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INDUSTRIAL PLANTS PERFORMANCE EVALUATION USING DYNAMIC DEA

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Abstract: The objective of the paper is to evaluate the energy efficiency performance of industrial plants based on energy audit measures using dynamic Data Envelopment Analysis. The paper demonstrates a three-stage DEA based on slacks-based measure approach to evaluate the energy efficiency of U.S. industrial plants. Also, a 3-step approach to select relevant variables to be employed in slacks-based measure model. The paper has revealed inefficiencies of industrial plants, which were considered as efficient ones examined individually in energy audit procedure. The results indicate that half of analysed plants are not performing at high energy efficiency, given a total of 6 facilities were operating efficiently. It shows that these industrial plants appear to have the potential to reduce their energy use and cost. Moreover, the results were enriched with the additional analysis of input excesses and output shortfalls and further suggestions for improving energy efficiency are provided.

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1. INTRODUCTION

Efforts to increase energy efficiency and reduce environmental footprint of these facilities have expanded or gained significant traction in USA (Thollander, Backlund, Trianni & Cagno, 2013). The major energy saving opportunities are probably bound to manufacturing processes optimization and energy process integration within manufacturing plants and energy intensive manufacturing industry (Saidur & Mekhilef, 2010; Yingjian, Jiezhi, Qi &Yafei, 2010; Noro & Lazzarin, 2014), and others. Currently available energy efficient and cost-effective technologies can improve energy performance efficiencies in lighting, heating, cooling, refrigeration, transportation, and other areas throughout the U.S. programs (Anderson & Newell, 2004; Thollander, Backlund, Trianni & Cagno, 2013). Further, the energy efficiency can be improved by a wide variety of technical actions including e.g. refurbishing equipment; replacing and retiring obsolete equipment, process lines to new and state of art technologies or using heat management to decrease heat loss and waste energy (Xue, Wu, Zang, Dai & Chang, 2015).

The potential for energy efficiency improvements remains untapped, especially in the SME sector in the European Union, where energy consumption is not always seen as a major cost factor. An evaluation of plants performance is an essential action thorough energy audits in identifying energy saving opportunities and devising goals for energy improvement. The analysis of energy – intensity plants has cantered traditionally on the analysis of economies (cost and energy savings) under the implicit assumption that all companies are efficient (Saidur & Mekhilef, 2010; Yingjian, Jiezhi, Qi &Yafei, 2010; Noro & Lazzarin, 2014). The empirical evidence is often based on aggregate data at country or industry level, or disaggregate firm level data in industrial and developing countries. Energy losses in manufacturing processes remain unavoidable even if all potential savings are exploited as the results of energy audits. Because of the above features, DEA has widely been used for the measurement of technology productivity improvement or processes and optimal allocation of resources in various manufacturing sectors (Onüt & Soner, 2007; Zaim, 2004). Furthermore, due to its measurement of technical change, DEA-SBM has gained popularity in energy efficiency analysis in many fields (Grösche, 2008; Moritaa, Hirokawa & Zhu, 2015). Hence, DEA-SBM was applied in measure and benchmark companies performance as an effective method for performance analysis with multiple inputs and outputs.

The objective of the paper is to evaluate the energy efficiency performance of industrial plants based on energy audit measures in order to separate efficient and inefficient manufacturers from the set of plant considered as efficient ones. Twelve industrial plants are considered as decision making units whose efficiencies were determined by energy-efficiency solutions recommended during energy audits. A DEA-SBM model is employed in improvement to illustrate the application of the model based on the U.S. industrial plants.

2. ENERGY EFFICIENCY MEASUREMENT FRAMEWORK

2.1. DEA and Different Efficiency Concepts

The measurement of efficiency in production units is defined as the quotient of the weighted sum divided by the weighted sum of the effects of inputs. Lovell defines the efficiency of a production unit in terms of a comparison between observed and optimal values of its output and input (Lovell, 1993). The comparison can take the form of the ratio of observed to maximum potential output obtainable from the given input, or the ratio of minimum potential to observed input required to produce the given output. In these two comparisons the optimum is defined in terms of production possibilities, and efficiency is technical (Daraio & Simar, 2007).

