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Evaluating environmental impacts of photovoltaic technologies using Data Envelopment Analysis

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Abstract. This study contributes to the literature by proposing a new method of complex evaluation of multiple life cycle environmental impacts of different PV technologies based on the Data Envelopment Analysis (DEA). The main advantage of DEA as a non-parametric technique is that it does not require prior knowledge of underlying production functions. An empirical production technology frontier is estimated based on best-practice boundary of the input-output relationship. DEA evaluates comparative or relative efficiency, which means the measurement with reference to some set of units we are comparing with each other. The proposed approach allows to aggregate disparate quantitative estimates of individual negative environmental effects from the literature and special databases in a transparent and easily understandable index or coefficient of ecology efficiency. The evaluation of environmental effects is performed on data from the EcoInvent Database. The results of this study clearly show that from an environmental point of view it is more practical to prefer technologies, which are less resource and energy intensive in manufacturing and upstream activities. As of right now, this requirement is met by thin-film technologies: amorphous silicon (a-Si), cadmium telluride (CdTe), and copper-indium-diselenide (CIS); however, their ecologic efficiency evaluation may change as we obtain more data on the final stages of the lifecycle for PV modules of various types. Our computational results show that 5 out of 19 PV technologies were identified as efficient compared to the other technologies against which they were assessed. CdTe, a-Si, and ribbon silicon laminated panels installed slanted-roof, CIS panel mounted slanted-roof, and open ground installation m-Si are demonstrated highest efficiency scores from an ecological point of view throughout the life cycle. Based on results of this study a number of opportunities for improving existing government incentives and rationalizing the design of state programs under elaboration can be identified.

Keywords: environmental impact categories; solar power; photovoltaic system; Life Cycle Assessment; Data Envelopment Analysis.

1. INTRODUCTION

Throughout the last decades, the global sales and installation of photovoltaic (PV) systems have grown rapidly. Annual installations of PV systems reached a record 98 GW in 2017, while global total installations attained 402 GW [37]. Although PV-technologies have very low environmental and human health impacts compared to conventional electricity generation, the processes of manufacturing, transportation, installation, and disposal of PV-modules are associated with significant energy consumption, usage of working fluids containing chlorates and nitrites, formation of sewage and other negative environmental effects that need to be considered.

At present, several photovoltaic technologies are being developed in the world: monocrystalline silicon, polycrystalline (multicrystalline) silicon and thin-film. It is well known,

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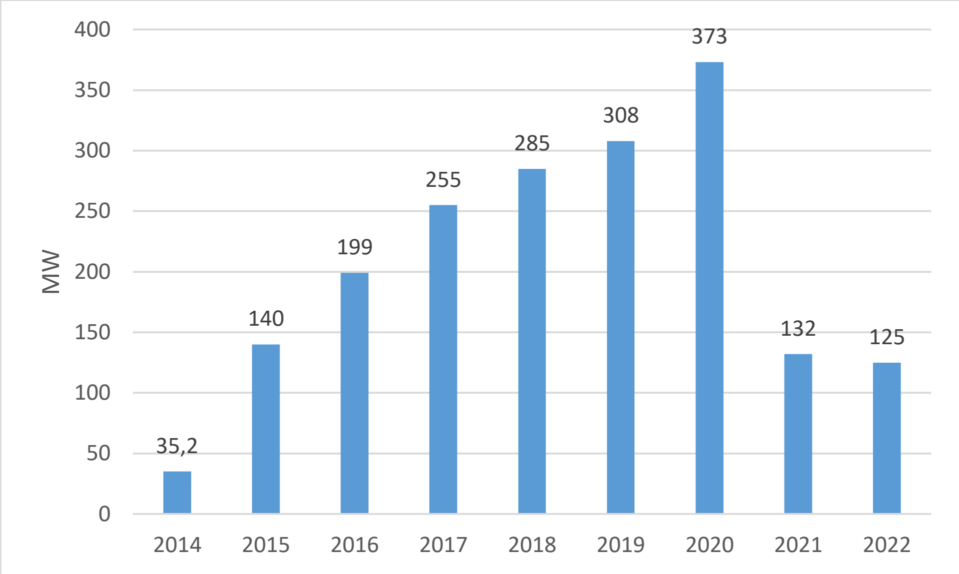
that silicon wafer manufacturing process is very energy intensive. Mono-crystalline cells require up to 1000 kWh/kg-Si and poly-crystalline cells' production needs up to 700 kWh/kg-Si [11]. Manufacturing of silicon-based PV cells is accompanied by emissions of such hazardous materials as silica dust, silanes, diborane, phosphine, and solvents. Heterojunction solar cells (SHJ) are produced from silicon wafers in a low-temperature process that does not exceed 200 °C, thus, the energy intensity of the manufacturing process and, consequently, its environmental impact should be lower. Besides, a low-temperature coefficient of SHJ cells leads to higher energy yields compared to conventional c-Si modules [29]. However, there is as of yet no precise data on the environmental effects of this technology over the whole life cycle due to its relative novelty.

It is also known, that mining cadmium and manufacturing CdTe solar cells can cause occupational health risks. Some questions also remain regarding the toxicity of PV modules' disposal [18,19]. Therefore, the environmental issues of cadmium telluride PV cells and module production and utilization are still under discussion. Tellurium is also considered as a rare earth element, so the problem of resource constraints must also be taken into consideration when choosing this technology [36].

The main negative environmental impacts of manufacture of copper indium gallium selenide (CIGS) photovoltaic cells, as is reported in [2] are connected with up-stream activities including extraction and processing of primary materials. For example, the extraction and processing of silver, which is needed for stringer and screen printing processes, is accompanied with emissions of toxic heavy metals such as mercury, lead, and arsenic. The mining of copper (used in the cable for the balance of the system and in co-production of selenium, gallium, and indium) is potentially associated with the exposure of radioactive materials. Such manufacturing processes as energy-intensive co-evaporation needed for to production of the CIGS layer and water-intensive surface washing of the cell's substrate also affect negatively on the environment. Another issue that needs to be considered is the scarcity of indium, which can restrict the production process [34].

