Adv Syst Sci Appl 2017; **4**; 78-92
Published online at http://ijassa.ipu.ru/ojs/ijassa/article/view/521

Developing a Strategy of Environmental Management for Electric Generating Companies Using DEA-Methodology

Svetlana Ratner, Pavel Ratner

V.A. Trapeznikov Institute of Control Sciences, Russian Academy of Sciences, Moscow, Russia

E-mail: lanaratner@gmail.com

Abstract: This paper investigates the possibility of utilization of the Data Envelopment Analysis (DEA), which is a non-parametric method of optimization, to solving problems of environmental management in electric generating companies. An advantage of DEA is the possibility to work with DMUs without any knowledge of the actual functional relation between inputs and outputs. We analyze methods of incorporating the negative ecologic effects into a model and propose an algorithm for applying the basic DEA CCR input-oriented model twice in succession for the purpose of developing an optimal (ecologically and economically) strategy for environmental management in electricity energy generating companies. The developed method consists of sequentially solving several DEA models: the first-stage model determines the effectiveness of DMUs from an ecologic perspective and calculates target values for decreasing negative ecologic effects of non-effective DMUs. The second stage requires solving one input-oriented CCR model for each non-effective object, using economic and social characteristics of projects meant to reduce negative environmental influence, and using the target values calculated in the first stage as outputs. Besides the problem of evaluation the comparative efficiency of DMUs, ecologically oriented studies also often needs to evaluate the changes in a DMU's efficiency dynamically. For this, the Malmquist productivity index (MPI) is used. MPI is a non-parametric method for analyzing time series that allows to track changes in DMU efficiency over time by means of DEA models. We test this algorithm on the statistical data provided by Russian electric companies for the period 2009-2011, and discuss methods for its practical application. The statistical data used in our calculations is averaged, and the results do not reflect the entire picture and should not be used to judge the quality of ecologic management in these companies. Nevertheless, the calculations can be used to evaluate the progress of completion and the practicality of investment projects of companies, from an environmental viewpoint. They also may be used to help develop state programs for support of modernization in electric energy industry, ecologic standards or energy-saving programs.

Keywords: data envelopment analysis, non-parametric optimization, ecologic effects, environmental management, ecology management, electric companies.

1. INTRODUCTION

Currently, electric generating objects that operate on hydrocarbon fuels are one of the largest emitters of greenhouse gases and other atmospheric pollutants (16% of total emissions from stationary sources in Russia), as well as consumers of fresh water (35% of total water use in Russia), pollutants of soil, underground and surface waters. Increasing the ecologic efficiency of electric generating companies is one of the primary conditions for sustainable development of both this industry and the country itself. One of the most important problems for ecologic optimization of the development of electric energy generation industry is decreasing negative environmental influence as much as possible, via a variety of environmental protection measures (both technologic and organizational), while maintaining the existing volumes of electricity production [20].

Investment priorities for energy companies directed towards decreasing negative ecologic effects are determined primarily by conventional system of ecologic penalties for overstandard pollution and rarely correspond to the actual ecologic situation of the region. Many sources (e.g. [5, 19]) consider the existing Russian economic mechanisms and incentives for minimizing negative environmental influence ineffective.

At the same time, there are currently no examples of successful transition to ecologically safe energy generation technologies at regional or national scales anywhere in the world. The well-known Brazil energy crisis of 2001 that happened due to the droughts and lack of water for hydro-power plants [9], the recent Chinese ecologic crisis due to the increase of coal use for power generation, the non-proportionally intensive growth of solar power plants in Czech Republic [10] show the complexity of the problem of optimizing the energy system configuration. A lack of complete understanding of the way certain energy-generating processes influence ecosystems as well as a lack of attention to ecologic aspects of energy systems on their planning stage can lead to unexpected and undesired results, where the decrease of negative influence from one parameter (or group) is completely overshadowed by the increase in another parameter (or group). For instance, attempting to capture CO2 to decrease greenhouse gas emissions leads to a significant increase in water use by power plants [11].

Increasing the amount of optimization criteria for incorporation while planning the structure of a region energy system (decrease of negative environmental influence, decrease of energy production price, maximization of useful social and economic effects) served as another reason for using non-parametric methods of Data Envelopment Analysis (DEA) for solving this class of problems.

Among the multitude of approaches to modelling energetic and ecologic problems in foreign literature, DEA has attained a leading position. One of the main reasons is the possibility to model comparatively the efficiency of various energy sectors in a variety of countries, which has become especially relevant with the liberalization of energy markets [24].