In determining the variables inputs and outputs expert knowledge or accepted practices can be useful (Morita & Avkiran, 2009). The selection of the inputs and outputs became in the concern of researchers since this issue can lead to misleading conclusions due to the different structures of the sectors (Saricam & Erdumlu, 2012) and company`s performance (Duzakin & Duzakin, 2007).

According to Charnes, Cooper & Rhodes, 1981, DMU is to be rated as fully efficient on the basis of available evidence if and only if the performances of other DMUs do not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs.

Table 1. The notation for an input- and output-oriented SBM-model

For an input-oriented SBM-model (1)		For an output-oriented SBM-model (2)	
minimize $p = 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}$		minimize $p = 1 + \frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{r0}}$	
subject to		subject to	
$\sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = x_{i0}$	**i = 1, 2, …, m**	$\sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = x_{i0}$	i = 1, 2, …, m
$\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = y_{r0}$	**r = 1, 2, …, s**	$\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = y_{r0}$	r = 1, 2, …, s
$\lambda_j, s_r^+, s_i^- \geq 0$	**j = 1, 2,…,n**	$\lambda_j, s_r^+, s_i^- \geq 0$	j = 1, 2,…, n

Various DEA models have been established as basic model modifications of C^2R model, which initially proposed by Charnes, Cooper & Rhodes, 1981. In this way, improving energy efficiency of industrial processes can be achieved by using the Slack-Based Measure Model (SBM). SBM model developed by Tone, 2002, can be used to measure company-level inefficiency providing an unambiguous measure of effectiveness. Efficiency is measured only by additional variables $s+$ and $s–$. The variables $s+$ and $s–$ measure the distance of inputs $X\lambda$ and outputs $Y\lambda$ of a virtual unit from those of the unit evaluated (Xo). The numerator and the denominator of the objective function of model (1) measures the average distance of inputs and outputs, respectively, from the efficiency threshold. DMU (x_{io}, y_{ro}) in model (2) is SBM-efficient unit, if p* = 1, that means $s_i^{*+} = 0$, $s_i^{*-} = 0$, as no slack variables for input and output in optimal solution. It provides an efficiency score between 0 and 1. The model formulas depending on either the input or output orientation, to ensure that the result is found from variables, which are under managerial control is expressed in Table 1, (Thanassoulis, 2003).

Other approach which extends existing SBM Network Data Envelopment Analysis is presented by Lozano, 2015. In this model the input and output slacks are measured at the system level instead of at the process level giving freedom to the different processes to increase some inputs or decrease some outputs. Therefore, it leaves a room for further research related to the relationship between the overall efficiency of the system and the efficiency of its processes (Lozano, 2015).

2.2. Empirical study of efficiency using SBM-DEA

The procedure for SBM-DEA measures energy efficiency of industrial plants in three stages (Fig. 1). In the first phase the author focuses on identifying the key elements of energy audits reports that provide the database to evaluate efficiency of industrial plants.

