Dimension reduction of preference profile for aggregation of energy audit data

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Abstract. The paper aims to improve a technique based on preference aggregation, which allows to process a big amount of data from instrumental examinations of energy losses by substations of electrical energy distribution networks. An approach to transformation of the initial preference profile into the hierarchical one is considered. The absence of the influence of such a transformation on the correctness of processing results is shown. The workability of the proposed method is demonstrated on the basis of real energy surveys using the example of the Khakass enterprise of the Backbone Electric Grids (BEGs), being a part of Siberian BEG of the Unified National Electric Network of Russia. The method makes it possible to identify sources of economically inefficient expenditure of energy resources and unjustified energy losses, and also to provide compression of large volumes of energy survey data without diminution of essential information. The proposed method allows obtaining and representing a great amount of data of instrumental survey of substation energy losses in a form of a compact integral estimate in the ordinal scale. It can be an appropriate and promising tool for organizations engaged in energy consulting.

1. Introduction

Resource conservation is an important factor in maintaining stability of society. An effective resource saving is ensured by systematic energy audits. Traditionally, energy audit outcomes analysis is a work with a large amount of unstructured data that is difficult to fully take into account [1,2].

In such cases, methods of multi-criteria decision making are traditionally used, such as, for example, the method of the generalized quality index or the analytic hierarchy process [3], which realize comparison of the analyzed objects on the basis of a weighted sum of partial indicators. However, these methods suffer from subjectivism, so do not lend themselves to serious axiomatization, and can lead to erroneous decisions [4]. These disadvantages can be avoided with the use of preference aggregation method [5–7], based on the treatment of exclusively binary relations, which does not require the calculation of weights, and gives a compact integral estimation of objects in the ordinal scale.

The paper aims to improve a technique based on preference aggregation, which allows to process a big amount of data from instrumental examinations of energy losses by substations of electrical energy distribution networks. The technique gives compact integral assessment of the data in an ordinal scale convenient for decision-making and visualization.

2. Preference aggregation

As the initial data, we use the table $V = \{v_{ij}\}$ of values of electric power losses, in MWh, of *i*-th substations by *j*-th attribute.

Let a set $\Lambda = \{\lambda_1, \lambda_2, ..., \lambda_m\}$ of *m* rankings of *n* substations of a set $A = \{a_1, a_2, ..., a_n\}$ be given. Each ranking is defined by indicating some attribute c_k from the list $C = \{c_1, c_2, ..., c_m\}$ according to which each pair of elements from *A* is a strict preference relation, $a_i \underset{c_k}{\succ} a_j$, or a tolerance relation, $a_i \underset{c_k}{\sim} a_j$, according to the following rule:

$$v_i \underset{c_k}{\gtreqqless} v_j \Leftrightarrow a_i \underset{c_k}{\succsim} a_j,\ i = 1,...,n; j = 1,...,m\ . \tag{1}$$

The set $\Lambda(m, n)$ of rankings constructed by the rule (1) for each of the attributes c_k, $k = 1, \ldots, m$, from the list *C*, we call *preference profile* for given *m* and *n*. The list *C* may, for example, consist of the following attributes: energy losses in the distribution line (c_1), in the power transformers (c_2), climate-related losses (c_3), losses of heating of buildings and of existing equipment (c_4), lighting (c_5), etc.

To aggregate *m* preferences defined over a set of *n* objects means to determine a unique preference relation β called the *consensus ranking*, which provides the best compromise among the rankings of the initial profile. A meaning of the concept "best compromise" depends on a preference aggregation rule used. In the proposed method, we use the Kemeny rule [5] consisting in determination of such linear order (Kemeny ranking) β of objects that the distance $D(\beta, \Lambda)$ (defined in terms of the number of pairwise inconsistencies between the rankings) from β to the rankings of the initial profile Λ is minimal for all possible strict orders the objects. To find all possible Kemeny rankings for a given initial preference profile, we use the self-developed *recursive branch-and-bound algorithm* RECURSALL [8].