Currently, DEA is a well-developed methodology for comparing the efficiency of various homogenous economic agents, operating in production or elsewhere, via a variety of mathematical programming models. The agents the efficiency of which is evaluated by DEA are usually known as “decision-making units” (DMUs). All DMUs perform the same production function that transforms a set of inputs into a set of outputs. An advantage of DEA is the possibility to work with DMUs without any knowledge of the actual functional relation between inputs and outputs. Russian economists conventionally employ DEA to analyze the efficiency of the budgetary system, regional authorities or banking structures, etc. [17, 18]; however, during the recent years, studies that use DEA to analyze ecologic aspects of economic activity, including electric energy [12], started appearing.

The classic DEA model known as CCR (named after its developers: Charnes A., Cooper W.W., and Rhodes E. [4]) involves solving a fractional linear programming problem that maximizes the ratio of the linear combination of weighted outputs to the linear combination of weighted inputs:

$$\max_{u,v} h = \frac{\sum_i u_i y_{ij}}{\sum_k v_k x_{kj}} \tag{1.1}$$

This ratio is known as the efficiency coefficient, and its value lies between zero and one. Any DMUs with their efficiency coefficient equal to one are considered efficient, and all the others are, inversely, deemed ineffective. If the efficiency coefficient is defined in the form of (1.1), the DEA problem itself is considered to be “input-oriented”. The other form for defining the efficiency coefficient (a ratio of the linear combination of weighted inputs to the linear combination of weighted outputs) is known as “output-oriented”. In our case, we’re dealing with an output-oriented problem.

Calculating the projections to the efficiency frontier for inefficient DMUs in the input/output space allows us to determine the estimated targets for decreasing inputs or increasing outputs. Achieving these projected values will allow the DMU to become efficient.

A peculiarity of using DEA for optimizing energy systems is the presence of so-called undesirable outputs, that is to say, the negative ecologic effects. For solving ecological problems, a special class of DEA models was developed: these are known as “environmental DEA (EDEA)”.

The goal of this paper is to review methods and approaches of accounting for undesirable outputs in environmental DEA models and developing an algorithm for applying the basic input-oriented DEA model for performing a comparative analysis of the ecologic efficiency of large electric generating companies of Russia. We tested the capabilities of the developed two-stage algorithm on 24 DMUs on its first stage and on detailed data of 11 power plants (that are part of OGK-2) on its second stage.

2. METHOGOLOGY OVERVIEW: DEA MODELS USED FOR OPTIMIZING ENERGY SYSTEMS BASED ON ECOLOGIC CRITERIA

In its coefficient form, the classic input-oriented CCR DEA model is as follows:

$$\max_{u,v} \sum_{m=1}^{M} u_m y_{m0} \tag{2.1}$$

s.t.

$$\sum_{m=1}^{M} u_m y_{mk} - \sum_{n=1}^{N} v_n x_{nk} \le 0 \quad k = 1,2,\cdots K,$$
$$\sum_{n=1}^{N} v_n x_{n0} = 1,$$
$$u_m, v_n \ge 0 \quad m = 1,2,\dots M \quad n = 1,2,\dots N;$$

where

0 – index of the DMU being optimized,

X – input vector of size *N*,

Y – output vector of size *M*,

K – amount of DMUs.

Or, in dual form:

$$\min_{\lambda} \quad \theta \tag{2.2}$$

s.t:

$$\sum_{n=1}^{N} x_{nk}\lambda_k \le \theta\, x_{no}, \quad n = 1,2,\dots N$$
$$\sum_{m=1}^{M} y_{mk}\lambda_k \ge y_{mo}, \quad m = 1,2,\dots M$$
$$\lambda_k \ge 0, \quad k = 1,2,\dots K$$

This model searches for the possibility of proportionally decreasing inputs without a decrease in outputs. The CCR production set is the following set of vectors (*X*, *Y*):

$$T = \left\{ (X,Y) \left| \sum_{j=1}^{n} X_j\lambda_j \le X, \quad \sum_{j=1}^{n} Y_j\lambda_j \ge Y, \quad \lambda_j \ge 0, \quad j = 1,\dots n \right. \right\} \tag{2.3}$$

Classic DEA models, including CCR, assume their inputs and outputs are strictly monotonous, in other words, the production set follows this rule:

$$\textit{if } (X;Y) \in T \textit{ and } X' \geq X \textit{ or } Y' \leq Y, \textit{ then } (X';Y) \in T \textit{ or } (X;Y') \in T \qquad (2.4)$$

However, this property does not always describe the real production situation. For instance, energy generation via hydrocarbon fuel will always be linked to the production of sulfur dioxide, and decreasing this output without a decrease in the corresponding input is technologically impossible. Thus, using a production set that follows (2.4) will lead to incorrect modelling results.

