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Environmental Performance of the United States Energy Sector: A DEA Model with Non-Discretionary Factors and Perfect Object

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***Abstract*—**It is suggested to evaluate environmental performance of energy sector using Data Envelopment Analysis with non-discretionary factors (DEA-ND) with relative indicators as inputs and outputs. The latter allows for comparison of the objects essentially different in size. Inclusion of non-discretionary factors serves separation of the indicators that are beyond the control of the objects. A virtual perfect object comprised of maximal outputs and minimal inputs was added to the group of actual ones. In this setting, explicit solution of the DEA-ND problem was obtained. Energy sector of the United States was analyzed using suggested approach for the period of 1980 – 2006 with expected values of economic indicators for 2030 used for forming the perfect object. It was obtained that environmental performance has been increasing steadily for the period from 7.7% through 50.0% but still remains well below the prospected level.

***Keywords*—**DEA with Non Discretionary Factors, Environmental Performance, Energy Sector, Explicit Solution, Perfect Object.

I. Introduction

ENVIRONMENTAL issues are among major concerns of contemporary society. Emissions of greenhouse gases are amid the main problems by both International Energy Agency (IEA) and Energy Information Administration (EIA), [1, 2]. Carbon dioxide (CO_2) is the most abundant human-caused greenhouse gas in the atmosphere. IEA expects the growth in greenhouse gases emissions by 35% in 2030 regarding the 2005 level. Energy demand is expected to grow by 1.6% yearly through 2030, with energy-related emissions component comprising 61% of 2030-total. Atmospheric concentrations of CO_2 have been rising at a rate of about 0.6 percent annually in recent years, and that growth rate is likely to increase. The expected increase is 45% regarding 2006, that is faster than total. In 2030, 76% of energy-related CO_2 emissions are expected from cities compared with 71% in 2006. About 75% of energy-related increase in emissions is expected from China, India and Middle East, while in OECD-countries, the emissions are expected to reach peak in 2020 and then decline. In Europe and Japan, expected emissions levels by 2030 are even lower than today. Publication [2] mentions that world energy-related CO_2 emissions are increasing at a rate of 2.1% per year, while its concentrations, by only about 0.6% percent per year. Among major reasons for the difference, is absorption by the Earth's oceans and soils. About 42% percent of CO_2 emitted has been absorbed by the planet rather than accumulated in the atmosphere. Among the measures aimed at decrease in CO_2 emissions the following may be mentioned [2]: reductions in energy demand growth, increases in nuclear electricity generation, increased use of hydropower and nonhydropower renewables for electricity generation, increased use of renewable fuels for transportation, and carbon capture and storage, [3].

Carbon dioxide emissions depend essentially on existing laws and policies. World energy sector will be the focus of 2009 Copenhagen conference aimed at setting international framework for greenhouse gas emissions. The choice of strategy should combine environmental requirements, technology and costs. In particular, it should be taken in consideration that energy sector has a relatively low rate of capital replacement, so that any essential changes in this sector will require sufficient time. Thus, [1] mentions that even if from now on all power plants were carbon-free, the emissions from the power sector would decrease by just 25% by 2020. There are five major emitters of energy-related CO_2: China, the European Union, India, Russia, and the United States (order is alphabetical). Taken together, they are responsible for about 67% of total. Suggested mechanisms of emissions control should combine cap – and – trade approach, sectoral agreements, and national measures. Publication [1] mentions also big investments needed for environment protection, especially in power plants and energy-efficient equipment. Different scenarios estimates range from 0.24% through 0.55% of world GDP that is from \$4.1 through \$9.4 trillion 2007-dollars.

