Vadim Strijov
Computing Centre of the Russian Academy of Sciences
Moscow, Russia
Goran Granić
Željko Jurić
Branka Jelavić
Sandra Antešević Maričić
Energy Institute Hrvoje Požar
Zagreb, Croatia

Integral Indicator of Ecological Footprint for Croatian Power Plants

The main goal of this paper is to present the methodology of construction of the Integral Indicator for Croatian Thermal Power Plants and Combined Heat and Power Plants. The Integral Indicator is necessary to compare Power Plants selected according to a certain criterion. The criterion of the Ecological Footprint is chosen. The following features of the Power Plants are used: generated electricity and heat; consumed coal and liquid fuel; sulphur content in fuel; emitted CO_2, SO_2, NO_x and particles. To construct the Integral Indicator the linear model is used. The model parameters are tuned by the Principal Component Analysis algorithm. The constructed Integral Indicator is compared with several others, such as Pareto-Optimal Slicing Indicator and Metric Indicator. The Integral Indicator keeps as much information about features of the Power Plants as possible; it is simple and robust.

INTRODUCTION

«The Directive concerning integrated pollution prevention and control and applying to all industrial plants, including HEP's large combustion plants, lays down measures designed to reduce emissions to air, water and soil and the generation of waste, measures to improve energy efficiency and water use, and measures to prevent accidents that have adverse impact on the environment, applying best available techniques. (…) HEP commenced preparatory activities for the alignment with national policy measures to mitigate climate change, such as the introduction of a carbon dioxide fee (CO_2) and preparations for joining the EU Greenhouse Gas Emission Trading Scheme». [1]

Nowadays the problem of the waste reduction, connected with electricity generation using fossil fuels, is very important [2, 3]. We consider the problem of measurements of the overall amount of waste and below we discuss several techniques for the integral indicators construction. The application area of these indicators is the ecological footprint of the Croatian Thermal Power Plants and Combined Heat and Power Plants.

The integral indicator is a measure of the object's quality. It is a combination of several object features (waste measurements) that describe a set of comparable objects. To construct an integral indicator several steps must be performed. First, the criterion of comparison must be chosen. The integral indicator must be constructed according to this criterion. The objects, here the Croatian Power Plants, must be comparable in the terms of their impact on the ecology. Second, a set of features must be selected according to the criterion. An optimal value must be assigned to each feature. Third, the measured data table «objects-features» must be completed. And the last, expert estimations of the integral indicator must be collected.

There are two approaches to the integral indicator construction. The first one is called «non-supervised method». According to this method, the integral indicator is defined by a selected model. Only measured data are required. The second one is called «supervised method». According to this method, to construct the integral indicator a selected model, measured data, expert estimations of the integral indicator and, if it is possible, expert estimations of the features' importance are required.

There are lots of ways to construct an integral indicator. However, when model is chosen and the integral indicator is calculated, the following question arises: how to show adequacy of it? To answer this question analysts invite experts. The experts express their opinion and then the second question arises: how to show that expert estimations are valid? Below the system of supervised and non-supervised algorithms is presented to show adequacy of the constructed integral indicators.

The first section introduces the selected model of the integral indicator and requirements to the measured data. The second section describes non-supervised algorithms: Pareto Slicing, Metric Algorithm and Principal Components Analysis. The third section describes supervised algorithms based on the expert estimations usage: Weighted sum, Expert-Statistical Method and Linear specification of the expert estimations. The last section constructs the Integral Indication for Croatian Power Plants.

1. INITIAL CONDITIONS

We have a sample set of m objects (power plants) and a set of n features (e.g. air pollutants). This defines the matrix $A \in \Re^{m\times n}$, where an element $a_{ij} \in A$ is j-th feature for i-th object. A row vector $\mathbf{a}_i = [a_{i1},...,a_{in}]$ of the matrix A is the description of i -th object and the column vector $\mathbf{a}^j = [a_{1j},...,a_{mj}]^T$ is the description of the j-th feature. Let us call the vector $\mathbf{a}_i$ the object and the vector $\mathbf{a}^j$ the feature, for short. The object and the feature have their own names, defined by the indices i and j.

