Energy Efficiency Modeling and Estimation in Petroleum Refining Industry - A Comparison Using Physical Data

A. Azadeh S.F.Ghaderi S.M.Asadzadeh
Research Institute of Energy Management and Planning and
Department of Industrial Engineering, Faculty of Engineering, University of Tehran
P.O. Box 11365 Tehran, IRAN

aazadeh@ut.ac.ir ghaderi@ut.ac.ir asadzadeh@engmail.ut.ac.ir

Abstract

In this paper, energy efficiency in petroleum refining industry has been analyzed using the non-parametric data envelopment analysis approach with physical data. The proposed model for evaluation of energy efficiency does not require energy data in the operational levels for considering the structural effects. The average weighted boiling point of refined products is used as structural indicator in the proposed model. Also, data envelopment analysis (DEA) is used as a sensitivity analysis tool for determination of the potentials and means of energy consumption improvement and optimization. The proposed model is applied to a set of data from Iran and some OECD countries. The results show that the potential of savings in fossil fuels are greater than that of electricity consumption in refineries. The unique feature of this study is based on the utilization of DEA for separation of structural effects from other effects which are referred to as activity and intensity effects. The proposed model is also verified and validated by principle component analysis (PCA) and non-parametric Spearman correlation technique.

I. INTRODUCTION

Petroleum refining is one of the largest energy consuming sectors, consuming approximately 4 percent of total global primary energy consumption. Most petroleum refining capacity can be found in OECD countries, Eastern Europe and former Soviet-Union, while the share of developing countries is growing [1]. In addition, in Iran, the petroleum refining industry is a large energy-consuming sector, having a share of 3.7 percent in manufacturing primary energy consumption, equivalent to 0.8 percent of total primary energy consumption [2]. In general, improving energy efficiency is considered to be an important option to reduce energy-related greenhouse gas emissions. In order to support national and international policy development, especially in petroleum refining industry and because of the large amount of energy consumed in this industry, it is necessary to have adequate information about the present levels of energy efficiency and the potentials of improving energy efficiency.

Commonly, energy intensity indicators measure energy efficiency, but as stated by Freeman et al. [3], energy intensity is not exactly an indicator of energy efficiency. Changes in intensity indicators can be due to the behavioral, technological, structural or efficiency changes. In this respect, structural changes have a large effect on energy consumption, especially in manufacturing industries.

The 'International Comparisons of Energy Efficiency project', initiated by Lawrence Berkeley National Laboratory and the department of Science, Technology and Society (Utrecht University, the Netherlands) aimed to develop indicators for measuring and comparing energy efficiency among countries. The methodologies developed and published in its proceeding Handbook [1], show that structural differences can be taken into account in cross-country comparisons of energy efficiency if appropriate physical energy efficiency indicators are used. Worrel et al. [4] have compared the physical and economic energy intensity indicators in the iron and steel industry. They have concluded that use of physical energy intensity indicators improves comparability between countries, provides greater information for policy-makers regarding intra-sectoral structural changes. Also Eichhammer et al. [10] and Farla et al. [11] emphasize the use of physical energy efficiency indicators in cross country comparisons and in pulp and paper industry, respectively.

Previous studies, [4], [5] and [6] have used a structure/efficiency plot to comparing the actual specific energy consumption (SEC) with the best-practice SEC in presence of structure indicator. Also, Ma et al. [7] have measured technical efficiency by dividing China's iron and steel enterprises into four groups according to the structure of their products to differentiating between technical and structural effects on energy consumption. They have used Data Envelopment Analysis (DEA) to examine the efficiency of the enterprises within each group. In this paper we propose to consider the structure of petroleum refining sectors directly into analysis with the aid of structural indicators defined in the next section. Moreover, the structure of petroleum refining is assessed by a structural indicator that will be used as a DEA output indicator. Also, by using sensitivity analysis the proposed model can determine the inefficiencies in consumption of each energy carrier withal the potential of efficiency improvements in each energy carrier usage.

In the proposed approach, DEA incorporates all defined variation sources such as energy consumption, activity and structure of refineries into evaluation by considering them as input and output indicators. This approach ranks refineries as decision-making units (DMUs) according to their efficiency of utilizing energy carriers to produce more energy intensive products within a specific structure. Furthermore, energy consumption indicators are defined and used as input indicators whereas activity and structural indicators are defined and used as the output indicators. This does not mean that the input side indicators are consumed to produce the outputs but it means that increases in such an output side indicators is accompanied by increases in input side indicators. Ramanathan [8] has employed this feature of DEA for analysis of energy consumption in countries of the Middle East and North Africa.