The main factors of CO_2 emissions in the U.S. are economic growth, energy consumption, and intensity of emissions, [1, 2]. As of 2006, the United States is responsible for 20.3% of the world CO_2 emissions. Economic growth of the U.S.is expected at an average rate of 2.5% per year in the period. Expected growth in energy consumption and emissions is moderate due to recently-enacted policies and high energy prices. Total primary energy consumption will increase at an average rate of 0.5% per year. In 2030, coal, oil, and natural gas continue meet the largest share of total primary energy consumption, although their share declines from 85 percent in 2007 to 79 percent in 2030. Rapid growth in renewables consumption is expected to be driven mainly by implementation of Federal Standard for transportation fuels and State Standard for electricity generation. Energy use per dollar of GDP is expected to decline by more than 30% from

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2007 to 2030; energy use per person will also decline at an annual rate of 0.5 percent. Petroleum-based liquids consumption is projected to be flat while consumption of biofuels, to grow. In the period of 2007 – 2030, growth in electricity use continues to slow with nonhydropower renewable power meeting 33% of total generation growth. Natural gas and renewables will provide most of the generating capacity added. Energy related CO_2 emissions will grow at the rate of 0.3 percent per year, and per capita emissions fall by 0.6 percent per year. Electricity generation will remain the dominant source of CO_2 emissions growth. With slower electricity growth and an increased use of renewables for electricity generations, electricity-related CO_2 emissions will grow by just 0.5 percent per year. CO_2 emissions from transportation activity will also slow compared to the recent past in particular, due to increase in use of alternative light vehicles. U.S. oil use will remain near its present level through 2030 as modest growth in overall liquids demand is met by biofuels. Energy-related CO_2 emissions will grow at 0.3 percent per year provided no new policies to control emissions.

Given these premises, we analyze in this paper below dynamics of environmental performance of the Energy sector of the United States for the period of 1980 – 2006 and compare it with situation expected by 2030. We use DEA model with non-discretionary factors (DEA-ND), and consider DEA efficiency index as a measure of environmental performance. Our main objective is to trace the environmental efficiency of the Energy sector in time with regards to its prospected value in 2030. To achieve this goal, a special modification of the DEA-ND is developed: a model with a Perfect Object (DEA-ND PO). The latter is an object that has minimal inputs and maximal outputs. Introduction of PO allows for obtaining DEA optimal solution in explicit form thus avoiding Linear Programming procedures. Data of 2030 are used to construct the PO.

II. Methodology

Methodology of the research in this paper is Data Envelopment Analysis (DEA) developed in [5, 6], its comprehensive description is given in [7]. DEA estimates relative efficiencies of objects in a group, referred to as Decision - Making Units (DMUs) that use inputs $\mathbf{X} = (X_j, j = 1,...,s)$ to produce outputs $\mathbf{Y} = (Y_i, i = 1,...,r)$. 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 [8]:

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

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

The main advantage of DEA is its ability to assign values to $\boldsymbol{u}$ and $\boldsymbol{v}$ objectively by solving a series of linear programming (LP) 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 to itself, no one DMU in the group receives 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. By doing so, the basic efficiency ratio (1) generates a series of optimization problems:

For each DMU_i, $i = 1,...,n$, find non-negative vectors $\boldsymbol{u}_i=(u_{i1},...u_{ir})$ and $\boldsymbol{v}_i=(v_{i1},...v_{is})$ such that:

$$E_i = \frac{\sum_{k=1}^{r} u_{ik} Y_{ik}}{\sum_{p=1}^{s} v_{ip} X_{ip}} \to max \tag{2}$$

subject to

$$E_j \le 1 \text{ with all } \boldsymbol{u}_i=(u_{i1},...,u_{ir}),\ \boldsymbol{v}_i=(v_{i1},...,v_{is}),\ i,j=1,...,n. \tag{3}$$

It may be noted that solution to the problem (2) - (3) is defined up to proportional change in $\boldsymbol{u}$ and $\boldsymbol{v}$. It was suggested in [5] to impose restrictions on $\boldsymbol{u}$ or $\boldsymbol{v}$ making them bounded:

$$\sum_{k=1}^{r} u_{ik} Y_{ik} \to max \text{ s.t. } \sum_{p=1}^{s} v_{ip} X_{ip} = 1 \text{ for each } DMU_i. \tag{4}$$

The modified problem is equivalent to set of linear programming (LP) problems:

For each DMU_i, $i = 1,...,n$, find non-negative vector $\lambda_i=(\lambda_{i1},\lambda_{i2},\ldots,\lambda_{in})$ and scalar ω_i such that

$$\omega_i \to min$$

subject to

$$\begin{aligned} &\sum_{j=1}^{n} \lambda_{ij} X_{jk} \le \omega_i X_{ik},\ k = 1,...,s; \\ &\sum_{j=1}^{n} \lambda_{ij} Y_{jp} \ge Y_{ip},\ p = 1,...,r; \\ &\lambda_{ij} \ge 0,\ j = 1,...,n; \\ &0 < \omega_i \le 1, \end{aligned} \tag{5}$$

where X_{jk} and Y_{jp} stand for the k-th input and p-th output of a DMU_j, respectively. A system of inequalities (5) is referred to as input – minimization (IM) DEA model with constant returns to scale (CRS), see [7] for details.