A literature review allows one to conclude, that a significant number of attempts to consider undesirable outputs in DEA models have been made. These fall into two main categories: i) recalculating (modifying) original data and using a traditional DEA model [22]; ii) using original data with models based on the concept of weak disposability [6-8].

When using the first approach, the overall efficiency of a company may be divided into technical/economic efficiency, defined as a ratio of the weighted sum of wanted outputs to the weighted sum of inputs, and ecologic efficiency, which is defined as the ratio of weighted sums of wanted and unwanted outputs.

Let the first k of M outputs of the model (2.1) be desirable, and the others undesirable. Then, the economic efficiency of DMU with the index of zero can be represented as:

$$h_{economy} = \frac{\sum_{r=1}^{k} \mu_r y_{r0}}{\sum_{i=1}^{M} v_i x_{i0}} \qquad (2.5)$$

and the ecologic efficiency as:

$$h_{eco\log y} = \frac{\sum_{r=1}^{k} \mu_r y_{r0}}{\sum_{s=k+1}^{p} \mu_s y_{s0}} \qquad (2.6)$$

To incorporate both efficiency measures in the basic CCR model, we have to somehow combine them in a way that corresponds to the general logic of the problem: maximization of desirable outputs and minimization of undesirable outputs and inputs. The following option (A) fits these conditions rather well:

$$h_A = \frac{\sum_{r=1}^{k} \mu_r y_{r0} - \sum_{s=k+1}^{p} \mu_s y_{s0}}{\sum_{i=1}^{M} v_i x_{i0}}$$

Besides that, undesirable outputs can be treated as inputs of the model (option B), which transforms the efficiency measure as follows:

$$h_B = \frac{\sum_{r=1}^{k} \mu_r y_{r0}}{\sum_{i=1}^{M} v_i x_{i0} + \sum_{s=k+1}^{p} \mu_s y_{s0}}.$$

In this case, the decrease in undesirable outputs happens simultaneously with the decrease of inputs.

Paper [17] provides the proof that basic CCR models that use option A are analogous to those which employ option B.

The production set corresponding to the property of weak disposability is defined thusly:

$$T_e = \left\{ \begin{array}{ll} (X,Y,U) \mid \sum_{k=1}^{K} z_k x_{nk} \le x_n & n = 1,2,\dots N, \\ \sum_{k=1}^{K} z_k y_{mk} \ge y_m & m = 1,2,\dots M, \\ \sum_{k=1}^{K} z_k u_{jk} = u_j & j = 1,2,\dots J, \\ z_k \ge 0, & k = 1,2,\dots K; \end{array} \right\}$$

where

U is a vector of undesirable outputs,

e is an index with the meaning of "environmental", since these types of production sets are used in environmental DEA.

Besides that, T_e also fulfills the following condition:

$$\text{if } (X,Y,U) \in T \text{ and } U=0, \text{ then } Y=0 \qquad (2.7)$$

This indicates that a complete elimination of undesirable outputs is only possible via a complete halt of the production process. This approach can be used for undesirable inputs as well: models with weakly disposability of inputs are introduced in [7, 16].

Besides disposability, operational characteristics of inputs and outputs (their unit measures) may also serve as a distinct characteristic of environmental DEA. Two models [1-2] often mentioned in the literature use categories for input and output variables. These models describe production processes during implementation of environmental laws rather well, and allow to consider the influence from other external factors that DMUs themselves have no control of.

Return to scale is also an important characteristic of the DEA production set. The basic CCR model uses constant return-to-scale. If we add the following condition to the set T:

$$\sum_{i=1}^{K} \lambda_i = 1,$$

we'll end up with the BCC model with variable returns to scale (while production grows, the scale effect changes from increasing to decreasing). Another popular approach is the use of non-increasing return to scale, defined as:

$$\sum_{i=1}^{K} \lambda_i \le 1.$$

Besides the orientation of the efficiency measure (input, output or undesirable output), an important property of environmental DEA problems is the method for reducing inputs and increasing outputs, that is to say, the direction of movement towards the efficiency frontier.

Radial efficiency measures are the ones most frequently encountered in any DEA models. In this case, the inputs decreasing proportionally by the same value of OC'/OC (radial movement from source point to efficiency frontier) (See fig. 1).

