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An analysis of the accuracy of selected indicators for sustainability assessment of energy savings performance projects supporting the life cycle analysis

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Abstract: More and more energy projects expect to improve their operating energy efficiency performance by applying a set of energy performance indicators supporting the life cycle analysis to make energy saving plans and to provide decision makers with the methods to analyse accuracy of the applied indicators. Energy savings are crucial from the environmental point of view to reduce the resources and the cost of energy conversion, distribution and use, resulting in high-energy intensities.
The purpose of the paper is to analyse the accuracy of selected indicators for energy-efficient performance projects supporting the life cycle analysis. Primary, the analytical hierarchy process method is used to determine relevant indicators being representatives of the whole picture of industrial energy projects. The indicators characterize the impacts of energy-related production operations on the energy efficient performance of industrial plants or energy projects residing in the three sustainability aspects: the environment, the economy and the social capital. Then, a multiple regression is used to analyse the accuracy of selected indicators to be evaluated in energy projects.
The results of the analysis are selected LCA-based energy-related indicators representing sustainability assessment of energy savings performance projects. These variables can be attributed to energy-efficient improvements for assessing the sustainability and making simple comparisons through analysing the values of particular indicators.

Keywords: sustainability assessment, AHP, multiple regression, energy projects, life cycle analysis

JEL codes: *C10, Q40*

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1. Introduction

Most energy projects have major effects on implementing the principles of sustainable development. Energy projects improve their energy efficiency performance by applying energy sustainability life cycle indicators-based centralized management. In turn, most energy savings result from the adoption of projects dealing with electricity and thermal systems (Anderson, Newell, 2004: 33-36). Those projects will continue to be developed in the coming years, especially in Poland; therefore, it is important to find effective methods for selecting appropriate energy sustainability indicators supporting the energy life cycle analysis. On the other hand, selection of indicators for sustainability assessment requires managerial decision making in performing analyses of the accuracy of selected indicators. Proper decisions related to the choice of indicators can strongly depend on renewable energy technology characteristics and energetic analysis of plants and their improvement opportunities (Lohmann and Wagner, 2010: 1-3).

The projects focusing on reduction of energy consumption and its associated greenhouse gas emission are important from the environmental, economic and social points of view minimizing the environmental impact arising from energy production and use. From the economical point of view, energy saving is a crucial issue for transition economies to reduce the cost of energy conversion, distribution and use, because they still use much energy to operate manufacturing activities, resulting in high energy intensities. “Unprofitable operations are a poor use of capital, so a useful indicator is one that addresses this, such as return on capital” (Klemeš, 2015: 483). Implementation of most of the evaluation methods must be preceded by an appropriate analysis and rely on surveys involving respondents’ subjective responses. Thus, the estimated effects may suffer from social desirability and other biases. Arguably for the lack of data (heterogeneity of measures and facilities), no evaluation has so far relied on an evaluation of the accuracy of the selection criteria with energy-related projects. On the other hand, under some studied program measures, the system for project evaluation criteria or key performance indicators did not fully allow equal treatment of particular technologies or enterprises causing the occurrence of disproportions in evaluating projects on ranking lists between different kinds of capital projects (Kaganski et al., 2017: 286). Thus, in the Operational Program called Infrastructure and Environment (OPI&E) Priority Areas: Energy for the years 2007-2013 all criteria (formal, additional formal and substantial criteria) were evaluated in terms of subcriteria, such as: accuracy, fairness, comprehensibility, measurability, arduousness (Agrotec, 2013: 14, 41), while for the years 2014-2010 substantial criteria were presented on the basis of the paradigm: "effectiveness" criteria, "characteristic" criteria, "index" criteria (Agrotec 2013: 16). Although sustainability assessment indicators have been suggested by various researchers (in the process of implementing projects), effective selection methods for energy sustainability indicators are unavailable. Considering this research gap, there are no approaches to select indicators for energy savings performance projects. Therefore, a comprehensive analysis of selecting indicators for energy savings performance projects that consider all aspects of the environment, human health, and economic value should be performed. Designated indicators as a result of performed energy audits and selected studies based on literature could provide the basis for evaluation of the accuracy of the selection criteria for energy projects.

The goal of this paper is to evaluate the accuracy of selected indicators for energy savings performance projects. Accordingly, to begin with, the main approaches and methods to promote energy-related indicators supporting the life cycle analysis (LCA) in the industry are presented. In order to select appropriate measurement indicators of performance of energy projects, a multiple regression is used. Relevant variables of energy savings performance projects that can be attributed to energy-efficient improvements are categorized into inputs and outputs in order to select appropriate variables. The importance of the variables affecting the energy projects is analysed with the regression model created by Minitab and PQSTAT. For the purpose of this paper, the author will discuss contemporary indicators, approaches and categorize selecting indicators for energy savings performance projects.