The LP-problems stated by formulas (5) have the following interpretation: for each DMU_i, DEA-algorithm seeks a virtual object that produces at least the same outputs as DMU_i using at most ω_i - share of its inputs. This virtual DMU is constructed of λ_i - multiples of all DMUs in the group, including the DMU_i itself. This LP-problem has at least one feasible solution:

$$\omega_i = 1,\ \lambda_{ii} = 1,\ \lambda_{ij} = 0 \text{ for } i \ne j, \tag{6}$$

which means that the 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 ω_i <1. Such DMUs can perform better by acquiring the expertise of their peers. The minimal values of ω_i obtained as solution of the LP-problem (5) and efficiency scores E_i corresponding to problem (2) - (4) are equal:

$$max\ E_i = min\ \omega_i \le 1. \quad (7)$$

The IM CRS DEA model (5) 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 if inputs/outputs have units of measurement or are normalized. It should be noted that DEA models are named *input minimization* (IM) or *output maximization* (OM), respectively, by their *envelope form* (5). This form is dual to the *ratio form* of the DEA models (2) – (4): IM ratio model corresponds to OM envelope model and vice versa, [7]. This observation is of importance when a model is designed, because choice of the model depends on manageability of inputs and outputs. If, for example, only inputs are manageable, then one should choose the *OM* ratio model to arrive at *IM* envelope one.

Applications of DEA to analysis of environmental performance are considered in [9 – 16], a review of recent results is given in [17]. In this paper, we analyze environmental performance using a DEA model not considered in these literature sources: a DEA with non-discretionary factors (DEA-ND). This model assumes that some inputs or outputs cannot be change at the discretion of DMU itself, the case typical for environmental performance. While technology and organization are at the discretion of a DMU, environmental policy and exogenous factors are not. DEA ND was developed in [18-23]. Its applications are considered in [24-27]. DEA-ND input minimization model with constant returns to scale used in this paper is this.

For each DMU$_i$, i=1,…,n, find

$\omega_i \to min$

subject to

$$\begin{aligned}
&\sum_{j=1}^{n}\lambda_{ij}X_{jk} \le \omega_i X_{ik},\ k=1,...,q<s;\\
&\sum_{j=1}^{n}\lambda_{ij}X_{jk} \le X_{ik},\ k=q+1,...,s;\\
&\sum_{j=1}^{n}\lambda_{ij}Y_{jp} \ge Y_{ip},\ p=1,...,r; \qquad (8)\\
&\lambda_{ij} \ge 0,\ i,j=1,...,n;\\
&0<\omega_i \le 1.
\end{aligned}$$

The difference is in separating the first group of inequalities into discretionary and non-discretionary inputs with the latter ones remaining unchanged in seeking optimal solution.

In the following section, we develop the DEA-ND model further by appending it with a Perfect Object. This modification allows us to obtain an explicit solution to the DEA-ND problem.

III. DEA - ND with Perfect Object Explicit Solution

Application of a Perfect Object (PO) to environmental performance DEA problems was suggested in [16]. PO is a virtual DMU assigned minimal inputs and maximal outputs. Fig. 1 presents geometric interpretation. Addition of the PO provides DEA with ability to go beyond relative efficiency. If all inputs of the PO are strictly less and its outputs are strictly greater than those of actual DMU's then PO is the only efficient DMU and an optimal solution will contain only the PO as a peer object. If equalities are allowed for some or all of inputs/outputs then this also is true but requires considerations beyond the scope of this paper. (The proof may be obtained from the author upon request.) Denoting the PO as DMU$_0$, we arrive at the following modification of the optimization problem (8):