Until recently, the choice between industrial developments of a particular technology was carried out, mainly, by two criteria: cost and efficiency (or energy conversion coefficient). However, with the growth of production capacities around the world, the ecological aspects, such as the emission of pollutants by production facilities into the air, water and soils, the consumption of rare earth metals, water, energy, etc., become more important when choosing a particular technology for development and support through multiple government policies. This problem become more relevant for Russia with the booming developing of PV-industry in recent years [5-6, 33].

With the enactment in 2013 of new government's renewable energy support scheme focusing on grid-connected power generation facilities more than 5 MW, the process of construction and connection of such facilities to the Federal Grid Company has notably intensified. In 2013–2018 period, more than 100 solar generation projects of a total capacity of 1.852 GW were selected for a subsequent support (Fig. 1).



Source: own calculations

Fig. 1. Planed PV-installations on the wholesale market supported by the State program in the framework of the Government Decree No. 449 (28 of May, 2013)

An important feature of the renewable energy support programs introduced in Russia is the high production localization index, which must be achieved in the project in order to be selected for financial support. Such support conditions are aimed at creating in the country own full-cycle production of photovoltaic modules and other types of equipment for renewable energy.

The active development of new PV-manufacturing technologies and the current and future increase in production volumes boost the relevance of the problem of estimating and predicting the possible negative environmental effects of photovoltaics at all stages of the life cycle: production, operation, and disposal.

Currently, life cycle assessment (LCA) followed the International Standards Organization (ISO) 14040 series is a mature methodology and a valuable tool for providing a comprehensive “cradle-to-grave” view of the environmental loads of a technology. It is often used for comparative analysis of manufacturing alternatives and optimization of product system design. Due to the fact, that a full life cycle assessment is usually a time-, energy-, and data-intensive process requiring sophisticated methodology, many scholars prefer to use a simplified approach and quantify only Greenhouse Gas (GHG) performance of the technology or product under consideration, though for each product this specific type of environmental influence is the most significant.

Current papers on life cycle assessment of PV technologies can be divided into three groups. The papers of the first group focus on detailed analysis of one or several types of negative ecologic effects of specific types of PV-technologies. For example, Hsu et al. [22] shows an analysis of GHG emissions from solar c-Si PV LCA. Kim [25] evaluates the same type of environmental impact from thin-film PV LCA. The research [20] analyzes and obtains estimates for CO_2 emissions and embedded energy of a hybrid photovoltaic–thermal module. Fthenakis [19] evaluates atmospheric Cd emissions from the life-cycle of CdTe models. The [28] research shows a very wide set of environmental impacts for new marine PV-technologies, including besides GHG emissions such categories as acidification potential, eutrophication, ecotoxicity, human toxicity, depletion of abiotic resources, terrestric ecotoxicity potential, and photochemical ozone creation potential. Results of these papers improve upon the existing knowledge on the influence of new technologies on the environment.

The second group compares multiple PV-technologies between each other or between other renewable energy technologies based on a specific category on environmental influence. Most of the time the researched category is the GHG emissions. For example, the study [2] compares in detail the environmental influence from the production of two thin-film photoelements based on

$Cu(In,Ga)Se_2$: in particular, whether the use of zinc oxysulfide (Zn(O,S)) or cadmium sulfide (CdS) minimizes the GHG emissions during the production of photoelements through screen printing and stringer. Paper [3] summarizes the results of over 75 researches performed via life cycle assessment (LCA) and focusing on GHG emissions for electricity and heat generation from photovoltaic, solar thermal, onshore and offshore winds, hydropower, marine technologies (wave power and tidal energy), geothermal, biomass, waste, and heat pumps. The results of these papers may be used to improve the production chain, choose better designs for production systems, as well as make decisions on regional and national government levels to support one type of technology over another. However, for a full comparison of the ecologic influence of different technologies one must evaluate not just one (perhaps important) category of environmental influence, but the entire range of negative ecologic effects.

Hence, in modern literature the amount of works, which compare PV-technologies against each other or other renewable energy tech with multiple environmental influence categories in mind, is constantly increasing. Furthermore, these comparisons can be performed both separately and using various aggregate indicators. For example, [27] low-concentration PV and conventional PV are compared separately in the climate change (GHG emissions), acidification potential, eutrophication potential, human toxicity, and ozone layer depletion categories. The same approach is used in [30], where mc-Si, InGaP and InGaP/mc-Si solar modules are compared in climate change, abiotic resource depletion, acidification, human toxicity, and fresh water ecotoxicity separately. In [41] one can find a comparative analysis of environmental impacts of organic and conventional PV-technologies completed using ReCiPe v1.0.5 midpoint (H) impact categories. Celik et al. [7] shows an aggregate indicator of toxicity (toxicity for humans, ecotoxicity of sea and freshwater, ecotoxicity of sea and freshwater bottom sediments), which is used to compare conventional Si PV technologies and perovskite solar cells. Paper [34] investigates GHG emissions, embedded energy and presents an aggregate indicator for environmental influence: the normalized environmental impact (eco-points) of several popular silicon-based PV technologies.

In the case that several environmental effects are taken into consideration for comparison of designs of products or manufacturing processes, another important research question arises: which of these negative environmental impacts are more important and how should it be accounted for?

This study contributes to the literature by proposing a new method of complex evaluation of multiple life cycle environmental impacts of different PV technologies based on the data envelopment analysis (DEA). DEA is a methodology for evaluating the relative performance of a set of homogeneous units, which transform multiple inputs into multiple outputs [9]. The main advantage of DEA as a non-parametric technique is that it does not require prior knowledge of underlying production functions. An empirical production technology frontier is estimated based on best-practice boundary of the input-output relationship. DEA evaluates comparative or relative efficiency, which means the measurement with reference to some set of units we are comparing with each other. The efficiency score has a clear economic meaning. It shows how much the DMU should reduce its resources or increase its outcome to become efficient.