2. Analysis of variables affecting energy savings performance projects

There is rapidly expanding literature detailing a wide range of indicators that affect the observed energy consumption in multiple disciplines. The value of a particular indicator can be traced back through an analysis to a particular activity, which is especially useful in benchmarking improvement actions. The performance of solutions can be assessed by using a global indicator, allowing also assessment of each requirement of a project (Koukkari et al., 2013: 5). Each indicator evaluates one aspect of the sustainability dimension, the environmental, social or economic performance. Three indicators are used to measure the environmental impact:

"pressure indicators" (e.g., CO_2 emissions), "impact category (such as climate change, stratospheric ozone depletion, smog, eutrophication, acidification, toxicological stress on human health and ecosystems, resource depletion, water use, land use, noise)" (Seppälä et al. 2005: 121, 123-126; Azapagic, Clift 1999: 360-361), with its indicators (e.g., CO_2 equivalents in the case of climate change), and the total impact indicator (aggregating different impact category indicator results into a single value (Soltani at al., 2016: 392-393). Among the developed indicators measuring environmental sustainability are the following: eco-efficiency as a link between environmental and economic performance; net present value or net benefit, environmental footprint (Hoekstra, 2015: 82) and many others (Cucek et al., 2012: 9-20). All these indicators and others presented in units of area (Cucek et al., 2015: 141-151) aim to reduce the environmental impact with achieving economic values or profits (Skowrońska and Filipek, 2014: 10).

In general, there may be either non trade-offs or trade-offs within environmental, social, economic indicators (Cucek et al., 2015: 150). General sustainability indicators developed by the United States Environmental Protection Agency (Fiksel et al., 2012: 22) require the measurement of economic, environmental and social considerations (IAEA, 2005: 11-15), while specific indicators could be "defined differently in accordance to the characteristics of each technology", industry or project (Shen et al., 2011: 442). Complementary indicators within each of these categories can be developed as the need for further areas of decision support arises.

A number of studies on energy indicators have already been discussed, focusing on improving energy efficiency within individual manufacturing sectors (Boyd et al., 2008: 711-712) and they can compare energy performance against that within other ones (Lindberg at al., 2015: 1786-1787). Many organizations are using diverse indicators to integrate LCA-based indicators, energy efficiency performance indicators in energy projects. Moreover, environmental sustainability indicators based on energy use can be related to either energy resources or local energy systems or infrastructure capacity in industrial plants.

Current assessment methods do not employ sufficient understanding of the interrelations of the sustainability concerns (social, economic and environmental) (Adinyira et al., 2007: 2). There may be either non trade-offs or trade-offs within environmental, social, economic indicators (Cucek et al., 2015: 150). Kluczek (2017: 691-696) produced a comparative study of an integrated energy sustainability applied to manufacturing sectors that describe the LCA-based methodology and its indicators combining energy LCA, Life Cycle Costing, Social Life Cycle Analysis and identified relations between them. Input and output selections are limited to those items entail energy efficiency of the production systems represented by industrial plants. ISO 14040 highlights that LCA is "A systematic set of procedures for compiling and examining the inputs and outputs of materials and energy [in this paper energy-related indicators] and the associated environmental impacts directly attributable to the functioning of a product throughout its life cycle" (ISO 14040, 1997). Due to the comprehensive scope or nature of LCA, this method allows scientifically supporting the calculation of more cohesive and consistent indicators, "shifting" environmental problem to other issues, e.g. sustainability. Fiksel et al. (2012: 21) provides criteria for the selection of indicators relevant to sustainability assessment, focusing on problem-specific indicators.

Although the general principles of the indicators are included in the life cycle analysis methods, indicators used within other methods and energy projects are still under discussion, and the uncertainty arising from the variability of measurements or from the lack of data or model assumptions, remains one of the main problems significantly affecting the decision-making process, particularly with respect to input data. Therefore, Data Envelopment Analysis (DEA) could be valuable to take into consideration the number of inputs and outputs to be considered in LCA analysis due to having an impact on the number of the production systems included in decision-making units on the environmental sustainability (Kluczek, 2017: 691-696).

The majority of sustainability assessment literature could be written if experts selected energy indicators through the application of a multi-attribute decision analysis, e.g. the analytical hierarchy process (AHP) (Armina, Vilsi, 2015: 21-23; Saaty, 2008: 85-95), or aggregation methods.

Interesting observations could be done based on statistical results (Hsu, 2015: 145-154). Proposals for the use of statistical analysis can be found in most research related to energy efficiency, also dependent on context use of the basic groups of statistical analysis (1) descriptive analysis; (2) information on impact. For example, multiple regression does not include the weights of each indicator, which assist the measurement decision process (Han and Han, 2004: 522-524). However, just one question will be considered: Are the energy project indicators more accurate and reliable after making a selection? According to the discussion in the previous section, the variables which are most consistent in predicting future movements in energy savings performance projects are superior indicators. Assessment of the accuracy of the selected indicators for energy projects can find energy efficiency improvements offer a reduction of CO_2 emissions, while providing such important ancillary benefits as energy cost savings, reduction in pollutants, reduction in the dependence on imported fuels and improved economic competitiveness.

Breaking the numbers of research papers down by project perspectives, Table 1 presents potential indicators for the selection of sustainable energy projects.