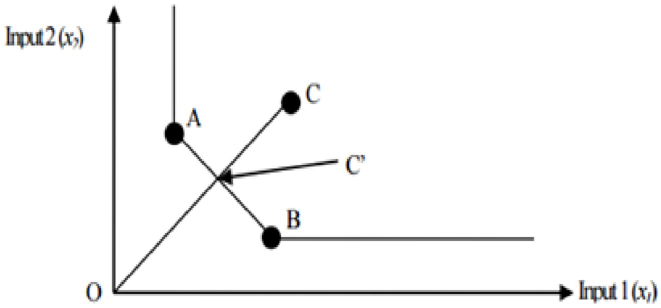

Fig. 2.1 Graphical illustration of the radial efficiency measure in a basic CCR model (2D case)

Combining radial efficiency measures with different production sets allows us to obtain a variety of DEA models, including the basics: CCR and BCC. For example, the papers [7, 22, 23] use the production set T_e with a radial efficiency measure:

$$\min \theta : (X_0, Y_0, \theta U_0) \in T_e$$

Non-radial efficiency measures allow to decrease inputs and increase outputs non-proportionally, and usually have a better discriminative power than radial measures. A particularly well-known example is the non-radial Russell measure:

$$\min \left\{ \frac{1}{N} \sum_{n=1}^{N} \theta_n : (X_0 \boldsymbol{\theta}, Y_0) \in T \right\},$$

where

$\boldsymbol{\theta}$ is a diagonal matrix containing $\theta_1,...\theta_n$.

If $\theta_1,...\theta_n$ have different weights, a weighted non-radial efficiency measure may be used. Such measures reflect the preferences of specific DMUs [25].

A hyperbolic efficiency measure, also known as the graphical measure, decreases inputs and increases outputs by the same value at the same time (moving towards the efficiency frontier hyperbolically):

$$\left\{ \boldsymbol{\theta} : (\boldsymbol{\theta} X_0, {}^{Y_0}\!/\!_{\boldsymbol{\theta}}) \in T \right\}$$

This efficiency measure works best when both desirable and undesirable outputs are present.

The Directional Distance Function (DDF) is an efficiency measure that allows one to simultaneously increase desirable outputs and decrease inputs using a directed vector. This is a generalized form of the traditional radial efficiency measure [3].

3. RESULTS

3.1. Analyzing the comparative efficiency of energy generating companies in Russia with ecologic indicators

Let's consider the problem of evaluating the efficiency of the Russian energy generating companies based on a set of ecologic parameters. To calculate the ecologic efficiency with the basic input-oriented CCR model (2.1) with a radial efficiency measure, we'll use freely available statistical information [15] on ecologic aspects of the activity of the main players on the electric energy market: five wholesale generating companies (OGK) that unify the largest heat power-plants, and some territorial generating companies (TGK) that unify the power plants of several neighboring regions that did not become parts of OGK and work as isolated energy systems (24 DMUs total).

We view atmospheric emissions (in thousands of tons), solid waste (in thousands of tons) and freshwater consumption (in millions of cubic meters) as our unwanted outputs. We consider the generated electricity as our sole wanted output.

The results of our calculations, done in the MaxDEA software, using a radial and a non-radial efficiency measure, represented in Table 3.1.

Table 3.1. Scores of ecologic efficiency of generating companies in 2011

Company name	Radial efficiency	Non-radial efficiency
OGK-1	0.374	0.190
OGK-2	0.168	0.115
OGK-3	0.142	0.101
OGK-4 OJSC «E.ON Rossiya»	0.611	0.543
OGK-5 «Enel OGK-5»	0.132	0.093
TGK-1	0.300	0.265
TGK-2	0.112	0.111
OJSC «Mosenergo» (TGK-3)	**1.000**	**1.000**
TGK-4 OJSC «Kvadra»	0.558	0.477
TGK-5	0.428	0.402
TGK-6	0.591	0.412
OJSC «Volzhskaya TGK» (TGK-7)	**1.000**	**1.000**
TGK-9	0.122	0.096
OJSC «Fortum» (TGK-10)	0.366	0.299
TGK-11	0.532	0.206
OJSC «Kuzbassenergo» (TGK-12)	0.115	0.081
OJSC «Eniseyskaya TGK» (TGK-13)	0.089	0.075
TGK-14	0.717	0.475
Generiruyushchiye kompanii «Lukoyl»	**1.000**	**1.000**
OJSC «Dal'nevostochnaya GK»	0.177	0.091
OJSC «Irkutskenergo»	0.528	0.284
OJSC «Tatenergo»	**1.000**	**1.000**
OJSC «Bashkirenergo»	0.678	0.616
OJSC «SIBEKO»	0.136	0.101

The DMU efficiency score herein is to be interpreted as a ratio of the minimal possible negative ecologic effects to the real ones. That is to say, the effective DMUs are those who use the best available technologies and the cleanest fuel (from the ecologic point of view). The efficiency coefficient for the effective DMUs is equal to 1, and highlighted in bold. It is easy to note that the efficiency coefficient of non-effective DMUs is greater when calculated with the radial measure than with the non-radial one.

