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# TECHNICAL AND ENVIRONMENTAL PERFORMANCE ASSESSMENT OF THE IRANIAN POWER PLANTS: A SEMI-DISPOSAL DEA APPROACH

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**Highlights**

- This paper performs an environmental assessment of Iranian power plants considering a flexible scenario called semi-disposability.
- We distinguished state ownership and private ownership power plants.
- We analyzed the returns to scale properties of power plants in the study.
- Scale efficiency of power plant is analyzed considering all type of disposability assumption.

**Abstract.** One of the most important issues is to achieve maximum production of energy from a particular energy source, which ensures the complete protection of the environment. The current paper as the first application of flexible and powerful semi-disposability approach, performs an empirical technical and environmental efficiency analysis for 39 natural gas and gasoline power plants, including governmental and private property, during the years 2011–2016. Different scenarios for environmental analysis, namely, weak disposability, strong disposability and semi-disposability with different returns to scale assumptions are performed in the analysis. The primary results of multivariate assessment based on constant returns to the scale shows that 7 power plants with state ownership and 8 power plants with private ownership were among the most efficient power plants from the technical-environmental perspective. Parametric and non-parametric tests are performed and the result shows better performance of private power plants compared with governmental power plants.

**Keywords:** technical-environmental efficiency, private and governmental power plant, semi-disposability, return to scale, data envelopment analysis.

## Introduction

Modern economies depend on the reliable and affordable delivery of electricity. At the same time, the need to address climate change is driving a dramatic transformation of power systems globally. The IEA is working with countries around the world to support a secure and economic transition to low-carbon power systems. Growing demand for electricity can be attributed to the economic structure, climate change, and technology structure. On the other hand, due to increased demand, the use of these resources is expected to increase, which may be due to loss of resources or decrease. Electricity is produced from various sources of energy (International Energy Agency, 2018). In some marginal and distant areas, diesel power plants (DDP) are usually used to supply electricity (Ahmad et al., 2011). However, diesel power plants have environmental issues and of course the margin cost is high also they have maintenance costs. In other words, given the cost of capital, diesel electric is relatively cheap, but with a ratio of $ 3.7 to $ 1, the cost of capital to operational costs in the low energy supply chain and low energy production units indicate the systematic maintenance and maintenance of this system. Given the similar difficulty of using diesel generators, they are at the expense of their high productivity and environmental performance (Rozali et al., 2016). DDP is a type of power generators in the electrical field that seems it is the leading energy; it converts fossil fuel into electrical energy. As a result of UNFCCC[1], climate

1 The Paris Agreement is an agreement within the United Nations Framework Convention on Climate Change (UNFCCC), dealing with greenhouse-gas-emissions mitigation, adaptation, and finance, starting in the year 2020.

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policies have been influenced by various decision makers at the local, national and international levels. Decisions are generally not entirely consistent with the goals and methods of decision-makers, and the existence of a multi-layered government may be able to encourage strategic behaviour of local power-market players who are trying to upgrade their position. Because it affects the cost of climate regulation (Bonilla et al., 2018). For example, a common strategy to reduce greenhouse gas emissions is a combination of a mixture of fuel from petroleum to biofuels, called carbon zero. However, such a transition may result in a sharp decrease in $CO_2$ But biofuels often result in an increase in NOx, solids (PM), carbon monoxide (CO) and organic emission (VOC) in the Earth's atmosphere (Riccardi et al., 2012). Iran's energy ministry has been considering fuel that could replace high-carbon fuels (such as coal and oil). In order to reduce carbon emissions in strategies, according to available sources for experts, natural gas is a very suitable option. In a global example, Sweden can see that with such an approach, it has been able to implement the largest decline in publishers with maximum production in the leading and strategic industries. In all of the combustion processes, the greenhouse gas emissions produced by CHP are generally increased by carbon volume, while the NOx emission and control of $CO_2$ and NOx pressure control are different according to the design characteristics of each power plant. The possibility of investing in the technology usually requires huge costs and budgets, and results in minimal emissions of $CO_2$. The use of such technologies as CT (combustion of fuel cylinders) clearly needs investment costs, which indicates the difference between steam boilers and their capacity (von Geymueller, 2009). In addition, some technologies are commercially available and not accessible due to instability and lack of confidence in political and regional relationships throughout the world. The supposition and the above are of particular interest to the implementation of strategies that require constant and available technology at different times (Vaninsky, 2006). One of these key strategies and practices is the use of identifying and measuring the efficiency and efficiency of existing executive levels, including refineries, power plants and maternal industries in different parts of the country (Tone & Tsutsui, 2011).

