

Environmental Efficiency of Electric Power Industry of the United States: A Data Envelopment Analysis Approach

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Abstract—Importance of environmental efficiency of electric power industry stems from high demand for energy combined with global warming concerns. It is especially essential for the world largest economies like that of the United States. The paper introduces a Data Envelopment Analysis (DEA) model of environmental efficiency using indicators of fossil fuels utilization, emissions rate, and electric power losses. Using DEA is advantageous in this situation over other approaches due to its nonparametric nature. The paper analyzes data for the period of 1990 - 2006 by comparing actual yearly levels in each dimension with the best values of partial indicators for the period. As positive factors of efficiency, tendency to the decline in emissions rates starting 2000, and in electric power losses starting 2004 may be mentioned together with increasing trend of fuel utilization starting 1999. As a result, dynamics of environmental efficiency is positive starting 2002. The main concern is the decline in fossil fuels utilization in 2006. This negative change should be reversed to comply with ecological and economic requirements.

Keywords—Environmental efficiency, Electric power industry, DEA, United States.

I. INTRODUCTION

A problem of climate change is one of the main concerns of the contemporary world community. United Nations Convention on Climate Change set stabilization of atmospheric concentrations of greenhouse gases as one of the main objectives, with carbon dioxide (CO₂) emissions being the most important problem. As Nakicenovic & Wien [34] mention, the Intergovernmental Panel on Climate Change developed a set of 40 emissions scenarios that cover most underlying ranges in main driving forces and emissions. Electric power industry is one of the main sources of CO₂ emissions and its impact is expected to grow in view of increasing demand for energy and for electric energy in particular.

Electric energy is the only energy type that allows for easy and relatively cheap transportation over long distances and convertibility to other types of energy needed at the point of consumption: thermal or mechanical. At the same time, electric energy is not available directly: it is a result of

multistage transformations of energy of other types, for instance, chemical to thermal to mechanical to electric. Another problem is inability to store electric energy in large amounts for future use. On the consumer side, demand for electric energy is highly volatile by seasons and time of a day. As a result, main electric energy producers are thermal electric power plants that burn fuels, mainly fossil fuels, and thus, add to the problem of global climate change. As stated in *Key World Energy Statistics* [24], power plants using coal, oil, and gas produce 66.6% of the world electricity.

Though some of the OECD countries have adopted emissions reductions commitments through the Kyoto Protocol, the problem cannot be resolved through decrease in electric energy generation. Alternative solution may be in increase in the share of electric energy produced by nuclear power plants, which constitutes 15.2% of the world's electricity, *Key World Energy Statistics* [24]. However, use of nuclear power plants also causes environmental and safety problems that fall beyond the objectives of this paper. Just as an example, while France produces 80% of its electric energy on nuclear power plants, Austria and Ireland have no active nuclear power plants at this time.

Thus, the main course of resolving energy and climate problems together is an increase in environmental efficiency of electric power industry worldwide. This problem is multifaceted and includes a set of technical, technological, societal, and legislative problems. In this paper an approach is suggested that allows for estimation of a success in its resolution at the national level. United States producing 24.3% of the world electric power is considered as an example.

As stated in the *Electric Power Annual 2006* [17], the three primary energy sources for generating electric power in the United States are coal, natural gas, and nuclear energy. In 2006, they provided 88.6% of total net generation. Petroleum's share of total net generation has declined to 1.6% in 2006 after its peak of 3.6% in 1998. The average annual growth in natural gas-fired electric power generation from 1995 to 2006 was 4.6 percent. Most of the new electric power plants placed in service since 1999 have been natural gas-fired, which are generally cleaner and more efficient than coal plants. Electricity generation from coal continued to decline from its peak of 52.8% in 1997 to 49.0% in 2006. Coal is the only fossil fuel that has continued to increase in cost at electric plants each year since 2000; in 2006, coal delivery cost was 9.7 percent higher than 2005. However, coal-fired plants are the primary source of baseload generation. Estimated carbon