As soon as the Kemeny rule allows the existence of multiple solutions, the number *N* of possible consensus rankings β can exceed 10^7 even for small $m = 4$ and $n = 15$ [9]. To transform all the multiple consensus rankings $\mathrm{B} = \{\beta_1, \beta_2, \ldots, \beta_N\}$ into a single final consensus ranking β_{fin} we apply the special *convolution rule* [10]. Let $\mathrm{B}(N, n) = \{\beta_1, \beta_2, \ldots, \beta_N\}$ be a set of all consensus rankings determined by the Kemeny rule for the profile $\Lambda(m, n)$ given over some set of alternatives $A = \{a_1, a_2, ..., a_n\}$ and *rank* r_i^k be a position of an alternative a_i in the consensus ranking $\beta_k \in \mathrm{B}$, $k = 1, \ldots, N$. Let a *total rank* r_i of the alternative a_i be defined as $r_i = \sum_{k=1}^{N} r_i^k$. Then, for all $i < j$, $i, j = 1, \ldots, n$,

$$r_i < r_j \Rightarrow a_i \succ a_j \text{ and } r_i = r_j \Rightarrow a_i \sim a_j, \tag{2}$$

where both of the relations $\succ$ and $\sim$ are in the single final consensus ranking β_{fin}.

3. Conversion of initial profile into hierarchical one

The problem of finding the Kemeny ranking is *NP*-complete, i.e. having an exponential growth of the solution time as a function of the dimension $n = |A|$ of the problem. Notice that, at problem dimension $n \leq 20$ suitable for practical application, it is possible to find all exact solutions within a reasonable time. In situations where $n > 20$, one should resort to partitioning the set *A* into N_{p} disjoint subsets A_k, i.e.

$$A = A_1 \cup A_2 \cup \ldots \cup A_{N_{\text{p}}}\ ;\ \bigcap_{k=1}^{N_{\text{p}}} A_k = \varnothing\ ;\ |A_k| \leq 20,\ k = 1, \ldots, N_{\text{p}};\ \sum_{k=1}^{N_{\text{p}}} |A_k| = n\ . \tag{3}$$

The operation of the set *A* partition results in *decomposition* of a preference profile Λ into subprofiles, see figure 1. This action transforms the linear profile structure to hierarchical one.

The decomposition process of the initial profile into subprofiles can be described in terms of *partition* of the set *A* into subsets. For this aim, define a *quotient set* over the set of substations *A* generated by some *h*-th equivalence relation ε_h on it. The equivalence relation occurs if a pair of elements $a_i, a_j \in A$ has a certain common property. For instance, one of the possible equivalence relations can be produced due to the substations' property "to have a bandwidth that differs by no more than 2.5 times".

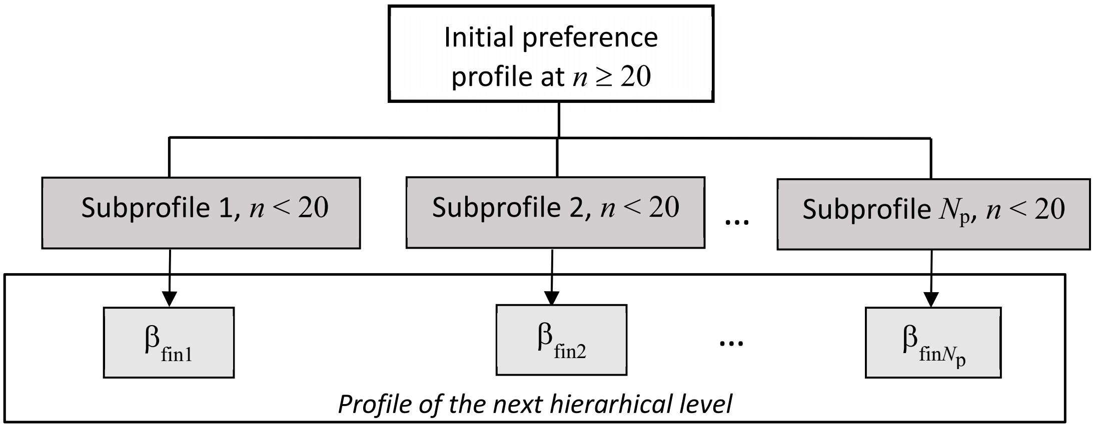

Figure 1. Decomposition of the preference profile.

