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Project management based on life circle analysis: the case of energy sector in transition economies

Gestión de proyectos basada en el análisis del círculo de vida: el caso del sector energético en las economías en transición

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Abstract
The aim of the paper is to develop an environmental effects evaluation methodology based on ecological impact categories through all the stages of lifecycle of renewable energy technologies. We used DEA-based calculation of the efficiency score for each renewable energy technology. EcoInvent database on CML 2001 methodology has been chosen as a source of eco-indicators. We assume that the efficiency ratio will remain unchanged, when transferring estimates of the life cycle of renewable energy facilities to another territory. This allows to extrapolate comparative assessments. The results of the presented work might be useful for policymakers for a more consistent energy strategy deployment.
Keywords: renewable projects, external effects, LCA analysis, ecological impact

RESUMEN
El objetivo del trabajo es desarrollar una metodología de evaluación de efectos ambientales basada en categorías de impacto ecológico a través de todas las etapas del círculo de vida de las tecnologías de energía renovable. Utilizamos un cálculo basado en la DEA del puntaje de eficiencia para cada tecnología de energía renovable. Se ha elegido la base de datos EcoInvent sobre la metodología CML 2001 como fuente de ecoindicadores. Suponemos que el índice de eficiencia se mantendrá sin cambios, al transferir estimaciones del círculo de vida de las instalaciones de energía renovable a otro territorio. Esto permite extrapolar evaluaciones comparativas. Los resultados del trabajo presentado podrían ser útiles para los formuladores de políticas para un despliegue de estrategia energética más consistente.
Palabras clave: proyectos renovables, efectos externos, análisis LCA, impacto ecológico

1. Introduction

In the recent decades, in post-soviet countries such as Russia, has launched several large-scale programs of state support for renewable energy. One of the most effective programs is about the competitive support for

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investment projects for the construction of power facilities with a capacity of at least 5 MW connected to a utility line. A special feature of the program is the high requirements for the localization of equipment production for energy facilities: at least 70% of equipment and components must be produced in Russia, which allows to create new jobs in the field of power engineering, stimulate innovation and increase the multiplicative effects of investments (Ratner and Klochkov, 2017). Driven by this program, photovoltaics has received a particularly powerful impetus to development: at present, more than 200 MW of solar power plants have been introduced in the country, and a full cycle of photovoltaic panels manufacturing has been created (Ratner and Nizhegorodtsev, 2017). In the coming years, wind power is expected to receive the same impetus. Thus, Rosatom, one of the largest high-tech Russian companies, plans to construct wind parks, as well as product wind turbines in Russia.

The implementation of these plans will reduce the high energy and carbon intensity of the Russian electric power industry, especially when new renewable-based energy facilities are introduced in the regions where coal-fired power plants are located (Ratner S.V. and Ratner P.D., 2017). However, the development of renewable energy cannot be considered as completely free from negative environmental impacts. Despite the fact that at the stage of operation, power facilities based on renewable sources scarcely do not produce negative environmental effects, such effects can be observed at the stage of power equipment manufacturing, installation, and also at earlier stages of the power object life cycle. For example, it is known that the production and utilization of solar panels is associated with significant energy consumption, the use of working fluids containing chlorates and nitrites, the formation of wastewater, etc. (Dubey et al. 2013). The production of wind turbines is associated with the significant consumption of energy-intensive metallurgical industries products, as well as with the use of rare earth metals (Nizhegorodtsev and Ratner, 2016). Therefore, the choice of renewable energy technology for state support should be carried out with some caution, considering not only potential positive, but also possible negative effects from the deployment of large-scale production according to the methodology of life cycle analysis. For example, in such touristic regions as Krasnodar region (region of Russia,) where the development of solar energy is of a high importance because there is a lot of solar insolation and the region is consuming more energy than producing, environmental aspects of all innovative projects are very important (Ratner and Zaretskaya, 2018).