Table 1. Indicators for the selection of sustainable energy projects

Selected energy sustainability indicators	Related literature	Perspectives
Electricity reliability, oil security, energy efficiency, environmental quality	(Brown, Sovacool, 2007: 342)	Energy policy in infrastructure projects
Growth in GDP; effect on environment expressed in external costs; effect on job market, equity, technological innovation, and security of energy supply	(Klevas et al., 2009: 159)	Energy infrastructure projects
SO_2 and CO_2 emissions per capita from power plants, SO_2 and CO_2 emissions per unit of electricity produced (GWh) from power plants; electricity system performance indices, distribution of electricity consumption figures across the population, total electricity consumption per capita, electricity portfolio, transmission and distribution losses	(Rosenthal, 2004: 33, 98, 109,140)	Electricity infrastructure projects
CO_2 emissions from energy consumption per tonne of manufactured products; Electricity consumption per tonne of manufactured products; Total energy consumption vs. best available technology	(IEA, 2007: 54)	Methodologies for energy-related indicators and their application in the industry sector

Source: author's own elaboration

To ensure accuracy and thoroughness, calculation of indicators throughout the entire life cycle is of great importance for sustainability assessment of energy projects. This paper is mostly motivated by the above-mentioned research, in which the author enlarges or extends original scope of the LCA to include calculation of other LCA-based indicators, which are relevant for the sustainability assessment of energy savings performance projects.

3. Research methodology: Selecting energy indicators for the evaluation of sustainability assessment of energy saving projects

The research has been carried out by applying the analytical hierarchy process (AHP) and multiple regression to select the number of variables to be used in a sustainability assessment of energy savings performance. The multiple regression analysis studies “the simultaneous emotions that some independent variables have over one dependent variable” (Turóczy, Liviu, 2012: 510). In multiple regression, often dealing with variable selection, asking the following question seems to be highly appropriate: Which of the many predictor variables should be selected for inclusion in the assessment of energy savings project? For an ease of application, a set of twelve indicators are formulated with addressing the environmental, economic and social sustainability issues. The indicators characterize the impacts of energy-related production operations on the energy efficient performance of energy projects residing in the three sustainability criteria: the environment, the economy and the social capital.

Due to different specifications and technologies used in each energy project, common indicators could be selected from energy audits reports and from the literature review on LCA-based sustainability energy indicators. Table 2 provides a set of key LCA-based assessment indicators that are formed for fifty-one energy projects. The choice of the energy savings performance projects will require some trade-offs among the criteria.

In this paper, the selection of key LCA-based sustainability assessment indicators used in energy-related projects is limited to the items which:

1) are appropriate to the energy projects and their objectives,
2) are not governed by how measurable they are,
3) have to be quantifiable,
4) are “useful to decision makers” (Li et al., 2016: 113-114),
5) are characterized by “feasibility for a model to be applied in real life according to resource availability” (Li et al. 2016: 113-114),
6) are sustainability-oriented.

A pair-wise comparison is often preferred by decision makers, allowing them to derive weights of criteria from comparison matrices rather than quantify weights directly applied for selection of sustainable energy-related indicator projects (KAeIs) based on a life cycle analysis framework to be used further in a regression model. When policy-makers are asked to choose the best project`s energy sustainability indicators, they have to find a solution that gives the best outcome in terms of the above-mentioned criteria (Klevas et al., 2009: 159-160).

Table 2. Overview of key LCA-based assessment variables used in AHP to select sustainable energy indicators

Variable	Var	Description
Energy estimated savings	C1	The actual energy consumption that the firms could save if they utilized all the technical possibilities (improvements)
Annual primary energy consumption	C2	This is a specific energy consumption treated as an energy efficiency indicator widely used in industry for measuring the energy efficiency of different processes. For a given part to be formed the quantification of energy required in a certain operation would be necessary in order to compare two different processes eventually available. This means to consider, besides the required loads, also the time consumed in a process.
Total GWP for energy savings	C3	A sum of greenhouse gases saved as a result of identified opportunities of improvements in a facility
CO_2 emissions per year	C4	The indicator measures emissions of CO_2 grams per kWh of energy. The amount of emitted CO_2 depends on energy carriers used to run technology or operations.
Life cycle cost (LCC)	C5	$$LCC = C_m + \sum_{n=1}^{N} \frac{C_{energy} * C_{use,n}}{(1+i)^n} \quad (1)$$ where: C_{energy} - an industrial cost of electrical energy (in \$/kWh; 0.734\$/kWh), $E_{use,n}$ - the total energy consumption in year n (in kWh), n - the lifetime of an investment (5 year), i - is a discount rate based on real interest rate and inflation rate (3.8%), and Cm is the manufacturing cost (in \$) calculated, based on the total estimate for plant cost (TPC). The electric energy consumption of a biogas plant is influenced by a variety of factors. The stirrers and the CHP unit consume most energy whilst pumps, disintegrators, valves, and controlling units use just some energy (based on: Dhillon, 2010: 56-57).
Potential energy cost saving	C6	Potential energy saving is mainly generated by waste utilization and input sparing. Such practices as heat generating by waste incineration, changing electric heaters into appliances fuelled by natural gas providing possibilities to save costs.
Net Present Value (NPV)	C7	Future costs and benefits (recurrent or one-time) are discounted to present value using Equation (2): $$NPV = \sum_{t=0}^{n} NFV\ (1+r)^{-t} \quad (2)$$