Let an equivalence class A_k^h, $k = 1, \ldots, N_p$, generated by element a_i, be the set of all such elements a_j of A that $(a_j, a_i) \in \varepsilon_h$; where N_p is a number of equivalence classes by relation ε_h. Then the set of equivalence classes

$$A/\varepsilon_h = \{A_1^h, A_2^h, \ldots, A_{N_{ph}}^h\} \tag{4}$$

is called quotient set by relation ε_h, which, accounting (3), defines corresponding partition of the set A into subsets, i.e. $A = A_1^h \cup A_2^h \cup \ldots \cup A_{N_{ph}}^h$.

Thus, if H equivalence relations $\varepsilon_1, \ldots, \varepsilon_h, \ldots, \varepsilon_H$ are considered, then partitions of the set A into subsets are possible by these relations, that is

$$A = A_1^1 \cup A_2^1 \cup \ldots \cup A_{N_{p1}}^1 = A_1^2 \cup A_2^2 \cup \ldots \cup A_{N_{p2}}^2 = \ldots = A_1^H \cup A_2^H \cup \ldots \cup A_{N_{pH}}^H, \tag{5}$$

and appropriate quotient sets A/ε_1, A/ε_2, …, A/ε_H are defined. In its turn, each equivalence class A_k^h defines the subprofile Λ_k^h consisting of m rankings of elements of the set A_k^h by attributes of the list C.

Notice that consensus rankings β_{fink}^h, found for the sets A_k^h, do not intersect each other. Therefore, it is necessary to develop a strategy for ascertaining preferences between alternatives included in different consensus rankings. It is impossible to just combine all the alternatives, because the result of such a union would be the original set A with unacceptably large n.

Therefore, choose n_u best alternatives (that is alternatives occupying 1-st, 2-nd, …, and n_u-th position) in each β_{fink}^h and compose of them the set

$$A_{sup}^h = \bigcup_{k=1}^{N_{ph}} \left\{ a_i \mid r_i^k \leq n_u \right\}, \tag{6}$$

where rank r_i^k is a position of alternative a_i in the consensus ranking β_{fink}^h. Build a profile Λ_{sup}^h consisting of rankings of alternatives from A_{sup}^h by attributes of C. Final consensus relation $\beta_{fin\_sup}^h$ obtained for this profile is the ranking of $|A_{sup}^h| = n_u \cdot N_{pH}$ alternatives, where the first alternative is best among the best, and the last alternative is worst among the best.

In the same way, choosing n_u worst alternatives (that is alternatives occupying n_u last positions) in each β_{fink}^h, build a profile Λ_{inf}^h consisting of rankings of alternatives from the set

$$A_{inf}^h = \bigcup_{k=1}^{N_{ph}} \left\{ a_i \mid r_i^k \leq (|\beta_{fink}^h| \square n_u) \right\} \tag{7}$$

by attributes of C. Final consensus relation $\beta^h_{\text{fin\_inf}}$ obtained for this profile is the ranking of $|A^h_{\text{inf}}| = n_{\text{u}} \cdot N_{\text{p}h}$ alternatives, where the first alternative is best among the worst, and the last alternative is worst among the worst.

Recommended value for the number n_{u} can be 3, however one should keep in mind that there is an upper bound for it conditioned by expression (3) whence it follows that

$$n_{\text{u}} < 20 / N_{\text{p}h} . \quad (8)$$

Clear that, with a large number of alternatives in the original set A, the decomposition process described above can be repeated as many times as necessary.

4. Practical example

Let us demonstrate a workability of the proposed decomposition process by an example of the set of 17 substations of the Khakass enterprise of the Backbone Electric Grids (BEGs), being a part of Siberian BEG of the Unified National Electric Network of Russian Federation.