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dioxide emissions by U.S. electric generators and combined heat and power facilities decreased by 2.2 percent from 2005 to 2006. This was the first decrease reported since 2001. The decline reflects both the decrease in total net generation of electric power from fossil fuels and the changes in the contribution of each fossil fuel to electric power generation. Coal consumption declined 1.1 percent, petroleum consumption declined 43.3 percent, while consumption of natural gas, which contributes the least amount of carbon dioxide per Btu consumed, rose by 5.6 percent in 2006. Overall, electric power generation by these three fossil fuels fell 0.9 percent from 2005 to 2006. Emissions trends followed the use of fossil fuels and the impacts of Federal and State pollution control regulations on power plant operations. One factor is the increase in required installations of new pollution control equipment. Another factor affecting emission decreases is changes in fuel mix. Many plants have switched from bituminous coal to subbituminous coal that emits less sulfur dioxide and nitrogen oxides when burned due to the relatively low sulfur content and low combustion temperature associated with subbituminous coal.

The question arises how all these improvements can be estimated numerically with regards to environmental concerns. This problem is the subject of this paper that suggests a method of quantifying environmental efficiency. The paper is in line with publications devoted to environmental issues of electric power industry. Majumdar & Marcus [31] discussed whether environmental regulations hinder productivity with focus on United States electric utilities. They stress that while economists believe that environmental regulation tends to inhibit productivity, business strategists believe the contrary. By developing a study based on DEA and data for all major investor-owned electric utilities in the U.S. authors found that locally-based and administered regulation that give companies more latitude has a positive influence on productivity, while national requirements with inflexible guidelines have a negative impact. Agrell & Bogetoft [1] applied DEA to the Danish heating and cogeneration system and assess the impact of governmental, market and managerial policies on environmental and economic efficiency.

In contrast to these publications, this paper makes stress on combining of both policies and technological issues. It provides a big picture of environmental efficiency based on a descriptive model presented in Fig. 1 that underlies the suggested approach to measuring environmental efficiency. It depicts a sequence of processes leading to conversion of energy of different types, like chemical, thermal, mechanical, or nuclear, into electric energy available for consumption. As our main concern in this paper is CO₂ emissions, chemical energy of fossil fuels is shown separately. By burning of fossil fuels electric power plants convert chemical energy into thermal, then into mechanical, and finally, into electric energy. Carbon dioxide CO₂ appears as an undesirable outcome. Two problems arise in the connection with this process. The first is how efficiently the conversion is performed, or, in other words, how much electric energy is obtained from one unit of chemical energy. This paper is devoted to a part of this

problem only that allows direct measurements: what percentage of thermal energy is generated as an output of electric power plants. In Fig. 1, this is shown as conversion losses. Another problem is how clean is the technology of fossil fuels burning. In this paper, the quality of burning is estimated as amount of CO₂ emitted in the process of generation of one unit of electric energy. It should be mentioned that though these two indicators are related through the amount of fossil fuels used for generation of one unit of electric energy, they do not coincide. In particular, improvement in one of them may lead to the deterioration of the other indicator. Another aspect of efficiency is percentage of generated electric energy available for productive use or consumption. As locations of electric energy generation and consumption are usually very distant from each other, and high voltage of transmission is very different from low voltage of productive use or consumption, generated electric energy is lost in the processes of transmission and distribution. As follows from the data of the International Energy Agency of the United Nations (IEA), electric energy losses may exceed 25 - 30% in some countries. World wide, this indicator is at the level of 9 - 10 %, and is in the range of 6 - 7 % in the United States. In the model, this factor is named "transmission and distribution losses". The descriptive model is refined and quantified further in this paper below in the framework of DEA methodology.

Our main goal is getting a quantitative measure of how federal, state, and local governments regulations combined with technological improvements have led to better use of fuels, lower emissions and decrease in electric energy losses. To achieve this goal, a set of partial indexes is suggested with each presenting a specific aspect of environmental efficiency. These partial indexes are further combined into one indicator, environmental efficiency index, using DEA methodology.

The paper is organized as follows. Section 2 presents methodology of the research, section 3, data, results and their discussion. Conclusive remarks are given in section 4.