		It is the present value of net economic cost, where *NFV* is the net future costs, *r* is the real interest rate, and *n* is the total number of periods. Calculation of the *NPV* involves summing all the net cash flows associated with the proposed technologies throughout the economic life cycle, discounted to unify their financial value (Solatni, et al., 2016: 390).
Total Production Cost (TPC)	C8	TPC total estimate for plant cost = n*DEC, Dhillon proposed to estimate the total plant costs from the delivered equipment cost by using three factors as multipliers: n = 3.10 (for solid process plants), n = 3.63 (for solid-fluid); DEC is delivered equipment cost.
Job-years/saved kWh	C9	The number of full-time equivalent jobs created with duration of one year per unit of energy saved in terms of improvement scenario
Job-years/consumed kWh	C10	The number of full-time equivalent jobs created with duration of one year per unit of energy saved in terms of baseline scenario
Investment per person employed	C11	Index of investment cost of energy project represented by all energy efficiency improvements recommended to a facility divided by the number of persons employed
Operating hours/Production	C12	Number of employees per energy-intensive plant

Source: author’s own elaboration

Once criteria are formulated and corresponding indicators within sustainability considerations accepted, the pair-wise comparisons of key assessment indicators must be established using the AHP method, as presented in Figure 1. It allows developing an approach which can be applied by decisions-makers to select relevant sustainability indicators through ranking ones with the greatest value associated with each sustainability dimension. Then, the selected indicators are further examined through an analysis their accuracy and the representativeness of sustainability of energy savings performance projects. Pairwise comparisons are made by providing the question asking which indicator *i* or *j* is more important in the measurement of sustainability (Kluczek, 2016: 69). Activities in the AHP method can be summarized at four stages (Kluczek, 2016: 69):

(a) Identifying criteria to compare elements;

(b) Gathering value judgments on relative importance of the criteria;

(c) Constructing a set of pair-wise comparison matrices (size n × n) for each element by using the relative scale measurement described above and their synthesizing. After normalization of all the columns, they are computed to the individual row averages. The received result is the priority vector *wj* (denoted as the relative importance or weight of Ai over Aj).

(d) Calculating the consistency index CI by using the eigenvalue λmax as follows: CI = $(\lambda max - n)/ (n - 1)$, where λmax is the maximum eigenvalue of the matrix of priorities. The calculation of the consistency ratio C.R. ensures the consistency of the responses. The consistency ratios of the matrices were calculated. If C.R. is less than 0.1, then the judgment matrix is consistent. If it is greater, the pairwise comparisons should be re-evaluated. The last column of each matrix represents the eigenvectors indicating the absolute priority weight of each rated considered indicators.

The pair-wise comparisons for categorical indicators are based on a standardized comparison Saaty`s scale from 1-9 levels; see Figure 1 (Saaty, 2008: 86). According to this scale, the values for the pair-wise comparisons are members of the set: {9, 8, 7, 6, 5, 4, 3, 2, 1, 1/2, 1/3, 1/4, 1/5, 1/6, 1/7, 1/8, 1/9}. A procedure for calculating weights was provided by Kluczek (2016: 69).

The result of the AHP for weight estimation in terms of their contribution to the best representative of energy projects (with substantially higher values) is depicted in the pair-wise comparison matrix, Figure 1 and summarized in Table 3.

Figure 1. Multi-criteria method used to select LCA-based energy-related indicators within sustainability dimensions

ANALYTICAL HIERARCHY PROCESS MATRIX TO STUDY SELECTION OF REPRESENTATIVES FOR ENERGYSUSTAINABLE CATEGORY

ENV	C1	C2	C3	C4
C1	1	7	7	8
C2	0.14	1	7	8
C3	0.14	0.14	1	8
C4	0.13	0.13	0.13	1
TOTAL	1.41	8.27	15.13	25

ECO	C5	C6	C7	C8
C5	1	0.50	0.33	0.33
C6	2	1	0.13	0.20
C7	3	8	1	0.33
C8	3	5	3	1
TOTAL	9	14.5	4.46	1.87

SOC	C9	C10	C11	C12
C9	1	0.33	0.33	0.20
C10	3	1	0.13	0.20
C11	3	8	1	2
C12	5	5	0.5	1
TOTAL	12	14.33	1.96	3.40

NORMALIZED SCORE TABLE

C1	0.709	0.847	0.463	0.320	2.338	0.58
C2	0.101	0.121	0.463	0.32	1.005	0.25
C3	0.101	0.017	0.066	0.320	0.505	0.13
C4	0.089	0.015	0.008	0.040	0.152	0.04
TOTAL	1	1	1	1	4	1

NORMALIZED SCORE TABLE

C5	0.111	0.034	0.075	0.179	0.399	0.10
C6	0.222	0.069	0.028	0.107	0.426	0.11
C7	0.333	0.552	0.224	0.179	1.288	0.32
C8	0.333	0.345	0.673	0.536	1.887	0.47
TOTAL	1	1	1	1	4	1

NORMALIZED SCORE TABLE

C9	0.083	0.023	0.170	0.059	0.336	0.08
C10	0.250	0.070	0.064	0.059	0.442	0.11
C11	0.250	0.558	0.511	0.588	1.907	0.48
C12	0.417	0.349	0.255	0.294	1.315	0.33
TOTAL	1	1	1	1	4	1

Source: author`s own elaboration

The selected relevant indicators classified within the sustainability category as environmental, economic and social have been presented as a basis for analysing the accuracy indicators for the sustainability assessment of energy savings performance projects supporting the life cycle analysis. Hence, multiple regressions have been used in this case.