Determine one of the feasible quotient sets (i.e. H = 1) over the substations set $A = \{s_1, s_2, ..., s_{17}\}$ generated by the equivalence relation ε_1 over it: "to have a throughput that differs by no more than 2 times". Then the quotient set by relation ε_1 is

$$A/\varepsilon_1 = \{A^1_1, A^1_2, ..., A^1_{N_{\text{p}1}}\} \quad (9)$$

and the equation is valid:

$$A = A^1_1 \cup A^1_2 \cup ... \cup A^1_{N_{\text{p}1}} . \quad (10)$$

In table 1 the initial data of energy losses V by 9 attributes in the Khakass enterprise are shown.

Table 1. Values v of electrical energy losses by 9 attributes, MWh.

Substations	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9
s_1	520.35	372.10	245.43	183.00	21.30	32.34	21.90	7.20	5.88
s_2	633.25	396.11	120.69	927.54	17.33	132.12	137.25	7.10	5.88
s_3	788.01	423.54	327.88	1077.31	83.11	328.09	1449.60	7.00	4.91
s_4	366.54	253.69	142.30	218.30	15.30	88.20	26.16	7.10	3.75
s_5	823.65	387.55	241.03	831.02	38.40	317.52	828.01	7.60	6.74
s_6	308.44	241.33	150.23	355.88	7.69	62.30	30.07	7.10	2.80
s_7	702.47	315.87	222.55	1151.47	12.03	110.20	283.78	7.10	3.75
s_8	652.88	325.44	279.66	1287.32	13.19	54.13	384.39	7.10	4.93
s_9	1230.54	541.23	362.10	1134.15	114.23	448.24	1449.60	7.00	8.20
s_{10}	685.03	300.55	214.30	525.32	22.41	182.31	179.52	7.10	4.91
s_{11}	387.08	274.65	197.13	375.84	15.61	202.32	262.80	7.10	2.80
s_{12}	358.11	202.52	182.49	273.45	11.18	100.57	5.95	7.10	1.88
s_{13}	300.28	187.54	168.22	612.35	14.16	174.70	262.80	7.10	1.87
s_{14}	421.31	234.72	103.24	713.33	8.20	9.18	17.60	7.10	3.75
s_{15}	203.21	111.54	86.23	44.80	3.00	8.70	3.25	3.30	0.15
s_{16}	310.23	123.01	112.38	658.96	24.53	110.20	75.09	7.10	8.20
s_{17}	473.24	204.39	148.91	994.31	10.78	110.20	328.56	7.10	2.80

On the base of data of table 1 one can shape the preference profile Λ by the rule (1):

λ_1: $s_{15} \succ s_{13} \succ s_6 \succ s_{16} \succ s_{12} \succ s_4 \succ s_{11} \succ s_{14} \succ s_{17} \succ s_1 \succ s_2 \succ s_8 \succ s_{10} \succ s_7 \succ s_3 \succ s_5 \succ s_9$

λ_2: $s_{15} \succ s_{16} \succ s_{13} \succ s_{12} \succ s_{17} \succ s_{14} \succ s_6 \succ s_4 \succ s_{11} \succ s_{10} \succ s_7 \succ s_8 \succ s_1 \succ s_5 \succ s_2 \succ s_3 \succ s_9$

λ_3: $s_{15} \succ s_{14} \succ s_{16} \succ s_2 \succ s_4 \succ s_{17} \succ s_6 \succ s_{13} \succ s_{12} \succ s_{11} \succ s_{10} \succ s_7 \succ s_5 \succ s_1 \succ s_8 \succ s_3 \succ s_9$

λ_4: $s_{15} \succ s_1 \succ s_4 \succ s_{12} \succ s_6 \succ s_{11} \succ s_{10} \succ s_{13} \succ s_{16} \succ s_{14} \succ s_5 \succ s_2 \succ s_{17} \succ s_3 \succ s_9 \succ s_7 \succ s_8$