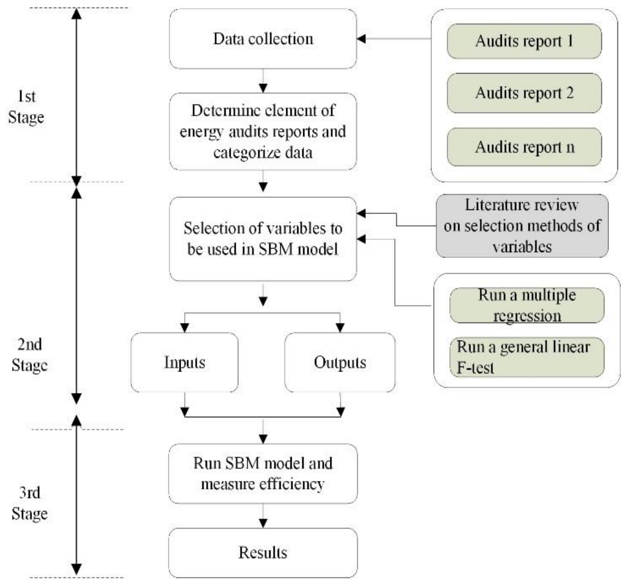

Fig. 1. Structure of research framework

Relevant elements of energy audits that can be attributed to efficiency improvements are categorized into inputs and outputs in order to select appropriate variables. In the second stage multiple regression is used to select variables in order to be evaluated using SBM-DEA model. Then, based on the application of SBM model, the experimental results will be evaluated in the third step. In this study, the data was collected for twice in 2013 and 2014 respectively. Quantitative measures data of various processes were obtained by means of energy audits. This study is built upon the results of energy audits carried out by the author with the Industrial Assessment Center`s experts at the University of Michigan.

2.2.1. Data collection

Manufactures must meet criteria described in Alhourani & Saxena, 2009. The analysis was established for 12 facilities from the industries classified to the North American Industry Classification System (NAICS) based on production-oriented principles as industrial performance consists of fluid power valves and hose fittings, manufacturing processed milk products, metal coating, semiconductor and related device manufacturing, motor vehicle brake system manufacturing.

2.2.2. Determining elements of energy audits reports

Table 2. Steps for setting variables

Step	Description	Results
1	List variables that have relationship with efficiency of plants from audit reports	(x1) Production ; (x2) Total electricity cost; (x3) Total gas cost; (x4) Electricity consumption; (x5) Gas consumption; (x6) Potential electricity estimated savings; (x7) Potential gas estimated savings; (x8) Electricity saving; (x9) Gas saving
2	Run a multiple regression using all nine x-variables as predictors. *Assumption: Variables X i Y both a normal distribution*	Analysis of Variance Source DF SS MS F P Regression 8 6.35864E+15 7.94830E+14 23.82 0.012 Residual Error 3 1.00087E+14 3.33623E+13 Total 11 6.45873E+15
3	Run a general linear F-test $H_0 : \beta_7=0$ $H_A : \beta_7 \neq 0$	**General Linear F** procedure was used to see whether it is reasonable to declare that non-significant variable can be dropped from the model (*p*-values for the variables **(x7)** *Potential gas estimated savings*, is not at a statistically significant level). Finally, a decision is made: there is not enough evidence at the α level to conclude that there is lack of linear fit. The *full model* includes all eight variables; SSE(full) = 1.00087E+14, the full error df = 3, and MSE(full) = 3.33623E+13. The *reduced model* includes almost all variables (x1- x6; x8, x9) besides x7. From analysis variance output, we see that SSE(reduced) = SSE(X7) = 2.59460E+14 , with df = 4, and MSE(reduced) = MSE(X7) = 6.48649E+13. With these values obtained from the reduced model, we obtain the test statistic for testing H_0: $\beta_7 = 0$: 4.777 $$F = \frac{\frac{SSE(reduced) - SEE(full)}{err\ df\ for\ reduced - err\ df\ for\ full}}{MSE\ (full)} \quad (3)$$ Because p = 0.88 (not at a statistically significant level), so we do not reject the null hypothesis and it is reasonable to remove electricity savings from the model.

The elements for determining energy efficiency found in the audit reports such actual cost of energy, cost savings, energy conservation opportunities, and production, are based upon the observations, measurements of industrial plant operations performed by the IAC team during the plant visit.

2.2.3. Selection of variables

In order to select significant variables to be evaluated in SBM model, the author provided a 3-step process where in the first step x-variables are distributed from energy audits reports (Table 2). In the second step the variables are run by a multiple regression and in the third step a general linear F-test to see whether it is reasonable to declare that non-significant variable can be dropped from the model.