Table 3. Selected LCA-based energy-related indicators within the sustainability category to be analysed through the multiple regression analysis

Sustainability category	**Sustainable energy-related indicators**	**Variable [weight]**
Environmental issue [ENV]	Energy estimated savings [kwh/yr]	C1 [0,58]
Economic issue [ECO]	Potential energy estimated savings [$/yr]	C8 [0,47]
Social issue [SOC]	Investment per person employed [$/n]	C11 [0,48]

Source: author’s own elaboration

4. Results

Using the PQSTAT and Minitab program kit in the case of multiple regressions, the following results could be achieved as presented in Table 4.

In this study, the dependent variable is simple payback periods (C6) determined by total recommended implementation cost/total recommended cost savings, while the independent variables are the following C1, C8, C11, as presented in Table 4. Regression results for the full and reduced model are presented in Table 5.

Table 4. Data needed to perform the multiple regression analysis

#	C1	C11	C8	C6	#	C1	C11	C8	C6
1	114103.13	93.25	33849.75	1.14	27	2614034.10	290.30	105378.90	0.17
2	90728.13	57.59	12334.74	1.00	28	366356.29	192.94	59532	0.75
3	-2635509.40	1642.46	727379.40	2.20	29	398203	71.17	55539.00	0.40
4	1089926.10	109.70	172425	0.60	30	1103206.60	166.95	123674.10	0.59
5	3993164.30	9185.61	2200687.50	2.91	31	2479115.40	2830	667738.50	1.46
6	38115.03	508.09	99596.31	5.99	32	691295.83	217.24	114345	1.01
7	2676699.40	56250.00	19602000	16.16	33	1141806.70	305.94	299856.15	1.13
8	4323826	11680.00	1907928	2.74	34	851089	225.58	102358.74	0.67
9	2475927	148.19	145200	0.40	35	5837777.40	3340.91	1067220.00	2.72
10	2159483.70	479.44	156634.50	0.46	36	378660	350.61	91635.72	1.35
11	1456640.50	166.76	248800.20	0.89	37	189736.40	75.82	130716.30	3.81
12	34459	357.71	181790.40	1.35	38	48742	7.17	12342.00	0.58
13	1536803.70	25520.33	5650966.20	16.52	39	4849772.70	138.79	208071.60	0.37
14	322039.33	45.50	16516.50	0.29	40	1565954.50	214.50	130026.60	0.79
15	702861.15	342.86	43560	0.37	41	1321681.60	289.66	91476	1.12
16	156291.77	1678.93	426615.75	1.49	42	223090	280.75	122294.70	1.73
17	483152	122.25	108722.13	0.47	43	1533464.70	2002.59	843249	3.44
18	60867	748.78	108722.13	3.75	44	302361.62	98.50	35755.50	0.51
19	202302.29	732.50	159538.50	0.79	45	169710	87.50	22869	0.42
20	284358	86.43	78437.04	0.74	46	700717.47	633.33	172425	1.09
21	455525.14	152.17	127050	1.03	47	1224068.10	262.60	139174.20	0.80
22	-8278807	6035.00	1971634.5	-104.99	48	1477732.70	564.44	372528.75	1.85
23	-1661952	4275.00	806949	8.07	49	23676277	8260.65	5997231.90	2.17
24	661739	1038.45	211095.39	0.68	50	876824.96	97.40	65053.23	0.48
25	333925	642.73	256641	1.25	51	5174094.90	1107.21	482299.95	0.97
26	211874	81.95	100551	1.21					

Source: author’s own elaboration

The regression analysis describes the relationship between a dependent variable and independent ones. The full model is the model thought to be most appropriate for a set of data answering the question: "Does the full model describe the data well enough?", while a reduced model does not include all variables considered previously (in the full model). For simple linear regression, a common null hypothesis[1] is H_0: β1, β8, β11= 0. The full model might be reduced if indicators (variables) are not significant or due to the necessity of additional error degrees of freedom, assuming that certain variables are zero. In other words, the reduced model might be appropriate in describing the lack of relationship between response variable and variables.

Table 5. Results of multiple regression for the first iteration*

	1st iteration – full model		
	coefficient	**p-value**	**T stat.**
Intercept	1.171106	0.000041	4.52
C1	-0.00000000	0.983096	-0.02
C11	0.0006687	0.000004	5.25
C8	-0.00000108	0.008711	-2.74

*Significant at the 0.05 level, with dependent variable: Simple payback period (C6)

Source: author`s own elaboration

Table 6. Model Summary

Model (full)	**R**	**R Square R-Sq**	**Adj R Square R-Sq(adj)**	**Std. Error of the Estimate**	**P-value**
	0.877	0.772	0.758	1.607	0.000001

Source: author's own elaboration

To determine whether the relationship between the response and each sustainable energy-related indicators model has regression, the t-test must be used.