λ_5: $s_{15} \succ s_6 \succ s_{14} \succ s_{17} \succ s_{12} \succ s_7 \succ s_8 \succ s_{13} \succ s_4 \succ s_{11} \succ s_2 \succ s_1 \succ s_{10} \succ s_{16} \succ s_5 \succ s_3 \succ s_9$

λ_6: $s_{15} \succ s_{14} \succ s_1 \succ s_8 \succ s_6 \succ s_4 \succ s_{12} \succ s_7 \sim s_{16} \sim s_{17} \succ s_2 \succ s_{13} \succ s_{10} \succ s_{11} \succ s_5 \succ s_3 \succ s_9$

λ_7: $s_{15} \succ s_{12} \succ s_{14} \succ s_1 \succ s_4 \succ s_6 \succ s_{16} \succ s_2 \succ s_{10} \succ s_{11} \sim s_{13} \succ s_7 \succ s_7 \succ s_8 \succ s_5 \succ s_3 \sim s_9$

λ_8: $s_{15} \succ s_3 \sim s_9 \succ s_2 \sim s_4 \sim s_6 \sim s_7 \sim s_8 \sim s_{10} \sim s_{11} \sim s_{12} \sim s_{13} \sim s_{14} \sim s_{16} \sim s_{17} \succ s_1 \sim s_5$

λ_9: $s_{15} \succ s_{12} \sim s_{13} \succ s_6 \sim s_{11} \sim s_{17} \sim s_4 \sim s_7 \sim s_{14} \succ s_3 \sim s_8 \sim s_{10} \succ s_1 \sim s_2 \succ s_5 \succ s_9 \sim s_{16}$

For the obtained profile, the algorithm RECURSALL has found the following consensus ranking:

$$\beta_{\text{fin}}: s_{15} \succ s_6 \succ s_{12} \succ s_4 \sim s_{13} \sim s_{14} \succ s_{16} \succ s_{11} \sim s_{17} \succ s_1 \succ s_2 \succ s_{10} \succ s_7 \succ s_8 \succ s_5 \succ s_3 \succ s_9. \quad (11)$$

It is clear from (11) that the most problematic substations that require special attention and corrective measures to reduce electricity losses are s_5 (Aluminievaya), s_3 (Abakanskaya), and s_9 (Oznachennoe).

Now we are going to show that the decomposition of the original profile when applying preference aggregation does not lead to a significant change in the result of processing energy audit data. For this aim, the set of substations of the Khakass enterprise is decomposed by the throughput in correspondence with expression (9).

For each subprofile, the substations lists obtained as a result of the decomposition are shown in table 2.

Table 2. Substation set A decomposition by the throughput, i is substation a number in a subprofile, h is number of equivalence relation.

Subprofile	Substation name	Throughput, MWh	s / a_i^h
Subprofile A_1 (Throughput up to 40000 MWh)	Ak-Dovurak	13371.961	s_4 / a_1^1
	Askiz	15356.933	s_6 / a_2^1
	Alyuminievaya	27831.932	s_5 / a_3^1
	Teya	32215.143	s_{12} / a_4^1
	Tuim	32290.467	s_{13} / a_5^1
	Khandagayty	33199.701	s_{15} / a_6^1
	Chadan	37371.961	s_{16} / a_7^1
Subprofile A_2 (Throughput up to 80000 MWh)	Abaza	54967.813	s_1 / a_1^1
	Kyzylskaya	56010.371	s_7 / a_2^1
	Oznachennoe	52405.760	s_9 / a_3^1
	Turan	63078.134	s_{14} / a_4^1
Subprofile A_3 (Throughput up to 160000 MWh)	Abakan-rayonnaya	15258.769	s_2 / a_1^1
	Minusinsk-opornaya	147648.053	s_8 / a_2^1
	Shushenskaya-opornaya	120798.929	s_{17} / a_3^1
Subprofile A_4 (Throughput up to 320000 MWh)	Abakanskaya	313093.425	s_3 / a_1^1
	Sora	271848.496	s_{11} / a_2^1
	Oznacheno-rayonnaya	237257.394	s_{10} / a_3^1

For each subprofile, consensus rankings β_{fin} were obtained (see table 3 and figure 2). Rankings in the table are represented in a vertical form, in which the more preferred element is located higher than the less preferred; tolerant elements occupy the same position (for example, elements a_2^1 and a_4^1 in the ranking λ_8 of subprofile A_2).