Assume the integral indicator for an object is the linear combination of the object features

$$q_i = \sum_{j=1}^{n} w_j g_j(a_{ij}), \tag{1}$$

where g_j is a normalization function, which maps the feature values into a unified scale:

$$g_j : a_{ij} \mapsto (-1)^{s_j} \frac{a_{ij} - \min_j(a_{ij})}{\max_j(a_{ij}) - \min_j(a_{ij})} + s_j. \tag{2}$$

If the denominator in the fraction (2) is zero for some j, then j-th feature can not be used in the integral indicator and so it must be excluded from consideration. Without limitation of the applicability assume the following. Greater value of i-th object, given feature, involves greater value of the integral indicator for this object. This principle is called “the bigger the better”. The function g_j transforms the source data into the data, which satisfy the following conditions. First, each feature satisfies the principle “the bigger the better”. The modifier is $s_j \in \{0,1\}$. If $s_j = 1$, then the components of the feature will be inversed and it means that the desired values of the feature must be minimal. Second, g_j maps all values of given feature into the segment $[0,1]$ by the affine transformation so that all the features in the sample set could be comparable. When the condition (2) is satisfied, the model (1) can be represented as $q_i = \sum_{j=1}^{n} w_j a_{ij}$ or

$$\mathbf{q} = A\mathbf{w}, \tag{3}$$

where the integral indicator $\mathbf{q} = [q_1,...,q_m]^T$ and the feature weights $\mathbf{w} = [w_1,...,w_n]$. Let us call the integral indicator both the vector corresponded to the object set and the scalar corresponded to the object.

From the condition (2) it follows that the feature weights are positive. Since the integral indicator is expected to be invariant to scaling, define additional condition of the weights: $\|\mathbf{w}\|_2 = 1$.

Thus, the matrix A must be prepared to satisfy the conditions above. The matrix must fit the concept “the bigger the better”. It means that an expert expect an object with bigger feature values has bigger indicator. An object of the maximal indicator is considered to be the best as well as a feature of the maximal weight is considered to be the most important.

2. NON-SUPERVISED METHODS

The main goal of these methods is to provide the clear and reasonable way to construct the integral indicator with no expert estimations. Each of the suggested methods uses principles of the object comparison. The first method uses notion of domination: there are cases when we can definitely say that one object is better than the other. The second method uses notion of distance: one object can be nearer to the best object than the other. And the third method uses notion of informativity: we can combine all elements of the object’s description in the one feature and call this feature the integral indicator.

2.1. Pareto Slicing

Introduce the relationship of domination on the set of the objects $\{\mathbf{a}_i\}_{i=1}^m$. The object $\mathbf{a}_i$ dominates $\mathbf{a}_k$, $\mathbf{a}_i \succ \mathbf{a}_k$, if all components of $\mathbf{a}_i$ are not less than the corresponding components of $\mathbf{a}_k$, $a_{ij} \geq a_{kj}$, $j = 1,...,n$. Define the Pareto-optimal front P_1 as the set of non-dominated objects (for each object $\mathbf{a}_k \in \mathrm{P}_1$ there is object $\mathbf{a}_i$, such that $\mathbf{a}_i \succ \mathbf{a}_k$ for $j = 1,...,n$, $j \neq k$). Define the integral indicator $q_i = S - s$ for the object $\mathbf{a}_i$ as the value of the index s of the POF P_s, where $\mathbf{a}_i \in \mathrm{P}_s$. The POF P_s is defined as the set of non-dominated objects in $\left\{\{\mathbf{a}_i\}_{i=1}^m \setminus (\varnothing \cup P_1 \cup ... \cup P_{s-1})\right\}$; S is overall number of the POFs. The vector of the integral indicators is $\mathbf{q}_{POF} = [q_1,...,q_m]^T$.

The advantage of this method is simplicity. There are no requirements for data scaling, so the data might be in the ordinal scales or might be transformed by any monotonous mapping. The serious drawback of this method is the following. If the number of features is greater than the number of objects, all the objects might be placed in the same POF and so the objects will have the same value of the integral indicator.