Looking at the results of regression coefficients and t-test for each predictor in Table 7, the relationships between simple payback period (response variables) and C11 is statistically

[1] The null hypothesis is that the indicator's coefficient is equal to zero, which indicates that there is no relation between the indicator and the response. A significance level of 0.05 indicates a 5% risk of concluding that an association exists when there is no actual relationship.

significant, because the p-values of these indicators are less significant at the 0.05 significance level. It means that the model is described by F-test of variance analysis: $p < 0.000001$ and the small standard error of estimation SEe = 1.6065. In addition, the coefficient of multiple determination R^2 indicating the per cent of how much of the total variance is explained by the independent variable is 77.20% as well as by the corrected coefficient R^2adj = 0.758 (Table 6). The analysis of variance in the first iteration for multiple regressions is presented in Table 7.

Table 7. ANOVA – analysis of variance output

Source	**Degrees of freedom (dF)**	**Sum of squares (SS)**	**Mean square (MS)**	**F-ratio (F)**	**P-value (p)**
Regression	3	410.94	136.98	53.08	0.000001
Residual Error	48	121.30	2.58		
Total	51	532.24			

Source: author's own elaboration

To get coherent information, the values of coefficients of partial and semi-partial correlation allow finding those variables in the model which are superfluous. The data included in Table 8 indicate that the smallest contribution to the constructed model is that of C1. However, this variable is the least correlated with model residuals, which is indicated by the low value R^2 and the relatively high tolerance value and the result of t-test (Table 5).

Table 8. Semi partial correlation

predictors	**partial**	**semi-partial**	**tolerance**	**R^2**	**t. stat.**	**p-value**
C1	-0.00311	-0.001483	0.651293	0.3487	-0.021301	0.983096
C11	0.607869	-0.365465	0.042046	0.958	5.248288	0.000004
C8	-0.37085	-0.190634	0.039182	0.9608	-2.73761	0.008711

Source: author's own elaboration

Finally, it is worth examining residuals to check the assumption of homoscedasticity. This assumption might be confirmed if that point was rejected. A part of the analysis of residuals is depicted in Figure 2. The distribution of residuals does not depart from a regular distribution (the value *p* of Lilliefors test is $p = 0.000001$). The obtained model can be corrected by removing the six outlier (observations # 22)[2] from the model, it deviates by more than three standard deviations from the mean value.

In order to test the validity of the null hypothesis, the F-test procedure[3] is applied. The procedure requires an analysis of the variance identified in the ANOVA table (see Table 7). Comprising the F value for the first iteration of multiple regression with $F_{critical}$ taken from the F-distribution table (2.802) the alternative hypothesis H_A is accepted that not $\beta = 0$. Hence, an evaluation for a particular regression coefficient using the student test must be calculated. The t-values taken from Table 2 are compared with the critical value of t at a significance level of 0.05 in the case of a two-tailed test. The results are presented as follows:

$t_{C1} > t_{critical}$ (-2.010) $\rightarrow$Ho is accepted and that $\beta_1 = 0$,

$t_{C11} > t_{critical}$ (2.010) $\rightarrow$Ho is rejected and that $\beta_{11} \neq 0$,

$t_{C8} < t_{critical}$ (-2.010) $\rightarrow$Ho is rejected and that $\beta_8 \neq 0$,

The result of the t-test for each predictor (variable) depicts that C11 and C8 have a significant influence on the sustainability of energy savings performance projects. A new regression can be repeated for this reduced model. This will give the information that follows in Figure 2.

[2] The assumption of homoscedasticity is confirmed by rejecting that point.

[3] Comparing the F-values, it results that it is compulsory to accept the alternative hypothesis, meaning that not all regression coefficients are equal to zero. This means that a significant influence of multiple regression model occurs over the dependent variables.