The target indicators (for 2011) that have to be reached by non-efficient companies (calculated under a radial efficiency measure) to become efficient are presented in Table 3.2.

Table 3.2. Values of target indicators for inputs that need to be reached in 2011

Company name	Target indicators		
	Emissions	Waste	Water consumption
OGK-1	34.256	84.108	332.035
OGK-2	63.444	155.770	614.933
OGK-3	26.513	65.097	256.985

OGK-4 OJSC «E.ON Rossiya»	55.864	147.106	412.725
OGK-5 «Enel OGK-5»	43.741	121.476	241.682
TGK-1	16.385	29.442	158.045
TGK-2	9.305	26.654	40.894
TGK-4 OJSC «Kvadra»	11.685	19.870	112.633
TGK-5	10.929	31.453	46.131
TGK-6	15.532	18.012	270.476
TGK-9	14.927	42.799	65.070
OJSC «Fortum» (TGK-10)	18.787	51.954	106.641
TGK-11	9.231	26.567	38.964
OJSC «Kuzbassenergo»	19.991	52.513	149.342
OJSC «Eniseyskaya TGK»	11.266	31.170	63.775
TGK-14	26.226	75.477	110.700
OJSC «Dal'nevostochnaya GK»	23.341	67.172	98.520
OJSC «Irkutskenergo»	63.063	181.488	266.183
OJSC «Bashkirenergo»	20.362	53.769	148.491
OJSC «SIBEKO»	11.243	31.417	59.607

When the indicators given in Table 3.2 are reached, each of these companies can match its reference point on the efficiency frontier in the multi-dimensional input/output space. The process of calculation of target indicators under non-radial efficiency measure has shown that their values change only in case then DMU has several benchmarks (See Table 3.3.)

Table 3.3. Changes in target indicators depending from the type of efficiency measure

Company name	Reference points	$\Delta_{emissions}$	Δ_{waste}	Δ_{water}
OGK-4	«Mosenergo»; «Tatenergo»	5.93	24.50	-71.27
OGK-5	«Mosenergo»; «Tatenergo»	-3.51	-14.52	42.22
TGK-1	«Mosenergo»; «Volzhskaya TGK»	3.39	-2.45	32.13
TGK-2	«Mosenergo»; «Tatenergo»	-0.10	-0.41	1.20
TGK-4	«Mosenergo»; «Volzhskaya TGK»	2.77	-2.01	26.27
TGK-6	«Mosenergo»;	6.25	-4.77	180.53
TGK-9	GK Lukoyl	-0.13	-0.52	1.53
TGK-10	«Mosenergo»; «Tatenergo»	-1.68	-6.96	20.24
TGK-12	«Mosenergo»; «Tatenergo»	-4.00	-16.53	48.08
TGK-13	«Mosenergo»; «Tatenergo»	-0.99	-4.13	12.01
OJSC «Bashkirenergo»	«Mosenergo»; «Tatenergo»	2.25	9.30	-27.05
OJSC «SIBEKO»	«Mosenergo»; «Tatenergo»	-0.75	-3.09	8.99

Moving towards the efficiency frontier non-radially leads to some target parameters being greater than in the radial efficiency measure (such differences are indicated as negative numbers), and in some cases, they will be smaller (which is indicated by a positive number). Which of these two efficiency measures is the best depends on the expenditure of the specific company trying to reach these target indicators.

3.2. Dynamic of ecology efficiency of generating companies

In this section we investigate how ecologic efficiency of generating companies changes through time. Table 3.4 shows efficiency scores of generating companies throughout 2009-2011, calculated according an input-oriented CCR model with a radial efficiency measure.

Table 3.4. Ecology efficiency of generating companies in 2009-2011

Company name	2009	2010	2011
OGK-1	0.374	0.387	0.374
OGK-2	0.173	0.165	0.168
OGK-3	0.171	0.158	0.142
OGK-4 OJSC «E.ON Rossiya»	0.624	0.577	0.611
OGK-5 «Enel OGK-5»	0.147	0.126	0.132
TGK-1	0.534	0.378	0.300
TGK-2	0.130	0.115	0.112
OJSC «Mosenergo» (TGK-3)	**1.000**	0.993	**1.000**
TGK-4 OJSC «Kvadra»	0.588	0.400	0.558
TGK-5	0.505	0.464	0.428
TGK-6	0.338	0.366	0.591
OJSC «Volzhskaya TGK» (TGK-7)	0.731	0.627	**1.000**
TGK-9	0.136	0.118	0.122
OJSC «Fortum» (TGK-10)	0.438	0.308	0.366
TGK-11	0.667	0.714	0.532
OJSC «Kuzbassenergo» (TGK-12)	0.123	0.107	0.115
OJSC «Eniseyskaya TGK» (TGK-13)	0.097	0.078	0.089
TGK-14	0.099	0.079	0.717
Generiruyushchiye kompanii Lukoyl (before 2010: «YUGK TGK-8»)	**1.000**	**1.000**	**1.000**
OJSC «Dal'nevostochnaya GK»	0.208	0.189	0.177
OJSC «Irkutskenergo»	0.719	0.597	0.528
OJSC «Tatenergo»	**1.000**	**1.000**	**1.000**
OJSC «Bashkirenergo»	0.527	0.510	0.678
OJSC «SIBEKO»	0.142	0.126	0.136