Since DEA was first introduced, there have been a large number of papers written on DEA or applying this methodology on various sets of managerial, operational and economic problems. Today DEA is not only a tool for technical-efficiency analysis but also an increasingly popular performance management tool for benchmarking in many areas of research including energy sector [15].

The evaluation of environmental effects is performed on data from the EcoInvent Database which is currently one of the most reliable and complete information resources for a significant number of industrial products. The paper's added value as compared to above-mentioned research consists in the following: a) the work takes into account a much wider range of negative environmental effects; b) the developed method of their complex comparison allows to rank the technology according to the degree of aggregated environmental impact, as well as to determine the target parameters for reducing negative environmental effects. First attempts to apply DEA to the problem of choosing the most ecologically efficient solar power technologies has been made in an earlier work of one of the authors [35], and it is thanks to that we could prove the applicability of this approach to compare different photovoltaic technologies from the environmental perspective. However, during the last year data on photovoltaic technology has significantly expanded and updated thanks to progress both in R&D and in production. Besides that, the aforementioned paper has shown a suboptimal choice of indicators of environmental impact: some impact categories haven't been accounted for in the analysis. In [35] we also compared ecologic impact of photovoltaic technology without considering the method of solar panel installation which could have distorted the results of the analysis. This paper addresses and eliminates these issues, and considers the newly-attained results from a perspective of policy applications.

The remainder of the paper is organized as follows: section 2 provides an overview of LCA methods, used in the EcoInvent Database, and explains the choice of datasets and impact categories, which we used in the evaluation of PV-technologies. It also provides insight into the methodology (DEA). In Section 3 we discuss the results of the DEA-based evaluation of modern PV technologies and the possibilities to develop a proposed approach for management applications as well as its limitations. Section 4 concludes and offers policy recommendations.

2. DATA AND METHODOLOGY

In rest of the paper we use the following abbreviations for PV technologies and types of PV-installations:

PV technologies

a-Si amorphous silicon
CdTe cadmium telluride
CIS copper-indium-diselenide
m-Si multicrystalline silicon
r-Si ribbon silicon
s-Si singlecrystalline silicon

PV-installations

FI facade installation
FRI flat-roof installation
LI integrated laminate
OGI open ground installations
PM mounted panel
SRI slanted-roof installation

In this study, we used the data from the EcoInvent database (a non-profit association of research organizations in Switzerland) for assessment of the environmental impact of the photovoltaic life cycle. Currently, EcoInvent is the world's leading Life Cycle Assessment (LCA) database compliant with the ISO 14040-14044 standards and contains life-cycle data sets of more than 12,800 products and services [31]. It is important to emphasize that the Ecoinvent database is not simply a library of individual LCA datasets. The data are interrelated in such a way that all semi-finished products, input streams, electricity consumption, demand for raw materials and materials and equipment requirements depend on sub-processes of production and delivery of semi-finished products and services for product redistribution. Thus, LCA results are calculated in a matrix system, so that any update in one set of process data will affect the accumulated LCA results in all other connected data sets.

Version 3.3 (2016) of the database contains 356 datasets on photovoltaic energy, from which 227 datasets are devoted to electricity production, 43 – to transportation of semi-finished products such as mounted systems, cells, panels, modules, wafers and single crystals of silicon, 3 – to cell and panel factory contraction, 32 – to installations, 10 – to cell/panel production, 12 – to laminate production, 2 – to single wafer production, 2 – to single crystal production, 10 – to panel production, 7 – to mounting system production and 4 – to treatment of waste form silicon cells and panel production. Each data set of environmental effects includes effects from all upstream activities under evaluation, therefore the consideration of last activity in a production chain is sufficient. There are no datasets in the database devoted to disposal and recycling of PV models and panels because even the earliest PV-installations considered in the database are still in operation. Lifecycle ends with low voltage electricity produced with the 3 kWp module, assuming an average yield.

The 3 kWp module has been chosen in most of the datasets devoted to electricity production as the basic module for building integrated PV electricity production, due to the fact that larger modules can easily be built with 3 kWp modules without producing a significant error in environmental impact calculations. The datasets represent several mature PV technologies: multicrystalline silicon (m-Si), singlecrystalline silicon (s-Si), amorphous silicon (a-Si), cadmium telluride (CdTe), copper-indium-diselenide (CIS), and ribbon silicon (r-Si). The modules made of m-Si, s-Si, a-Si, and r-Si can be installed of different parts of the building (facade installation (FI), flat-roof installation (FRI) or slanted-roof installation (SRI)) as an integrated laminate (LI) of a mounted panel (PM). The modules made of CdTe can be installed in the form of integrated laminate only while CIS models only in the form of a mounted panel. Besides this, the database contains several datasets for 570 kWp m-Si open ground installations (OGI). Thus, we have different production chains specified by the cells and module production technologies, form and place of installation. The referent product in all datasets on electricity production is low voltage 1 kWh[1]. The simplifying assumption was made in all datasets that all electricity is directly provided as low voltage electricity so that no transformation has to take place. The lifetime of all PV modules is supposed to be 30 years.

In order to compare energy technologies, we need to choose the datasets, yield (or calculated by extrapolation of field data) for the same geographic location, which is characterized by the value of specific solar yield in kWh per kilowatt peak installed. Since the most reliable statistical data in the database is collected for Switzerland (the longest period of observation), we chose data on various options (19 total) for electricity production using photovoltaic installations in this geographic location (Table 1). One should note that this dataset can be used for comparison of energy technologies only, but not for assessment of average production patterns in different geographic locations, for example, in Russia.