Section 2 introduces the input and output indicators and data sources used in our study. Also, the philosophy of utilizing these indicators is mentioned. In sections 3 and 4 a conceptual description of DEA and DEA sensitivity analysis and principle component analysis (PCA) are explained. Moreover, PCA is used to verify and validate the results of DEA approach of this study. In section 5, DEA models is applied to a set of real data including Iran and some OECD countries and the results are presented and verified, validated and discussed.

II. Data And Indicators

In petroleum refining, energy consumption figures were composed of fuel consumption, refinery losses and electricity consumption. As recommended by Phylipsen et al. [1], both energy use and refinery losses should be counted as internal consumption but access to data on refinery losses is limited. So, we distinguish between fossil fuels consumption (FOSS) and electricity consumption (ELECT) as two DEA input indicators. We obtain the energy consumption of OECD countries from the IEA/OECD publications [ISIS, energy consumption statistics in manufacturing industry, 2000]. Energy consumption data for Iran are obtained from national statistics [census of industrial units]. Fossil fuels approximately have a share of 95 percents in total primary energy consumption in refineries of selected countries.

The structural indicators for petroleum refining industry have been defined as product mix and the type of crude oil [1]. As stated by Worrel et al [6], the type of crude oil can influence the energy consumption of Crude Distillation Unit by 24% but unfortunately we cannot take this variation into account because no data concerning the crude oil types used are available. Therefore, it is assumed that the structure of the petroleum refining to be only the mix of products. We embody this structural aspect in our analysis in figure of an output indicator that is average weighted boiling point (AWBP) of all produced fractions.

Crude oil is a complicated mixture of hydrocarbons with a varying composition depending on its source. The hydrocarbons in crude oil have different boiling points, according to the number of carbon atoms their molecules contain and how they are arranged. The more carbon atoms a hydrocarbon molecule has, the heavier it is and the higher is it's the boiling point. Each refined product may have different types depending on its carbon chain length and so has a boiling range. For example, gasoline has 4-8 carbon molecules in its carbon chain and has a boiling range of 20 to 200 ^{o}C. We use an average boiling point for each fraction in our analysis. The Industrial Commodity Statistics of the UN distinguish 14 petroleum refinery product groups, which are aviation gasoline, jet fuels, motor gasoline, Naphtha, Kerosene, White spirit/industrial spirit, gas-diesel oil (distillate fuel oil), residual fuel oils, lubricants, petroleum wax (paraffin), petroleum coke, Bitumen (asphalt), LPG and refinery gas. We use an average boiling point for each of these 14 fractions to calculate the AWBP. Data needed are derived from the handbook of petroleum products [9]. This handbook gives a sound working knowledge of each product's properties and characteristics. Average boiling points are shown in Table I.

TABLE I
AVERAGE BOILING POINT OF UN STATISTICS FRACTIONS

Refinery product	Average boiling point	Refinery product	Average boiling point
LPG	20	White/industrial spirit	175
LPG	20	Gas-diesel oil	287
Aviation gasoline	87	Residual fuel oils	330
Jet fuels	157	Lubricants	427
Motor gasoline	129	Petroleum wax & coke	480
Naphtha	150	Petroleum coke	480
Kerosene	168	Bitumen (asphalt)	530

As suggested by Phylipsen et al. [1, page 188], a structural indicator could be developed according to light and heavy fractions. As mentioned by Worrel et al. [6], the production of light fractions consumes more energy, since more processing steps are involved. On the other hand, light fractions have lower boiling point compared to heavy fractions. So, in a standard modern refinery with a specific level of production, as the average boiling point is decreased for all produced fractions, more energy is consumed.

We use the AWBP as a structural indicator. This indicator is nested into output side indicators in DEA model. As mentioned, an increase in an output side indicator is accompanied by increases in input side indicators. Thus, the inverse of AWBP is used as a DEA output indicator in our analysis. For convenience all numbers are multiplied by 1000. Therefore, the AWBP is calculated as (1):

$$AWBP = \sum_j \frac{P_j \times ABP_j}{\sum_j P_j} \tag{1}$$

Moreover, our DEA output indicator calculated as (2)

$$1000\ AWBP^{-1} = 1000 \times \frac{1}{AWBP} \tag{2}$$

In the above expression j is the index of refined products and P_j is the production of product j. ABP_j is the average boiling point of product j. The production data of the refined products are collected from the UN Industrial Commodity statistics, 2001.

