable way in applying traditional DEA models is to consider only one of the complementary variables [59, 60]. The other reason is that labor input is a very small and relatively insignificant part of input resources. Capital stock is relatively fixed once the plant related to fuel has been constructed. Hence, incorporating only the fuel type as the main contributor in electricity generation helps to identify the pollution in its simplest way as possible for environmental and government officials' information [9].

Towards this aim, DEA constant return to scale model, which is known as CCR in honor of Charnes, Cooper and Rhodes who introduced DEA [61] , can be written as follows:

$$\min_{\lambda} \theta$$
$$st$$
$$\sum_{j=1}^{J} x_{jn}\lambda_j \leq \theta x_{kn} \quad n=1,\dots,N \qquad (1)$$
$$\sum_{j=1}^{J} y_{jm}\lambda_j \geq y_{km} \quad m=1,\dots,M$$
$$\lambda_j \geq 0,\ j=1,\dots,J$$

where j=1,…,J observation for n=1,…,N inputs and m=1,…,M outputs representing $x_j=(x_{j1},\dots,x_{jn})\in R^N_+$ and $y^j=(y_{j1},\dots,y_{jM})\in R^M_+$. Our study includes m = 1 output (Generated Electricity) and n = 3 input variables (natural gas with substitute fuels like gas oil and fuel oil), whereas DEA score θ estimates the technical efficiency of the target DMU k.

In order to measure environmental efficiency as in model (2), which are also input oriented and reflects constant returns to scale we show these in vector form [7, 8]. The term of input-oriented indicates that an inefficient unit is made efficient through the proportional reduction of its inputs while its outputs are held constant.

$$Ex^* = min_{x\lambda} Ex$$
$$St$$
$$x \geq X\lambda \qquad (2)$$
$$y_0 \leq Y\lambda$$
$$\lambda \geq 0$$

In the case of environmental efficiency, E represents the SO_2 content of each fuel type and assumed common for all observations. The vector x^* contains the target DMU inputs that minimize SO_2 byproduct, the matrix X contains the input values for all DMUs to be included in the analysis, and the matrix Y contains the output values for all DMUs included in the analysis. The vector y_0 contains the original outputs for the target DMU, and λ is the vector of intensity weights.

RESULTS AND DISCUSSION

The first stage analysis

We illustrate our estimation by using DEA–MBP linear programming models. Data included fuel type, quantity, Btu content measured in millions of Btu (MBtu) and sulfur content information. Our DEA model is used to measure technical and also environmental efficiencies, which are input oriented, and reflects constant returns to scale. All DEAs were conducted with DEAP 2.1 (CEPA).

As demonstrated in Table 1, the mean (to give more weighting data) technical efficiencies are higher in winter and autumn than in other seasons, which clearly demonstrate that it is due to higher heating value of heavy fuels used in cold seasons. Meanwhile, environmental efficiency (mean Sulfur per MBtu is 1 unit for gas, 447 units for Diesel, and 1637 units for Mazut) shows proportionally lowest value during winter and autumn.

SO_2 outcomes for our first stage analysis are summarized in Table 2. The last row of the table indicates that the average output of the plants would reduce SO_2 by 80.14 percent and 91.73 percent if they attained technical efficiency and environmental efficiency respectively. The first DMU or Tabriz plant attains the fully technical and environmental efficiency in summer; however, during winter it is technically efficient but is not environmentally efficient. In order to attain the environmental efficiency, the SO_2 amount would have to be decreased by 99 percent in the winter by using natural gas. With this analysis, specific policy could be formulated taking into consideration new incentives to supply fuels, operational techniques and other factors which are needed to reduce SO_2.