2.2. Metric algorithm

This algorithm uses as a measure of object's quality the distance from some selected object to the best (worst) object. Let us call the best (worst) object is an object that contains the maximal (minimal) values of the features, $\mathbf{a_1} = [\max_j a_{1j},...,\max_j a_{mj}]^T$, ($\mathbf{a_0} = [\min_j a_{1j},...,\min_j a_{mj}]^T$). The integral indicator for the object $\mathbf{a}_i$ is the distance to the best (worst) object, $q_i = \rho(\mathbf{a}_i, \mathbf{a_1})$, (or $q_i = \rho(\mathbf{a}_i, \mathbf{a_0})$), where $\rho(\mathbf{a}_i, \mathbf{a}_k) = \sqrt[r]{\sum_{j=1}^n (a_{ij} - a_{kj})^r}$ for given r.

This method is widely used; however this method does not allow one to analyse feature importance weights in the constructed integral indicator. It is the main drawback if the method. Also note that the first and the second proposed methods ignore the accepted model (3) of the integral indicator.

2.3. Principal Components Analysis

Here the constructed indicator keeps the maximum information about data [4, 5]. To keep the maximum information here means to find the new orthogonal system of coordinates such that the square sum of distance between the objects and their projections to the new coordinates is minimal. This new coordinates are called principal components. To make the integral indicator we consider projections only to the first principal component.

To find the first principal component, one must to find the orthogonal matrix W of the linear combination $Z^T = A^T W$ of column-vectors of the matrix A, such that the column-vectors $\mathbf{z}_1,...,\mathbf{z}_n$ of the matrix Z have the maximal variances, $\sum_{j=1}^n \sigma^2(\mathbf{z}_j) \to \max$. Here $\sigma^2(\mathbf{z}) = \frac{1}{m}\sum_{i=1}^m (z_i - \bar{z})^2$ and $\bar{z} = \frac{1}{m}\sum_{i=1}^m z_i$. According to the Principal Components Analysis, the row-vectors of the matrix W are eigenvectors of the covariance matrix $\Sigma = A^T A$. Therefore the integral indicator $\mathbf{q}_{PCA} = A\mathbf{w}$ is the projection of the row-vectors of the matrix A to the first principal components and $\mathbf{w}$ is the first row-vector of the matrix W (this vector corresponds to the maximal *eigenvalue* of the covariance matrix Σ.

The Principal Components Analysis is the basic method for construction of the Integral Indicator.

3. SUPERVISED METHODS

Expert estimations play important role in the integral indicator construction. We assume the expert has his own opinion. The opinion is not biased by the public one. The expert estimations must be the result of the experience and skill of the expert. In the methods discussed below the expert estimations are used as depended variables of precedents. The result of the expert estimations usage is validated integral indicators and explained expert estimations.

2.1. Weighted sum

Consider expert estimations of the features' importance. Assume we have these estimations in the linear scale. Then, the integral indicator of the objects is the linear combination of the columns of the matrix A, $\mathbf{q}_1 = A\mathbf{w}_0$. Here $\mathbf{w}_0$ is the vector of the expert estimations and $\mathbf{q}_1$ is the computed integral indicator.

This is the simplest method of the integral indicator construction. The main drawback of it is lack of robustness of the result indicator. The robustness here depends on the condition number of the matrix A and on the precision of the expert estimation. In case of ill-conditioned matrix A, small changes in the expert estimations may cause drastic changes in the computed indicators. Paper [6] shows that experts are not able to give estimations of complex systems' features in linear scales, as it is required for this method.

3.1. Expert-Statistical Method

Consider expert estimations $\mathbf{q}_0$ of the objects' quality. Assume we have these estimations in the linear scale. Obtain the weights $\mathbf{w}$ of the features according to the model (3) as the argument of minimum of the Euclidian distance between the estimated integral indicators $\mathbf{q}_0$ and the calculated integral indicators $\mathbf{q}_1 = A\mathbf{w}_0$:

$$\mathbf{w}_1 = \arg\min_{\mathbf{w}\in\Re^n} \| A\mathbf{w} - \mathbf{q}_0 \|_2^2 .$$

The solution of this problem is given by the least squares method, so that $\mathbf{w}_1 = (A^T A)^{-1} A^T \mathbf{q}_0$ and the result integral indicator $\mathbf{q}_{ESM} = A\mathbf{w}_1$.