2. Research background

Based on the concept in Life Cycle Analysis (LCA) methodology (Lewin, A.Y., Lovell C.A.K.,1995) by which manufacturers or service, energy providers can analyze the environmental impacts and effects of their products and services for the regional economy, social structure. The duration of this assessment extends across the entire life cycle of products and services (“cradle-to-grave”). This process allows for product comparison and strategic decision making with regard to systemic inputs and outputs, as well as the development and incorporation of End-of-Life design strategies.

It should be taken into account that before the LCA concept had been presented, there were different methods to address human, societal, economy and ecosystem concerns. Cost-benefit analysis (CBA) is used to identify the alternative with the lowest cost, multi-criteria analysis (MCA) is to evaluate the alternatives based on a set of measurable criteria. Neither of these methods emphasized on the environmental side. On a global scale successful attempts were taken to standardize the principles and framework for LCA. Thus, ISO 14040, 14041, 14042 and 14043 were approved. Nowadays the requirements of these standards have been widely applied in a great number of firms relating to different processes and products.

Alongside with maximizing social and economic benefits it is important to keep up with a minimum permissible level of environmental negative effects. This approach coheres with the concept of sustainable development which includes the three-sphere framework and enhances it by adding sustainable development goals and numeric indicators on different scale levels (global, regional, national etc.).

According to one of the Bloomberg NEF studies, (Acheampong A. O., 2018) the cost of non-fossil fuels-based electricity has been showing a steady decline. It is also forcing out fossil fuel power from all stages of energy mix – in bulk generation, in dispatchable power and in grid flexibility. Levelized costs of electricity (LCOE) of fast developing technologies like wind, solar photovoltaic, pump hydro, battery+wind pairs or battery+solar pairs are now at the same level or even exceed the LCOE of traditional energy transformation. This can be demonstrated through the growth worldwide production and continual improvement of applied technologies.

Thus, it is becoming more evident there is a need to consider “green” electricity production from all stages of the lifecycle, not only form economic efficiency side. The stages include raw material extraction, manufacturing processes, transport, installation, operation, maintenance and end-of-life (dismantling, recycling and final disposal). Each green energy technology contains its own bottlenecks within the stages of the lifecycle. For example, wind energy production is accompanied by a high level of carbon footprint and energy consumption at the material phase. The production and disposal of solar panels result in high level of water use and toxic chemicals such as hydrochloric acid, sulfuric acid, nitric acid, hydrogen fluoride, 1,1,1-trichloroethane and acetone.

Attempts to determine the most preferable energy technology from an environmental point of view have been made in the literature more than once. However, in most cases, researchers are limited to considering only one or two of the most significant environmental effects, for example, CO2 emissions (Yifei et al. 2018, Acheampong, 2018).

It should be noted that the simultaneous consideration of multidirectional environmental effects is rather complicated task. Thus, according to one indicator of the negative impact on the environment, technology A can surpass technology B, on the contrary, technology B can surpass technology A. As a possible solution, we can offer an aggregation of all negative environmental factors. To achieve this, it is necessary to determine the weights of each indicator of negative environmental impact, for example, using expert estimates. However, obtaining objective and universal weights is not always possible even with the involvement of experts, since that in different regions (or local territorial entities) some categories of environmental impact may be of a high importance, and in other regions they might be less important. (Ratner S.V. and Ratner P.D., 2017). A promising method for constructing such a complex integral indicator is the application of DEA analysis, first performed for comparative evaluation of several photovoltaic technologies in (Ratner and Iosifov, 2017). In this paper, DEA approach is developed and generalized to the case of a comparative evaluation of several renewable energy technologies of different nature and physical nature.

3. Methodology and data model

Data Envelopment Analysis (DEA) (Charnes et al., 1978) is a method for evaluating performance of peer decision making units (DMUs) with multiple performance measures that are specified as inputs and outputs. DEA first establishes an 'efficient frontier' formed by a set of DMUs that exhibit best practices and then assigns the efficiency level to other non-frontier units according to their distances to the efficient frontier. Over the years, DEA has been enriched and modified.