Petroleum refining produces a wide variety of products. The best activity indicator would include the total variety of products, produced in all processes. In our study total weighted production of all produced fractions (TWP) is used as activity indicator. We use the best practice SECs (Table II), proposed by Worrel et al. [6] as weighting factors for aggregating all amount of different products into one activity indicator. This aggregated indicator also is the amount of primary energy that could be consumed in industry according to the present mix of products in best practice mode. We consider this indicator as one of the DEA-output side indicators because in a specific mix of products, the ratio of best-practice primary energy consumption to actual electricity or fuel consumption is an indicator, representing the potential of energy savings and efficiency of energy consumption.

In 1994, Worrel et al. [6] in their study in the European Union, propose a set of best practice SECs for six groups of fractions. They distinguished six fraction groups, i.e. gases (LPG and refinery gas), gasoline (aviation gasoline, Jet fuels, and Motor gasoline), Kerosene, gas oil (gas-diesel oil, naphtha and white spirit), fuel oil (residual fuel oils) and others (Lubricants, petroleum wax, petroleum coke and asphalt). The best practice SECs and relevance between Worrel study production groups and UN statistics production groups proposed by Worrel et al. [6] are shown in Table II. The best practice SECs, are based on a typical standard refinery, consuming 6.5% of throughput, with a mixed feedstock of Arabian light and Brent blend [6].

The TWP for each DMU is calculated by summing all amounts of refinery products production multiplied by their corresponding best practice SECs as in (3):

$$TWP = \sum_j P_j \times SEC_j^{BP} \tag{3}$$

It should be noted that j is the index of refined products and P_j is the production of product j. SEC_j^{BP} is the best practice SEC for product j proposed by Worrel t al [6]. Data used in our analysis are presented in Table III.

TABLE II
RELEVANCE BETWEEN WORREL STUDY PRODUCTION GROUPS AND UN STATISTICS [6]

Oil refinery product (Worrel study groups)	Oil refinery product (UN statistics groups)	SECBP (TJ/ktone)
Gases	LPG and refinery gas	1.3
Gasoline	Aviation gasoline, Jet fuels, Motor gasoline	3.8
Kerosene	Kerosene	1.6
Gas oil , naphtha	Gas-diesel oil, naphtha and white spirit	3.2
Fuel oil	Residual fuel oils	1.8
Others	Lubricants, Petroleum wax, Petroleum coke and Asphalt	1.8

III. DATA ENVELOPMENT ANALYSIS

DEA is a non-parametric programming method for estimating the efficiency in a given set of decision-making units (DMUs). Envelope models could be input or output oriented. In an input oriented model the level of all output remain constant and technical efficiency score Θ measures the minimal radial contraction of the inputs. Since we are interested to evaluate the efficiency of refineries under a fixed structure and on the other hand, the output indicators in our DEA models reflect the structural properties of refineries, we use the input oriented DEA models. The efficiency scores derived from the input oriented models for inefficient refineries deal with the potential of conservation in consumption of each input (energy carrier). In addition, for efficient refineries the efficiency scores show how well a refinery use the electricity and fuels to produce the refined products.

Assume a sample that covers n DMUs, and that each of them uses m inputs with the property of s outputs. It is an input-orientated measurement of efficiency:

$$\begin{aligned}
&\operatorname{Min} \theta \\
&s.t. \\
&\quad \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{i0} \qquad i = 1,2,\ldots m \\
&\quad \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0} \qquad r = 1,2,\ldots s \\
&\quad \lambda_j \ge 0, \forall \text{j and } \theta \text{ is free}
\end{aligned} \tag{Model 1}$$

The Model 1 assumes constant returns to scale (CRS) and at first was introduced by Charnes et al. [12] and known as CCR model. However, variable returns to scale (VRS) can be incorporated in it by appending the constraint ($e\lambda = \sum_{j=1}^{n} \lambda j = 1$) and the resulting model is called BCC model [13]. Scale efficiency of a DMU is obtained as the ratio of CCR efficiency and BCC efficiency. Since, in input oriented models, the VRS efficiency of a DMU is always more than or equal to the CRS efficiency, scale efficiency of a DMU is equal to one if the DMU is operating at its most productive scale size; otherwise scale efficiency is less than one.