In the primary discussions of math planning, efficiency is measured as the ratio of output to input. This implies an initial performance level that describes a system or process that uses the lowest inputs to produce the highest output (Zhou & Ang, 2008). Measuring system efficiency and productivity can be a powerful tool for identifying the best solutions, exercises and potential improvements in operational measures and strategies. Energy efficiency is highlighted with its potential to address a number of challenges faced by electricity services. These challenges include increased demand for electricity, reduced operational capacity and reduced system reliability and flexibility (Sueyoshi & Goto, 2017). To overcome the system, productivity measurement is applied to the system's performance, so that it identifies sources of technical and operational resources or other influential factors. Several studies have been conducted to evaluate the efficiency of power plants for the infusion of technology. However, production and environmental and distribution systems are rarely considered as the main goal of the research. Çelen (2013) analysed the efficiency of the Turkish electricity distribution companies by stochastic frontier analysing (SFA). The purpose of this study is to evaluate the performance of the electrical distribution areas affected by its distribution areas. His performance review shows that companies that are mostly residential customers are more than other companies. Cheng et al. (2018) in an article on energy efficiency and carbon dioxide emissions china has been analysing areas in China. The purpose of this study was to evaluate the efficiency and estimation of the input/output costs of the environmental using the SBM model. The results of this research in the investigated areas show that energy efficiency and carbon dioxide emissions in renewable areas are modestly increasing, while the amount of output gas emissions from production in some areas is decreasing. Rácz and Vestergaard (2016) in the research paper, measured the efficiency and productivity of Danish biogas power plants with the data envelopment analysis (DEA) model during the year 1992–2005. The results of the DEA and Malmquist models used in this survey indicate that the average annual productivity increased 2.5% times in the period under study, while the average technology efficiency is 1.1%. In the study by (Bongo et al., 2018), 12 power distribution lines have been measured using the DEA model. Abdulwakil et al. (2020) investigated bioenergy efficiency of 28 region in Europe in period of 1990–2013. They analyzed both technical and scale efficiency indicators and found an increasing rate in the study period and found the scale efficiency as the main contributor in their finding. In another study, (Alsaleh & Abdul-Rahim, 2018) took the allocative efficiency indictor to analysis the optimal combination of used resources in the bioenergy sector in 28 region in Europe. They found rather equal cost or allocative efficiency rate for bioenergy industries of both developing member and developed member of EU28 (Alsaleh et al., 2017) studied the technical efficiency determinants of bioenergy industries in the Europe. They distinguished the country-specific and macroeconomic determinant of technical efficiency for the countries. Wu et al. (2019) in an article titled "measuring environmental efficiency of thermoelectric power plants" an assessment of the environmental efficiency of 30 thermal power plants has been evaluated with attention to undesirable outputs and the use of the new data analysis method in China. In recent years, power plants including thermoelectric power plants are an important factor in the emission of pollutants that are of high importance for the study. Because this information and data analysis can provide important notification and decisions for energy managers with the goal of improving their environmental performance. Finally, extraction of results from the model shows good performance of half of china thermal power plants, which can be promoted with key reforms in the other half of the plant. Wu et al. (2018) entitled input optimization, could be used to reduce the risk of environmental hazards undesirable outcomes using a DEA model in China. The purpose of this study was to provide an acceptable method for controlling gas volume by optimizing input resources and an innovative approach to calculating the emission of sensitivity to exhaust gases and the impact of on the input indicators. The results of this study indicate that input indicators are too high, except for the workforce and the high rate of greenhouse gases the result is $SO_2$ emissions and coal consumption which is respectively 78% and 67.18% and 61.18. The magnitude of these pollutant gases, other than Beijing, Tianjin and Shanghai, is far exceeded. Ghiyasi (2017) investigated the environmental and energy efficiency of industrial sector in Iran. He went one step forward and used inverse DEA models for energy planning, considering the environmental issues. Emrouznejad et al. (2019) investigated the allocation of $CO_2$ as an important emission in the process efficiency analysis. They also utilized the inverse structure of the DEA models for getting to their aim. Wegener and Amin (2019) also used the inverse framework of DEA for minimizing the greenhouse gas emissions in an oil and gas industry. Ghiyasi (2019) also proposed a methodology for utilizing the emission permission values considering the environmental efficiency level of production units. He performed a gradual emission reduction framework and analysed the status of selected Iranian economic sector in the environmental efficiency analysis and emission level. Emami Meybodi and Mokari (2016) used total productivity factor analysis for investigating the productivity of Iranian natural gas refineries for period of 2009–2015. Miao et al. (2019) performed a comprehensive environmental analysis for air emission pollutant of chines regions using Luenberger productivity indicator. They considered both the pollution rate and performance change in their analysis. Like most of the countries, electricity supply is a vital issue for many reasons, it the energy source of many manufactures and an essential need for all household. On the other hand, power plants are one of the main source of pollutions nowadays. Thus, the object of current paper is investigating the technical and environmental efficiency of 39 major Iranian power plants, regarding to the important role of power plants in energy supply and security from one hand and considerable emission production of this sector, specifically those that use fossil fuels on the other hand. We utilized a generalized and flexible DEA methodology capable of dealing with environmental efficiency. Thus, the purpose of this study is to provide an acceptable method for controlling gas volume by optimizing input resources and an innovative approach to calculating the emission of sensitivity to exhaust gases and the impact. As a matter of fact, we analysis the technical performance, environmental performance and the scale effect of 39 major power plants in Iran. We assume all power plants are homogeneous, meaning that they use the same type of resources and produce the same product on the other side. The products include both desirable and undesirable products. The former is of course electricity and the latter is pollution. The results indicate that input indicators are too high, except for the workforce. High rate of greenhouse gases the result is $SO_2$ emissions and coal consumption which is respectively 78% and 67.18% and 61.18 is found. Although the application of rather new flexible and power full method of semi-disposability in the environmental efficiency analysis of different sectors is growing, but with the best knowledge of authors, is not used for the environmental efficiency analysis of not only Iranian power plant but also other place in the world. Thus, the current paper is the first application of semi-disposability for environmental efficiency analysis of power plants as one the main sources of pollutions in the world. The rest of paper is organized as follows. Section 1 described the utilized methodology and the theoretical background of the study. Section 2 analyses the technical and environmental efficiency of 39 Iranian power plants. In Section 3, we provide more discussion and summarized the research. The final section concludes the study.

## 1. Methodology

Technical and environmental assessment is a prerequisite for sustainable economic development. A common method for evaluating performance optimization is DEA that is a non-parametric method for evaluating the relative efficiency of DMUs with multiple inputs and outputs (Zhou et al., 2018). The technical-environmental assessment takes into account the optimal output generated during the production process as well as the adverse outflow, such as pollutants and waste products. This is because adverse outputs are decisions that are anticipated, but usually occur during the actual production process with desirable output. The DEA model with undesired outputs was presented by (Färe et al., 1989). This approach has now been widely used to examine the issue of environmental assessment around the world. Also, strong and weak integrated assumptions for undesirable outcomes based on previous studies DEA were focused on technical evaluation. Given the strong assumption about inappropriate output, a reduction can be reduced to decision-makers' decisions freely or at no cost. On the other hand, according to the disposability assumption, the undesired outputs should be reduced with the desired outputs, because there is a desirable and undesirable common production in this case. Yang and Pollitt (2010) emphasis to recognize the weak and strong assumption disposability the undesirable outcomes of the environmental assessment, and proposed a model for identifying them based on the technical characteristics of undesirable outcomes. Sueyoshi et al. (2017) argued that with the weak disposability assumption of undesirable outcomes, reducing unproductive outputs results with lower output which cannot reflect the benefits of managerial efforts and technological innovations in a sustainable environment.

However, different assumption disposability for undesirable outputs results in a series of different production activities that may have different assessment results. Therefore, for the DEA technical and environmental assessment, developing a scientific hypothesis is essential to save on undesirable outcomes. In general, the greatest defect and problems with the weak and strong assumptions disposability are that these assumptions cannot explain the various characteristics of the various undesirable outputs during real production. Therefore, this study utilized a recently developed concept of so called "semi-disposability" to determine unsustainable outputs under constant return to scale (CRS) and variable-to-scale returns (VRS). As a matter of fact, the purpose of this study is to use a semi-disposability model for 39 power stations of state and non-government power in order to maintain maximum optimal production and the highest level of environmental security.

### 1.1. Weak and strong disposability models

As mentioned in the previous section (Färe et al., 1989) have suggested Weak and strong assumptions disposability for undesirable outputs. So based on studies $x=(x_1,x_2,\ldots,x_m)\in R_+^m$ as input vectors, $y=(y_1,y_2,\ldots,y_s)\in R_+^s$ as vectors of desirable output and $z=(z_1,z_2,\ldots,z_h)\in R_+^h$.

Also Production technology includes all the features (*x*, *y*, *z*) that $T=\{(y,z,x)\,\|\,x\to(y,z)\}$ are shown. In this way, the output set $p(x)=\{(y,z)\,\|\,(y,z,x)\in \mathrm{T}\}$ can be specified in this way. Suppose that there is n to *DMU*, so the weak assumption CRS can be defined as:

$$P^w(x)=\{(z,y):\sum_{i=1}^n\gamma_i y_i\ge y,\sum_{i=1}^n\gamma_i z_i=z,\quad \sum_{i=1}^n\gamma_i x_i\le x,\gamma_i\ge 0(i=1,\ldots,n)\}. \tag{1}$$

According to weak disposability assumption we see disposability inputs and outputs with inequality constraints $\sum_{i=1}^n\gamma_i x_i\le x$ and $\sum_{i=1}^n\gamma_i y_i\ge y$, respectively.