Data envelopment analysis or DEA is a flexible methodology for assessing efficiency of DMUs. In many DEA applications, the issue of calculating technical, economic or environmental efficiency arises in the presence of nondiscretionary/environmental inputs. It is possible to calculate the efficiency of every DMU within a certain sampling. While estimating efficiency, manifold indicators can be considered. In general, there are several approaches to employ DEA models in the literature: traditional DEA models with simple translation of data (Tsai-lienYeh et al.,2010) traditional DEA models treating undesirable outcomes as inputs (Jin-Li Hu et al., 2006). Two-level DEA approaches in research evaluation (Meng et al., 2008) and DEA models employing the concept of weak disposability technology (Lewin and Lovel, 1995, Färe et al., 2008)

Let x_{ij} and y_{rj} denote the level of input *i*, *i*=1, 2…, m, and output *r, r* =1, 2…, s, respectively, of DMU*j*, *j*=1, 2…, n. The CCR model developed by Charnes et al. (1978) for measuring the relative efficiency of DMU0 assuming a constant return to scale can be written as

$$E_0^{CCR} = Max \sum_{r=1}^{s} u_r y_{rk}$$

$$\sum_{r=1}^{s} u_r y_{rk} - \sum_{i=1}^{m} v_i x_{ij} \leq 0; j = 1, 2, \dots, n$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1$$

$u_r, v_i \geq \varepsilon; r = 1, 2, \dots, s; i = 1, 2, \dots, m$

where u_r and v_i represent the weights of the associated factors and ε is a small non-Archimedean number imposed to prevent any unfavorable factor from being ignored. DMU_j is relative efficient; when E_j=1, DMU_j is also called an efficient DMU.

In recent years the applications of DEA have increased in field of environmental and energy economics, in areas, for example; energy performance, energy savings, and energy efficiency. In this regard, various DEA models were employed in different industries and sectors such as non-radial DEA (Djordjević et al., 2018), bootstrap DEA (Jebali et al., 2017), CCR (Hosseinzadeh Lotfi et al., 2010) models, DEA window analysis (Halkos and Polemis, 2018), directional distance function (DDF) (Lee and Choi, 2018), DEA-Malmquist (Jin et al., 2014), slacks-based DEA (Kuhn et al., 2018) , DEA-bargaining game (Tavana et al., 2018) network DEA (Badiezadeh et al., 2018) etc.

One of the challenges researchers face with is the lack of comprehensive methodology which would consider reliable data of all stages of lifecycle. One of the most explicit datasets is EcoInvent, (Färe R., Grosskopf S. (2004) it provides researchers and decision makers with trusted data on environmental effect from different technologies, e.g. electricity, waste treatment, consumption mixes, etc. For the case described in this article the following energy producing technologies had been chosen:

Table 1
Specific characteristics of energy technologies

Type of technology	Specific characteristics of the technology
Wind electricity production	< 1 MW onshore
	> 3 MW
	1-3 MW onshore
Biogas	heat and power co-generation, biogas, gas engine
Geothermal	deep geothermal
Photovoltaic	3kWp slanted-roof installation, multi-Si, panel, mounted
	3kWp slanted-roof installation, single-Si, panel, mounted

Source: EcoInvent database (Jin J., Zhou D., Zhou P. (2014)

EcoInvent database rests on CML 2001 methodology, which considers the following generalized eco-impact categories for each technology:

Table 2
Description of eco-impact categories

Eco-impact category	Description	Unit of measurement
acidification potential	The main chemical oxidants are SO2, NOx, HCl and NH3. Acid gases react with water in the atmosphere and thereby "acid rain" is formed. Increasing the oxidation potential is observed when fuel is burned for energy production. The oxidation potential is measured as the sum of the hydrogen ions produced per kg of matter bound to SO2	kg SO2-Eq
climate change	It is believed that the emissions of certain types of gases (carbon dioxide CO2, methane CH4, nitrous oxide N2O, fluorinated gases) cause a greenhouse effect, leading to climate change, desertification of lands, rising global ocean level, spread of diseases. As the reference gas, carbon dioxide	kg CO2-Eq
eutrophication potential	Eutrophication includes the potential effects of a high content of macronutrients in the environment, the most important of which are nitrogen and phosphorus. An increase in the nutrient content can cause an undesirable change in the composition of the species and an increase in biomass in both the aquatic and terrestrial ecosystems	kg NOx-Eq
freshwater aquatic ecotoxicity	The most toxic substances are heavy metals (hexavalent chromium, mercury, lead, nickel, copper, dioxins, barium and antimony). The effect of all elements is recalculated to the equivalent of dichlorobenzene 1,4-DCB, which has a harmful effect on human health, animals and plants	kg 1,4-DCB-Eq
freshwater sediment ecotoxicity		
marine sediment ecotoxicity		
marine aquatic ecotoxicity		
terrestrial ecotoxicity		
stratospheric ozone depletion	With the reduction of the ozone layer, a higher volume of ultraviolet radiation penetrates to the Earth's surface, which adversely affects the biosphere. The main factors of thinning the ozone layer are substances containing chlorine and bromine. All of them are associated with a representative substance for this category - CFC-11 trichlorofluoromethane	kg CFC-11-Eq

Source: authoring

When we try to evaluate the complex environmental efficiency, we face the problem of aggregation all disparate indicators of negative environmental effects and the calculation of an integral index. Such index would consider the importance of different categories of negative energy exposure for the environment. In case that the significance of all categories is identified, then this problem may be solved with the help of weighting coefficients method. Alternatively, when the significance of indicators is impossible to "weight", non-parametric methods can be applied, e.g. data envelopment analysis.

In this research we calculated the efficiency of different configurations within biogas, wind, geothermal and photovoltaic energy generation technologies. Input-oriented model, generalized eco-impact categories as a level of efficiency (output) were chosen for the DEA modelling.

It should be noted that the EcoInvent database does not yet have data on renewable energy facilities in Russia, with the exception of photovoltaic facilities, data on which was obtained by calculation. However, the purpose of the study is to compare technologies among themselves and their ratio will remain unchanged, when transferring estimates of the life cycle of renewable energy facilities to another territory. This allows us to use data obtained in other regions of the world, to extrapolate comparative assessments and make the choice of the most environmentally preferable technology.

The following countries of Central Europe were chosen for the analysis: Austria, Hungary, Germany, Poland, Czech Republic and Switzerland. The set of the countries was preconditioned by their geographical position, data availability and economical homogeneity of the region. As there are no countries with the access to sees or oceans, offshore wind technologies were not included into the set of DMUs.

MaxDEA 7 Basic was used to perform DEA modelling. We used radial input-oriented CCR-DEA with energy technologies as DMUs, EcoInvent indicators as the inputs and 1 as efficiency rate (output) of the model.

Some input parameters turned out to have extremely small number and, therefore, they were excluded from the DEA model. They are the following: 1) acidification potential; 2) eutrophication potential; 3) ionizing radiation: 4) photochemical oxidation (summer smog); 5) stratospheric ozone depletion. Therefore the inputs of the DEA model are: 1) climate change; 2) freshwater aquatic ecotoxicity; 3) freshwater sediment ecotoxicity; 4) human toxicity; 5) land use; 6) malodours air; 7) marine aquatic ecotoxicity; 8) marine sediment ecotoxicity; 9) depletion of bio – resources; 10) terrestrial ecotoxicity.

4. Results and discussion

The results of the model show that geothermal and biogas technologies are the most preferable from an environmental point of view, which is demonstrated through the highest possible score. The least effective technologies are both modification of PV with the minimum efficiency score.

Table 3
Efficiency score for each DMU (technology) Source?