The CCR model is not capable of ranking efficient units as it assigns a common index of one to all the efficient DMUs. Therefore, this model was modified by Andersen and Petersen [14] for DEA based ranking purposes. (AP model)

$$\begin{aligned}
&\operatorname{Min} \theta \\
&s.t. \\
&\quad \sum_{\substack{j=1 \\ j \ne o}}^{n} \lambda_j x_{ij} \le \theta x_{i0} \qquad i = 1,2,\ldots m \\
&\quad \sum_{\substack{j=1 \\ j \ne o}}^{n} \lambda_j y_{rj} \ge y_{r0} \qquad r = 1,2,\ldots s \\
&\quad \lambda_j \ge 0, \forall \text{j } j \ne o \text{ and } \theta \text{ is free}
\end{aligned} \tag{Model 2}$$

We use the AP Model (Model 2) for full ranking the DMUs. In AP model a DMU is an efficient DMU if the efficiency score of that DMU is equal or greater than one. All inefficient DMUs have an efficiency score less than one.

Since each refinery has its own inherent tradeoffs among the energy carriers that significantly influence the performance, it is extremely important to know the critical energy carrier. By using super-efficiency DEA models, the sensitivity analysis of DEA efficiency classification can be easily achieved. For sensitivity analysis, we use input oriented measure specific super efficiency DEA model that proposed by Zhu, [15]. The DEA sensitivity analysis methods we have used are all developed for the situation where data variations are only applied to the test DMU and the data for the remaining DMUs are assumed fixed. This approach is independent of identifying DEA weights or DEA multipliers mentioned in [16]. We assume constant return to scale. In Model 3, the kth input is given the preemptive priority to change such that:

$$
\begin{aligned}
&\text{Min } \theta_k \\
&s.t. \\
&\quad \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j x_{ij} \le \theta_k x_{io} \quad i = k \\
&\quad \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j x_{ij} \le x_{io} \quad i = 1,2,...m, \; i \neq k \qquad \text{(Model 3)} \\
&\quad \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j y_{rj} \ge y_{ro} \quad r = 1,2,...s \\
&\quad \theta_k, \lambda_j, (j \neq o) \ge 0
\end{aligned}
$$

It is obvious that larger optimal values to Model 3 correspond to greater stability of the test DMU in preserving efficiency if perturbation in data occurs. From the management perspective, we can provide a *what-if* tool to the standard DEA analysis kit. The results of sensitivity analysis for an efficient refinery could help us to determine the energy carrier that increases in its consumption make the DMU an inefficient DMU. On the other hand, for the inefficient DMUs, we can determine the energy carrier that decreases in it could make the DMU an efficient DMU more rapidly. A full description of the procedure of determining the critical input indicators can be found in [15]. For the first input (ELECT) the optimal value of Model 3 (Θ_1^*) for an inefficient DMUo is the minimum contraction in ELECT that cause to DMUo be an efficient DMU on the frontier and be a best practice DMU. Θ_1^* also is the amount of potential reduction in ELECT compare to the best observed DMU. As stated by Zhu [15] it is clear that for an inefficient DMU, if $\Theta_1^* > \Theta_2^*$ then the input1 is critical input and therefore the potential of savings in input2 is greater than the potential of savings in input1. It should be noted that for an inefficient DMU the optimal values of Model 3 for all its inputs are less than one. The more the optimal value of Model 3 for an input, the less the potential of savings in that input. Further work on concepts of sensitivity analysis and its application is done by [17,18,21]

IV. PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is widely used in multivariate statistics such as factor analysis. It is used to reduce the number of variables under study and consequently ranking and analysis of decision-making units (DMUs), such as industries, universities, hospitals, cities, etc [20-22]. These DMUs utilize a variety of sources as inputs to produce several outputs. In this paper, we use this method for verifying and validating DEA ranking results. The procedure of ranking with PCA in our analysis is the procedure proposed by Zhu [23]. Zhu compares two DEA and PCA approaches in aggregating multiple inputs and multiple outputs in the evaluation of the economic performance of Chinese cities. As mentioned by Zhu, these two methods yield consistent and mutually complementary results. More conceptual descriptions of ranking with PCA can be found in [23] and [24].

V. THE PROPOSED APPROACH

The DEA analysis of the data presented in Table III, has been performed using the Lingo software package. The efficiency scores of refineries in different years and sensitivity analysis results are indicated in Table III. Note that the efficiencies reported are only relative, i.e. efficiencies relative to the best performing country (countries).