Table 1. Comparing electricity production options for Switzerland

Option	Period of observation
3kWp FI m-Si LI	2005-2016
3kWp FI m-Si PM	2005-2016
3kWp FI s-Si LI	2005-2016
3kWp FI s-Si PM	2005-2016
3kWp FRI m-Si	2005-2016
3kWp FRI s-Si	2005-2016
3kWp SRI a-Si LI	2005-2016
3kWp SRI a-Si PM	2005-2016
3kWp SRI CdTe LI	2005-2016
3kWp SRI CIS PM	2005-2016
3kWp SRI m-Si LI	2005-2016
3kWp SRI m-Si PM	2005-2016
3kWp SRI m-Si PM label-certified	2010-2016
3kWp SRI r-Si LI	2005-2016

[1] Although it is known that large central photovoltaic power stations in the higher kilowatt to megawatt range can feed directly into the medium- or high voltage grid, in order to treat all photovoltaic installations the same way, low voltage electricity is assumed as a product in this dataset

3kWp SRI r-Si PM	2005-2016
3kWp SRI s-Si LI	2005-2016
3kWp SRI s-Si PM	2005-2016
3kWp SRI s-Si PM label-certified	2010-2016
570kWp OGI m-Si	2008-2016

Life cycle impact assessment can be carried out using several indicator methods, which differ from each other in the spectrum of considered environmental impact categories. The latest version of EcoInvent uses 13 basic methods, of which, according to our opinion, CML2001 is the most complete and informative. This method was developed by Center of Environmental Science of Leiden University and published in 2001 as a new operational guide for implementation of ISO environmental management standards [21]. In addition to such basic categories of environmental impact as greenhouse gas emissions, this method takes into account many other negative environmental effects. According to [8] it gives more accurate estimates of chemical impacts on human health. Main impacts on the environment, according to CML2001 method can also be considered at different time horizons. Table 2 summaries impact categories, covered in CML2001, their indicators and measure units.

Table 2. CML2001 environmental impact categories and their indicators

Impact category group	**Name of the impact category in the method**	**Unit**
Acidification	Acidification potential - average Europe Acidification potential – generic	kg SO_2-Eq
Climate change	Climate change - GWP100 Climate change - GWP20 Climate change - GWP500 Climate change - lower limit of net GWP100 Climate change - upper limit of net GWP100	kg CO_2-Eq
Depletion of abiotic resources	Depletion of abiotic resources - elements, economic reserve Depletion of abiotic resources - elements, reserve base	kg antinomy-Eq
Ecotoxicity	Freshwater aquatic ecotoxicity - FAETP infinitive Freshwater aquatic ecotoxicity - FAETP100 Freshwater aquatic ecotoxicity - FAETP20 Freshwater aquatic ecotoxicity - FAETP500 Freshwater sedimental ecotoxicity - FSETP infinitive Freshwater sedimental ecotoxicity - FSETP100 Freshwater sedimental ecotoxicity - FSETP20 Freshwater sedimental ecotoxicity - FSETP500 Marine aquatic ecotoxicity - MAETP infinitive Marine aquatic ecotoxicity - MAETP100 Marine aquatic ecotoxicity - MAETP20 Marine aquatic ecotoxicity - MAETP500 Marine sedimental ecotoxicity - MSETP infinitive Marine sedimental ecotoxicity - MSETP100 Marine sedimental ecotoxicity - MSETP20 Marine sedimental ecotoxicity - MSETP500	kg 1,4-DCB-Eq

	Terrestrial ecotoxicity - TETP infinitive Terrestrial ecotoxicity - TETP100 Terrestrial ecotoxicity - TETP20 Terrestrial ecotoxicity - TETP500	
Eutrophication	Eutrophication - generic Eutrophication - average Europe	PO_4-Eq NO_x-Eq
Human toxicity	Human toxicity - HTP infinitive Human toxicity - HTP100 Human toxicity - HTP20 Human toxicity - HTP500	kg 1,4-DCB-Eq
Ionising Radiation	Radiation	DALYs
Land use	Land use - land competition	m2a
Odour	Odour (malodours air)	m3 air
Ozone layer depletion	Ozone layer depletion - ODP steady state Ozone layer depletion - ODP10 Ozone layer depletion - ODP15 Ozone layer depletion - ODP20 Ozone layer depletion - ODP25 Ozone layer depletion – ODP30 Ozone layer depletion – ODP40 Ozone layer depletion - ODP5	kg CFC-11-Eq
Photochemical oxidation (summer smog)	Photochemical oxidation - EBIR (low NOx) Photochemical oxidation - high NOx Photochemical oxidation - low NOx Photochemical oxidation - MIR (very high NOx) Photochemical oxidation - MOIR (high NOx)	kg formed ozone kg ethylene-Eq kg ethylene-Eq kg formed ozone kg formed ozone

Some of the environmental effects of photovoltaics presented in Table 2 (such as ionising radiation, ozone layer depletion, and photochemical oxidation) are negligibly small (less than 1×10^{-8}), therefore, in order to compare the various variants of electricity generation with solar cells, we chose the following impact categories: acidification potential, climate change, eutrophication potential, ecotoxicity (all types), land use, malodorous air and depletion of abiotic resources. The duration of the impact/accumulation of each negative ecological effect was set to 100 years (medium-term period). All input data for comparative analysis of different PV-technologies is presented in Table A.1, see Appendix A.

For complex evaluation of multiple life cycle environmental impacts of different PV technologies we use Data Envelopment Analysis (DEA). Based on the work initiated by Farrell [16], Charnes, Cooper and Rhodes [9] developed linear programming technique now called DEA to estimate a production frontier. It is a tool to evaluate the relative efficiency of a set of homogeneous decision making units (DMU). In traditional DEA models, each DMU is assumed to be a black-box whose internal structure is not considered, i.e. DMU is regarded as the entity responsible for converting inputs into outputs and whose performances are to be evaluated. In the energy sector, DMUs can be, for instance, manufacturing plants, power plants, power distribution divisions etc. In this paper we consider a number of selected combinations of PV technology and installation method having common input and environmental outputs as distinct DMUs.

In DEA model, the relative efficiency score of any DMU is determined as a measure of the relative improvements in inputs and outputs between the DMU and its assigned target. In order to provide relative comparisons, a collection of DMUs is used to evaluate each DMU against each other. The efficiency score can be assessed by minimization of input keeping its output levels constant (input-oriented model), or by maximization of output keeping the inputs at the same rate (output-oriented model) [40].