DMU	Score
electricity production, wind, <1MW turbine, onshore, AT	0,7637
electricity production, wind, <1MW turbine, onshore, HU	1
electricity production, wind, <1MW turbine, onshore, DE	0,691544
electricity production, wind, <1MW turbine, onshore, PL	0,812307
electricity production, wind, <1MW turbine, onshore, CZ	0,683651
electricity production, wind, <1MW turbine, onshore, CH	0,727926
electricity production, wind, >3MW turbine, onshore, AT	0,763676
electricity production, wind, >3MW turbine, onshore, HU	1
electricity production, wind, >3MW turbine, onshore, DE	0,691479
electricity production, wind, >3MW turbine, onshore, PL	0,812246
electricity production, wind, >3MW turbine, onshore, CZ	0,618011
electricity production, wind, >3MW turbine, onshore, CH	0,618011
electricity production, wind, 1-3MW turbine, onshore, AT	0,763749
electricity production, wind, 1-3MW turbine, onshore, HU	1
electricity production, wind, 1-3MW turbine, onshore, DE	0,691554
electricity production, wind, 1-3MW turbine, onshore, PL	0,812358
electricity production, wind, 1-3MW turbine, onshore, CZ	0,683675
electricity production, wind, 1-3MW turbine, onshore, CH	0,727943
heat and power co-generation, biogas, gas engine, CH	1
heat and power co-generation, biogas, gas engine, AT	1
heat and power co-generation, biogas, gas engine, HU	1
heat and power co-generation, biogas, gas engine, DE	1
heat and power co-generation, biogas, gas engine, PL	1
heat and power co-generation, biogas, gas engine, CZ	1
electricity production, deep geothermal, AT	1
electricity production, deep geothermal, HU	1
electricity production, deep geothermal, DE	1
electricity production, deep geothermal, PL	1
electricity production, deep geothermal, CZ	1
electricity production, deep geothermal, CH	1
electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted, AT	0,250519

DMU	Score
electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted, CH	0,301026
electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted, CZ	0,226275
electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted, HU	0,301026
electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted, DE	0,241285
electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted, PL	0,26899
electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted, AT	0,249845
electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted, CH	0,25676
electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted, CZ	0,225668
electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted, DE	0,240636
electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted, HU	0,272588
electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted, PL	0,26827

In addition to the values of the efficiency measures, the main results of the calculations should also include the values of the target parameters of each input (in the case of an input-oriented model). In DEA Projection column demonstrates the value of the input at which the DMU becomes effective. For efficient DMUs the values of the target parameters are equal to the corresponding values of the inputs, for inefficient ones, they are always less than the real inputs.

Technology developers should strive to achieve target parameters, include them in R&D planning at the stage of a production system design developing, in environmental management plans at a production stage, etc. Moreover, the achievement of all target parameters at the same time is rarely possible, thus, it is necessary to choose a strategy in achieving those parameters, which either cost less or provide maximum progress towards the border of efficiency (Iosifov et al., 2017). Target values for each input (technology) can be found in Appendix A.

Results of the conducted study proved that deep geothermal and biogas technologies are in the group of the eco-efficiency leaders of Central Europe. There are also technologies of relatively high environmental performance (wind) and technologies of relatively low environmental performance (PV). This evidence may also be proved by the value of inputs, e.g. for “inefficient” PV technologies the values are higher for most input parameters.

5. Conclusions

Environmental DEA allows to select economic agents that produce maximum volumes of useful products with minimal negative impact on the environment in a country, especially in the countries of transition economies and Russia, which is vital when it comes to improving environmental management, identifying the best available technologies, estimate the level of development of eco-innovations in enterprises, etc.

Target parameters can significantly simplify the management process aimed at improving technologies, as well as the development of innovative wind and biogas technologies. Thus, as a result of the several studies obtained applied results which can be used for development of state and industry long-term energy strategies in Russian economy as well as in the transition economies cases in the context of constantly tightening environmental requirements. In addition, from methodological point of view, the presented algorithm of environmental analysis may be applied for extended technical economic analysis while designing innovation products with the advanced requirements for environmental friendliness. The results of the modelling may be useful for policy and decision makers in Russian and in transition economies, as well as for applying them while building environmental management system within an enterprise or for a region or a state.

Life-cycle approaches enrich DEA through appropriate criteria selection and quantification, while DEA enriches the interpretation phase of life-cycle studies providing easy-to-report environmental scores and benchmarks oriented towards decision-, energy- and eco- policy-makers.

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