Obviously for an expert it is much easier to assign estimations of the objects' quality than of the features' importance. If the expert can assign both estimations we can introduce the expert estimations specification procedure [7]. This method resolves contradiction between data and expert estimations, which appears when expert assigns his estimations. The second advantage on this method is explanation of the expert preferences: features with bigger weights are more important from the expert's point-of-view.

3.2. Linear specification of the expert estimations

Denote by $\mathbf{q}_0$ and $\mathbf{q}_1$ estimated and computed integral indicators. Denote by $\mathbf{w}_0$ and $\mathbf{w}_1$ estimated and computed weights of the features. Assume the computed indicator $\mathbf{q}_1 = A\mathbf{w}_0$ and computed weights $\mathbf{w}_1 = A^+\mathbf{q}_0$. Here the pseudo-inverse linear operator A^+ is given by the Singular Value Decomposition of the linear operator A. According to the Singular Value Decomposition any linear operator can be represented as $A = U\Lambda V^T$, where $UU^T = I_m$ and $V^T V = I_n$ are the orthogonal matrices and $\Lambda = \mathrm{diag}(\lambda_1, ..., \lambda_{r=\min(m,n)})$ is the diagonal matrix and $\lambda_1 \ge ... \ge \lambda_r \ge 0$. The pseudo-inverse linear operator $A^+ = V\Lambda^{-1}U^T$ satisfies the conditions $AA^+ = I_m$ and $A^+A = I_n$.

In general case the computed and estimated integral indicators are different, $\mathbf{q}_1 \ne \mathbf{q}_0$, as well as the weights, $\mathbf{w}_1 \ne \mathbf{w}_0$. Let us resolve this contradiction by specifying the expert estimations. Find non-contradicted expert estimations $\mathbf{w}_\alpha, \mathbf{q}_\alpha$ in the segments $[\mathbf{w}_1, \mathbf{w}_0]$ and $[\mathbf{q}_1, \mathbf{q}_0]$. In this case the solution is defined by the expression

$$\mathbf{w}_\alpha = \alpha\mathbf{w}_0 + (1-\alpha)A^+\mathbf{q}_0,$$
$$\mathbf{q}_\alpha = (1-\alpha)\mathbf{q}_0 + \alpha A\mathbf{w}_0.$$

The parameter α defines expert preferences to estimations of indicators versus estimations of weights. If α tends to zero the expert trust the estimations of weights, if α tends to one the expert trust the estimations of indicators. In the practice one could allow expert to assign the parameter according to his own preferences. Another way to set the parameter is to define the parameters so that the sum of the residuals $\| \mathbf{w}_0 - \mathbf{w}_\alpha \|_2 \, n^{-1} + \| \mathbf{q}_0 - \mathbf{q}_\alpha \|_2 \, m^{-1}$ will be minimal.

4. CONSTRUCTION OF THE INTEGRAL INDICATOR

In this section the Integral Indicator of Ecological Footprint for Croatian Power Plants is constructed and compared with alternative integral indicators. The installed electricity generating capacities in the Republic of Croatia include hydro and thermal power plants owned by the HEP Group (Croatian Power Company), a certain number of industrial power plants and a few privately owned power plants (wind power plants, small hydro power plants). One of the goals of the HEP Group is to investigate the Ecological Footprint of the Thermal Power Plants.

4.1. Data description

The Integral Indicator is based on the data in the report [1] «*Hrvatska Elektroprivreda* and the Environment 2005–2006». The data include features for the most important anthropogenic greenhouse gas (CO_2) and other air pollutants (SO_2, NO_x and Particles) from Croatian Thermal Power Plants and Combined Heat and Power Plants, as well as several another features as it is shown in the Table 1.