Then, X-variables are categorized into input (I) and output (O) to be evaluated on SBM model as shown in Table 3. The outputs of each plant are potential electricity estimated savings (Y1), electricity savings (Y2), gas savings (Y3) was measured. The input data include production (X1), total electricity cost (X2), total gas cost (X3), electricity consumption (X4), total gas consumption (X5).

2.2.4. SBM-DEA evaluation and results analysis

The results of an energy efficiency measures based on application of a slacks-based measure model in DEA model for efficient manufacturing plants individually are presented in Table 4. With data in Table 2, the technical efficiency of facilities through DEA Solver Pro 5.0 is calculated.

Table 3 represents the energy efficiency of the 12 industrial plant, which is the result of employing SBM-input oriented model (1). The paper single out productive units DMU 3, DMU 7, DMU 8, DMU 10, DMU 11, and DMU 12 as efficient. Substantial inefficiency between six plants (DMU 1, DMU 2, DMU 4, DMU 5, DMU 6, DMU 9) are far from achieving an energy-efficient regime. The lowest inefficiency score is 0.38 assigned to the DMU 5. The main reason for being an inefficient manufacturer is excess use of electricity and gas. The inefficient DMUs 1 and 2 are very close to each other, moreover, DMUs 1 and 2 in comparison with DMUs 4, 5, 9 are more inefficient and other technical efficient DMUs do not dominate them. It is also observed that these considered inefficient plants get lower scores than the average efficiency score of 5.91 for 12 facilities, as shown in Fig. 2a.

The efficiency of the facilities allowed getting a ranking of efficient companies. The ranks of these DMUs are illustrated in the last column of Table 3 which shows the following ranking: DMU 12 = DMU 11 = DMU 10 = DMU 3 = DMU 8 = DMU 7 > DMU 5 > DMU 4 > DMU 9 > DMU 2 > DMU 1 > DMU 6. Fig. 2b depicts the results of descending values of efficiency scores of the SBM model for particular plants using the percentages. U.S.

The performances of the facilities are evaluated on annual industrial data and the input excesses and shortfalls leading inefficiencies are determined. By observing input excesses in Table 5, the most input excess is observed in the production input with values of 5033787.4; 2969957.6; 11983096; 27830925; 499984.31; 2137188.3 respectively for plant 1, 2, 4, 5, 6 and 9. These show that the capacity utilization in terms of that input requires more effort to be improved.

Table 3. Selected variables of 12 DMUs with their efficiency evaluation

DMU	(I) Production [tons]	(I) Total electricity [US$]	(I) Total gas [US$]	(I) Electricity consumption [kWh]	(I) Gas consumption [MMBTU]	(O) Potential electricity estimated savings	(O) Electricity saving [kWh]	(O) Gas saving [MMBTU]	SBM Score (overall efficiency)	Rank
1	5036762	130407	13014	1033826	1671	6575	47576	227	0.131	11
2	2971690	90822	4764	760480	529	2440	24201	119	0.136	10
3	20000000	258690	23004	3346231	3339	136240	1510567	-14147	1	1
4	12000000	970272	57713	10023119	7465	62706	528695	1915	0.195	8
5	27913794	958492	474635	8451840	105000	174190	1822680	7406	0.386	7
6	500000	75136	12918	665920	1407	4463	34352	13	0.100	12
7	130000	844098	993745	8270143	199739	327614	2276631	1365	1	1
8	4267200	509979	258082	5508246	47159	143338	1823072	8533	1	1
9	2200000	1298194	648492	18764077	93744	65690	1067780	4805	0.153	9
10	85000000	226690	47313	2562672	6001	123858	2384967	321	1	1
11	500000	598531	121134	5491116	17207	56672	333925	17207	1	1
12	300	291361	14578	2262900	1715	85354	661739	1715	1	1