Table III shows that 3 of the 48 DMUs have been considered efficient (in terms of the energy consumption) under the CRS assumption. They are Austria in the years 1991, 1993, 1995. These three DMUs have been considered in this study as having low electricity and fossil fuel consumption compared to the others as the effect of products structure (in the form of AWBP) has been eliminated. When VRS is assumed, Canada 1998 and Iran in years 1995-1998 have also been considered efficient. Czech Republic is rated as the least efficient country under the CRS and VRS assumption. Table III also gives information about Peer(s) for DMUs considered inefficient in the analysis. For example, Iran's peer is Austria 1993, meaning that Iran can try to emulate Austria (as far as the energy consumption is considered) in order to register the consumption of carriers that will enable it to be considered best in the DEA study. As expected, the VRS efficiencies that measure pure technical efficiencies excluding effects of scale of operations are larger than the corresponding CRS efficiencies. For example, the CRS efficiency of Iran is 0.1-0.16, and its score increases to 1 under the VRS assumption. The CRS efficiency score is lower because this country does not operate at a best possible scale size. The ratio of CRS and VRS efficiency is the scale efficiency. Table III provides the details on scale efficiencies of the countries. For example, the scale efficiency of Poland is almost 0.3, meaning that the country is not able to register unit efficiency because it is not operating at the most productive scale size, and its present size of operations reduces its pure technical efficiency (i.e. the VRS efficiency) by 70%. When VRS is assumed, Japan and UK in some years are considered efficient indicating that the CRS inefficiency of these two countries is due to the fact that they are not operating at the best possible scale size.

A full ranking of countries in different years has been performed (Table III). Austria in years 1991, 1993 and 1995 has the best efficiency in term of energy consumption in its petroleum refining industry. The result of DEA full ranking has been validated using the multivariate statistical method of principal component analysis (PCA). The Spearman correlation between the rankings of DEA and PCA is 99.1 percent. Compared to Austria, all remaining countries are inefficient in consumption of energy carries (ELECT & FOSS) in their refining industries. The score efficiency of each DMU is a coefficient that tells us the amount of potential savings in consumption of each energy carrier. Also, the potential of improvement in energy consumption in refineries under study can better be derived from the results of sensitivity analysis.