II. METHODOLOGY

Data Envelopment Analysis (DEA) was developed in Charnes, Cooper & Rhodes [10], and Banker, Charnes & Cooper [8], its comprehensive description is given in Cooper, Seiford & Tone [13]. DEA estimates relative efficiencies of objects in a group, referred to as Decision - Making Units (DMUs) that use inputs $\mathbf{X} = (X_j, j = 1, \dots, s)$ to produce outputs $\mathbf{Y} = (Y_i, i = 1, \dots, r)$.

DEA allows all indicators to be combined into a single efficiency score scaled between 0 and 1. Efficient objects receive a score equal to 1, inefficient objects, less than 1. To measure efficiency, DEA uses the efficiency ratio suggested in Farrell [18]:

$$E = \frac{\sum_{k=1}^r u_k Y_k}{\sum_{l=1}^s v_l X_l}, \quad (1)$$

where $u=(u_1, \dots, u_r)$ and $v=(v_1, \dots, v_s)$ are non-negative weights assigned to outputs and inputs, respectively.

The main advantage of DEA is its ability to assign values to u and v objectively by solving a series of appropriate linear programming problems. To calculate an efficiency score, DEA allows each DMU to assign its own weight coefficients to each input and output favorably. However, the ability of a given DMU to achieve maximal possible efficiency score is restricted by the requirement that with the weight coefficients assigned by any given DMU to itself, no one other DMU in the group received an efficiency score greater than one. This means that a poorly performing DMU cannot achieve a high efficiency score for itself by playing with the weight coefficients, since an object that performs really well would have received the efficiency score greater than one.

The basic efficiency ratio (1) therefore, generates the following series of optimization problems:

For each DMU_{*i*}, $i=1, \dots, n$, find non-negative vectors $u_i=(u_{i1}, \dots, u_{ir})$ and $v_i=(v_{i1}, \dots, v_{is})$ such that:

$$E_i = \frac{\sum_{k=1}^r u_{ik} Y_{ik}}{\sum_{p=1}^s v_{ip} X_{ip}} \rightarrow \max \quad (2)$$

subject to

$$E_j \leq 1 \text{ with all } u_i=(u_{i1}, \dots, u_{ir}), v_i=(v_{i1}, \dots, v_{is}), i, j=1, \dots, n. \quad (3)$$

DEA changes the set of optimization problems given by formulas (2) and (3) to a set of equivalent linear programming (LP) procedures of the following structure: For each DMU_{*i*}, $i=1, \dots, n$, find non-negative vector

$\lambda_i=(\lambda_{i1}, \lambda_{i2}, \dots, \lambda_{in})$ and scalar ω_i such that

$$\omega_i \rightarrow \min$$

subject to

$$\begin{aligned} \sum_{j=1}^n \lambda_{ij} X_{jk} &\leq \omega_i X_{ik}, \quad k=1, \dots, s; \\ \sum_{j=1}^n \lambda_{ij} Y_{jp} &\geq Y_{ip}, \quad p=1, \dots, r; \\ \lambda_{ij} &\geq 0, \quad j=1, \dots, n; \\ 0 &< \omega_i \leq 1 \end{aligned} \quad (4)$$

where X_{jk} and Y_{jp} stand for the k -th input and p -th output of a DMU_{*j*}, respectively.

The LP-problem stated by formulas (4) has the following interpretation: for each DMU_{*i*}, DEA-algorithm designs a virtual object that produces at least the same outputs as DMU_{*i*}

while using at most ω_i - share of its inputs. This virtual DMU is constructed of λ_{ij} - multiples of all DMUs, including DMU_{*i*} itself. This LP-problem has at least one feasible solution:

$$\omega_i = 1, \lambda_{ii} = 1, \lambda_{ij} = 0 \text{ for } i \neq j \quad (5)$$

which means that a virtual DMU is the same as the DMU_{*i*} itself. For some DMUs this is the only solution, meaning that their performance cannot be improved by simulating peer DMUs. For other DMUs in the group, better solutions exist with a smaller value of $\omega_i < 1$. Such DMUs may perform better by acquiring the properties of their peers. The minimal value of ω_i given by LP-problem (4) and efficiency score E_i corresponding to problem (2), (3) are equal:

$$\max E_i = \min \omega_i. \quad (6)$$

DMUs with $E_i = 1$ are called efficient, otherwise, inefficient.