Table 3. Subprofiles and their consensus rankings for the substation set of Khakass enterprise decomposed by throughput.

Subprofiles	Rankings									
	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	β_{fin}
Subprofile A_1	a_6^1	a_6^1	a_6^1	a_6^1	a_6^1	a_6^1	a_6^1	a_6^1	a_6^1	a_6^1
	a_5^1	a_7^1	a_7^1	a_1^1	a_2^1	a_2^1	a_4^1	$a_1^1\ a_3^1\ a_2^1\ a_4^1\ a_7^1$	$a_1^1\ a_2^1\ a_4^1\ a_5^1\ a_7^1$	a_2^1
	a_2^1	a_5^1	a_1^1	a_4^1	a_4^1	a_1^1	a_1^1			a_5^1
	a_7^1	a_4^1	a_2^1	a_5^1	a_5^1	a_4^1	a_2^1			a_1^1
	a_4^1	a_2^1	a_5^1	a_2^1	a_1^1	a_7^1	a_7^1			a_4^1
	a_1^1	a_1^1	a_4^1	a_7^1	a_7^1	a_5^1	a_5^1			a_7^1
	a_3^1	a_3^1	a_3^1	a_3^1	a_3^1	a_3^1	a_3^1	a_5^1	a_3^1	a_3^1
Subprofile A_2	a_4^1	a_4^1	a_4^1	a_1^1	a_4^1	a_4^1	a_4^1	$a_2^1\ a_4^1$	a_2^1	a_4^1
	a_1^1	a_2^1	a_2^1	a_2^1	a_2^1	a_1^1	a_1^1		a_4^1	a_1^1
	a_2^1	a_1^1	a_1^1	a_4^1	a_1^1	a_2^1	a_2^1	a_1^1	a_1^1	a_2^1
	a_3^1	a_3^1	a_3^1	a_3^1	a_3^1	a_3^1	a_3^1	a_3^1	a_3^1	a_3^1
Subprofile A_3	a_1^1	a_3^1	a_1^1	a_1^1	a_3^1	a_2^1	a_1^1	$a_1^1\ a_2^1\ a_3^1$	a_3^1	a_3^1
	a_2^1	a_2^1	a_3^1	a_3^1	a_2^1	a_3^1	a_3^1		a_2^1	a_1^1
	a_3^1	a_1^1	a_2^1	a_2^1	a_1^1	a_1^1	a_2^1		a_1^1	a_2^1
Subprofile A_4	a_2^1	a_3^1	a_2^1	a_2^1	a_2^1	a_3^1	a_3^1	$a_3^1\ a_2^1$	a_2^1	a_2^1
	a_3^1	a_2^1	a_3^1	a_3^1	a_3^1	a_2^1	a_2^1		a_3^1	a_3^1
	a_1^1	a_1^1	a_1^1	a_1^1	a_1^1	a_1^1	a_1^1	a_1^1	a_1^1	a_1^1