Second stage analyses

Due to the fact that most of the effective factors may not have been adequately captured in our first stage DEA-MBP analysis, the efficiency scores were re-examined to upgrade the technical and environmental efficiencies for any inefficient

Table 1. Mean technical and environmental efficiencies in all seasons

	Winter	Spring	Summer	Autumn
Technical Eff.	0.919	0.875	0.875	0.881
Environmental Eff.	0.034	0.01	0.01	0.052

Table 2. DEA-MBP environmental results for the plants

Firm	Season	Original SO_2 per unit output	Changes in Sulfur per unit output		Firm	Season	Original SO_2 per unit output	Changes in Sulfur per unit output	
			OrigtoTE	OrigtoEE				OrigtoTE	OrigtoEE
Firm 1	Winter	14580.272	0.00	-99.93	Firm 10	Winter	13667.957	-99.93	-99.93
	Spring	1247.508	-99.20	-99.20		Spring	2601.236	-99.62	-99.62
	Summer	9.963	0.00	0.00		Summer	4870.530	-99.80	-99.80
	Autumn	7819.578	-99.87	-99.87		Autumn	9049.994	-99.89	-99.89
Firm 2	Winter	12282.241	-99.92	-99.92	Firm 11	Winter	6493.241	-99.85	-99.85
	Spring	3029.117	-99.67	-99.67		Spring	752.256	-98.68	-98.68
	Summer	4029.299	-99.75	-99.75		Summer	762.251	-98.69	-98.69
	Autumn	7275.605	-99.86	-99.86		Autumn	3797.777	-99.74	-99.74
Firm 3	Winter	13077.650	0.00	-99.92	Firm 12	Winter	776.853	-98.72	-98.72
	Spring	4211.494	-99.76	-99.76		Spring	11.692	-14.81	-14.79
	Summer	4141.676	-99.76	-99.76		Summer	57.448	-82.66	-82.66
	Autumn	8617.497	-99.88	-99.88		Autumn	40.734	-75.55	-75.54
Firm 4	Winter	13233.398	-99.92	-99.92	Firm 13	Winter	4401.220	-99.77	-99.77
	Spring	4817.218	-99.79	-99.79		Spring	101.799	-90.22	-90.21
	Summer	5285.521	-99.81	-99.81		Summer	247.355	-95.97	-95.97
	Autumn	8208.535	-99.88	-99.88		Autumn	851.634	-98.83	-98.83

Table 2. DEA-MBP environmental results for the plants

Firm	Season	Original SO_2 per unit output	Changes in Sulfur per unit output		Firm	Season	Original SO_2 per unit output	Changes in Sulfur per unit output	
			OrigtoTE	OrigtoEE				OrigtoTE	OrigtoEE
Firm 5	Winter	12718.709	0.00	-99.92	Firm 14	Winter	10936.838	0.00	-99.91
	Spring	3001.600	0.00	-99.67		Spring	3055.206	-99.67	-99.67
	Summer	3714.014	-99.73	-99.73		Summer	4454.310	-99.78	-99.78
	Autumn	8490.886	-99.88	-99.88		Autumn	8691.349	-99.89	-99.89
Firm 6	Winter	10959.773	-99.91	-99.91	Firm 15	Winter	1392.245	0.00	-99.28
	Spring	1384.560	-99.28	-99.28		Spring	96.280	0.00	-89.65
	Summer	3085.390	-99.68	-99.68		Summer	103.850	-90.41	-90.41
	Autumn	7824.281	-99.87	-99.87		Autumn	520.053	-98.08	-98.08
Firm 7	Winter	12444.304	-99.92	-99.92	Firm 16	Winter	9315.512	0.00	-99.89
	Spring	541.316	-98.16	-98.16		Spring	1705.137	-99.42	-99.42
	Summer	18.107	-44.99	-44.98		Summer	979.480	-98.98	-98.98
	Autumn	4324.904	-99.77	-99.77		Autumn	5981.548	-99.83	-99.83
Firm 8	Winter	13594.585	-99.93	-99.93	Firm 17	Winter	9385.250	-99.89	-99.89
	Spring	4532.610	-99.78	-99.78		Spring	5877.698	-99.83	-99.83
	Summer	6702.882	-99.85	-99.85		Summer	4974.411	-99.80	-99.80
	Autumn	9188.180	-99.89	-99.89		Autumn	7421.058	-99.87	-99.87
Firm 9	Winter	18.201	-45.28	-45.26					
	Spring	17.871	-44.27	-44.25					
	Summer	17.709	-43.76	-43.74					
	Autumn	16.744	-40.52	-40.50					
						Mean	4968.19	-80.14	-91.73