For each DMU$_i$, i=1,…,n, find $\omega_i \to min$

subject to

$$\begin{aligned}
&\lambda_{i0}X_{0k} \le \omega_i X_{ik},\ k=1,...,q<s;\\
&\lambda_{i0}X_{0k} \le X_{ik},\ k=q+1,...,s;\\
&\lambda_{i0}Y_{0p} \ge Y_{ip},\ p=1,...,r; \qquad (9)\\
&\lambda_{i0} \ge 0,\ j=1,...,n;\\
&0<\omega_i \le 1.
\end{aligned}$$

This is an input minimization DEA-ND model with constant returns to scale with perfect object referred to below as DEA-ND IM CRS PO. Solution to problem (9) can be obtained in explicit form, as given by the following theorem.

Theorem. Solution to the DEA-ND IM CRS PO model is

$$E_{ND\,IM\,CRS\,PO} = min\ \omega_i = \max_{1\le p\le r}\frac{Y_{ip}}{Y_{0p}}\ \min_{1\le k\le q}\frac{X_{0k}}{X_{ik}},\ i=1,...,n, \quad (10)$$

where lower index i stands for an ordinal number of DMU$_i$ in a group.

Proof.

From the first subsetset of inequalities in (9) it follows that:

$$\omega_i \ge \frac{\lambda_{i0}X_{0k}}{X_{ik}},\ k=1,...,q<s. \quad (11)$$

As we seek $min\ \omega_i$, we should take

$$\omega_i = min\ \lambda_{i0}\min_{1\le k\le q<s}\frac{X_{0k}}{X_{ik}}. \quad (12)$$

Using second and third subsets of inequalities in (9), we get as follows:

$$\lambda_0 \le \frac{X_{ik}}{X_{0k}},\ k=1,...,q<s; \quad (13)$$

$$\lambda_0 \ge \frac{Y_{ip}}{Y_{0p}},\ p=1,...,r. \quad (14)$$

By the definition of the PO,

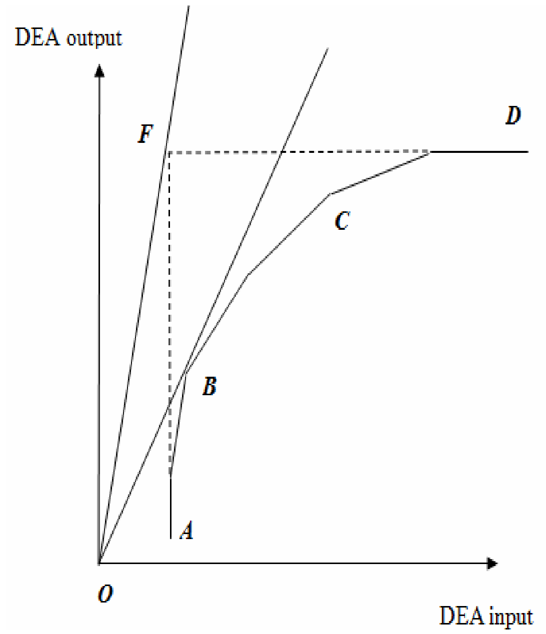

Fig. 1 DEA frontiers [16]

A Perfect Object (DMU$_0$) is located at point F: $X_{01} = min\ X_{k1}$, $Y_{01} = max\ Y_{k1}$, $k= 1,...,N$. Frontiers: OB—constant returns to scale; $ABCD$—variable returns to scale; OF—constant returns to scale with the Perfect Object; AFD—variable returns to scale with the Perfect Object

$$\frac{Y_{ip}}{Y_{0p}} \leq 1 \leq \frac{X_{ik}}{X_{0k}},\ k = 1,...,s;\ p = 1,...,r;\ i = 1,...,n\ , \qquad (15)$$

so that (13) and (14) do not contradict each other. Moreover, as we seek min ω_i, we should take minimal value of λ_0 in (12) equal to

$$min\ \lambda_{i0} = \min_{1 \leq p \leq r} \frac{Y_{ip}}{Y_{0p}}. \qquad (16)$$

Substitution of (16) into (12) proves the theorem. ∴

Similar theorems may be proved for different modifications of DEA-ND PO models. The theorems allow for avoiding using Linear Programming procedures when solving DEA-ND PO problems. Spreadsheet formulas are sufficient. It may be noticed that suggested solution does not contain non-discretionary inputs and thus, does not depend on them. This observation requires further considerations and discussions.