A version of DEA used in this paper is referred to as input-minimization DEA with constant returns to scale (IM CRS). It is a natural extension of an intuitively clear formula (1) and possesses some properties that are important for the objectives of this paper. First, efficiency scores remain the same if the input-minimization model is changed for the output - maximization one (OM CRS). Thus, choice of a basic model becomes unambiguous. Second, efficiency scores preserve their values if one or several inputs or outputs are changed proportionally. This is important for the problem in question because some indicators may have units of measurement.

Applications of DEA to the electric power industry may be traced back to 1980th. It is interesting to note that electric power plants were among the first objects that DEA was applied to: Banker [7], one of the publications that invented DEA, applied it to the estimation of most productive scale sizes of stem-electric generation plants. Cote [14], Hjalmarsson & Veiderpass [21], Bagdadioglu [5] and Bagdadioglu, Price & Weyman-Jones [6], applied DEA to the analysis of impact of ownership on efficiency, Miliotis [33] used DEA for comparative analysis of the efficiency of electricity distribution, and Golany & Roll [20] used DEA for measurement and evaluation of the operating-efficiency of Israeli power plants. Yunos & Hawdon [49] considered organizational efficiency comparisons at the international level, and Sueyoshi [41] explored a Marginal-Cost- based pricing system using DEA and investigated the tariff structure of Japanese electric power companies.

A series of publications appeared in early 2000's. Scarsi [40] analyzed technical efficiency of local electricity distribution in Italy using deterministic and stochastic frontier analysis, and DEA. Sueyoshi & Goto [42] investigated performance of electric power generation in Japan, Chen [11] presented an assessment of technical efficiency and cross-efficiency in Taiwan's electricity distribution sector, Domah [16] conducted a comparative technical efficiency analysis of electricity generators in small island economies using two methodologies: DEA and stochastic frontier analysis. Pacudan & Guzman [36] researched productive efficiency of electricity distribution in the Philippines, Korhonen & Syrjanen [26], cost efficiency in Finnish electricity distribution, Nemoto & Goto [35], dynamic efficiency of electric power production in

Japan, Pahwa, Xiaoming & Lubkemann [37] suggested a method for benchmarking performance of electric distribution utilities in the U.S., and Sanhueza & Rudnick [39] used DEA for evaluation of efficiency of electric distribution utilities. Lam & Shiu [27] used DEA to analyze the total factor productivity for the State Power Corporation of China, Blose & Tankersley [9] applied DEA as a diagnostic tool for effective management of service quality by retail electric service providers. Among recent publications, Delmas & Tokat [15] analyzed how the process of retail deregulation affects the efficiency of governance structures, Vitaliano & Stella [48] found inefficient overuse of capital by regulated electric power utilities, Tanure, Tahan, Lima & Marangon, [44] proposed DEA-based methodology and procedure for performance target setting related to continuity metrics in electricity distribution networks, Thakur [45] used DEA for accessing comparative efficiencies of Indian state owned electric utilities, Vaninsky [47] considered efficiency of electric power generation in the United States, Liu & Gu [30] used hierarchical data envelopment analysis for assessing black-start plans, and Li & Wang [29] compared technological efficiencies of coal and nuclear power plants. Arocena [4] estimated the impact that alternative forms of unbundling have on the cost and quality of electric power supply, Honma & Hu [22] applied DEA to investigation of regional total-factor energy efficiency in Japan, and Zhou, Zhao, Wang & Li [50] used DEA for assessment of operation performance of distribution utilities in China.

Applications of DEA within the electric power industry are also presented in a series of publications posted on the Internet. Meimodi [32] applied DEA to the analysis of efficiency of electricity production and price policy in Iran, Ajodhia, Petrov & Scarci [2] presented a DEA-based benchmark model aimed at simultaneous analysis of costs and quality levels, and applied the model to a sample of British, Dutch, Hungarian and Malaysian distribution firms; and Tahvanainen, Viljainen, Honkapuro, Lassila, Partanen et al. [43] evaluated the measures undertaken by several European countries implementing quality regulation in the electricity distribution business.