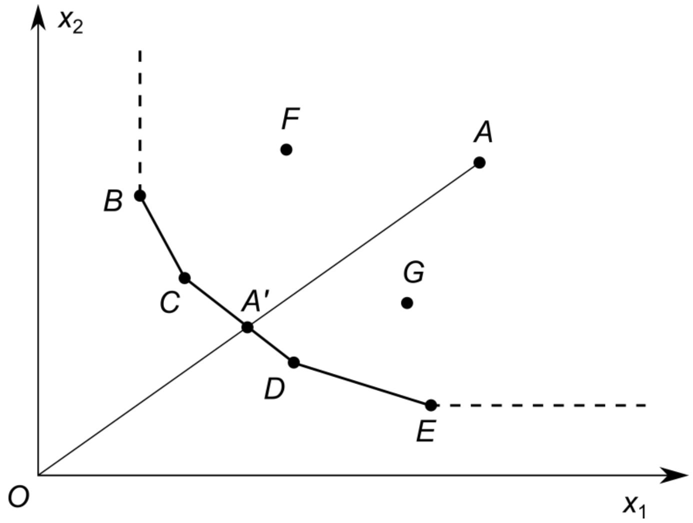


Fig. 2. Efficiency evaluation in DEA approach

Fig. 2 explains the basic idea of DEA approach for efficiency evaluation. Points *A*-*G* are the set of DMUs under assessment. Units *B*-*E* are efficient, they form efficient frontier *BCDE* against which other inefficient units are assessed. The efficiency score of inefficient unit *A* can be measured relative to the projection *A'* obtained by simultaneous minimization of inputs. The ray from the origin shows the direction of radial projection of unit *A* onto efficient frontier. Thus, the radial input efficiency score of unit *A* is equal to *OA'/OA.*

Selection of inputs and outputs plays important role in benchmarking studies using DEA [12]. The inputs and the outputs should reflect the resources utilized by the DMUs and its production, respectively. DEA environmental assessment usually considers both desirable and undesirable outputs to assess the performance of DMUs. See for example, Sueyoshi and Goto [39], Zhou et al. [43], Førsund [17]; Wang et al. [42], etc.

In this study, all environmental impact categories are treated as undesirable outputs, and desirable output is electricity production. We also assume that the maintenance costs per 1 kWh for all PV technologies are the same, and therefore input parameters are not considered. For this reason, we consider environmental impacts (undesirable outputs) as inputs in the efficiency evaluation process [39]. Since all environmental impact indicators are provided per 1 kWh electricity production, no return to scale assumption is needed. Therefore, the DEA model chosen in this work to identify the efficient frontier is CCR model introduced by Charnes et al. [9] based on constant return to scale assumption. The basic motivation of the paper is to compare the performance of PV technologies under minimization of environmental impacts, hence input oriented CCR model is chosen. The input-oriented CCR model is written as:

$$\theta_o = \min \theta - \varepsilon \left\{ \sum_{k=1}^{m} s_k^- + \sum_{i=1}^{r} s_i^+ \right\}$$

$$\theta x_{ko} - \sum_{j=1}^{n} x_{kj}\lambda_j - s_k^- = 0,\ k = 1,\ldots,m \qquad (1)$$

$$\sum_{j=1}^{n} y_{ij}\lambda_j - s_i^+ \geq y_{io},\ i = 1,\ldots,r$$

$$\lambda_j \geq 0,\ j = 1,\ldots,n\,,$$

where n is the number of DMUs,

m is the number of inputs,
r is the number of outputs,
$X_j = (x_{1j},\ldots,x_{mj})$ is the vector of inputs of DMU$_j$,
$Y_j = (y_{1j},\ldots,y_{rj})$ is the vector of outputs of DMU$_j$, and
(X_o,Y_o) is the vector of inputs and outputs of DMU$_o$ under evaluation,
θ_o, optimal objective function, is the relative efficiency score of DMU$_o$, $1 \le o \le n$,
λ_j, $j = 1,\ldots,n$, are the coefficients of linear combination for assessing DMU$_o$;
$s_1^-,\ldots,s_m^-$ and $s_1^+,\ldots,s_r^+$ are slacks variables,
ε is an infinitesimal constant (a non-Archimedean quantity).

We can avoid handling ε, but then problem (1) has to be solved in two stages [9]. Next, we assume that each model is solved in this way. DEA efficiency scores θ_o are evaluated as the distance from the DMUs to the efficient frontier. From the model formulation, it follows that $0 < \theta_o \le 1$. If efficiency score $\theta_o = 1$, and optimal slacks $S^{-*} = (s_1^{-*},\ldots,s_m^{-*})$ and $S^{+*} = (s_1^{+*},\ldots,s_r^{+*})$, then DMU$_o$ is efficient; if optimal solution satisfies $\theta_o = 1$, then DMU$_o$ is weakly efficient; units with $\theta_o < 1$ are inefficient.

3. RESULTS AND DISCUSSION

Model (1) is solved in the present paper using FrontierVision software [26] that calculates relative efficiency scores and target impacts. The efficiency scores reported in Table 3 show that 5 out of 19 DMUs were identified as efficient compared to the other DMUs against which they were assessed. CdTe, a-Si, and r-Si laminated panels installed slanted-roof, CIS panel mounted slanted-roof, and open ground installation m-Si are demonstrated highest efficiency scores from an ecological point of view throughout the life cycle.