Figure 2. Residual analysis

predicted value	residual	residual	standard residual	<=-3sd	(-3sd;2sd]	(-2sd;sd]	(-sd;sd)	[sd;2sd)	[2sd;3sd)	>=3sd
1	1.19676	-0.052589	-0.032735				*			
2	1.196132	-0.196132	-0.122086				*			
3	1.490344	0.712045	0.443226				*			
4	1.056832	-0.456599	-0.284219				*			
5	4.936181	-2.021378	-1.258245			*				
6	1.403475	4.585829	2.854535						*	
7	17.66626	-1.510787	-0.940418				*			
8	6.918975	-4.178361	-2.6009		*					
9	1.109512	-0.705022	-0.438854				*			
10	1.319271	-0.86038	-0.53556				*			
11	1.012098	-0.118778	-0.073936				*			
12	1.214386	0.131055	0.081578				*			
13	12.14687	4.372369	2.721664						*	
14	1.183147	-0.890561	-0.554347				*			
15	1.352212	-0.984576	-0.612868				*			
16	1.833958	-0.339261	-0.21118				*			
17	1.134874	-0.665246	-0.414095				*			
18	1.554551	2.199648	1.369212					*		
19	1.488689	-0.69674	-0.433699				*			
20	1.143883	-0.399858	-0.248899				*			
21	1.13519	-0.107923	-0.067179				*			
22	3.163362	4.907654	3.054862							*
23	1.636959	-0.955644	-0.594859				*			
24	1.323839	-0.076309	-0.0475				*			
25	1.117191	0.097402	0.06063				*			
26	1.247228	-1.073653	-0.668315				*			
27	1.235331	-0.489876	-0.304933				*			
28	1.158144	-0.759364	-0.472681				*			
29	1.147101	-0.561142	-0.349293				*			
30	2.340001	-0.883848	-0.550168				*			
31	1.191985	-0.181722	-0.113116				*			
32	1.050708	0.0811	0.050482				*			
33	1.210203	-0.543237	-0.338148				*			
34	2.245626	0.474808	0.295553				*			
35	1.306163	0.047185	0.029371				*			
36	1.080628	2.733991	1.701824					*		
37	1.162469	-0.581173	-0.361762				*			
38	1.031494	-0.660939	-0.411414				*			
39	1.171767	-0.382137	-0.237868				*			
40	1.26397	-0.141126	-0.087846				*			
41	1.226686	0.504468	0.314016				*			
42	1.599262	1.84426	1.147995					*		
43	1.197898	-0.687562	-0.427986				*			
44	1.204649	-0.779834	-0.485423				*			
45	1.407648	-0.320468	-0.199481				*			
46	1.194667	-0.397636	-0.247516				*			
47	1.385831	-0.618417	-0.384945				*			
48	1.14471	0.700897	0.436287				*			
49	0.19467	1.979998	1.232487					*		
50	1.164625	-0.684902	-0.42633				*			
51	1.383135	-0.409529	-0.254919				*			

Source: author’s own elaboration

Table 9. Results of multiple regression for the second iteration*

	2st iteration – reduced model		
	coefficient	**p-value**	**T stat.**
Intercept	1.0748	0.0001	5.07
C11	0.00062882	0.0001	6.46
C8	-0.0000096	0.002	-3.31

*Significant at the 0.05 level, with dependent variable: Simple payback period (C6)
Source: author's own elaboration

Table 10. Model Summary

Model (reduced)	**R**	**R Square R-Sq**	**Adj R Square R-Sq(adj)**	**Std. Error of the Estimate**	**P-value**
	0.898	0.805	0.797	1.432	0.0001

Source: author's own elaboration

Table 11. ANOVA – analysis of variance output for reduced model

Source	**Degrees of freedom (dF)**	**Sum of squares (SS)**	**Mean square (MS)**	**F-ratio (F)**	**P-value(P)**
Regression	2	398.72	199.36	97.26	0.0001
Residual Error	47	96.34	2.05		
Total	49	495.05			

Source: author's own elaboration

The estimated results of regression equation (1) using the reduced model are shown in Table 9.

$$C6 = 1.07 + 0.000629\ C11 - 0.000001\ C8 \quad (1)$$

F-test procedure is applied again that requires an analysis of the variance identified in the ANOVA table (see Table 11). In consequence, the model`s degree of explaining the variance in the dependent variable is $R^2 = 81\%$ and the corrected coefficient $R^2adj = 80\%$ (Table 11).

Because F97.26 is greater than $F_{critical}$ (4.7571) it is obvious that the alternative hypothesis will be accepted. Using the student test, the calculated *t* values (from Table 8 for 2nd iteration) are compared with the critical value of t (2.013) at a significance level of 0.05 in the case of a two-tailed test. The results are presented as follows:

$t_{C11} > t_{critical}$ →Ho is rejected and that $\beta_{11} \neq 0$,

$t_{C8} < t_{critical}$ →Ho is rejected and that $\beta_{8} \neq 0$.

Therefore, these predictors C11 and C8 should not be removed from the model.

To find out how well the model fits the data, the goodness-of-fit statistics in the model summary Table 5 and Table 9 are examined (for full and reduced model).

As a result, the obtained reduced model is encumbered with a smaller error and is more adequate. The interrelations between all indicators (2^{nd} iteration, see Table 9) are statistically significant because the *p*-values for these terms are less than the significance level of 0.05.

From this output, it is seen that SSE(reduced) = SSE(X_1, X_2) = 96.34 with df = 2, and MSE(reduced) = MSE(X_1, X_2) = 2.58. With these values obtained, the F-test statistic for testing H_0: $\beta_{11} = \beta_8 = 0$ is obtained:

$$F = \frac{\dfrac{SSE(reduced) - SEE(full)}{err\ df\ for\ reduced - err\ df\ for\ full}}{MSE\ (full)} = 9.674 \qquad (2)$$

Because p is very small (the value comes from an $F_{2,47}$ distribution, $p = 1 - 0.9993$), therefore the null hypothesis is rejected in favour of the alternative H_A: $\{\beta_{11} = \beta_8\} \neq 0$ (at least one of β_i coefficients is non-zero) and it is reasonable not to remove the energy estimated savings (C1) from the model. With the F-test statistic of 9.674 and *p*-value less than 0.001 (remember that the *p*-value is not 0 but 0.000 is interpreted as being less than 0.001), the null hypothesis at a 0.05 level of significance would be rejected in favour of the alternative HA: $\{\beta_{11} = \beta_8\} \neq 0$ (at least one of β_i coefficients is non-zero) and it is reasonable not to remove the energy estimated savings (C1) from the model. The p-value (less than 0.001) for the analysis of variance shows that indicators C8 and C11 are more useful in sustainability assessment of energy projects than not taking into account the two predictors. It needs mentioning that this does not mean that the model with the two predictors is the best model.