In 2009 and 2010, out of all analyzed DMUs, only 3 companies: OJSC “Mosenergo” and the generating companies of the “Lukoil” and “TatnefT” groups, were ecologically effective. Another company joined this list in 2011: OJSC “Volzhskaya TTK”. However, it is not correct to judge changes in actual ecologic efficiency merely by these coefficients, since the efficiency frontier itself may shift from year to year.

To evaluate the dynamic changes of DMU efficiency in DEA problems, the Malmquist productivity index (MPI) is used. This is a non-parametric method for analyzing time series [13]. In its general from, the MPI can be defined with a distance function as its base, however, it can also be presented as a ratio of efficiency measures.

Let $\theta^t(X_0^t, Y_0^t)$ and $\theta^{t+1}(X_0^t, Y_0^t)$ be the input-oriented efficiency measures for DMU$_0$, calculated using inputs and outputs from the solution of (2.2) during the moment *t* and the production set *T,* in the moments *t* and *t+1.* Let $\theta^t(X_0^{t+1}, Y_0^{t+1})$ и $\theta^{t+1}(X_0^{t+1}, Y_0^{t+1})$ be the input-oriented efficiency measures for DMU$_0$, calculated using inputs and outputs from the solution of (2.2) during the moment *t+1* and the production set *T,* in the moments *t* and *t+1*. Then, the input-oriented MPI can be defined as:

$$MPI_0 = \left[\frac{\theta^t(X_0^{t+1}, Y_0^{t+1})}{\theta^t(X_0^t, Y_0^t)} \cdot \frac{\theta^{t+1}(X_0^{t+1}, Y_0^{t+1})}{\theta^{t+1}(X_0^t, Y_0^t)} \right]^{1/2} \tag{3.1}$$

Values of MPI_0<1, MPI_0=1 and MPI_0>1 signify, respectively, a decrease, an increase or constancy in the efficiency of DMU$_0$ throughout the research period [13].

Various sources often employ the following form for the Malmquist index:

$$MPI_0 = \left[\frac{\theta^t(X_0^t, Y_0^t)}{\theta^{t+1}(X_0^t, Y_0^t)} \cdot \frac{\theta^t(X_0^{t+1}, Y_0^{t+1})}{\theta^{t+1}(X_0^{t+1}, Y_0^{t+1})} \right]^{1/2} \times \frac{\theta^{t+1}(X_0^{t+1}, Y_0^{t+1})}{\theta^t(X_0^t, Y_0^t)} \tag{3.2}$$

The form (3.2) defines changes in efficiency in a decomposed format, with the first part representing the frontier shift effect, and the second part – the catch-up effect.

The calculated Malmquist indices are shown in table 3.5.

Table 3.5. Malmquist index values (output-oriented) throughout 2009-2010 and 2010-2011

Company name	MPI 2009-2010	MPI 2010-2011
OGK-1	0.9522	0.9426
OGK-2	0.8574	0.9784
OGK-3	0.9522	0.9426
OGK-4 OJSC «E.ON Rossiya»	0.6700	**1.0242**
OGK-5 «Enel OGK-5»	0.8805	**1.0170**
TGK-1	0.5365	0.6175
TGK-2	0.8805	0.9484
OJSC «Mosenergo» (TGK-3)	0.9723	0.9865
TGK-4 OJSC «Kvadra»	0.6705	**1.3079**
TGK-5	0.8805	0.9200
TGK-6	0.8469	**1.2539**
OJSC «Volzhskaya TGK» (TGK-7)	0.7708	**1.2641**
TGK-9	0.8805	0.9520
OJSC «Fortum» (TGK-10)	0.8891	**1.1160**
TGK-11	0.8805	0.9200
OJSC «Kuzbassenergo» (TGK-12)	0.8556	**1.0659**
OJSC «Eniseyskaya TGK» (TGK-13)	0.8157	**1.1212**
TGK-14	0.8805	**1.2143**
Generiruyushchiye kompanii Lukoyl	**1.0171**	**1.0569**
OJSC «Dal'nevostochnaya GK»	0.8805	0.9200
OJSC «Irkutskenergo»	0.8805	0.9200
OJSC «Tatenergo»	0.9383	1.0000
OJSC «Bashkirenergo»	0.7630	**1.3424**