Note: Original SO_2 per unit output is calculated from the 2007-2009 seasonal value. Plant 1 in summer in bold is both technically and environmentally efficient with 9.96 SO_2 per unit output . The SO_2 per unit output to attain an environmentally efficient point (OrigtoEE) for all DMUs is 9.963. For instance, the percentage that the SO_2 could decrease by moving to the SO_2 efficient point for firm 12 in the spring is (9.96-11.69)/ 9.96 = 14.79%. The negative value of environmental efficiency indicates that if all plants were using currently-available technology efficiently, the sulfur output would decrease by the respective degree.

plants in order to correct and catch up with the frontiers.

With reference to McDonald's work [10], we estimated the regression model by using the White's [62] transformation involving DEA scores as the dependent variable, which is robust to heteroskedasticity and distribution of the disturbance. In the second stage, our technical and environmental efficiencies' scores were re-estimated by employing Ordinary Least Square (OLS) method with respect to a set of the most important internal (power plant size, age) and external (fuel type, year of observation) factors. This is somewhat different from other approaches in the literature. The software, STATA 11.0 (2009) was used to estimate the parameters involved in the Ordinary Least Square (OLS) model. The list and definition of explanatory variables used in the study are presented in Table 3.

Descriptive statistics

A general overview of the descriptive statistics used in the second stage is briefly presented in Table 4:

By quantifying the relationships between the explanatory variables and the technical efficiency

Table 3. List of explanatory variables

Inefficiency determinants	Variable type	Measurement
Age	Value	Weighted average plant age
Plant size(dumS)	Dummy	1= small size 0= otherwise
Plant size(dumL)	Dummy	1= large size 0= otherwise
Fuel type	Dummy	1= gas fired 0= otherwise
Year	Value	Year of observation

Table 4. Summary statistics of the variables

	Technical efficiency		**Environmental efficiency**	
Variable	**Mean**	**Std. error**	**Mean**	**Std. error**
Efficiency score	0.7679	0.1280	0.0980	0.2137
Age of the plant (year)	0.4166	0.4942	27.3137	12.3965
Year of Observation	1644.692	430.2729	2	0.8185

Note: the other explanatory variable includes dummy and the year of observation, which are excluded due to the fact that dummy variables (size, fuel type and year of observation) are the proportional data.

(TE) and environmental efficiency (EE) scores, the study characterized the other factors, which are not appropriately modeled in the first stage and hence have to be considered in the second stage.

Technical and environmental efficiency effect model

As demonstrated in the first stage technical efficiency analysis, the majority of the Iran's steam energy plants are not operating within the technical and environmental efficient frontier. To find other exogenous factors which may affect the efficiency scores and were not considered in the first stage analysis, we kept continue our analysis to apply Ordinary Least Squares (OLS) [10]. Results for all explanatory variables (age, size, fuel types and the year of observation) of the technical and environmental efficiency effect models are presented in Table 5.

The model for technical and environmental efficiency is specified as follows:

$$TE=0.877-0.115sizedumS_{it}+0.02sizedumL_{it}-0.002Age_{it}-0.04FuelType-0.003Year_{it}+u_{it} \quad (3)$$

Then, the same analysis is done to investigate the explanatory variables that may have some influence on environmental efficiency;

$$EE=0.011-0.125\ sizedumS_{it} + 0.00096\ sizedumL_{it} - 0.00095\ Age_{it} + 0.5\ FuelType - 0.005Year_{it} + u_{it} \quad (4)$$

Where,

u_{it} stands for the error term;

Based on the second stage analysis as demonstrated in Table 5, plant size (small) variable failed to be rejected that may not have any influence on technical and environmental efficiency. How-