Table 3. Efficiency scores

Installation method, PV technology	Eff. score, %
3kWp FI m-Si LI	65.76
3kWp FI m-Si PM	61.20
3kWp FI s-Si LI	64.20
3kWp FI s-Si PM	59.19
3kWp FRI m-Si	92.77
3kWp FRI s-Si	90.61
3kWp SRI a-Si LI	100.00
3kWp SRI a-Si PM	85.32
3kWp SRI CdTe LI	100.00
3kWp SRI CIS PM	100.00
3kWp SRI m-Si LI	98.75
3kWp SRI m-Si PM	80.79
3kWp SRI m-Si PM label-certified	90.31
3kWp SRI r-Si LI	100.00
3kWp SRI r-Si PM	91.81
3kWp SRI s-Si LI	97.49
3kWp SRI s-Si PM	77.81
3kWp SRI s-Si PM label-certified	87.42
570kWp OGI m-Si	100.00

Table 3 shows that slanted-roof installations are more efficient than flat-roof installations. Facade installations have the lowest efficiency scores. This result is quite expected and can be explained by the fact that a tilt angle of a slanted roof is close to the local latitude in Switzerland (46°N average) and thus allows to harvest the maximum amount of solar radiation on an annual basis [10] and, therefore, produce more electricity for its lifespan. Also, it should be noted that laminated integrated panels are more ecologically efficient in comparison with mounted panels. It can be explained by the absence of aluminum frame and some other construction details due to integration straight into the roof, which leads to exclusion from the life cycle of several production activities.

The higher efficiency of 570 kWp open ground PV plant is also an expected result due to the fact that the system on the ground has more airflow to cool down the panels and, thus, to keep up an optimal temperature for PV modules' operation and to extend its carrying capacity and increase its overall electricity production [38].

Comparing the ecological effectiveness of s-Si, m-Si and thin-film PV technologies (CdTe, CIS, a-Si), we can see that the mean of efficiency scores of single-Si modules for different installation methods is 79.45%, the mean of multi-Si is 81.6% and the mean of thin-film PV is 96.33% (see Tables 4-6).

Table 4. Efficiency scores for s-Si technology

Installation method, PV technology	**Eff. score, %**
3kWp FI s-Si LI	64.20
3kWp FI s-Si PM	59.19
3kWp FRI s-Si	90.61
3kWp SRI s-Si LI	97.49
3kWp SRI s-Si PM	77.81
3kWp SRI s-Si PM label-certified	87.42

Mean score 79.45%

Table 5. Efficiency scores for m-Si technology

Installation method, PV technology	**Eff. score, %**
3kWp FI m-Si LI	65.76
3kWp FI m-Si PM	61.20
3kWp FRI m-Si	92.77
3kWp SRI m-Si LI	98.75
3kWp SRI m-Si PM	80.79
3kWp SRI m-Si PM label-certified	90.31

Mean score 81.60%

Table 6. Efficiency scores for thin-film technologies

Installation method, PV technology	**Eff. score, %**
3kWp SRI a-Si LI	100.00
3kWp SRI a-Si PM	85.32
3kWp SRI CdTe LI	100.00
3kWp SRI CIS PM	100.00

Mean score 96.33%

It is important to understand that these results cannot be explained by PV cells or module efficiency, traditionally measured as percentage of the incident solar energy that the PV cell converts into electricity under the standard rating conditions (Table 7), and correspond mainly to resource and energy intensity of production processes [10-11]. Therefore, the bigger amount of energy produced by silicon-based PV systems in the exploitation period comparing the amount of energy produced by thin-film PV systems does not compensate the negative ecological effects of upstream processes.

Table 7. Cell/module efficiency for different PV technologies [13, 31-32]

PV technology	Cell efficiency (%)	Module efficiency (%)
s-Si	15.3	14.0
m-Si	14.4	13.2
r-Si	13.1	12.0
a-Si	6.5	6.5
CdTe	10.9	10.9
CIS	10.7	10.7

Comparing the results obtained by DEA-approach with the results of simple ranking of PV-technologies by one of the indicators of environmental or energy efficiency (see table 8), it can be noted that the technology performance indicator calculated by the DEA-model, although correlated with the ratings for Energy Pay Back Time, GHG emissions and Human Toxicity, overall gives a more consistent and balanced result.

Table 8. Ranks of PV-technologies according to DEA model (own calculation), Energy Pay-Back-Time [23], GHG-emissions (EcoInvent, version 3.3) and Human Toxicity (EcoInvent, version 3.3.)

Installation method, PV technology	Rank on eff.score	Rank on EPBT	Rank on GHG	Rank on HT
3kWp FI m-Si LI	12	9	16	17
3kWp FI m-Si PM	14	9	17	19
3kWp FI s-Si LI	13	10	18	16
3kWp FI s-Si PM	15	10	19	18
3kWp FRI m-Si	4	6	7	6
3kWp FRI s-Si	6	8	13	5
3kWp SRI a-Si LI	1	n/a	2	12
3kWp SRI a-Si PM	9	5	10	15
3kWp SRI CdTe LI	1	2	1	11
3kWp SRI CIS PM	1	3	4	7
3kWp SRI m-Si LI	2	n/a	5	3
3kWp SRI m-Si PM	10	4	12	14
3kWp SRI m-Si PM label-certified	7	n/a	8	10
3kWp SRI r-Si LI	1	n/a	3	2
3kWp SRI r-Si PM	5	1	6	8
3kWp SRI s-Si LI	3	n/a	11	4
3kWp SRI s-Si PM	11	7	15	13
3kWp SRI s-Si PM label-certified	8	n/a	14	9
570kWp OGI m-Si	1	n/a	9	1

In addition, the DEA solution also allows obtaining target values for each indicator of the environmental impact for each inefficient PV technology. The target impacts for each of the inefficient PV technology were calculated according to the following equation:

$$x_{ko}^{*} = \sum_{j=1}^{n} \lambda_j^{*} x_{kj}, \quad k = 1, \dots, m, \tag{3.1}$$

where λ_j^* , $j = 1,\dots,n$ are optimal λ-variables in problem (1). The values of the target impacts are presented in Table A.2, see Appendix. Knowledge of the target parameters that each of the photovoltaic technologies needs to achieve in order to become efficient in environmental terms can significantly simplify the process of managing applied research aimed at improving these technologies, as well as developing new photovoltaic technologies, such as organic PV.