In this paper a DEA model is suggested aimed at the estimation of environmental efficiency of the electric power industry based on the descriptive model given above. A DEA model uses two inputs, CO₂ emissions rate and electric energy losses, and one output, fossil fuels utilization. The latter indicator measures the amount of electric energy generated by a unit of thermal energy of fossil fuels. The general DEA model is refined for the objectives of this paper as

$$E = \frac{u_1 \text{FossilFuelUtilization}}{w_1 \text{EmissionsRate} + w_2 \text{EnergyLosses}}, \quad (7)$$

where coefficients u_1 , w_1 , and w_2 are calculated individually for each year. The input-minimization constant returns to scale DEA model (IM CRS) was used. The CRS DEA model is insensitive to the units of measurement and results in the same efficiency scores as output maximization model (OM CRS). Such choice makes the results more robust. One more

innovation is using a virtual "best-practice" object using minimal inputs and maximal outputs. By doing so, efficiencies of all objects are calculated with regards to the virtual one that serves as a benchmark. Such approach allows, in particular, for automatic ranking of all objects thus avoiding the problem of ranking the efficient ones and allows making a step towards measuring absolute efficiency, see Torgersen, Føørund & Kittelsen [46], Jahanshahloo, Lotfi, Rezai & Balf, [23], Amirteimoori, Jahanshahloo & Kordrostami [3], Khodabakhshi [25], Li, Jahanshahloo & Khodabakhshi [28], and Fuh-Hwa & Hao [19] for more details. Geometric interpretation of the best-practice object is shown in Fig. 2.

III. DATA, RESULTS, AND DISCUSSION

Information for calculations was obtained on website of the Energy Information Administration (EIA) of the United States, <http://www.eia.doe.gov> [51]. The following data were collected for period of 1990 through 2006: electric energy net generation and consumption; transmission and distribution losses, consumption of combustible fuel for electricity generation; average thermal output and CO₂ emissions for fossil fuels of different types. The data were used to form DEA inputs/outputs shown in Table I as follows.

Fossil fuels utilization is a ratio of the amount of electric energy generated using a unit of thermal energy. To calculate this indicator, data on average thermal energy productivity of combustible fuels used for electricity generation, separately for coal, gas and oil, and on amounts of each type of fuel were used. In calculations, we used a coefficient 3412 Btu per 1 kWh for conversion. Emissions rate was measured as mass of CO₂ emission per unit of generated electric energy. This indicator accounts implicitly for electric energy generated without fossil fuels combustion. Thus, its value was lower in the years when greater share of electric energy was generated using clean technologies. Energy losses indicator represents losses occurred in both transmission and distribution processes. It is equal to percentage of generated electric energy lost on the way to customers. Taken together, the indicators represent factors of environmental efficiency shown in Fig. 1. They are combined in the framework of DEA model to form the environmental efficiency index.

Fig. 3 represents dynamics of each indicator for the period 1990 through 2006. A dashed curve is a trend line obtained using quadratic approximation. When analyzing the data of this figure, it should be noted that the period of observation was the time of essential changes in the regulation of the Electric Power Industry of the United States, see Rungsuriyawiboon & Stefanou [38] for details. As authors mention, regulations in early 1900s were aimed mainly at protection the industry from the competitive pricing dominated at that time. As a result, they helped creating incentives to invest strongly in capital and to operate at inefficient levels of production. Later legislation acts of 1992 and 1996 served to force utilities to deliver power at nondiscriminatory cost-based rates. Customers were allowed choosing their own supplier, so that competition became possible and operation at optimal scale was promoted. Movement towards open markets has led to appearance of

new competitors and restructuring of the industry. Vertical integration has diminished, and incentives for the operation at lower costs and technical and scale efficiency were created. Another factor is steep rise in fuel prices starting early 2000th that changed the rules of efficiency game totally. And last but not least is climate change concerns. Though the United States is not among the countries signing the Kyoto Protocol, both Federal and State governments impose different regulations aimed at the decrease of negative ecological impact of electric power plants.