TABLE III

ROW DATA, RELATIVE EFFICIENCIES, RANKING AND CRITICAL ENERGY CARRIER FOR EACH COUNTRY-YEAR

DMUs	Row Data				Relative Efficiencies				Ranking			Sensitivity Analysis		
Country-Year	ELECT (MWh)	FOSS (Toe)	TWP (Kton or TJ)	$1000^{*}AWBP^{-1}$ (1000/oC)	CCR Efficiency	BCC Efficiency	Scale Efficiency	Peer(s)	AP Efficiency	AP Rank	PCA Rank	ELECT Efficiency	FOSS Efficiency	Critical Index
Austria-1991	5080	470.723	24609	3.98	1.000	1.000	1.000	-	1.034	2	3	1.0344	Infeasible	EL.
Austria-1992	5352	471.219	25106.2	3.982	0.970	0.989	0.981	Austria-1991,3,5	0.967	4	5	0.9674	0.68314	EL.
Austria-1993	5224	482.223	25446.3	3.936	1.000	1.000	1.000	-	1.007	3	4	1.0065	Infeasible	EL.
Austria-1994	5858	356.079	26048.5	4.021	0.947	1.000	0.947	Austria-1993,5	0.943	5	2	0.9431	0.71530	EL.
Austria-1995	5286	238.093	24349.6	4.012	1.000	1.000	1.000	-	1.879	1	1	Infeasible	1.87873	FO.
Canada-1991	5744444	6597685.8	236859.5	5.016	0.008	0.804	0.011	Austria-1993	0.008	38	38	0.0085	0.00035	EL.
Canada-1992	5977778	6752356.5	234573.8	4.998	0.008	0.770	0.010	Austria-1993	0.008	40	40	0.0081	0.00034	EL.
Canada-1993	5988889	6830133.7	242830.4	5.037	0.008	0.801	0.010	Austria-1993	0.008	39	39	0.0083	0.00035	EL.
Canada-1994	5936111	6662782.7	245668.9	5.017	0.008	0.818	0.010	Austria-1993	0.008	37	37	0.0085	0.00036	EL.
Canada-1995	4888889	6547800.5	249874.1	5.047	0.010	0.901	0.012	Austria-1993	0.010	35	34	0.0105	0.00037	EL.
Canada-1996	5113889	6999347.4	265318	5.041	0.011	0.901	0.012	Austria-1993	0.011	33	33	0.0107	0.00037	EL.
Canada-1997	5155556	6805728.3	282089.2	5.139	0.011	0.988	0.011	Austria-1993	0.011	30	30	0.0112	0.00041	EL.
Canada-1998	5169444	6651368.1	280327.2	5.2	0.011	1.000	0.011	Austria-1993	0.011	31	31	0.0111	0.00041	EL.
Czech Rep-1993	1761877	1925880	16684.8	3.948	0.003	0.003	0.992	Austria-1991	0.003	47	47	0.0029	0.00012	EL.
Czech Rep-1994	1740944	1852457.6	14870.6	3.782	0.003	0.003	0.950	Austria-1991	0.003	48	48	0.0028	0.00012	EL.
Czech Rep-1995	1679665	1918977.8	17561.2	3.773	0.003	0.003	0.948	Austria-1991	0.003	46	46	0.0029	0.00012	EL.
Czech Rep-1996	270568	350939.41	19084	3.796	0.018	0.019	0.954	Austria-1991	0.018	14	13	0.0179	0.00064	EL.
Czech Rep-1998	268795	451316.19	17903.2	3.646	0.017	0.019	0.916	Austria-1991	0.017	16	16	0.0173	0.00048	EL.
Denmark-1993	321601	457789.18	23862	3.833	0.015	0.016	0.969	Austria-1991,3	0.015	19	17	0.0153	0.00051	EL.
Denmark-1995	328504	521190.21	27788.2	3.971	0.017	0.030	0.577	Austria-1993	0.017	15	12	0.0174	0.00052	EL.
Denmark-1996	368121	577794.85	30795.7	4.074	0.017	0.176	0.098	Austria-1993	0.017	17	14	0.0172	0.00052	EL.
Denmark-1997	293010	478368.08	25962.6	4.183	0.018	0.309	0.059	Austria-1991,3	0.018	13	11	0.0183	0.00053	EL.
Iran-1995	185959	950197.03	133849.9	3.749	0.148	1.000	0.148	Austria-1993	0.148	7	7	0.1478	0.00138	EL.
Iran-1996	172917	1877171	136262.9	3.717	0.162	1.000	0.162	Austria-1993	0.162	6	6	0.1618	0.00071	EL.
Iran-1997	202965	1950596.7	140502.5	3.735	0.142	1.000	0.142	Austria-1993	0.142	8	8	0.1421	0.00070	EL.
Iran-1998	305921	1955375	152578.2	3.802	0.102	1.000	0.102	Austria-1993	0.102	9	9	0.1024	0.00076	EL.
Japan-1991	7887656	6984074.3	474693	4.055	0.012	0.959	0.013	Austria-1993	0.012	26	26	0.0124	0.00066	EL.
Japan-1992	8114521	7132583.4	500979	4.068	0.013	1.000	0.013	Austria-1993	0.013	23	25	0.0127	0.00069	EL.
Japan-1993	8687887	7577609.1	516809.3	4.084	0.012	0.988	0.012	Austria-1993	0.012	27	27	0.0122	0.00067	EL.
Japan-1994	9165131	7673828.2	540181.9	4.063	0.012	1.000	0.012	Austria-1993	0.012	28	28	0.0121	0.00069	EL.
Japan-1995	9572277	7480247	546564.9	4.101	0.012	1.000	0.012	Austria-1993	0.012	29	29	0.0117	0.00071	EL.
Japan-1996	10160375	7571889.9	544727.9	4.124	0.011	0.976	0.011	Austria-1993	0.011	32	32	0.0110	0.00070	EL.
Japan-1997	10936947	7518016.4	562250.3	4.152	0.011	1.000	0.011	Austria-1993	0.011	34	35	0.0106	0.00073	EL.
Japan-1998	11049917	7911617.4	556280.1	4.19	0.010	1.000	0.010	Austria-1993	0.010	36	36	0.0103	0.00069	EL.
Newzland-1998	233964	471886.22	15921.9	4.658	0.025	1.000	0.025	Austria-1991	0.025	10	10	0.0254	0.00059	EL.
Norway-1992	471704	807307.95	43856.9	4.414	0.019	0.692	0.028	Austria-1993	0.019	12	15	0.0191	0.00053	EL.
Norway-1993	706305	838242.97	43374.9	4.489	0.013	0.762	0.017	Austria-1993	0.013	24	22	0.0126	0.00051	EL.
Norway-1994	711696	824884.32	44904.2	4.492	0.013	0.805	0.016	Austria-1993	0.013	21	21	0.0130	0.00053	EL.
Norway-1995	647944	700123.43	40129.4	4.515	0.013	0.895	0.014	Austria-1993	0.013	22	20	0.0127	0.00056	EL.
Norway-1996	532108	800777.86	44281.4	4.531	0.017	0.889	0.019	Austria-1993	0.017	18	19	0.0171	0.00054	EL.
Norway-1997	500222	835494.36	46602.9	4.502	0.019	0.853	0.022	Austria-1993	0.019	11	18	0.0191	0.00055	EL.
Poland-1994	1583521	17263397	39105.8	3.91	0.005	0.016	0.313	Austria-1993	0.005	44	41	0.0051	0.00002	EL.
Poland-1995	1638439	17252438	38532.3	3.865	0.005	0.015	0.319	Austria-1993	0.005	45	44	0.0048	0.00002	EL.
Poland-1996	1653867	20596853	41135.5	3.857	0.005	0.017	0.294	Austria-1993	0.005	43	42	0.0051	0.00002	EL.
Poland-1997	1705269	27193352	43213.9	3.799	0.005	0.019	0.278	Austria-1993	0.005	41	43	0.0052	0.00002	EL.
Poland-1998	1833802	20759437	46023.5	3.804	0.005	0.020	0.261	Austria-1993	0.005	42	45	0.0052	0.00002	EL.
UK-1997	5076733	5646515.8	326258.7	4.657	0.013	1.000	0.013	Austria-1993	0.013	20	23	0.0132	0.00056	EL.
UK-1998	5191626	5427617.1	314546.1	4.649	0.012	0.992	0.013	Austria-1993	0.012	25	24	0.0124	0.00057	EL.