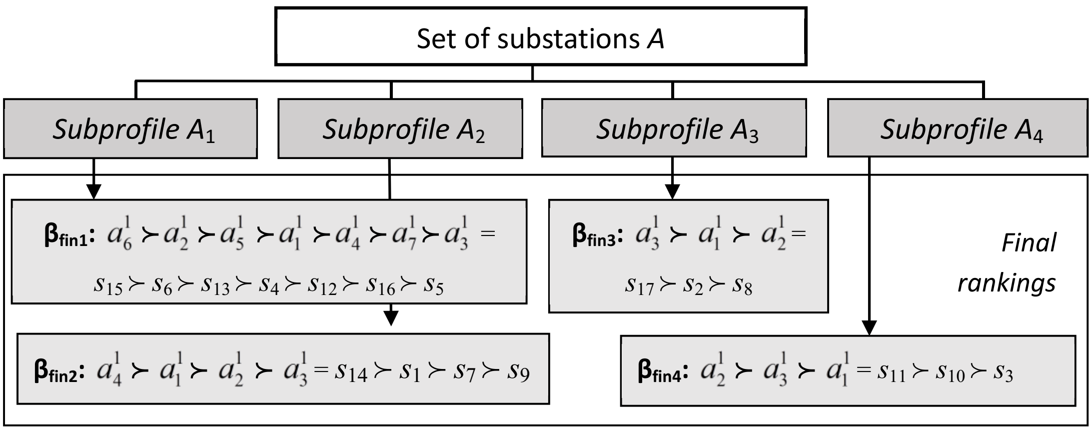

Figure 2. Consensus rankings found for subprofiles 1-4.

On can see from table 3 and figure 2 that the consensus rankings β_{fin1}, …, β_{fin4} do not intersect each other. Having taken $n_u = 3$ we compose the set of the best alternatives A^1_{sup} by formula (5), see table 4.

Table 4. Set A^1_{sup} of the best alternatives of subprofiles.

Subprofile	*Subprofile* A_1	*Subprofile* A_2	*Subprofile* A_3	*Subprofile* A_4
Best substations	$s_{15},\ s_6, s_{13}$	s_{14}, s_1, s_7	s_{17}, s_2, s_8	s_{11}, s_{10}, s_3

The profile Λ^1_{sup}, shaped of the best alternatives of the subprofiles on the base of Table 1 data, is as follows:

$$\lambda_1: s_{15} \succ s_{13} \succ s_6 \succ s_{11} \succ s_{14} \succ s_{17} \succ s_1 \succ s_2 \succ s_8 \succ s_{10} \succ s_7 \succ s_3$$
$$\lambda_2: s_{15} \succ s_{13} \succ s_{17} \succ s_{14} \succ s_6 \succ s_{11} \succ s_{10} \succ s_7 \succ s_8 \succ s_1 \succ s_2 \succ s_3$$
$$\lambda_3: s_{15} \succ s_{14} \succ s_2 \succ s_{17} \succ s_6 \succ s_{13} \succ s_{11} \succ s_{10} \succ s_7 \succ s_1 \succ s_8 \succ s_3$$
$$\lambda_4: s_{15} \succ s_1 \succ s_6 \succ s_{11} \succ s_{10} \succ s_{13} \succ s_{14} \succ s_2 \succ s_{17} \succ s_3 \succ s_7 \succ s_8$$
$$\lambda_5: s_{15} \succ s_6 \succ s_{14} \succ s_{17} \succ s_7 \succ s_8 \succ s_{13} \succ s_{11} \succ s_2 \succ s_1 \succ s_{10} \succ s_3$$
$$\lambda_6: s_{15} \succ s_{14} \succ s_1 \succ s_8 \succ s_6 \succ s_7 \sim s_{17} \succ s_2 \succ s_{13} \succ s_{10} \succ s_{11} \succ s_3$$
$$\lambda_7: s_{15} \succ s_{14} \succ s_1 \succ s_6 \succ s_2 \succ s_{10} \succ s_{11} \sim s_{13} \succ s_7 \succ s_{17} \succ s_8 \succ s_3$$
$$\lambda_8: s_{15} \succ s_3 \succ s_2 \sim s_6 \sim s_7 \sim s_8 \sim s_{10} \sim s_{11} \sim s_{13} \sim s_{14} \sim s_{17} \succ s_1$$
$$\lambda_9: s_{15} \succ s_{13} \succ s_6 \sim s_{11} \sim s_{17} \succ s_7 \sim s_{14} \sim s_{10} \sim s_3 \succ s_8 \succ s_1 \sim s_2$$

Obtained for this profile consensus ranking has the view:

$$\beta^1_{fin\_sup} = \{ s_{15} \succ s_6 \succ s_{14} \succ s_{13} \succ s_{11} \succ s_{17} \succ s_1 \succ s_2 \succ s_{10} \succ s_7 \succ s_8 \succ s_3 \}. \quad (12)$$

Compose set A^1_{inf} of the worst alternatives by formula (6), see table 5.