The linear programming model for measuring output efficiency of *DMU* under evaluation, that is, $DMU_o$ is as follows:

$$\begin{aligned}
&\varphi_o^w=Max\,\varphi^w;\\
&s.t.\ \sum_{i=1}^n\gamma_i x_{di}\le x_{do}\qquad d=1,\ldots,m;\\
&\sum_{i=1}^n\gamma_i y_{ri}\ge\varphi^w\,y_{ro}\quad r=1,\ldots,s;\\
&\sum_{i=1}^n\gamma_i z_{fi}=z_{fo}\qquad f=1,\ldots,h;\\
&\gamma_i\ge 0\quad i=1,\ldots,n,
\end{aligned}\tag{2}$$

where $\varphi_o^w$ indicates efficiency $DMU_o$ based on the weak disposability assumption and considering CRS. Sueyoshi and Goto (2015) proposed the following output set based on strong assumptions disposability.

$$P^s(x)=\{(y,z):\sum_{i=1}^n\gamma_i y_i\ge y,\sum_{i=1}^n\gamma_i z_i\le z,\ \sum_{i=1}^n\gamma_i z_i\le z\quad \sum_{i=1}^n\gamma_i x_i\le x,\gamma_i\ge 0(i=1,\ldots,n)\}, \tag{3}$$

where inequality constraints indicates the strong disposability assumption of undesirable outputs, therefore, under CRS, the output of the axis measurement for a particular $DMU_o$ is as follows:

$$\begin{aligned}
&\varphi_o^s=Max\,\varphi^s;\\
&s.t.\ \sum_{i=1}^n\gamma_i x_{di}\le x_{do}\qquad d=1,\ldots,m;\\
&\sum_{i=1}^n\gamma_i y_{ri}\ge\varphi^s y_{ro}\quad r=1,\ldots,s;\\
&\sum_{i=1}^n\gamma_i z_{fi}\le z_{fo}\qquad f=1,\ldots,h;\\
&\gamma_i\ge 0\quad i=1,\ldots,n,
\end{aligned}\tag{4}$$

where $\theta_o^s$ is the efficiency of $DMU_o$ based on strong disposability assumption.

### 1.2. Semi-disposal technology

The new concept of semi-disposability provides more flexible environment in terms of disposability assumption. This assumption is more general compared with the classical strong and weak possibility. If we define $\alpha$ as the non-disposal degree of undesirable output between zero and unity we may have the following semi-disposal production technology of (Chen et al., 2017) as follows:

$$P^{SE-CRS}(x)=\{(y,z):\sum_{i=1}^n\gamma_i y_i\ge y,\sum_{i=1}^n\gamma_i z_i\le z,\quad \sum_{i=1}^n\gamma_i z_i\ge\alpha z,\sum_{i=1}^n\gamma_i x_i\le x,\gamma_i\ge 0\ (i=1,\ldots,n)\}, \tag{5}$$

where vector of $\alpha=(\alpha_1,\alpha_2,\ldots,\alpha_n)\in R_+^h$ is the non-disposal vector for undesirable output.

Compare with traditional production technology we have two sets of constraint associated with semi-disposability assumption of undesirable output. The following linear programming model gauges the efficiency of $\mathrm{DMU_o}$ based on above technology.

$$\begin{aligned}
&\varphi_o^{SE-CRS}=Max\,\varphi^{SE-CRS};\\
&s.t.\ \sum_{i=1}^n\gamma_i x_{di}\le x_{do}\qquad d=1,\ldots,m;\\
&\sum_{i=1}^n\gamma_i y_{ri}\ge\varphi^{SE-CRS}\,y_{ro}\quad r=1,\ldots,s;\\
&\sum_{i=1}^n\gamma_i z_{fi}\le z_{fo}\qquad f=1,\ldots,h;
\end{aligned}\tag{6}$$

$$\sum_{i=1}^{n}\gamma_i z_{fi} \geq \alpha_{fo} z_{fo} \quad f=1,\ldots,h;$$
$$\gamma \geq 0 \quad i=1,\ldots,n,$$

where the $DMU_L$ efficiency is based on the semi-disposability assumption in the CRS. It should be noted that the degree of not disposal $\alpha_{fo}(f=1,\ldots,n)$ is a fixed amount. This can be determined using qualitative analysis methods such as the Delphi method. Given these mental methods, $\alpha_{fo}$ is based on expert experiences (Chen et al., 2017).

### 1.3. Semi-disposability model for the case of VRS:

The semi-disposability model of undesired output under the CRS was presented in the previous sections. The strong principle disposal under the VRS can be defined as the following vector:

$$P^{SE-VRS}(x)=\{(y,z):\sum_{i=1}^{n}\gamma_i y_i \geq y, \sum_{i=1}^{n}\gamma_i z_i \leq z,$$
$$\sum_{i=1}^{n}\gamma_i x_i \leq x, \sum_{i=1}^{n}\gamma_i = 1, \gamma_i \geq 0 \ (i=1,\ldots,n)\}. \quad (7)$$

Considering above production technology we can find the following linear programming model for $DMU_o$ with semi-disposability and VRS assumption.

$$\varphi_o^{SE-VRS} = Max\, \varphi^{SE-VRS};$$
$$s.t. \quad \sum_{i=1}^{n}\gamma_i x_{di} \leq x_{do} \quad d=1,\ldots,m;$$
$$\sum_{i=1}^{n}\gamma_i y_{ri} \geq \varphi^{SE-VRS}\, y_{ro} \quad r=1,\ldots,s;$$
$$\sum_{i=1}^{n}\gamma_i z_{fi} \leq z_{fo} \quad f=1,\ldots,h; \quad (8)$$
$$\sum_{i=1}^{n}\gamma_i z_{fi} > \alpha_{fo} z_{fo} \quad f=1,\ldots,h;$$
$$\sum_{i=1}^{n}\gamma_i = 1;$$
$$\gamma_i \geq 0 \quad i=1,\ldots,n.$$

Based on the above linear programming model $\varphi_o^{SE-VRS}$ indicates the efficiency of $DMU_o$ under the VRS is semi-disposability assumption (Chen et al., 2017). Finally, considering the models mentioned above, with comparisons of all production units at the level of current production technology, technical and environmental assessments can be made on the basis of semi-disposability in different dimension most efficiency levels. The following flowchart in the Figure 1 shows the procedure of our study.

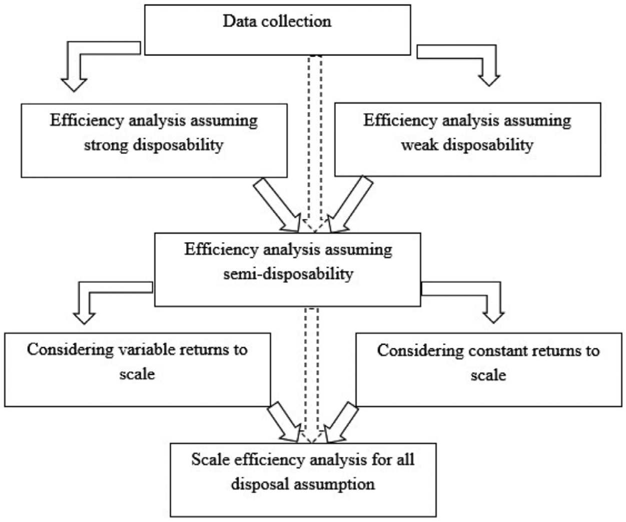


Figure 1. Flowchart of the study procedure

## 2. Empirical analysis and result

In this section, the environmental and technical performance of 39 Iranian power plant is analysed using different disposal assumptions. The difference between the strong and weak assumptions disposability and semi-disposability as output-oriented technical-environmental assessment is distinguished in process of environmental efficiency of power plants that use fossil fuel. Four inputs and four outputs are considered in the period of analysis that is 2011–2016. Inputs include rating power, operational power, operational cost and operation hours. Outputs include power generation, thermal efficiency, power use and pollutions.