5. Conclusion

The research analyses to settle the question whether or not the energy-related indicators assessments in the standard model (received from AHP methods) were significantly predictive of the project size based on the multiple regression.

A study objective was to evaluate the accuracy of selected indicators for sustainability assessment of energy saving projects. Fifty-one energy projects were examined in order to get in the first round of variables selection, categorized within sustainability considerations to be used in the further analysis (accuracy of indicators). Primary selection of indicators was done using the analytical hierarchy process method which is applied to determine ranking of relevant energy indicators in terms of sustainability dimensions. Then, the representatives of sustainability energy-related indicators assessment for their accuracy were examined by using multiple regression. In the first regression model, energy estimated savings (C1) and potential energy estimated savings (C8) were not the significant predictors for the project size. For this reason, a new model was depicted. On examining the separate variables by the F-test, it was found that the C8 made a contribution to the model. In addition, by performing the new evaluation and using global F-test statistics to check whether it is reasonable to declare that non-significant variable (C1) can be dropped from the model. In this case the regression model will no longer contain C1 variable (the predictor must be removed from the model).

As a result of the conducted study, different recommendations and conclusions were formulated:

- The three sustainability LCA-based energy-related indicators describe energy savings projects. One indicator should be removed from the key assessment (energy-related) indicators, thus increasing the evaluation of the accuracy and the effectiveness of selection of indicators in energy projects.
- Observation of the individual results does not allow drawing conclusions relating to their essence. Only the analysis of a large number of cases and related indicators reveals regularity. Each project is different in terms of complexity, specification, size and profit generated. The list of indicators could be extended due to the specification of each energy project, in which various variables/dimensions could be treated.
- The evaluation of the project selection indicators used within energy saving performance projects can contribute to the creation of a coherent and adequate evaluation system, enabling a choice of indicators from the sustainability point of view.

- The proposed evaluation method can be used in high value energy projects or large-scale application where a wide range of energy-related indicators have been used in order to improve the energy efficiency. This will save time and reduce resources that are necessary to implement the indicators in energy savings performance projects.
- The multiple regression can be helpful in selection of energy-efficient projects and use in the following areas:

i. selecting significant LCA-based energy-related indicators for assessing the sustainability effects of facility performance (activity);

ii. selecting energy-efficient technologies that optimally utilize energy resources for energy projects and use, e.g. by benchmarking alternative technologies;

iii. integrating with well-known operation research techniques to handle more difficult problems and assist in the decision-making process; e.g. fuzzy AHP, DEMATEL-ANP allow ranking KAeIs that would make a high impact on the results.

The future research should be focused on combining different methodologies into one general approach in order to adopt a KAeIs selection model. In addition, the expert group could be participating in the analysis of a set of energy indicators providing reliability of the analysis and weights appointment. On the other hand, an application of other selection methods, e.g. fuzzy AHP, DEMATEL-ANP allow ranking KAeIs, thus making a high impact on the results

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Analiza trafności wybranych wskaźników dla projektów energetycznych wspierających ocenę cyklu życia

Streszczenie

Coraz więcej projektów energetycznych oczekuje poprawy efektywności energetycznej w przedsiębiorstwach poprzez zastosowanie zestawu wskaźników efektywności w celu dostarczenia decydentom niezbędnych narzędzi umożliwiających tworzenie planów oszczędnościowych pod kątem efektywnego wykorzystania energii oraz wspierających ocenę cyklu życia projektów. Oszczędność energii ma zasadnicze znaczenie z punktu widzenia ochrony środowiska w celu zmniejszenia zużycia surowców energetycznych związanych z ich konwersją, dystrybucją i użytkowaniem, co pociąga za sobą wysokie koszty eksploatacji. Celem artykułu jest analiza trafności wybranych wskaźników dla efektywnych projektów energetycznych wspierających ich ocenę przy wykorzystaniu metody oceny cyklu życia (LCA). Pierwotnie zastosowano metodę analitycznej hierarchii procesu służącą do określenia odpowiednich wskaźników będących reprezentantami oceny projektów energetycznych jako całości w podziale na wymiary zrównoważonego rozwoju. Zestaw wskaźników zostanie opracowany z punktu widzenia operacji produkcyjnych i rekomendacji poaudytowych. Do analizy trafności wybranych uprzednio wskaźników użyto regresji wielorakiej. Wynikiem zastosowanej są wybrane wskaźniki energetyczne oparte na analizie LCA, reprezentujące stopień zrównoważenia projektów zorientowanych na oszczędność energii. Wskaźniki te, w zależności od specyfiki projektów energetycznych i rodzaju zastosowanych usprawnień technologicznych mogą być wykorzystywane do oceny trafności poprzez porównanie/analizę poszczególnych ich wartości. Wskaźniki mogłaby służyć jako próbka reprezentacyjna w całej populacji projektów energetycznych.

Słowa kluczowe: ocena stopnia zrównoważenia, AHP, regresja wieloraka, projekty.