IV. Modeling of the U.S. Energy Sector

To calculate and analyze dynamics of environmental performance of the United States Energy sector, we used statistical information provided by the Energy Information Administration (EIA) and the Bureau of Economic Analysis (BEA) available at http://www.eia.doe.gov and http://www.bea.gov, respectively. The following data were collected: Population (P), GDP (G), Energy Consumption (N) and CO_2 Emissions (S). The objective was to put emissions against energy consumption, GDP and population. To do this, we used an approach suggested in [28] and formed all possible ratios of the quantitative indicators. It may be shown, that only three of the ratios are functionally independent. For instance, ratios S/P and P/S are inverses of each other, while ratios $r_1 = (P/S)$, $r_2 = (N/S)$ and $r_3 = (N/P)$ are related as $r_1r_2 = r_3$. We intended to avoid using the functionally related ratios in DEA model. Keeping in mind traditionally used indicators of environmental performance: Emissions per Capita (S/P) and Emissions per Dollar of GDP (S/G) we included them into the DEA-ND PO model and appended them with the GDP per Capita indicator (G/P). Two former ratios served as inputs, the latter, as output. Emissions per Capita indicator was considered as a non-discretionary input because population growth is beyond the control of Energy sector. Considering DEA efficiency index as an indicator of environmental performance, we arrived at the following DEA model:

$$E_{ND\,IM\,CRS\,PO} = \frac{u_1 Y_1}{v_1 X_1 + v_2 X_2}, \qquad (17)$$

where $X_1 = S/P$ stands for Emissions per Capita (non-discretionary input), $X_2 = S/G$, for Emissions per Dollar of GDP, and $Y_1 = G/P$, for GDP per Capita. Ratios X_1, X_2 and Y_1 are functionally independent in the sense that there is no smooth function F such that $F(X_1(P,G,N,S), X_2(P,G,N,S), Y_1(P,G,N,S))=0$. The last can be proved by calculating functional determinants, as shown in [29]. All relative indicators were calculated as ratios of corresponding quantitative indicators, GDP was taken in chained 2007 dollars. For better scaling of the information, all of the ratios were normed to their 2030-values.

TABLE I
DEA - ND IM CRS PO Model of the U.S. Energy Sector Environmental Efficiency with Normalized Inputs/Outputs

Year	X_1 ND	X_2	Y_1	X_{01}/X_1	X_{02}/X_2	Y_1/Y_{01}	Efficiency[a]
1980	1.2305	2.9108	0.2232	0.8127	0.3436	0.2232	0.0767
1981	1.1874	2.7666	0.2491	0.8422	0.3615	0.2491	0.0900
1982	1.1143	2.6731	0.2590	0.8975	0.3741	0.2590	0.0969
1983	1.0950	2.5362	0.2753	0.9133	0.3943	0.2753	0.1086
1984	1.1467	2.4995	0.3063	0.8721	0.4001	0.3063	0.1225
1985	1.1333	2.3935	0.3257	0.8824	0.4178	0.3257	0.1361
1986	1.1256	2.3186	0.3390	0.8884	0.4313	0.3390	0.1462
1987	1.1550	2.3221	0.3590	0.8658	0.4306	0.3590	0.1546
1988	1.1974	2.3329	0.3866	0.8352	0.4287	0.3866	0.1657
1989	1.2037	2.2866	0.4070	0.8307	0.4373	0.4070	0.1780
1990	1.1764	2.2182	0.4239	0.8500	0.4508	0.4239	0.1911
1991	1.1500	2.2012	0.4318	0.8696	0.4543	0.4318	0.1962
1992	1.1571	2.1723	0.4489	0.8643	0.4603	0.4489	0.2067
1993	1.1668	2.1614	0.4631	0.8571	0.4627	0.4631	0.2143
1994	1.1700	2.1090	0.4866	0.8547	0.4742	0.4866	0.2307
1995	1.1688	2.0798	0.5066	0.8556	0.4808	0.5066	0.2436
1996	1.1960	2.0762	0.5303	0.8361	0.4817	0.5303	0.2554
1997	1.1990	2.0157	0.5635	0.8340	0.4961	0.5635	0.2796
1998	1.1910	1.9446	0.5869	0.8396	0.5142	0.5869	0.3018
1999	1.1906	1.8825	0.6150	0.8399	0.5312	0.6150	0.3267
2000	1.2146	1.8730	0.6444	0.8233	0.5339	0.6444	0.3440
2001	1.1831	1.8279	0.6580	0.8453	0.5471	0.6580	0.3600
2002	1.1847	1.8183	0.6737	0.8441	0.5500	0.6737	0.3705
2003	1.1847	1.7902	0.6991	0.8441	0.5586	0.6991	0.3905
2004	1.1921	1.7543	0.7384	0.8389	0.5700	0.7384	0.4209
2005	1.1861	1.7114	0.7783	0.8431	0.5843	0.7783	0.4548
2006	1.1574	1.6397	0.8191	0.8640	0.6099	0.8191	0.4995
2030[b]	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