### 2.1. Primary results

The technical and environmental efficiency of 39 power plants are analysed using semi-disposability approach and the average results are reported in the following table.

In the first analysis we look at the technical efficiency level of power plants considering both CRS and VRS assumption. This yields to the scale efficiency analysis and hence a decomposition of the overall (CRS) efficiency scores to the scale efficiency and pure technical efficiency (VRS). Therefore, we use VRS efficiency and pure technical efficiency measures identically in this paper. As expected from the production principle of CRS and VRS technologies we the lower values for the former index compared with the latter. The average of inefficiency is about 11 percent in the CRS case and this value is about 9 percent for the VRS case. Another observation is that these measure have almost a same pattern for all power plants, namely, when one increase then another one also increase and vice versa. The gap between these two measure, as can be seen in the Figure 2 is not too much and they coincide for the most of power plants. We will have more deep analysis when we discuss about the scale efficiency later on.

According to our model, we found 15 most efficient power plant base on technical and environmental efficiency under CRS between 39 private and governmental power plants. Governmental efficient power plants are P3, P4, P5, P8, P11, P12 and P14 while private efficient power plants are P18, P23, P32, P34, P35, P36, P39. In the first place, these can be one of the power plants with the

Table 1. Average results of natural gas-gasoline power plants based on various assumptions during 2011–2016

| Power plants | CRS (OVERALL EFFICIEBCY) | | | | VRS (PURE TECHNICAL EFFICIENCY) | | | |
|---|---|---|---|---|---|---|---|---|
| | Strong $\varphi_k^{S-CRS}$ | Weak $\varphi_k^{W-CRS}$ | Semi-disposability strong $\varphi_k^{SEU-CRS}$ | Semi-disposability weak $\varphi_k^{SEL-CRS}$ | Strong $\varphi_k^{S-VRS}$ | Weak $\varphi_k^{W-VRS}$ | Semi-disposability strong $\varphi_k^{SEU-VRS}$ | Semi-disposability weak $\varphi_k^{SEL-VRS}$ |
| P1 | 1.230 | 1.230 | 1.230 | 1.230 | 1.227 | 1.227 | 1.227 | 1.227 |
| P2 | 1.088 | 1.053 | 1.086 | 1.061 | 1.022 | 1.022 | 1.022 | 1.022 |
| P3 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P4 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P5 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P6 | 1.345 | 1.345 | 1.345 | 1.345 | 1.315 | 1.315 | 1.315 | 1.315 |
| P7 | 1.184 | 1.177 | 1.184 | 1.182 | 1.177 | 1.167 | 1.176 | 1.174 |
| P8 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P9 | 1.762 | 1.158 | 1.660 | 1.490 | 1.704 | 1.154 | 1.562 | 1.400 |
| P10 | 1.003 | 1.003 | 1.003 | 1.003 | 1.000 | 1.000 | 1.000 | 1.000 |
| P11 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P12 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P13 | 1.675 | 1.675 | 1.618 | 1.618 | 1.573 | 1.582 | 1.573 | 1.573 |
| P14 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P15 | 1.011 | 1.011 | 1.011 | 1.011 | 1.000 | 1.000 | 1.000 | 1.000 |
| P16 | 1.005 | 1.005 | 1.005 | 1.005 | 1.000 | 1.000 | 1.000 | 1.000 |
| P17 | 1.049 | 1.039 | 1.046 | 1.042 | 1.029 | 1.004 | 1.026 | 1.022 |
| P18 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P19 | 1.181 | 1.000 | 1.173 | 1.108 | 1.171 | 1.000 | 1.161 | 1.080 |
| P20 | 1.102 | 1.095 | 1.102 | 1.098 | 1.098 | 1.092 | 1.097 | 1.094 |
| P21 | 1.035 | 1.025 | 1.035 | 1.034 | 1.029 | 1.000 | 1.029 | 1.028 |
| P22 | 1.249 | 1.216 | 1.249 | 1.237 | 1.109 | 1.000 | 1.109 | 1.101 |
| P23 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P24 | 1.066 | 1.054 | 1.066 | 1.065 | 1.065 | 1.010 | 1.065 | 1.064 |
| P25 | 1.161 | 1.000 | 1.146 | 1.073 | 1.129 | 1.000 | 1.114 | 1.096 |
| P26 | 1.036 | 1.009 | 1.036 | 1.036 | 1.021 | 1.000 | 1.021 | 1.015 |
| P27 | 1.301 | 1.256 | 1.295 | 1.284 | 1.293 | 1.235 | 1.288 | 1.278 |
| P28 | 1.474 | 1.464 | 1.469 | 1.464 | 1.457 | 1.447 | 1.456 | 1.451 |
| P29 | 1.268 | 1.000 | 1.192 | 1.080 | 1.254 | 1.000 | 1.182 | 1.075 |
| P30 | 1.207 | 1.180 | 1.207 | 1.199 | 1.160 | 1.062 | 1.159 | 1.136 |
| P31 | 1.004 | 1.000 | 1.004 | 1.003 | 1.003 | 1.000 | 1.003 | 1.003 |
| P32 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P33 | 1.019 | 1.000 | 1.011 | 1.004 | 1.000 | 1.000 | 1.000 | 1.000 |
| P34 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P35 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P36 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| P37 | 1.084 | 1.084 | 1.083 | 1.083 | 1.000 | 1.000 | 1.000 | 1.000 |
| P38 | 1.029 | 1.023 | 1.029 | 1.026 | 1.022 | 1.022 | 1.022 | 1.022 |
| P39 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

*Note*: where $\varphi_k^{S-CRS}$, $\varphi_k^{W-CRS}$, $\varphi_k^{SEU-CRS}$ and $\varphi_k^{SEL-VRS}$ show the efficiency score of pow replant considering strong disposability, weak disposability and semi-disposability for the CRS respectively. The rest of columns show the same measures for the case of VRS. As our analysis is in output orientation we see that all measure in Table 1 are greater than or equal to unity. Those power plant with unity measure are efficient and others are inefficient. More deviation from the unity show more level of inefficiency. In fact, $(1-\varphi_k) \geq 0$ shows the percentage of output shortfalls, that is the percentage of output that should be produced but are not reached.