Table 5. Technical and environmental effects model results

	Technical Efficiency		Environmental Efficiency	
	Coefficient	*T*-Statistic	Coefficient	*T*-Statistic
Constant	0.8775	18.60	0.0112	0.31
Age	-0.0027	-1.80	0.0009	0.83
Size (dum small)	-0.1150	-2.54***	-0.1257	-3.42***
Size (dum large)	0.0204	0.69	0.0009	0.04
Fuel type	-0.0485	-2.73***	0.5280	17.97***
Year of obsrv.	-0.0030	-0.55	-0.0055	-0.57
F-Statistic	46.31***		*Wald chi2*	414.61***
No. observ.			204	

***, ** and * indicates significant at 1, 5 and 10% significance levels.

ever, the next complementary variable explicitly indicates that technical and environmental efficiencies do not vary with the large generating capacity of power plants. It may be interpreted that the large generating capacity partly has access to high quality management skills. The finding is also in compliance with other studies implying that the large steam plant operators have fewer problems of management skills and coordination in comparison to small steam plants (e.g., [48, 53, 54, 56, 58]).

Based on the second stage analysis, the next explanatory variable viz. fuel type does vary with negative coefficient suggesting that power plants using mixed fuel tend to be technically more efficient than power plants using natural gas alone. In fact, this is due to the higher heating value of heavy fuels in comparison to natural gas which led to better technical efficiency of the plants. On the contrary, the coefficient of fuel type for environmental efficiency score is estimated positive with strong relationship which clearly demonstrates that gas fired power plants are environmentally more efficient than power plants using other fuel types. In the next section the results of our study are summarized and discussed.

The study also indicates that plant performance over time (trend) does not affect the technical and also environmental efficiency scores. This might be due to ascending learning progress during plants' lifetime or because of periodical maintenance and planned overhauls that cause plants not to be technically retired over time. This result could also be supported by the last (the year of observation) variable estimation results. Our second stage analyses properly demonstrate that the technical and environmental efficiency scores do not tend to change over time.

The pervasive analysis is to encourage the generation of electricity which might cause less stress on environment and technically efficient use of energy. It seems necessary to verify that accurate information is a necessity of the day. Thereby, this study examines the technical and environmental efficiencies of steam power plants based on seasonal data over a three-year period from 2007 to 2009 using a two-stage DEA-MBP approach in the first stage and OLS model in the second stage, which is the novelty so far. This study found that the mean technical and environmental efficiencies of the plants are 0.767 and 0.098 respectively. The results also indicated that the mean seasonal technical efficiency in winters is greater than other seasons. It demonstrates that using more heavy fuels in winters and the higher heating value of these fuels results in high technical efficiency, whereas on the contrary environmental efficiency with the mean of 0.034 in winters shows the lowest due to the emission of more SO_2 pollution. The DEA-MBP methodology allows the study to gather useful information on technical and environmental efficiencies swiftly. The analysis is intended to help public officials and environmental scientists to be informed when formulating specific policy or new incentive systems in selecting technologies, fuel supply and other factors that might help to produce more SO_2 free production.

The results from the second stage indicate that small generating capacity would negatively affect the technical and environmental efficiency. Fuel type also does affect the technical and environmental efficiency conversely while the influence for technical efficiency in negative direction indicating that applying heavy fuel due to its higher heating value seems more efficient. Meanwhile, high positive coefficient degree of fuel type in environmental efficiency second stage analysis demonstrates the most important and effective variable for the environmental efficiency analysis suggesting that power plants that use natural gas are more environmentally efficient than the other plants. Due to the abundance of natural gas in Iran, exploring the most important feature provides the government information for their policy considerations. Explanatory variables with large impact can be targeted relatively easily by the government in formulating a policy.