Fig. 3 presents the cumulative effect of all these changes in the period. As follows from the figure, CO₂ emissions rates had tendency to the rise until 1996, but changed it for the decline starting 2000. It was especially notable in 2006 with regards to 2005 when the decrease constituted 2.08%. Dynamics of electric energy losses was mixed for the period resulting from big structural changes in generation, transition, and distribution in the period. Tendency may be evaluated as positive, that is change for decline may be mentioned. Fuel utilization was on the decline until 1998, and then on the increase. In our opinion, it is a natural reaction of the industry on sharp increase in fuel prices. The decrease in 2006 with regards to 2005 may be noticed and deserves special consideration that is beyond the scope of this paper. Tendency of increase in fuel utilization may be considered as improvement of the situation in 1997, when Rungsuriyawiboon & Stefanou [38] mentioned underutilization of fuel in the U.S. electric power industry.

DEA efficiency index combines the partial indicators into a single efficiency index shown in Fig. 4. As previously, a dashed curve is a trend line obtained using quadratic approximation. Efficiency scores were obtained with regards to the best-practice values of the indicators for the period. As follows from the figure, environmental efficiency index had tendency for the decline until 1995 that has been changed for the increase in the following period. In 2006, efficiency level exceeded 99% and was pretty close to the maximal value achieved in 2001.

TABLE I
DEA INPUTS/OUTPUTS

Indicator	Fuel utilization	Emissions rate	Energy Losses
Role in DEA	Output	Input	Input
Units of measurement	r.u.	g/kWh	%
Max	0.331	642.2	7.02
Min	0.326	606.9	5.39
Average	0.329	623.9	6.18

Note: r.u. stands for relative units.

IV. CONCLUSION

The paper analyzes environmental efficiency of the electric industry of the United States using Data Envelopment Analysis approach. Efficiency of the industry is considered as a result of interaction of the factors having opposite environmental impacts: CO₂ emissions rate and losses of

electric energy in transition and distribution processes on one hand, and utilization of fossil fuels on the other hand. DEA model was designed so that actual yearly levels of all indicators were compared with their virtual best-practice values observed in the period of study. Based on statistical data for 1990 through 2006, it was shown that environmental efficiency of the U.S. electric power industry has positive tendency starting 1995. In 2006 it exceeded 99% level and was pretty close to the maximal value for the period. It was revealed also, that emissions rates had tendency for the decline from 2000, while dynamics of electric energy losses was mixed though declining slightly. Fossil fuels utilization was on the increase, though small negative change in 2006 as compared with 2005 may be mentioned. Industry participants and policy makers should undertake measures to avoid its further decline to comply with ecological and economic requirements.

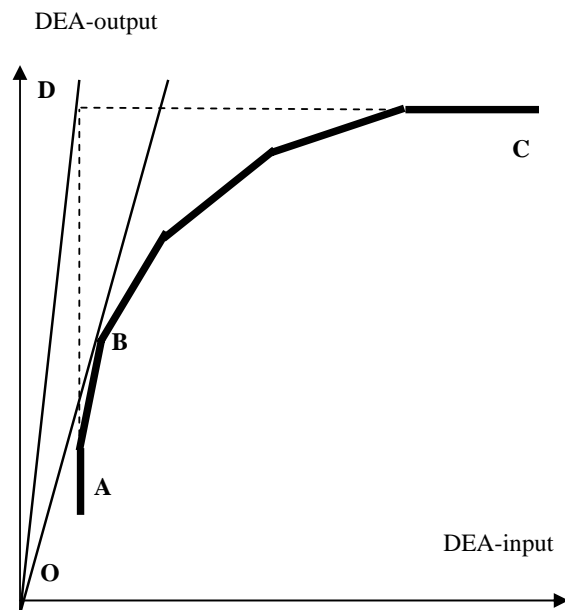
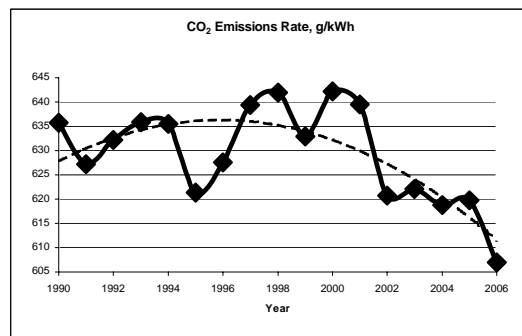
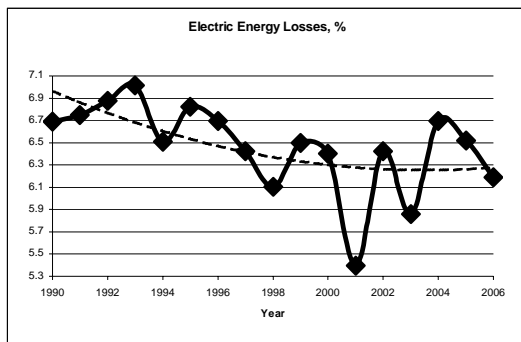