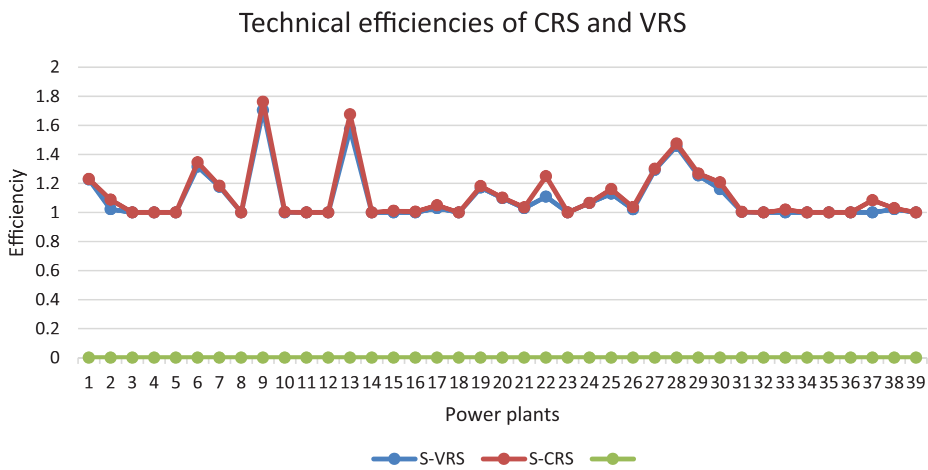


Figure 2. Technical efficiency considering CRS and VRS (overall v.s pure technical efficiency)

potential to grow along the frontier. As They can move by with administrative and structural reforms in the production line and inputs-outputs. A significant contribution to the maximum production and supply of electricity to the network, while maintaining the least waste of resources and environmental damage to the environment. Secondly, these observation identifies seven efficient power plants in each category, namely, governmental and private sector. These numbers show a better performance in the governmental sector, regarding to the total number of governmental and private power plants that are 17 and 22. On the other side, there is ten percent potential improvement in average for entire power plants. The private sector share in this case is also higher compared with governmental power plants. If we look at the result when assuming VRS, namely, pure technical efficiencies, we find almost the same result. However, the differences reveal some interesting fact too. According the results is in by comparing the results of VRS assumption; the effect of the semi-disposability assumption in the VRS is significant. Therefore, based on the extracted results, the pure technical efficiency of 15 natural gas-gasoline power plants are unity based on the technical-environmental frontier. As such they are: P3, P4, P5, P8, P11, P12, P14, P18, P23, P32, P34, P35, P36, P39. So if these power plants can make key changes in their inputs and outputs based on pure technical efficiency's capacity, they can use this template to provide the technical-environmental performance circuitry for maximum production and at least destruction of resources and environmental damage. Based on the results of the assumptions CRS in Table 1, we see that for each DMU when the disposal grade is smaller and equal to the unit, the potential for improvement is more efficient and this is due to the differences between them $\varphi_k^W$ and $\varphi_k^{SE-U}$ that reflects the issue. Based on these differences, it can be seen in the field of production technology application of advanced management technology. The efficiency of these power plants can be believed by reducing the undesirable outputs and desirable output will be improved. For some of the undesired outputs that cannot be freely reduced, effect on efficiency is directly reflected in the difference between $\varphi_k^S$ and $\varphi_k^{SE-U}$. In this situation, it is impossible to reduce undesirable and desirable outputs with inputs given in the scope of current production technology. Dealing

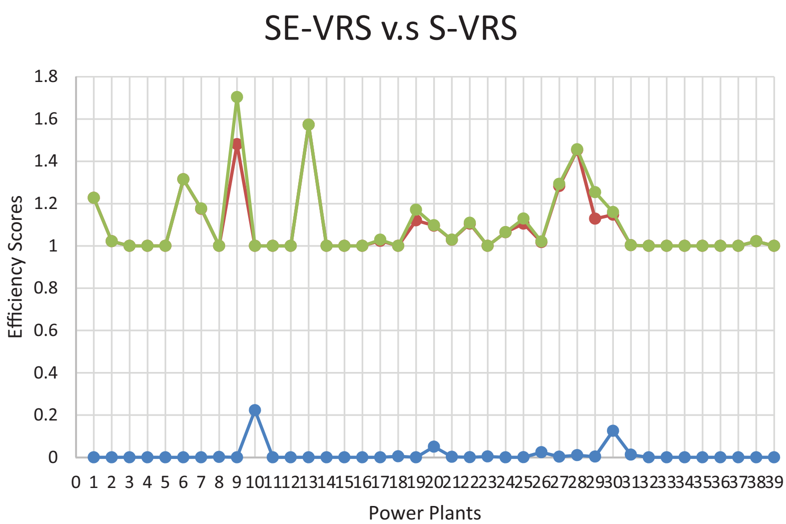


Figure 3. Strong disposability vs semi-disposability for pure technical efficiencies

with pure technical efficiency, that is, taking VRS into consideration, Figure 3 depicts the differences between efficiency measures assuming strong disposability and semi-disposability. Horizontal axis shows power plants and vertical axis shows the efficiency measures. Green scatter lines are associated with strong disposability measures, red scatter lines are related to semi-disposability and blue lines show the different between these two measures. We observe four power plant that show diversity between aforementioned measures, namely, P10, P19, P24 and P29. Thus, beside potential technical improvement there exist a potential for environmental improvement for these power plant in comparison with other power plants.

In a similar style Figure 4 compare the efficiency measure when assuming weak disposability and strong disposability. Compare with Figure 3 we observe more differences in this case. We find almost one fourth of power plant that show different efficiency measure when switching from weak disposability to strong disposability. Look at P10 that has the highest difference in this sense for instance. The flexibility and power on the semi-disposability allow us to compare these two chart and find a better insight out of the analysis. A general perspective of comparison between these two charts reveals more tendency to the strong disposability compared with weak disposability in our case study.

In contrary side, looking on the worst cases also provide interesting information about the status of power plant during the study period. The worst efficiency and techno-environmental deficient power plants among power plants that has been investigated in this article according to our model under VRS are P9 with 1.704, P13 1.573 and P28 1.457. With respect to results and discussing with the expert in the field we can find some source of problems as profit return to scale in production and management system, imbalance of financial costs and operational, supply and maintenance in path with the use of expert labour, the absence of a cycle of equipment and tools based on perspectives and conditions forward non-adoption of incentive and punitive policies in productive units, and unsuitable times to change the ownership of some state-owned power plants to private ones. These are some key factors that should be considered by decision makers when making policy and regulations.

## 2.2. Scale efficiency analysis

In the next analysis we investigate the technical production size of power plants and then consider the environmental aspect of the production size. This analysis is based on the primary result out of the previous subsection. In fact, scale effects are measured by distinguishing between overall (CRS) efficiency and pure technical (VRS) efficiency. This analysis is shown in Table 2 where we report the scale efficiency of power plants for all production assumption discussed in the study, namely, strong disposal, weak disposal and semi-disposal assumption.

The first important observation is a low scale efficiency measure of P22 considering all disposal assumptions. This power plant is operating below the optimal production no matter what disposal assumption is considered, strong, weak or semi-disposal. In other words, if care about environmental issue or not this power plant needs a reconsideration on its production scale. Ignoring this power plant, the overall scale efficiency of all power plants are quit high meaning a good situation in terms of production size for most of power plants. However, there exist some power plants like P9 that we observe a considerable difference between scale efficiencies when considering different disposal assumptions. Four percent difference for scale efficiency measure of this power plant is found when we consider semi-disposability instead of strong disposability. It actually means the production size of this power plant become worse when we consider the environmental aspects into consideration. This highlights the environmental issues that are highly affected by the scale size of the production.