Regarding the technical and environmental trade-offs explored by this study in the first stage and most important explanatory variables which may affect efficiency scores, it could be drawn on national research, experience and take top Iranian scholars' attention together to make the best proper incentives on 'next generation' policy approaches for building a greener and stronger environment. Thus, the second stage estimation reflects the impact of explanatory variables to be selected by the government, environmentalists and policy makers to properly allocate their technical and environmental assets. Further, according to available technologies, resources and environmental pollutions comprehensive energy policies would be necessary.

CONCLUSIONS

Due to the vital role of energy within the society, it is important that technology, environment and policy matters work harmoniously together. Otherwise, global energy problems cannot be tackled successfully. This is the first empirical study which simultaneously examines technical and environmental efficiencies of Iranian steam power plants that use heavy fuels when natural gas losses for power plants and industries occurred. This study also indicates that technical and environmental efficiencies are mostly exogenous (fuel type) to the main explanatory variables. Two important contributions of the study seem worth mentioning. First, while the study concerns just for the steam power plants in Iran, it is applicable for other industries, which mostly rely on fossil fuels and consequently could be responsible for environmental efficiency. Next, due to the proportional amount of the pollutant in using fossil fuels, our study measured a single aspect of environmental performance which relatively similar results could be expected in other applications. However, implementing cost of fuel to analyze most allocative efficiency of power plants along with technical and environmental efficiency analysis seems reasonable while is not considered in the scope of this study. Thus, advancement in interdisciplinary research helps to increase technical efficiency while reducing emissions by applying analytical methods, which may provide better information for decision making units. Hence, it is the management's responsibility to improve efficiency by modifying regulation and competition performance in this respect.

FINANCIAL SUPPORTS

The authors would like to thank the facility supported by the Natural Resource Policy Studies Department of University Putra Malaysia (UPM).

COMPETING INTERESTS

No competing interests have been declared by the authors.

ACKNOWLEDGEMENTS

This paper is extracted from the author's PhD thesis which has benefitted the *Long Run Research Grant Scheme* (LRGS) 2011-2016 funded by the Ministry of Higher Education, Malaysia for the *Low Carbon Economy* (LCE) Research Group.

ETHICAL CONSIDERATIONS

Authors have completely considered all ethical issues.

REFERENCES

[1] IEA. Keywords: energy statistics. Paris: 2008.
[2] information USDoE. "Country Analysis Brief: Iran". 2013.
[3] He B, Chen C. Energy ecological efficiency of coal fired plant in China. Energy conversion and management. 2002;43(18):2553-67.
[4] Ilinitch AY, Soderstrom NS, E Thomas T. Measuring corporate environmental performance. Journal of Accounting and Public Policy. 1999;17(4):383-408.
[5] Lanen WN. Waste minimization at 3M company: A field study in nonfinancial performance measurement. Journal of management accounting research. 1999(11):29-43.
[6] Kaminski J. Technologies and costs of SO2-emissions reduction for the energy sector. Applied Energy. 2003;75:165–72.
[7] Coelli T, Lauwers L, Van Huylenbroeck G. Formation of technical, economic and environmental efficiency measures that are consistent with the materials balance condition. Centre for Efficiency and Productivity AnalysisWorking Paper. 2005;6.
[8] Coelli T, Lauwers L, Van Huylenbroeck G. Environmental efficiency measurement and the materials balance condition. Journal of Productivity Analysis. 2007;28(1-2):3-12.
[9] Welch E, Barnum D. Joint environmental and cost efficiency analysis of electricity generation. Ecological Economics 2009;68:2336-43.
[10] McDonald J. Using Least Squares and Tobit in Second Stage DEA Efficiency Analyses. European Journal of Operational Research. 2009;197:792-8.
[11] Farrell MJ, . The measurement of productive efficiency. Journal of the Royal Statistical Society 1957;120:253-81.
[12] Charnes A, Cooper W, Rhodes E. Measuring the efficiency of decision making units. European journal of operational research. 1978;2(6):429-44.
[13] Banker RD, Charnes A, Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science. 1984;30(9):1078-92.
[14] Fare R, Grosskopf S, Lovell CAK. production Frontiers. New York: Cambridge University Press. 1994.
[15] Cook WD, Chai D, Doyle J, Green R. Hierarchies and groups in DEA. Journal of productivity analysis. 1998;10(2):177-98.
[16] Chung YH, Färe R, Grosskopf S. Productivity and Undesirable Outputs: A Directional Distance Function Approach. Journal of Environmental Management. 1997;51(3):229-40.
[17] Färe R, Grosskopf S, Norris M, Zhang Z. Productivity growth, technical progress, and efficiency change in industrialized countries. The American Economic Review. 1994:66-83.
[18] Färe R, Grosskopf S, Pasurka Jr CA. Accounting for air pollution emissions in measures of state manufacturing productivity growth. Journal of Regional Science. 2001;41(3):381-409.
[19] Knox Lovell CA, Pastor JT, Turner JA. Measuring macroeconomic performance in the OECD: A comparison of European and non-European countries. European journal of operational research. 1995;87(3):507-18.
[20] Tyteca D. Linear programming models for the mea-