N	Power Plant	Available net capacity (MW)	**Electricity (GWh)**	Heat (TJ)	SO_2 (t)	NO_x (t)	Particles (t)	CO_2 (kt)	Coal (t)	Sulphur content in coal (%)	Liquid fuel (t)	Sulphur content in liquid fuel (%)	Natural gas (10^3 m^3)
1	Plomin 1 TPP	98	**452**	0	1950	1378	140	454	198,454	0.54	431	0.2	0
2	Plomin 2 TPP	192	**1576**	0	581	1434	60	1458	637,924	0.54	367	0.2	0
3	Rijeka TPP	303	**825**	0	6392	1240	171	616	0	0	199,735	2.2	0
4	Sisak TPP	396	**741**	0	3592	1049	255	573	0	0	111,591	1.79	121,459
5	TE-TO Zagreb CHP	337	**1374**	481	2829	705	25	825	0	0	80,423	1.825	308,502
6	EL-TO Zagreb CHP	90	**333**	332	1259	900	19	355	0	0	38,982	2.1	125,879
7	TE-TO Osijek CHP	42	**114**	115	1062	320	35	160	0	0	36,668	1.1	24,337
	Optimal value	max	**max**	max	min	min	min	min	min	min	min	min	min

Table 1. The data used for the integral indicator construction

The data were preprocessed so that they satisfy the conditions described in the Section 1 of this paper. TPP Jertovac was excluded from the table data since it has not the same status as the other plants in the electricity system. TPP Jertovac is used as reserve plant and could not be valuated same as other like TPP Plomin 2 operating more than 7000 hours per year.

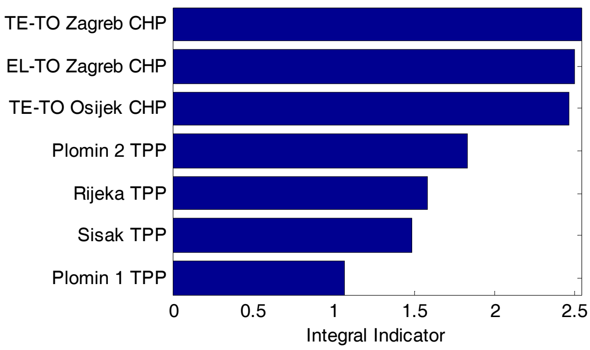

Figure 1. The Integral Indicator of Ecological Footprint for Croatian Power Plants, bar chart

In the Table 1, for TPP Plomin 1 and 2, the first column for sulphur represents sulphur content in coal, while second column represents sulphur content in fuel oil. Small amount of extra light fuel oil is used for initial firing of boilers; however we ignored this small amount of liquid fuels in TPP Plomin (1 and 2). Sulphur content is checked by dividing SO_2 emissions and fuel consumption.

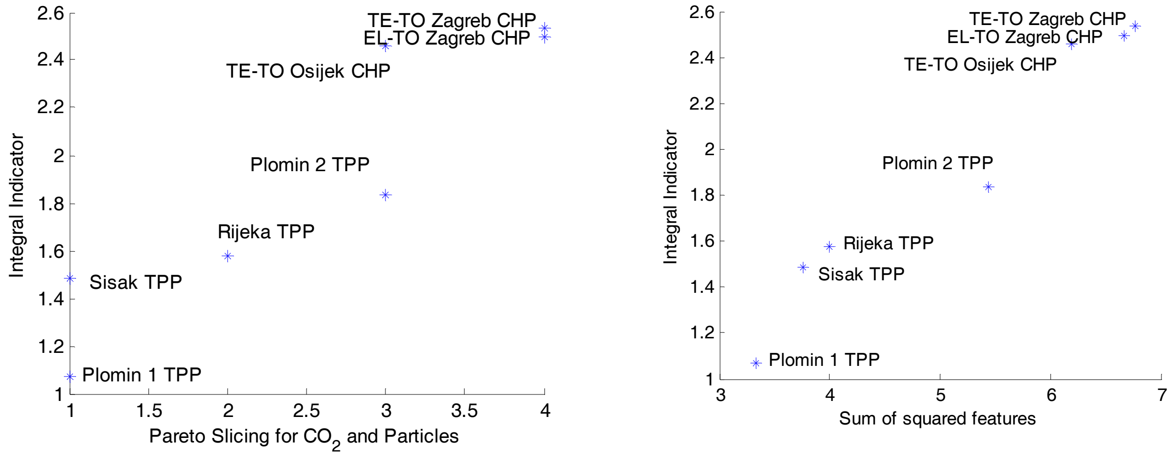

Figure 2. The constructed Integral Indicator in comparison with Pareto Slicing Indicator (left figure) and Metric Indicator (right figure)