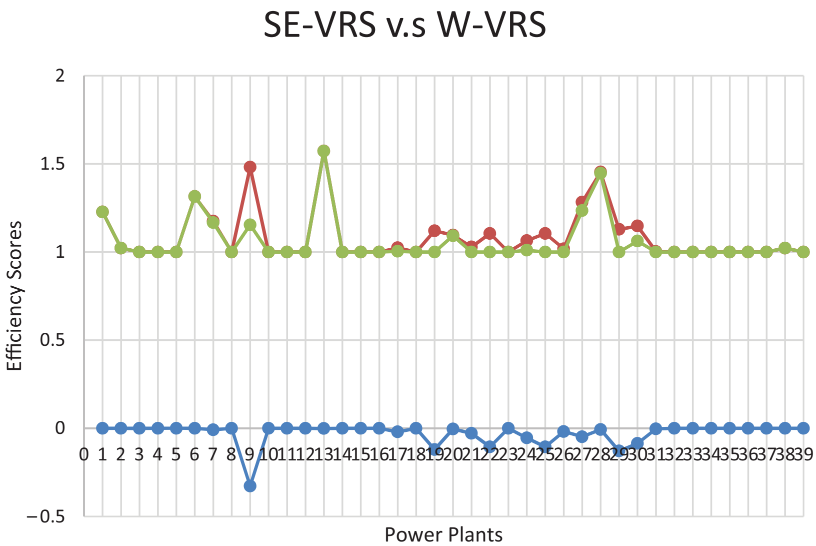


Figure 4. Strong disposability vs weak disposability for pure technical efficiencies

Table 2. Scale efficiency of assuming technical and environmental characteristics

| Power plants | Scale efficiency assuming Strong disposability | Scale efficiency assuming Weak disposability | Scale efficiency assuming Semi-disposability |
|---|---|---|---|
| P1 | 0.997561 | 0.997561 | 0.997561 |
| P2 | 0.939338 | 0.97056 | 0.952026 |
| P3 | 1 | 1 | 1 |
| P4 | 1 | 1 | 1 |
| P5 | 1 | 1 | 1 |
| P6 | 0.977695 | 0.977695 | 0.977695 |
| P7 | 0.994088 | 0.991504 | 0.993238 |
| P8 | 1 | 1 | 1 |
| P9 | 0.967083 | 0.996546 | 0.940317 |
| P10 | 0.997009 | 0.997009 | 0.997009 |
| P11 | 1 | 1 | 1 |
| P12 | 1 | 1 | 1 |
| P13 | 0.939104 | 0.972772 | 0.972188 |
| P14 | 1 | 1 | 1 |
| P15 | 0.98912 | 0.98912 | 0.98912 |
| P16 | 0.995025 | 0.995025 | 0.995025 |
| P17 | 0.980934 | 0.966314 | 0.980843 |
| P18 | 1 | 1 | 1 |
| P19 | 0.991533 | 1 | 0.982464 |
| P20 | 0.99637 | 0.99726 | 0.995909 |
| P21 | 0.994203 | 0.97561 | 0.9942 |
| P22 | 0.88791 | 0.822368 | 0.888978 |
| P23 | 1 | 1 | 1 |
| P24 | 0.999062 | 0.958254 | 0.999061 |
| P25 | 0.972438 | 1 | 0.995944 |
| P26 | 0.985521 | 0.99108 | 0.982625 |
| P27 | 0.993851 | 0.98328 | 0.994959 |
| P28 | 0.988467 | 0.988388 | 0.991135 |
| P29 | 0.988959 | 1 | 0.993398 |
| P30 | 0.96106 | 0.9 | 0.953865 |
| P31 | 0.999004 | 1 | 0.999502 |
| P32 | 1 | 1 | 1 |
| P33 | 0.981354 | 1 | 0.992556 |
| P34 | 1 | 1 | 1 |
| P35 | 1 | 1 | 1 |
| P36 | 1 | 1 | 1 |
| P37 | 0.922509 | 0.922509 | 0.922509 |
| P38 | 0.993197 | 0.999022 | 0.994647 |
| P39 | 1 | 1 | 1 |

### 2.3. Robustness analysis

In this subsection we perform a robustness analysis for the results founded I previous subsections. In fact, we statistically analysis these result if there is difference between performance of private power plants and governmental power plants, considering different types of efficiency measurement and different types of returns to scale in the analysis. Regarding with the nature of our analysis and founded measurements, we use Mann–Whitney Wilcoxon test that is non-parametric test for checking twin dependent samples coming from populations having the same distribution. We support this analysis with two more statistical series of other parametric (*t*-test) and non-parametric Kruskall–Wallis tests to obtain more robust results. Table 3 and Table 4 report detailed robustness tests of private and governmental power plants for the study period, considering overall technical efficiency measure and pure technical efficiency measures, respectively. Our general findings through robustness test have indicated to that considering both overall technical efficiency measures and pure technical efficiency measure, the null hypothesis of both parametric and non-parametric tests are rejected. This means that despite the different measures of overall technical efficiency and pure technical efficiency for private and governmental power plants, such a distinguish is not statistically significant. The details are reported as follows. Table 5 summarizes the results of three tests. Considering all types of measurements including semi-disposability, weak and strong disposability for the CRS and VRS case, we observe that private running power plants have better performance in overall. In fact, we find higher overall performance and pure technical performance for private power plants. Using *t*-test and taking the strong disposability into consideration for the case CRS, for instance, we observe higher mean performance for private power plants compared with governmental power plants (1.138 > 1.101). However, this statistically insignificant, regarding to the P value which higher than 10%. thus, private power plants and governmental power plants have potential of increasing electricity production with their current resource by 10% and 14%, respectively. Other two tests, namely, Mann–Whitney Wilcoxon test and Kruskall–Wallis test also support above finding. In the first place, using Whitney Wilcoxon test and considering strong disposability with CRS, Mann–Whitney Wilcoxon test shows higher performance for the private power plants compared with those which are running under the control of government (20.058 > 19.143). This is the same when we consider the pure technical efficiency measures, namely, we observe higher performance for the private power plants contrasted with governmental power plants (20.507 > 19.343), but both findings are statistically insignificant. When we consider the weak disposability for both overall ad pure technical efficiency we observe (20.117 > 19.848) and (20.55 > 19.557) respectively, for comparison between performance of private and governmental power plants. Secondly, when we use Kruskall–Wallis test for both overall ad pure technical efficiency, considering strong disposability for instance, then we conclude the same insight as previous test. We get higher mean performance for private power plants compared with governmental power plants for both cases, that is, (20.663 > 19.143) and (20.55 > 19.557), respectively which is statistically insignificant.