Table 9 presents a summary of peer frequency, i.e. number times each efficient PV technology is a peer for another. A sum of peer weights is calculated for each efficient DMU_k as a sum of variables λ_k^* in optimal solutions of problem (1) for all inefficient DMUs excluding DMU_k.

Table 9. Peer count summary

Installation method, PV technology	Peer frequency	Sum of peer weights
3kWp SRI a-Si LI	6	1.96
3kWp SRI CdTe LI	7	0.98
3kWp SRI CIS PM	0	0
3kWp SRI r-Si LI	13	10.83
570kWp OGI m-Si	13	0.23

Note that DMUs 3kWp SRI r-Si LI and 570kWp OGI m-Si are the peers for 13 inefficient technologies. However, first technology is more valuable because the sum of its weights is much greater. This means that this technology is closer to efficient targets of inefficient units than another. On the contrary, 3kWp SRI CIS PM technology is the self-evaluator peer according to the classification of Edvardsen et al. [14], because it only references itself.

Since all types of studied PV technologies are still under research and development, it is reasonable to consider the different technical possibilities to reach target indicators and make prevalent technologies more environmentally efficient. It will require deeper analysis for each of the environmental impacts considered at various stages of the life cycle. It is also necessary to mention that all obtained results so far do not include the environmental impacts of PV-systems' disposal due to the lack of primary data. The inclusion of such downstream stages of the life cycle as disposal and recycling can change the environmental efficiency estimates of PV-technologies in the future and proactive planning for a PV recycling infrastructure can contribute to the ecological efficiency of each technology.

4. CONCLUSIONS AND POLICY APPLICATIONS

A number of opportunities for improving existing government incentives and rationalizing the design of state programs under elaboration can be identified based on results of this study. Our evaluations of the complex ecologic efficiency of several commercially successful PV technologies may be used for developing various state programs for supporting PV equipment manufacturers in Russia and in other countries, which are just starting their own production of PV modules. The currently existing approaches to stimulation do not differentiate between technologies, leaving a choice to the customer, and most customers prefer PV modules with a higher cell efficiency. A change is necessary in the current order for sustainable development. The results of this study clearly show that from an environmental point of view it is more practical to prefer technologies, which are less resource and energy intensive in manufacturing and upstream activities. As of right now, this requirement is met by thin-film technologies (a-Si, CdTe, and CIS);

however, their ecologic efficiency evaluation may change as we obtain more data on the final stages of the lifecycle for PV modules of various types.

Considering the issue of the installation method of PV modules, open ground installations remain preferable. In this regard, the existing state support system for photovoltaics in Russia, which focuses on large power plants with capacities above 5 MW, is logical and can be deemed successful. While developing new microgeneration state support programs, it is reasonable to prefer slanted-roof installations and laminated integrated panels. Stimulating the population to use these specific installation types for PV systems can be done both via standardization and certification (for example, municipal standards for installation of solar panels), as well as via special educational events and training programs.

R&D support programs in the field of solar energy can also be constructed in a way that stimulates not just research targeting the growth of cost-competitiveness and energy efficiency of photovoltaics, but also improvement of their environmental efficiency. In the near future, we can use target environmental impacts, obtained in this research as benchmarks for emerging each of the currently existing, commercially viable PV technologies, which are presented in this study. As technologies develop and new data on their environmental impacts is obtained, these target parameters may be re-calculated using the herein suggested DEA approach.

Despite the fact that abovementioned practical conclusions have independent scientific value for environmental management, the main contribution of our research is the development of a method for the integrated assessment of the negative impact of renewable technology on the environment for the widest possible range of ecology effects taken into account. The combined LCA and DEA approach is proposed for a first time, therefore the paper expands the scope of practical applications of the popular decision-making methodology such as DEA.

The main advantage of proposed method of integrated assessment of the negative impact of PV-technologies on the environment during entire life cycle is its scalability: it is easy to integrate into the calculations both a greater number of new technologies and more identified environmental effects. Even for a large number of studied technologies and a large number of categories of environmental impact, there is still the possibility of ranking alternatives.

The main limitation of this study is the lack of empirical data on environmental impacts of new PV-technologies, which are only entering the stage of mass production: most importantly, heterojunction solar technologies, being developed by the biggest Russian PV-manufacturer Hevel Group. This problem opens a further area of research, which, however, can be easily integrated into the proposed approach of relative complex environmental efficiency evaluation.

Another limitation is connected with the lack of discrimination capability for efficient DMUs classical DEA models. Because of this, several technologies can have the highest rank in integrated environmental efficiency at the same time. As one can see in our study 5 technologies are classified as efficient ones. Therefore, complete ranking is not possible with CCR model. In order to generate a complete ranking of DMUs, many theoretical extensions of basic DEA models have been proposed by various researchers. A recent survey on complete ranking methods in DEA can be found in [1]. Each approach has their own strength and weaknesses and detailed discussion on those methods is beyond the scope of the present paper. We assume that further choice between eco-efficient PV technologies can be made using one of DEA ranking methods or with the help of traditional instruments of technical and economic analysis.