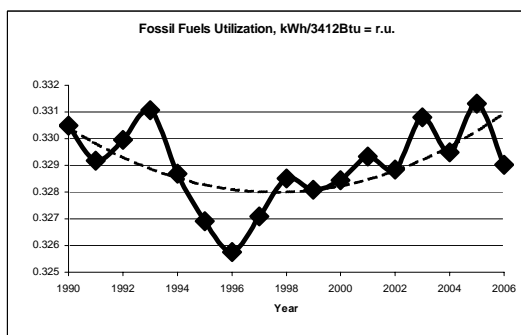
Fig. 2 DEA Frontiers. ABC - Variable Returns to Scale; OB - Constant Returns to Scale; OD - Best-Practice



(a) CO₂ emissions rate (DEA-input)



(b) Electric energy losses (DEA - input)



(c) Fossil fuels utilization (DEA - output). r.u. stands for relative units

Fig. 3 DEA inputs and outputs. Dashed is a trend line

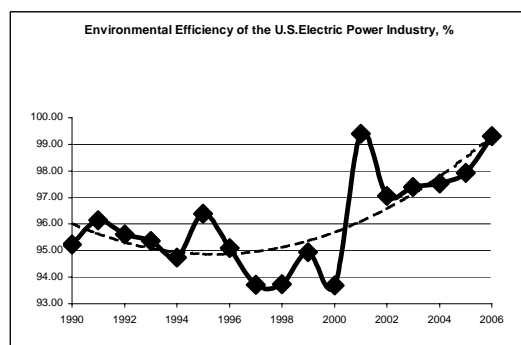


Fig. 4 Environmental efficiency of the U.S. Electric Power Industry. Dashed is a trend line

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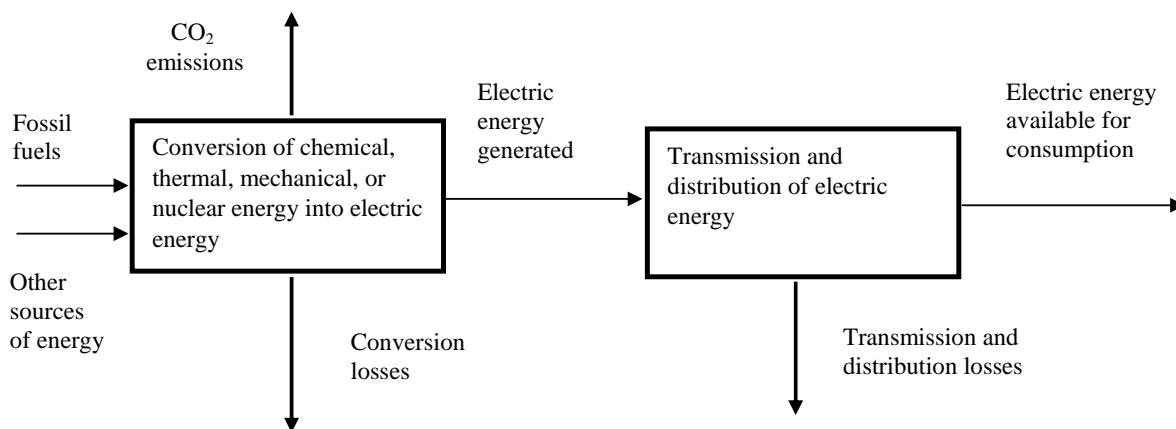


Fig. 1 Factors of environmental efficiency