Table 3. Statistical test results for overall efficiency (CRS)

| Year | Group | Summary of parametric and non–parametric tests for overall efficiency (CRS) | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Parametric test | | | | | | | | Non-parametric test | | | | | | | | | | | | | | | |
| | Overall efficiency measures | *t*–test | | | | | | | | Mann–Whitney Wilcoxon test | | | | | | | | Kruskal–Wallis | | | | | | | |
| | | s-CRS | *t* | w-CRS | *t* | SEU-CRS | *t* | SEL-CRS | *t* | s-CRS | *z* | w-CRS | *z* | SEU-CRS | *z* | SEL-CRS | *z* | s-CRS | Chi-square | w-CRS | Chi-square | SEU-CRS | Chi-square | SEL-CRS | Chi-square |
| 2011 | governmental | 1.130 | 0.644 | 1.075 | 0.553 | 1.124 | 0.615 | 1.113 | 0.653 | 19.82 | −0.104 | 19.47 | −0.361 | 19.82 | −0.104 | 19.76 | −0.139 | 19.82 | 0.011 | 19.47 | 0.130 | 19.82 | 0.011 | 19.76 | 0.019 |
| | private | 1.192 | | 1.1519 | | 1.191 | | 1.172 | | 20.14 | | 20.41 | | 20.14 | | 20.18 | | 20.14 | | 20.41 | | 20.14 | | 20.18 | |
| 2012 | governmental | 1.045 | 0.496 | 1.007 | 0.256 | 1.041 | 0.538 | 1.032 | 0.516 | 17.94 | −1.181 | 19.71 | −0.212 | 18.35 | −0.970 | 18.53 | −0.866 | 17.94 | 1.396 | 19.71 | 0.045 | 18.35 | 0.941 | 18.53 | 0.750 |
| | private | 1.078 | | 1.037 | | 1.068 | | 1.056 | | 21.59 | | 20.23 | | 21.27 | | 21.14 | | 21.59 | | 20.23 | | 21.27 | | 21.14 | |
| 2013 | governmental | 1.385 | 0.059 | 1.375 | 0.044 | 1.384 | 0.058 | 1.378 | 0.051 | 20.65 | −0.339 | 21.94 | −1.089 | 20.65 | −0.339 | 20.71 | −0.370 | 20.65 | 0.115 | 21.94 | 1.186 | 20.65 | 0.115 | 20.71 | 0.137 |
| | private | 1.089 | | 1.060 | | 1.085 | | 1.074 | | 19.50 | | 18.50 | | 19.50 | | 19.45 | | 19.50 | | 18.50 | | 19.50 | | 19.45 | |
| 2014 | governmental | 1.052 | 0.900 | 1.021 | 0.647 | 1.022 | 0.393 | 1.010 | 0.109 | 18.59 | −0.792 | 18.76 | −0.749 | 17.35 | −1.661 | 17.29 | −1.697 | 18.59 | 0.627 | 18.76 | 0.561 | 17.35 | 2.757 | 17.29 | 2.881 |
| | private | 1.048 | | 1.022 | | 1.043 | | 1.037 | | 21.09 | | 20.95 | | 22.05 | | 22.09 | | 21.09 | | 20.95 | | 22.05 | | 22.09 | |
| 2015 | governmental | 1.120 | 0.766 | 1.077 | 0.543 | 1.112 | 0.777 | 1.098 | 0.660 | 19.62 | −0.210 | 20.41 | −0.250 | 19.74 | −0.146 | 19.85 | −0.081 | 19.62 | 0.044 | 20.41 | 0.062 | 19.74 | 0.021 | 19.85 | 0.007 |
| | private | 1.100 | | 1.049 | | 1.095 | | 1.076 | | 20.30 | | 19.68 | | 20.20 | | 20.11 | | 20.30 | | 19.68 | | 20.20 | | 20.11 | |
| 2016 | governmental | 1.098 | 0.997 | 1.043 | 0.847 | 1.088 | 0.986 | 1.069 | 0.910 | 18.24 | −1.070 | 18.79 | −0.868 | 17.88 | −0.960 | 18.18 | −1.106 | 18.24 | 1.146 | 18.79 | 0.753 | 17.88 | 0.921 | 18.18 | 1.223 |
| | private | 1.097 | | 1.052 | | 1.088 | | 1.075 | | 21.36 | | 20.93 | | 20.68 | | 21.41 | | 21.36 | | 20.93 | | 20.68 | | 21.41 | |

Table 4. Statistical test results for pure technical efficiency measure (VRS)

| Year | Group | Summary of parametric and non–parametric tests for pure technical efficiency (VRS) | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pure technical efficiency measures | Parametric test | | | | | | | | Non-parametric test | | | | | | | | | | | | | | | |
| | | *t*–test | | | | | | | | Mann–Whitney Wilcoxon test | | | | | | | | Kruskal–Wallis | | | | | | | |
| | | s-VRS | *t* | w-VRS | *t* | SEU-VRS | *t* | SEL-VRS | *t* | s-VRS | *z* | w-VRS | *z* | SEU-VRS | *z* | SEL-VRS | *z* | s-VRS | Chi-square | w-VRS | Chi-square | SEU-CRS | Chi-square | SEL-VRS | Chi-square |
| 2011 | governmental | 1.100 | 0.581 | 1.058 | 0.571 | 1.098 | 0.581 | 1.093 | 0.608 | 19.53 | −0.295 | 19.88 | −0.085 | 19.53 | −0.295 | 19.59 | −0.258 | 19.53 | 0.087 | 19.88 | 0.007 | 19.53 | 0.087 | 19.59 | 0.067 |
| | private | 1.172 | | 1.129 | | 1.170 | | 1.159 | | 20.36 | | 20.09 | | 20.36 | | 20.32 | | 20.36 | | 20.09 | | 20.36 | | 20.32 | |
| 2012 | governmental | 1.036 | 0.586 | 1.000 | 0.34 | 1.032 | 0.583 | 1.022 | 0.530 | 17.35 | −1.806 | 19.00 | −1.259 | 17.35 | −1.806 | 17.35 | −1.806 | 17.35 | 3.262 | 19.00 | 1.586 | 17.35 | 3.262 | 17.35 | 3.262 |
| | private | 1.060 | | 1.017 | | 1.053 | | 1.041 | | 22.05 | | 20.77 | | 22.05 | | 22.05 | | 22.05 | | 20.77 | | 22.05 | | 22.05 | |
| 2013 | governmental | 1.356 | 0.046 | 1.349 | 0.023 | 1.377 | 0.043 | 1.372 | 0.038 | 20.82 | −0.462 | 22.74 | −1.784 | 21.06 | −0.594 | 21.12 | −0.627 | 20.82 | 0.213 | 22.74 | 3.182 | 21.06 | 0.353 | 21.12 | 0.393 |
| | private | 1.058 | | 1.014 | | 1.061 | | 1.050 | | 19.36 | | 17.89 | | 19.18 | | 19.14 | | 19.36 | | 17.89 | | 19.18 | | 19.14 | |
| 2014 | governmental | 1.030 | 0.677 | 1.001 | 0.234 | 1.017 | 0.283 | 1.007 | 0.063 | 18.24 | −1.107 | 20.18 | −0.161 | 17.79 | −1.439 | 17.50 | −1.630 | 18.24 | 1.226 | 20.18 | 0.026 | 17.79 | 2.070 | 17.50 | 2.658 |
| | private | 1.042 | | 1.012 | | 1.040 | | 1.037 | | 21.36 | | 19.86 | | 21.70 | | 21.93 | | 21.36 | | 19.86 | | 21.70 | | 21.93 | |
| 2015 | governmental | 1.103 | 0.613 | 1.066 | 0.443 | 1.087 | 0.722 | 1.075 | 0.635 | 21.41 | −0.810 | 22.21 | −1.439 | 20.35 | −0.214 | 20.47 | −0.285 | 21.41 | 0.656 | 22.21 | 2.070 | 20.35 | 0.046 | 20.47 | 0.081 |
| | private | 1.073 | | 1.033 | | 1.069 | | 1.053 | | 18.91 | | 18.30 | | 19.73 | | 19.64 | | 18.91 | | 18.30 | | 19.73 | | 19.64 | |
| 2016 | governmental | 1.087 | 0.946 | 1.040 | 0.830 | 1.071 | 0.957 | 1.053 | 0.968 | 18.71 | −0.810 | 19.29 | −0.541 | 18.71 | −0.812 | 18.59 | −0.886 | 18.71 | 0.659 | 19.29 | 0.293 | 18.71 | 0.659 | 18.59 | 0.784 |
| | private | 1.083 | | 1.031 | | 1.074 | | 1.055 | | 21.00 | | 20.55 | | 21.00 | | 21.09 | | 21.00 | | 20.55 | | 21.00 | | 21.09 | |