ELECT: Electricity Consumption; FOSS.: fossil fuel consumption; Toe: ton oil equivalent; Kton: Kilo ton; TJ: tera joule;
ELECT Efficiency: the optimal value of Model 3 when k = 1; FOSS Efficiency: the optimal value of Model 3 when k = 2

Sensitivity analysis with the aid of Model 3 has been applied to the data and the results have been presented in the last three columns of Table III. Data in Table III show that in all inefficient DMUs, the electricity is the critical carrier for the refining industry to be an efficient DMU. It means that for all countries except Austria, the percentages of potential improvements in fossil fuels are greater than the potential savings in electricity compared to the best practices (Austria in years 1991, 1993 and 1995). This is an interesting conclusion that is corresponded with our knowledge about refineries because more than 95 percents of primary energy consumption is due to fossil fuels consumptions and hence the potential of savings in the fossil fuels should predominantly be greater than the potential savings in electricity consumption.

VI. CONCLUSION

In this paper, energy efficiency in petroleum refining industry has been analyzed using the robust non-parametric DEA approach. Also, the DEA approach was verified and validated by PCA and Spearman correlation technique. Utilizing physical indicators in the analysis enhances the comparability between countries and gives a sound reliability to the results. The proposed model eliminates the need for energy data in the refineries operations level for considering the structural effect. The output indicator used as structural indicator incorporates the structure of the petroleum refining industry properly into analysis. Energy consumption in industry is a function of three indicators that are activity, structure and efficiency. This subject makes the energy efficiency analysis a multidimensional decision problem that DEA can help us in this respect. Determining the potentials of improving energy efficiency is a goal in each study of energy consumption. We do this with the aid of DEA sensitivity analysis models. The results of applying the model into a set of real data from Iran and some OECD countries show that the potential of savings in fossil fuels are frequently more than the potential of savings in the electricity consumption. In our case study the Austria in the years 1991, 1993 and 1995 has the best relative performance and the potential of savings in energy carriers are determined according to the properties of petroleum refining industry in this country as a benchmark. Because of limitations to access required data for crude oil, type of crude oil could not be considered as a structural indicator. Incorporating this aspect into present analysis as a quantitative or qualitative aspect can be a subject for the future studies.