Considering input excess the biggest value for the plant 9 can decrease its slack in total electricity. Regarding the input excesses in terms of total gas cost it reaches the greatest value of 415806.7 in plant 5, where in terms of gas consumption plant 5 also represents the biggest value. The average input excess value of 2182660.3 in the input electricity consumption becomes 8070183.2 and 14570351 for plants 4 and 9 respectively. DMU 9 depicts most output shortage of potential electricity estimated savings compared with the output shortage of DMU 5 and DMU 4, while DMU 2 is the smallest value (728.39). DMU 6 shows output shortage of gas saving before and after when it gets zero values for the following DMUs. Plants 1 shows most output shortfall of electricity savings after when it gets zero values until reaches a value corresponding to the plant 6. Then zero values occurs again for the rest of plants. Gas savings is lacking of output shortage except for the plant 6 which gets the highest value of 76.67 (above average shortage score). Considering of shortage output, potential electricity estimated savings became very painful for the plants 2, 4, 5, 9 whereas the rest ones get zero values in terms of efficiencies.

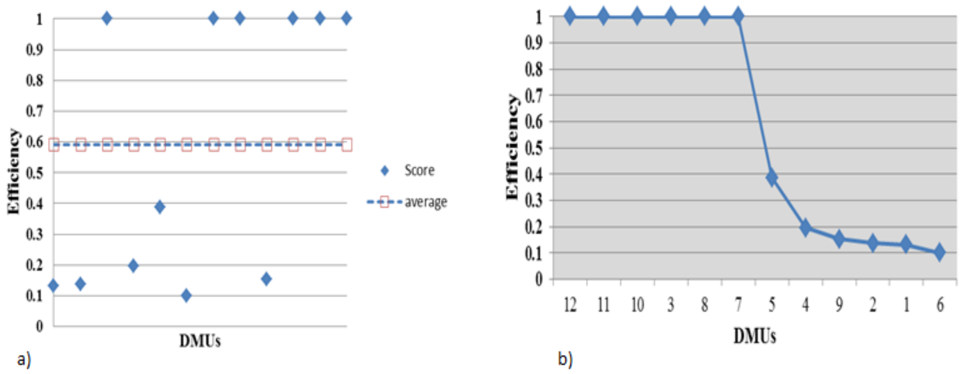

Fig. 2. a) Efficiency scores of the SBM model for individual plants; b) Descending efficiency scores of the SBM model for particular plants

Table 4. Inefficiency slacks from dynamic SBM model

DMU	Excess Production S-(1)	Excess Total electricity cost S-(2)	Excess Total gas cost S-(3)	Excess Electricity consum. S-(4)	Excess Gas consum. S-(5)	Shortage Potential electricity estimated savings S+(1)	Shortage Electricity saving S+(2)	Shortage Gas saving S+(3)
1	5033787.40	105570.70	11232.84	835955.5	1444	0	2776.46	0
2	2969957.60	78611.44	3839.01	662743.21	410	728.39	0	0
3	0	0	0	0	0	0	0	0
4	11983096	722437.20	42272.76	8070183.20	5550	5940.84	0	0
5	27830925	81865.18	415806.70	1505093.10	97594	63139.66	0	0
6	499984.31	59901.28	12155.74	547597.22	1317.33	0	249.09	76.67
7	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0
9	2137188.30	771755.2	610781.70	14570351	88939	73732.89	0	0
10	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0
Average	4204578.2	151678.4	91340.73	2182660.3	16271.19	11961.81	252.13	6.39

The output shortfall is the smallest for the plant 6 in terms of gas savings compared with electricity savings. With regards to input excess the biggest value for the plant 9 can decrease its slack in total electricity.

Regarding the input excesses in terms of total gas cost it reaches the greatest value of 415806.7 in plant 5, where in terms of gas consumption plant 5 also represents the biggest value. The average input excess value of 2182660.3 in the input electricity consumption becomes 8070183.2 and 14570351 for plants 4 and 9 respectively.