We distinguish net and gross capacity (MW) of TPPs. Gross capacity represents total capacity of a generator and corresponds to total generated electricity. Some amount (2-6%) of generated electricity is used for own purposes of TPPs. When we subtract capacity covering own consumption from Gross capacity, the result is Net capacity. Net capacity corresponds to electricity delivered to the power grid. So the feature «Available net capacity» is included in the set of the features.

Since the economics of the country requires electricity, it is reasonable to consider pollution in the ratio of generated electricity, but not its absolute value. The overall amount of emissions (and all by-products) depends on the volume of generated electricity. The following features were divided by the feature Electricity (plus heat for CHPs): Available net capacity, SO_2, NO_x, Particles, CO_2, Coal, Liquid fuel and Natural gas.

To normalize the data, optimal values of the features were used. The values are shown in the last row of the Table 1. The optimal values of Available net capacity, Electricity and Heat must tend to their maximal values, while the SO_2, NO_x, Particles and CO_2 must tend to minimum. After the normalization the data satisfy the principle «the bigger the better». So the Power Plant of the highest quality has biggest value of the Integral Indicator.

4.2. The result Integral Indicator

The Integral Indicator of Ecological Footprint for Croatian Power Plants was constructed using the Principal Components Analysis algorithm. It denoted on the figures as «Integral indicator». Figure 1 shows the list of Power Plants. The first Power Plants in the list have better quality and thus smaller impact to the environment.

Item	Features	Weight
6	Coal (t)	0.38
7	Sulphur content in coal (%)	0.37
3	NO_x (t)	0.35
8	Liquid fuel (t)	0.34
2	SO_2 (t)	0.34
4	Particles (t)	0.33
10	Natural gas (10^3 m^3)	0.30
5	CO_2 (kt)	0.29
9	Sulphur content in liquid fuel (%)	0.18
1	Available net capacity (MW)	0.12

Table 2. The Importance weights of the features in the Integral Indicator

To verify the Integral Indicator, Pareto Slicing and Metric algorithm were used. The right part of the Figure 2 shows relation between the Integral Indicator and the Pareto Slicing. The relation is a monotonous function. That means that results are the same in the rank scales. The Pareto Slicing method used only for features (SO_2, NO_x, Particles, CO_2), since the method places all the objects in the same set and assign the same integral indicator for greater number of features.

The left part of the Figure 2 shows relation between the Integral Indicator and the Metric algorithm. Square sum of the features here means the distance to the worst object. Again, the relation is a monotonous function. The only exception is Plomin 2 TPP, which has bigger value in the alternative case.

Table 2 shows the importance weights of the features according to the linear model. Here features with the biggest values of weight are considered to be more important than the others since they have greater impact.

Item	Power Plants	Integral Indicator
5	TE-TO Zagreb CHP	2.53
6	EL-TO Zagreb CHP	2.49
7	TE-TO Osijek CHP	2.46
2	Plomin 2 TPP	1.83
3	Rijeka TPP	1.57
4	Sisak TPP	1.48
1	Plomin 1 TPP	1.07

Table 3. The Integral Indicator of Ecological Footprint for Croatian Power Plants

CONCLUSION

In this paper we presented the Integral Indicator of Ecological Footprint for the Croatian PPs. The Thermal Power Plants and Combined Heat and Power Plants features were considered. The features were collected according to the report «Hrvatska Elektroprivreda and the Environment 2005–2006» and SO_2, NO_x, Particles, CO_2 were included with respect to the generated electricity and heat.

The Integral Indicator was constructed by Principal Component Analysis method and compared with the other methods, described in the paper. The following methods were considered as the alternatives: Pareto Slicing, Metric algorithm, Weighted sum, and Expert-Statistical Method.

In accordance with availability of the data the experts of Energy Institute Hrvoje Požar find that this indicator is generally adequate.

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