REFERENCES

[1]. Phylipsen G.J.M, Blok K. and Worrel E. *Handbook on international comparison of energy Efficiency in the manufacturing industry*, Dept. of Science, Technology and Society, Utrecht University, April 1998

[2]. Statistical Center Of Iran, Management & Planning Organization, http://www.sci.org.ir

[3]. Freeman Scott L., Niefer Mark J. Roop Joseph M. Measuring industrial energy intensity: practical issues and problems, *Energy Policy*, 1997; 25, (7-9): 703-714.

[4]. Worrell Ernst, Lynn Price, Nathan Martin, Jacco Farla and Roberto Schaeffer, Energy intensity in the iron and steel industry: a comparison of physical and economic indicators, *Energy Policy* 1997; 25, (7-9): 727-744

[5]. Phylipsen, G.J.M. K. Blok and E. Worrel, International comparisons of energy Efficiency. Methodologies for the manufacturing industry, *Energy Policy*, 1997; 25, (7-9), pp.715-725.

[6]. Worrel E., Cuelenaere R. F. A.,. Blok K, and Turkenburg W. C. Energy Consumption By Industrial processes in the European Union, *Energy* 1994; 19, (11): 1113-1129

[7]. Ma Jinlong, David G. Evans, Robert J. Fuller, Donald F. Stewart, Technical efficiency and productivity change of China's iron and steel industry, *Production Economics* 2002; 76: 293–312

[8]. Ramakrishnan Ramanathan, An analysis of energy consumption and carbon dioxide emissions in countries of the Middle East and North Africa, J. *Energy* 2005;30: 2831–2842

[9]. Guthrie, Virgil B. *Petroleum Products Handbook*, Edited, Knovel publications, 1960; 2005.

[10]. Eichhammer, W. and Mannsbart, W, Industrial energy Efficiency indicators for a European cross country comparison of energy Efficiency in the manufacturing industry. *Energy Policy*, 1997; 25, (7-9): 759-772.

[11]. Jacco Farla, Kornelis Blok and Lee Schipper, Energy Efficiency developments in the pulp and paper industry : A cross-country comparison using physical production data, *Energy Policy* 1997; 25, (7-9),): 745-758

[12]. Charnes A., Cooper W.W., Rhodes E., Measuring the efficiency of decision-making units, *European Journal of Operational Research* 1978; 2: 429–444.

[13]. Banker R.D.,. Charnes A, Cooper W.W., Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science* 1984; 30: 1078–1092.

[14]. Andersen Per, Niels Christian Petersen, A Procedure for Ranking Efficient Units in Data Envelopment Analysis, *Management Science*, 1993; 39,(10)

[15]. Joe Zhu. *Quantitative Models for performance Evaluation and Benchmarking*, Kluwer Academic publishers, 2003, Netherlands.

[16]. Cooper W., Seiford L.M, Tone K. *Data envelopment analysis: a comprehensive text with models applications references & DEA solved software*, Kluwer academic publishers,2002

[17]. Seiford Lawrence M. , Joe Zhu, Stability regions for maintaining Efficiency in data envelopment Analysis, *European Journal of Operational Research* 1998; 108: 127-I39

[18]. Joe Zhu, Super Efficiency and DEA sensitivity analysis , *European Journal of Operational Research* 2001;129: 443-455

[19]. Jahanshahloo G.R. , F. Hosseinzadeh b, N. Shoja b, M. Sanei b, G. Tohidi b , Sensitivity and stability analysis in DEA , Applied Mathematics and Computation 2005*; IN PRESS*

[20]. Azadeh, M.A. and Ebrahimipour, A., An Integrated Approach For Assessment And Ranking Of Manufacturing Systems Based On Machine Performance, *International journal of Industrial Engineering*, 2004, 11(4)

[21]. Azadeh, M.A. and Jalal, S., 'Identifying the Economic Importance of Industrial Sectors by Multivariate Analysis', 2001, *Journal of the Faculty of Engineering*, University of Tehran, Iran.

[22]. Tat, Y. and Raymond. Levels of Satisfaction among Asian and Western Travelers, *International Journal of quality Reliability Management*,2000, Vol.17 No.2, pp.116-131.

[23]. Zhu Joe, Data envelopment analysis vs. principal component analysis: An illustrative study of economic performance of Chinese cities Theory and Methodology, *European Journal of Operational Research*, 1998, 111, 50-61

[24]. Premachandra I.M., A note on DEA versus Principal Component Analysis, An Improvement to Joe Zhu Approach, *European Journal of Operational Research*, 2001, 132, 553-565