Table 5. Energy efficiency evaluation in terms of the suggested recommendations

DMU	Proposed technical recommendations	(I)Total investment/Implementation cost US[$]	(O)Potential electricity estimated savings [US$/yr]	(O)Electricity saving [Kwh/yr]	(O)Gas saving [MMBTU/yr]	Score	Rank
1	Install a cogeneration system	1383250	737517.2	9229081	-28838.4	2.05009814808607E-04	10
2	Replace Electric Heaters with Natural Gas boilers	94400	89276	1146670	-5500	1.08028307696926E-02	9
3	Duct outside air to compressor intakes	12850	20451	244774.4	0	0.245554003154489	7
4	Use gas heaters instead of electric heaters	600	945	10738	0	0.405557642260854	4
5	Lower steam operating pressure	10000	0	0	3167.52	0.354437550156172	6
6	Install high efficiency lighting	111390	42629	382739	0	2.56729479208925E-02	8
7	Install Insulation on Condensate Return Pipes	3000	0	0	860	0.398655755870139	5
8	Reduce compressor set point pressure in compressed air system	2700	11423	163022	0	1	1
9	Recover air compressor waste heat	1000	0	0	333.84	1	1
10	Install variable speed drive (VSD) pumps	7300	30355	490846.62	0	1	1

The same procedure like described in the section 2.2.3 and 2.2.4 is carried out for the suggested technical recommendations for the considered plants. Similarly, energy efficiency is calculated as shown in Table 5, which is the results of model (2). Inputs and outputs are selected from five variables; (x1) investment cost (x2) potential electricity and (x3) gas cost savings, (x4) electricity savings, (x5) gas savings (full model). The reduced model includes the variables; x1; x2; x4, x5 as predictors. From this output, it is seen that SSE(full) = 1.98155E+09, with df = 6, and MSE(full) = 3.30258E+08. Thus, this test statistic comes from F3,6 distribution, of which the associated p-value is 0.66 (P (F<= 1.39)). The largest potential for energy efficiency improvements is in in reduction compressor set point pressure, recovering air compressor waste heat and installation of VSD, with a value of equal to 1.

The results show that the obtained overall efficiency measures are much less (< 1) for the following plants (1, 2, 4, 5, 6, 9) than those corresponding to energy audits outcomes in efficiency and technology recommended, where energy audits solutions were considered as efficient ones (score 1). The proposed approach has also shown that not all processes of a DMU are efficient besides a DMU is efficient itself. The DEA-SBM analysis also helps identify possible directions to improve the inefficient DMUs. Thus, this can be the basis for policy-makers to promote the development of these DMU's.

3. CONCLUSION

The paper identifies six inefficient industrial plants, which were considered as efficient ones in previous research relying on performing energy audits. Based on the SBM-DEA results, it can be seen that plants 3, 7, 8, 10, 11, 12 may be regarded as efficient DMUs. These efficient plants can serve as a benchmark for other plants. It also can be seen that the efficiency scores of these six mentioned plants are much higher than the non-efficient plants (1, 2, 4, 5, 6, 9). Estimation of the efficiency across plants indicates that the inefficient plants suffer from poor performance. Given the above findings, it seems necessary to make a serious effort for the efficiency improvement of the energy efficiency for these plants. The fact that the greatest energy efficiency improvement potential in this data is found in support processes even for manufacturing firms does not necessarily reflect the “true potential” but could be a reflection of the knowledge and expertise of the energy auditors who has conducted the audits. Therefore, the results of this study indicate the need to develop in-depth research in energy-savings recommendations for improving energy efficiency.

A few limitations of this study should be noted because of the quality of the data which may contain errors on multiple level. Data was derived from energy audits conducted, and these audits may have measurement errors. On the other hand, data related to potential cost and energy saving in terms of different processes was aggregated and thus may have a worse quality. Additionally, a 3-step process to select criteria seems to be elementary but has the potential to become usefulness if combined with the other making decision methods, thus that could offer benefits for more intensive energy efficiency improvement.

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BIOGRAPHICAL NOTES

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