OJSC «SIBEKO»	0.8550	**1.0862**

Thus, a real increase in environmental efficiency has only been observed within the “Lukoyl” generating companies in 2009-2010, and it has decreased for the other companies. During 2010-2011, already 12 companies have exhibited an increase in ecology efficiency. Malmquist index values signifying an increase in efficiency are highlighted in bold in the above table.

4. POLICY APPLICATION: ELABORATION OF AN OPTIMAL ENVIRONMENTAL MANAGEMENT STRATEGY FOR GENERATING COMPANIES

It is necessary to mention that all of the calculations done so far only considered ecologic efficiency of DMUs, without taking into account any economic parameters of power plant operating. In fact, incorporation of economic parameters in analysis is possible with the use of methods described in section 2. However, we believe that elaboration of proactive environmental investment strategy for a generating company can be done with a far simpler approach, which involves solving the two basic DEA problem consistenly.

On the first step, we solve the problem of evaluating ecologic efficiency of the company’s activity using primary ecologic indicators, and calculate target values if the company ends up ineffective. On the second stage, we build another DEA model for each ineffective DMU, which uses economic parameters (cost, implementation time, etc.) of environmental projects (meant to reduce negative ecologic effects down to the calculated target value, or a value sufficiently close to that) as inputs. Solving these models allows us to choose projects that are most effective at achieving positive ecologic results, from an investor’s point of view.

Sequentially processing data for each of the power plants that is part of an OGK or a TGK, we obtain a problem for optimizing the development of the entire energy system.

Let us consider the problem of evaluating the efficiency of specific power plants that are part of OGK-2 (which is recognized as ineffective in 2011). Table 4.1 shows the results of a solving CCR DEA model with a radial efficiency measure, calculated in MaxDEA, using data from the company’s official 2013 reports (http://www.ogk2.ru).

Table 4.1. Ecologic efficiency of OGK-2 power plants (CCR model)

Power plant	Efficiency coefficient	Input target indicators		
		Emissions, thousands of tons	Waste, thousands of tons	Water, millions of cubic meters
Adlerskaya	1	743.25	3.09	642.33
Kirishskaya	1	2415.57	3.40	574645.2
Krasnoyarskaya-2	0.066	1572.01	1.26	34978.45
Novocherkasskaya	0.057	3262.63	2.57	52722.81
Pskovskaya	0.876	488.38	0.69	116182.1
Ryazanskaya	0.422	3507.38	14.60	3031.13
Serovskaya	0.039	645.04	0.49	3281.98
Stavropol'skaya	0.744	2489.71	3.51	592281.4
Surgutskaya -1	1	7432.52	5.57	21622.2
Troitskaya	0.237	1818.42	7.57	1571.507
Cherepovetskaya	0.041	932.33	0.72	11876.88

It can be seen that three power plants that belong to OGK-2 (Adlerskaya, Kirishskaya and Surgutskaya-1) are effective from an ecologic point of view. All three of these power plants use gas as their primary source of fuel; however, the Pskovskaya and Stavropolskaya power plants use gas also and are, nevertheless, ineffective. This means that the fuel type is not the only factor of ecologic efficiency.

The "closest" statistical indicator (meaning-wise) to our calculated efficiency coefficient, that is used in the practice of energy management in generating companies is the ratio of fuel consumption to generated energy, which characterizes the efficiency of different generating equipment (the linear Pearson correlation coefficient, calculated with OGK-2 power plant data, equals -0.81).

Improving ecologic indicators for generating companies is possible thanks to the implementation of the following projects, unrelated to changing fuel or the technology used for energy generation [12, 15, 19-20]:

1) Reduction of atmospheric emissions by implementation of low-toxicity burners for highly-concentrated dust, thereby decreasing nitrogen oxides, installation (or repairing) ventilation technologies, energy filters and ash collectors;

2) Reduction of water consumption by cleaning and discarding mineralized waste waters, installation (or repairing) treatment facilities for industrial wastewater, implementation of oil collectors;

3) Reduction of waste generation by recycling ashes, and/or developing technologies to increase the reliability of their storage;

4) Increasing overall environmental efficiency by implementation ISO 14001 compliant environmental management systems (currently implemented on the Stavropolskaya, Pskovskaya, Surgutskaya, Serovskaya and Troitskaya power plants), decrease fuel expenditure for energy generation.