Table 5. Set A^1_{inf} of the worst alternatives of subprofiles.

Subprofile	*Subprofile* A_1	*Subprofile* A_2	*Subprofile* A_3	*Subprofile* A_4
Worst substations	s_{12}, s_{16}, s_5	s_1, s_7, s_9	s_{17}, s_2, s_8	s_{11}, s_{10}, s_3

The profile Λ^1_{inf}, shaped of the best alternatives of the subprofiles on the base of table 1 data, is as follows:

$$\lambda_1: s_{16} \succ s_{12} \succ s_{11} \succ s_{17} \succ s_1 \succ s_2 \succ s_8 \succ s_{10} \succ s_7 \succ s_3 \succ s_5 \succ s_9$$
$$\lambda_2: s_{16} \succ s_{12} \succ s_{17} \succ s_{11} \succ s_{10} \succ s_7 \succ s_8 \succ s_1 \succ s_5 \succ s_2 \succ s_3 \succ s_9$$
$$\lambda_3: s_{16} \succ s_2 \succ s_{17} \succ s_{12} \succ s_{11} \succ s_{10} \succ s_7 \succ s_5 \succ s_1 \succ s_8 \succ s_3 \succ s_9$$
$$\lambda_4: s_1 \succ s_{12} \succ s_{11} \succ s_{10} \succ s_{16} \succ s_5 \succ s_2 \succ s_{17} \succ s_3 \succ s_9 \succ s_7 \succ s_8$$
$$\lambda_5: s_{17} \succ s_{12} \succ s_7 \succ s_8 \succ s_{11} \succ s_2 \succ s_1 \succ s_{10} \succ s_{16} \succ s_5 \succ s_3 \succ s_9$$
$$\lambda_6: s_1 \succ s_8 \succ s_{12} \succ s_7 \sim s_{16} \sim s_{17} \sim s_2 \succ s_{10} \succ s_{11} \succ s_5 \succ s_3 \succ s_9$$
$$\lambda_7: s_{12} \succ s_1 \succ s_{16} \succ s_2 \succ s_{10} \succ s_{11} \succ s_7 \succ s_{17} \succ s_8 \succ s_5 \succ s_3 \sim s_9$$
$$\lambda_8: s_3 \sim s_9 \succ s_2 \sim s_7 \sim s_8 \sim s_{10} \sim s_{11} \sim s_{12} \sim s_{16} \sim s_{17} \succ s_1 \succ s_5$$
$$\lambda_9: s_{12} \succ s_{11} \sim s_{17} \succ s_7 \succ s_{10} \sim s_3 \sim s_8 \succ s_1 \sim s_2 \succ s_5 \succ s_9 \sim s_{16}$$

Obtained for this profile consensus ranking has the view:

$$\beta^1_{fin\_inf} = \{ s_{12} \succ s_{16} \succ s_{11} \succ s_{17} \succ s_1 \succ s_2 \succ s_7 \succ s_{10} \succ s_8 \succ s_5 \succ s_3 \succ s_9 \}. \quad (13)$$

One can see that the final consensus rankings for the best (11) and the worst (12) alternatives of the decomposed preference profile substantially coincide with the consensus ranking (10) for original undecomposed ranking.

5. Conclusion

The results of the developed method application to real energy audit data have shown, that the decomposition of the profile does not lead to a significant change in the outcomes of the energy audit data processing. The validity of this statement is demonstrated by comparison of the consensus rankings obtained for the set of best substations and the set of worst substations composed of subprofiles consensus rankings with the consensus ranking obtained for the initial (undecomposed) profile. This means that the decomposition is allowable and justified way of reducing the dimension n when it is necessary.

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