surement of environmental performance of firms—concepts and empirical results. Journal of productivity analysis. 1997;8(2):183-97.
[21] Lauwers L. Justifying the incorporation of the materials balance principle into frontierbased eco-efficiency models. Ecological Economics. 2009;68(6):1605-14.
[22] Lauwers L, Van Huylenbroeck G, Rogiers G. Technical, economic and environmental efficiency analysis of pig fattening farms, Poster presentation at the 9th European Congress of Agricultural Economists, Warschau. Polen, August 24th-28th. 1999.
[23]Seiford LM. Data envelopment analysis: The evolution of the state of the art (1978–1995). Journal of productivity analysis. 1996;7(2):99-137.
[24] Emrouznejad A, Parker BR, Tavares G. Evaluation of research in efficiency and productivity: A survey and analysis of the first 30 years of scholarly literature in DEA. Socio-Economic Planning Sciences. 2008;42(3):151-7.
[25] Rogge N. Undesirable specialization in the construction of composite policy indicators: The Environmental Performance Index. Ecological Indicators. 2012;23:143-54.
[26] Shortall OK, Barnes AP. Greenhouse gas emissions and the technical efficiency of dairy farmers. Ecological Indicators. 2013;29(0):478-88.
[27] Song M, Guan Y. The environmental efficiency of Wanjiang demonstration area: A Bayesian estimation approach. Ecological Indicators. 2014;36:59-67.
[28] Thanassoulis E. Introduction to the theory and application of data envelopment analysis: a foundation text with integrated software: Springer; 2001.
[29] Likens GE, F.H. Bormann. Biogeochemistry of a forested ecosystem. Second Edition 2001 ed. N.Y.: Springer-Verlag; 1995. 162 p.
[30] Reinhard S. Econometric Analysi of Economic and Environmental Efficiency of Dutch Dairy Farms. Wageningen Wageningen University; 1999.
[31] Reinhard S, Thijssen G. Nitrogen efficiency of Dutch dairy farms: a shadow cost system approach. European Review of Agricultural Economics. 2000;27:167-86.
[32] Golany B, Roll Y, Rybak D. Measuring Efficiency of Power Plants in Israel by Data Envelopment Analysis. IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT. 1994;41(3):291.
[33] Zhou P, Ang BW, Poh KL. A survey of data envelopment analysis in energy and environmental studies. European Journal of Operational Research. 2008;189(1):1-18.
[34] Welch E, Barnum D. Joint environmental and cost efficiency analysis of electricity generation. Ecological Economics. 2009;68(8–9):2336-43.
[35] Färe R, Grosskopf S, Pasurka Jr C. Joint Production of Good and Bad Outputs with a Network Application. Encyclopedia of Energy, Natural Resources and Environmental Economics. 2011.
[36] Murty S, Russell RR, Levkoff SB. On modeling pollution-generating technologies. Journal of Environmental Economics and Management. 2012;64(1):117-35.
[37] Coelli TJ, Perelman S. A Comparison of Parametric and Non-Parametric Distance Functions: With Application to European Railways. European Journal of Operational Research. 1999;117(2):326-39.
[38] Cooper WW, L.M. S, Tone K. Data envelopment analysis: Kluwer Academic Publishers.; 2000.
[39] Grosskopf S. Statistical Inference and Nonparametric Efficiency: A Selective Survey Journal of Productivity Analysis. 1996;7(2-3):161-76.
[40] Wooldridge JM. Econometric analysis of cross section and panel data: MIT press; 2010.