[a] Calculated by formula (10): $E=(Y_1/Y_{01})(X_{02}/X_2)$
[b] Perfect Object

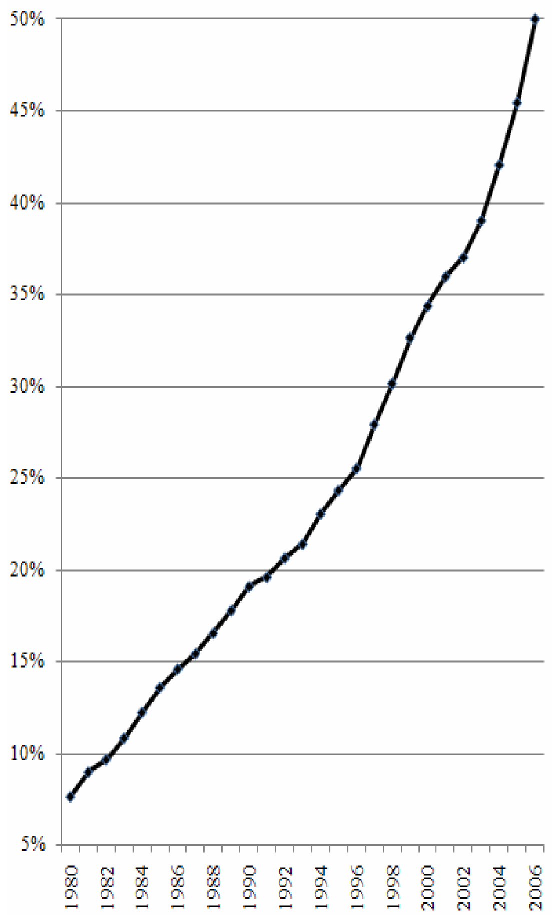

Fig. 2 U.S. Energy Sector Environmental Performance

A DEA-ND IM CRS PO model was used. Data and results are shown in Table I, a graph of the environmental performance indicator is shown in Fig. 2. As follows from the obtained results, environmental performance of the U.S. Energy sector has been on the rise in the period of 1980 – 2006 from 7.7% through 50.0%. This is a positive observation confirming that the United States follows the spirit of the Kyoto Protocol though not signing it formally. At the same time, it may be mentioned that only 50% of the 2030 projected level has been achieved. Technological and organizational measures should be undertaken and stricter environmental policies enforced to close this gap.

V. Conclusion

A DEA model with non-discretionary factors is suggested as a means of evaluation of environmental performance of energy sector. A model with relative and normalized inputs/outputs is proposed. Inclusion of the virtual perfect object, a DMU with minimal inputs and maximal outputs, allowed proving a formula for analytical solution to the problem. Energy sector of the United States was analyzed using suggested approach for the period of 1980 – 2006. The perfect object has been formed using expected data of 2030. Obtained results revealed increasing environmental efficiency of the U.S. energy sector over the period from 7.7% in 1980 to 50.0% in 2006. The remaining 50% represent an efficiency gap that should be closed by 2030.

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