Besides that, one also needs to consider the advanced technological capabilities for replacing existing fuel with cleaner alternatives or switching to completely different energy generation technologies (options of innovative development). The least expensive fuel option is currently to use natural gas for energy generation, and the least expensive options for new energy technologies, according to Russian experts, are photovoltaics and wind energy [15]. Atom energy and "clean coal" technologies that minimize atmospheric pollution are mid-range in terms of expense.

Cost and time indicators of the aforementioned projects (as well as some indicators of their social efficiency) can be used as input parameters for a next-level CCR DEA model. Same model can be used to optimize economic and social parameters of investment project meant to decrease negative environmental influence of the non-efficient power plants. As outputs, we can use the target indicators of ecologic effects calculated during the last stage. The overall algorithm with which the model can be built is shown on figure 4.1.

We cannot provide an example calculation for this case due to a lack of available statistical data on economic values of investment projects.

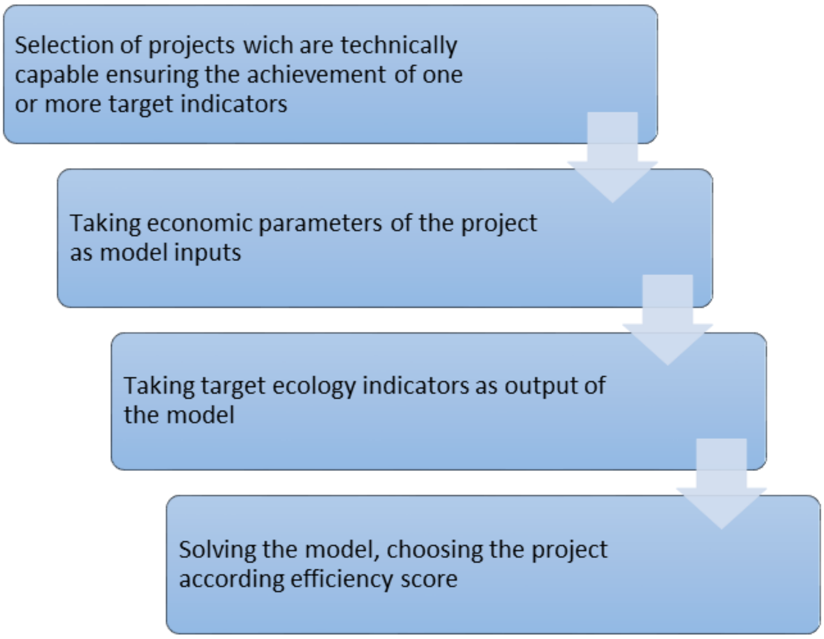

Fig. 4.1. Algorithm of second-level DEA model creation

6. CONCLUSION

The main result of this study is the proof of possibility for using a basic input-oriented CCR DEA model for solving the problem of choosing an optimal environmental management strategy for a generating company.

It is important to point out that each of the large generating companies analyzed in this research consists of several separate DMUs – power plants that work using different equipment and different generating technologies. Therefore, the statistical data used in our calculations is averaged, and the results do not reflect the entire picture and should not be used to judge the quality of ecologic management in these companies. Nevertheless, the calculations can be used to evaluate the progress of completion and the practicality of investment projects of companies, from an environmental viewpoint. They also may be used to help develop state programs for support of modernization in electric energy industry, ecologic standards or energy-saving programs.

The developed method consists of sequentially solving several DEA models: the first-stage model determines the effectiveness of DMUs from an ecologic perspective and calculates target values for decreasing negative ecologic effects of non-effective DMUs. The second stage requires solving one input-oriented CCR model for each non-effective object, using economic and social characteristics of projects meant to reduce negative environmental influence, and using the target values calculated in the first stage as outputs.

The choice of an efficiency measure (radial or non-radial) depends on the cost of the projects, and can only be determined while solving the second-stage DEA problems (determining economic efficiency). Besides the cost, the choice of an efficiency measure can be made by judging the importance of a specific ecologic effect for the specific region or territory.

Besides the problem of evaluation of the comparative efficiency of DMUs, ecologically oriented studies also often need to evaluate the changes in a DMU’s efficiency dynamically. For this, the Malmquist productivity index (MPI) is used. MPI is a non-parametric method for analyzing time series that allows to track changes in DMU efficiency over time by means of DEA models.

ACKNOWLEDGEMENTS

This study is partly supported financially by the Russian Foundation for Basic Research (RFBR), project No. 16-06-00147 “Development of data envelopment analysis models for optimizing development of regional economic systems based on ecologic parameters”.

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