Table 5. Summary of parametric and nonparametric mean tests

| Test groups (2011–2016) | | Parametric test | | Non-parametric test | | | |
|---|---|---|---|---|---|---|---|
| Individual test | | *t*-test | | Mann–Whitney [Wilcoxon] test | | Kruskall–Wallis test | |
| Hypothesis test | | *t*-test | | Median Government and Private | | Equality of populations test | |
| Test statistics | | $t$ $(P > t)$ | | $z$ $(P > z)$ | | $\chi^2$ $(P > \chi^2)$ | |
| | | Mean | $t$ | Mean rank | $z$ | Mean rank | $\chi^2(P > \chi^2)$ |
| strong | | | | | | | |
| CRS | Government | 1.138 | 0.644 | 19.143 | –0.616 | 19.143 | 0.557 |
| | Private | 1.101 | | 20.058 | | 20.663 | |
| VRS | Government | 1.119 | 0.575 | 19.343 | –0.882 | 19.343 | 1.017 |
| | Private | 1.081 | | 20.507 | | 20.507 | |
| weak | | | | | | | |
| CRS | Government | 1.086 | 0.482 | 19.847 | –0.588 | 19.847 | 0.310 |
| | Private | 1.062 | | 20.117 | | 20.117 | |
| VRS | Government | 1.086 | 0.407 | 20.550 | –0.878 | 20.550 | 1.388 |
| | Private | 1.039 | | 19.577 | | 19.577 | |
| SEU | | | | | | | |
| CRS | Government | 1.129 | 0.561 | 18.965 | –0.697 | 18.965 | 0.949 |
| | Private | 1.095 | | 20.640 | | 20.640 | |
| VRS | Government | 1.114 | 0.528 | 19.132 | –0.860 | 19.132 | 0.716 |
| | Private | 1.078 | | 20.670 | | 20.670 | |
| SEL | | | | | | | |
| CRS | Government | 1.117 | 0.483 | 19.053 | –0.710 | 19.053 | 0.836 |
| | Private | 1.082 | | 20.730 | | 20.730 | |
| VRS | Government | 1.104 | 0.474 | 19.103 | –0.915 | 19.103 | 1.208 |
| | Private | 1.066 | | 20.695 | | 20.695 | |

## 3. More discussion and summary

Taking the overall technical efficiency into consideration, we observe 11 percent of potential improvement for overall technical inefficiency while this index is about 9 percent for pure technical efficiency measures. This fact is due to flexible possibility of changing the production scale for the case of CRS. In fact, we ignore the scale effect when we deal with pure technical efficiency. Ignoring small deviation due to the method selection, this result agrees with other researches in the filed for technical efficiency analysis of Iranian power plants. A part of potential improvement of performance is related with the environmental issue. However, there is comprehensive analysis considering the environmental issues and environmental efficiency analysis for our case study. Overall outcome out of all type of disposability shows 7 percent potential improvement for the overall technical efficiency and about 9 percent for the pure technical efficiency measures. We may roughly conclude that 2 percent potentials room is regarded with environmentally improving the performance. Although, there exists more potential improvement and more discrimination power using generalized semi-disposability in contrast with classical weak disposability for environmental efficiency analysis, as we mentioned in the previous section. Thus, considering the semi-disposability gives a better environmental insight for decision maker, specifically those who are concerned with the environmental issue and pollutions out of the production. Hence, it is highly recommended to look at this result and perform more technical analysis by more useful data, if a decision maker plans to restructure the production or reconsider the scale size of electricity production. High potential improvement in term of technical and environmental issue is found for some power plants and some other have a good situation in term of environmental production size. The scale efficiency measures have rather good status, but there are concerns regarding with some power plants that have low scale efficiency when we consider weak disposability of semi-disposability. This fact is due to the deviation of overall technical efficiency and pure technical efficiency measures for these power plants. This shows the role of production size and environmental issues that means the production size of this power plant become worse when we consider the environmental aspects into consideration. Thus, decision maker specifically those who are concern about the pollution and environment should focus on this power plant and its production values for decreasing the pollution. This may happen by having analysing the internal technology and probably finding some rooms for improvement or making some investment for having modern environmental friendly technologies in a mid or long run. On the other side we also observe some power plants P25 that may stand in a high place in term of overall production size, but they have a good production size considering pollutions and environmental issue into account. Such a power plants are good benchmark for others to improve the environmental operation and production size. Policy maker also should consider these case and may provide encouragement packages for such a power plant to keep their production style and may even improve current situation in the future. We performed the statistical test for the result. Our observation out of the parametric and non-parametric tests reject relatively the null hypothesis that the means of efficiency measures in the private and governmental power plants are different and are taken from the different population. As mentioned in the introduction section, the electricity production is an important and vital sector both from social view and production view. This is due to daily need of all households and other economic sector of society. Therefore, more deep analysis is highly suggested, if any new policy making plans happens in this sector. This type of analysis should be involved and consider other relative economic sectors, including households.

## Conclusions

In this article we utilized a recent developed DEA methodology called semi-disposability for technical and environmental efficiency of 39 power plants in Iran. The strength and flexibility of this method allow us to compare different disposal assumption in the analysis. The overall perspective shows a rather good situation in terms of technical and environmental production. We found 9 percent potential improvement for the overall efficiency measures and about 11 percent for pure technical efficiency measures. Our finding show that environmental issue may roughly contribute by 2 percent when we consider an overall disposability for both overall efficiency and pure technical efficiency cases. We consider both private and governmental possession power plants in the analysis, in order to complete coverage on production and environmental potentials of power plants. Parametric and non-parametric statistical analysis shows mean performance of private power plants are higher that performance of governmental power pants, although the results are statistically insignificant. More comprehensive analysis considering more study year is highly suggested for future research to get a better insight in terms of environmental friendly production for Iranian power plants. This was a limitation on accessing more recent data for us. This result should be considered by decision makers specifically those who are more concerned about the pollutions and environmental issue when policy making and regulation.

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