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APPENDIX A

Table A.1. Input data for comparative analysis

Installation method, PV technology	SO2-eq (gen)	GWP-100a	NOx-eq	POx-eq	FAETP100a	FSETP100a	HTP100a	Land	Air	MAETP100a	MSETP100a	Resources
3kWp FI m-Si LI	0.00080479	0.11721	0.00036814	0.00040589	0.27186	0.63365	0.18929	0.009284	1388.1	0.91367	1.13230	0.0007772
3kWp FI m-Si PM	0.00082222	0.12094	0.00037988	0.00041474	0.30161	0.70768	0.19433	0.00945	1439.8	1.00800	1.26120	0.0008035
3kWp FI s-Si LI	0.00091488	0.13939	0.00042352	0.00044450	0.27868	0.64846	0.18877	0.009791	1410.9	0.93778	1.15750	0.0009270
3kWp FI s-Si PM	0.00093127	0.14289	0.00043456	0.00045282	0.30666	0.71806	0.19351	0.009947	1459.5	1.02650	1.27870	0.0009517
3kWp FRI m-Si	0.00548520	0.081018	0.00025345	0.00027563	0.20446	0.48003	0.12667	0.006288	956.25	0.68352	0.85491	0.0005488
3kWp FRI s-Si	0.00062211	0.095803	0.00029034	0.00030144	0.20776	0.48676	0.12636	0.006626	970.21	0.69560	0.86628	0.0006479
3kWp SRI a-Si LI	0.00047230	0.064313	0.00020003	0.00023177	0.18401	0.43101	0.13757	0.003955	318.82	0.61342	0.76251	0.0004385
3kWp SRI a-Si PM	0.00059623	0.085838	0.00026219	0.00027205	0.24332	0.57601	0.18127	0.004633	469.1	0.80436	1.01540	0.0005568
3kWp SRI CdTe LI	0.00043030	0.049012	0.00017623	0.00025864	0.18300	0.42532	0.13686	0.003735	318.36	0.61210	0.75626	0.0003297
3kWp SRI CIS PM	0.00051273	0.074027	0.00024123	0.00031670	0.20854	0.48391	0.12810	0.004859	454.52	0.69280	0.85354	0.0004850
3kWp SRI m-Si LI	0.00051316	0.074603	0.00023597	0.00026671	0.18190	0.42439	0.11706	0.006198	923.45	0.61103	0.75818	0.0005064
3kWp SRI m-Si PM	0.00062838	0.092526	0.00029008	0.00031474	0.22285	0.53606	0.14868	0.007206	1091.2	0.76381	0.95532	0.0006138
3kWp SRI m-Si PM label-certified	0.00055929	0.082354	0.00025819	0.00028014	0.20338	0.47712	0.13233	0.006414	971.26	0.67983	0.85029	0.0005463
3kWp SRI r-Si LI	0.00050074	0.070164	0.00023003	0.00026025	0.18086	0.42209	0.11463	0.005542	718.65	0.60785	0.75494	0.0004699
3kWp SRI r-Si PM	0.00055134	0.078666	0.00025441	0.00027498	0.20443	0.47994	0.13138	0.005779	771.09	0.68332	0.85597	0.0005136
3kWp SRI s-Si LI	0.00058886	0.089770	0.0002739	0.00029305	0.18654	0.43445	0.11733	0.006542	939.36	0.62744	0.77533	0.0006081
3kWp SRI s-Si PM	0.00071034	0.109050	0.00033121	0.00034343	0.23228	0.54382	0.14795	0.007578	1105.9	0.77763	0.96840	0.0007254
3kWp SRI s-Si PM label-certified	0.00063224	0.097058	0.0002948	0.00030567	0.20674	0.48403	0.13169	0.006744	984.31	0.69214	0.86193	0.0006456
570kWp OGI m-Si	0.00049902	0.083707	0.00025718	0.00020105	0.099367	0.22837	0.10382	0.042508	948.81	0.34096	0.40829	0.0005503

Table A.2. Efficient targets for PV technologies

Installation method, PV technology	SO2-eq (gen)	GWP-100a	NOx-eq	POx-eq	FAETP100a	FSETP100a	HTP100a	Land	Air	MAETP100a	MSETP100a	Resources
3kWp FI m-Si LI	0.00052923	0.077077	0.00024209	0.00026691	0.17878	0.41669	0.12448	0.006105	912.81	0.60083	0.74460	0.0005111
3kWp FI m-Si PM	0.00054069	0.079530	0.00024981	0.00027273	0.19834	0.46537	0.12779	0.006215	946.81	0.66286	0.82937	0.0005284
3kWp FI s-Si LI	0.00060163	0.091663	0.00027851	0.00029230	0.18326	0.42643	0.12414	0.006438	927.81	0.61668	0.76117	0.0006096
3kWp FI s-Si PM	0.00061240	0.093964	0.00028577	0.00029777	0.20166	0.47220	0.12725	0.006541	959.77	0.67503	0.84087	0.0006258
3kWp FRI m-Si	0.00360707	0.053277	0.00016667	0.00018125	0.13445	0.31567	0.08330	0.004135	628.83	0.44948	0.56219	0.0003609
3kWp FRI s-Si	0.00040910	0.063000	0.00019093	0.00019823	0.13662	0.32009	0.08309	0.004357	638.01	0.45743	0.56967	0.0004261
3kWp SRI a-Si PM	0.00039208	0.056447	0.00017242	0.00017890	0.16001	0.37878	0.11920	0.003046	308.48	0.52895	0.66773	0.0003662
3kWp SRI m-Si LI	0.00033745	0.049059	0.00015517	0.00017539	0.11962	0.27908	0.07698	0.004076	607.26	0.40181	0.49858	0.0003330
3kWp SRI m-Si PM	0.00041322	0.060845	0.00019076	0.00020697	0.14655	0.35251	0.09777	0.004739	717.57	0.50228	0.62822	0.0004036
3kWp SRI m-Si PM label-certified	0.00036779	0.054156	0.00016979	0.00018422	0.13374	0.31375	0.08702	0.004218	638.70	0.44706	0.55915	0.0003592
3kWp SRI r-Si PM	0.00036256	0.051731	0.00016730	0.00018083	0.13443	0.31561	0.08640	0.003800	507.07	0.44935	0.56289	0.0003377
3kWp SRI s-Si LI	0.00038723	0.059033	0.00018012	0.00019271	0.12267	0.28569	0.07716	0.004302	617.72	0.41260	0.50986	0.0003999
3kWp SRI s-Si PM	0.00046712	0.071711	0.00021780	0.00022584	0.15275	0.35762	0.09729	0.004983	727.24	0.51137	0.63682	0.0004770
3kWp SRI s-Si PM label-certified	0.00041576	0.063825	0.00019386	0.00020101	0.13595	0.31830	0.08660	0.004435	647.28	0.45515	0.56681	0.0004246