[41] Hoff A. Second stage DEA: Comparison of approaches for modelling the DEA score. European Journal of Operational Research. 2007;181(1):425-35.
[42] Papke LE, Wooldridge JM. Econometric methods for fractional response variables with an application to 401(k) plan participation rates. Journal of Applied Econometrics. 1996;6(11):619-32.
[43] Cook D, Kieschnick R, McCullogh B. Specification Errors in Studies of the Composition of Corporate Financing, University of Mississippi/University of Texas-Dallas. Drexel University, Working Paper, 2000.
[44] Banker RD, Natarajan R. Evaluating contextual variables affecting productivity using data envelopment analysis,. Operations Research. 2008;56:48-58.
[45] Banker R. Maximum Likelihood, Consistency, and Data Envelopment Analysis: A Statistical Foundation,. Management Science. 1993;39(10):1265-73.
[46] Barros CP. Efficiency analysis of hydroelectric generating plants: a case study for Portugal. Energy Economics. 2008;30:59-75.
[47] Barros CP, Antunes OS. Performance assessment of Portuguese wind farms:ownership and managerial efficiency Energy Policy. 2011;39(6):3055-63.
[48] Diewert WE, Nakamura AO. Benchmarking and the measurement of best practice efficiency: an electricity generation application. . Can J Econ. 1999;32(2):570-88.
[49] Electricity Supply Association of Australia. 1994.
[50] Hiebert DL. The determinants of the cost efficiency of electric generating plants: a stochastic frontier approach. South Econ J. 2002;68(4): 935-46.
[51] Khanna M, Mundra K, Ullah A. Parametric and semiparametric estimation of the effect of firm attributes on efficiency: the electricity generating industry in India. Trade Econ. 1999;Dev. 8 (4):419-30.
[52] Kumar S. Environmentally sensitive productivity growth: a global analysis using Malmquist-Luenberger index. Ecological Economics. 2006;56(2):280-93.
[53] Kumar S, Managi S. The Economics of Sustainable Development the Case in India. Springer. 2009.
[54] Meibodi AE. Efficiency considerations in the electricity supply industry: the case of Iran.: University of Surrey.; 1998.
[55] Pollitt MG. Ownership and Performance in Electric

Utilities: The International Evidence on Privatisation and Efficiency. Oxford University Press, Oxford. 1995.
[56] Pollitt MG. Ownership and efficiency in nuclear power production. Oxf Econ. 1996; 48(2): 342-60.
[57] Sarica K, Or I. Efficiency assessment of Turkish power plants using data envelopment analysis. . Energy Policy. 2007;32:1484-99.
[58] See KF, Coelli T. An analysis of factors that influence the technical efficiency of Malaysian thermal power plants. Energy Economics. 2012;34(3):677-85.
[59] Barnum DT, Gleason JM. Bias and precision in the DEA two-stage method. Applied Economics 2006;40(18):2305-11.
[60] Barnum DT, Gleason JM. Measuring the efficiency of electricity generating plants with fixed proportion technology indicators. 7th International Conference on Data Envelopment Analysis; July 2009; Philadelphia2008.
[61] Charnes A, Cooper WW, Rhodes E. Measuring the Efficiency of Design-Making Units. European Journal of Operational Research. 1978;2(6):429-44.
[62] White H. A heteroskedastic-consistent covariance matrix and a direct test for heteroskedasticity. Econometrica. 1980;48:817–38.