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Are Stakeholders' Opinions Redundant? †

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† In memoriam Rainer Bruggemann (28 October 1943–4 December 2022).

Abstract: Decision-making, bringing in the opinions of several stakeholders, may be a rather time- and resource-demanding process. Partial order-based methods like generalized linear aggregation (GLA) and average ranking appear as advantageous tools for considering several stakeholders' opinions simultaneously. The present study presents an approach where stakeholders' opinions/weights are substituted by a series of randomly generated weight regimes, leading to virtually identical rankings as demonstrated through comparisons to examples where true stakeholder opinions are applied, as demonstrated through a study on food sustainability. This study showed a high degree of agreement between the ranking based on random data and that based on real stakeholder data. The method, which is a top-down approach to the decision process, appears to be a highly resource-reducing decision-supporting process. However, the method, by default, excludes the possibility of incorporating specific knowledge from, e.g., employees or other stakeholders in the decision process.

Keywords: stakeholders' opinions; weight regimes; partial ordering; generalized linear aggregation; average ranking

1. Introduction

Decision-making is a common, if not daily, issue in a variety of situations, e.g., in most companies where decisions often require inclusion and thus analyses of a variety of parameters. One example that is used as an exemplary case in the present study comes from a study on food sustainability. Here, sugar, meat, fat, and salt consumption appear as crucial parameters, but the relative importance of these factors may be different from stakeholder to stakeholder. In the present case, the stakeholders are experts and politicians. However, such decision-making based on a group of parameters/elements, each being characterized by several indicators, often involves the aggregation of data into a single composite indicator by assigning weights to the single indicators followed by a simple arithmetic summation, despite the obvious problems associated with such a method, like compensation effects [1]. Nevertheless, using such composite indicators has obvious advantages, e.g., a subsequent ranking of the single elements based on these indicator values will lead to a strict, complete order. However, it is worthwhile to remember that when applying composite indicators, the role of the individual indicators is masked and no longer distinguishable [1,2].

A crucial point in such an aggregation process is the establishment of the weight regime, i.e., assigning weights to single indicators based on assumptions of the importance of the single indicators. The process of assigning weights typically involves a group of stakeholders [3–6] and can, in principle, be conducted in two different ways: (a) either a group of stakeholders mutually agrees on the weight regime, which may be a troublesome, time-consuming, and thus expensive process, or (b) each stakeholder comes up with their individual weight regime. The advantage of the first method is that eventually, only one single ranking is based on the agreed weight regime, whereas the disadvantage is that the weight regime is based on consensus, which may well be subject to controversy. The advantage of the second method is that each ranking is based on the single stakeholder's weight regime, whereas the disadvantage is that the result would be several rankings

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Citation: Carlsen, L. Are Stakeholders' Opinions Redundant? *Standards* **2024**, *4*, 39–51. https://doi.org/10.3390/standards4020003

Academic Editor: Peter Glavič

Received: 13 September 2023
Revised: 2 January 2024
Accepted: 7 April 2024
Published: 19 April 2024

equal to the number of stakeholders, which eventually need to be combined to give a final ranking. In two recent papers [7,8], a method, generalized linear aggregation (GLA), was introduced to circumvent this step. The GLA method is based on partial ordering [7,8] and results in a weak order based on average ranking, where all stakeholders' opinions simultaneously are considered. The involvement of several stakeholders is foreseen with various associated consequences, not least from an administrative point of view. On the other hand, the potentially troublesome agreement on one single weight regime is avoided. The objective of the present study is to elucidate the possibility that weight regimes that are constructed simply through a random generation of single weights, eventually saving both time and money, can, and possibly to what extent, substitute the involvement of 'real' stakeholders.

It should be mentioned in this connection that such a process is a purely top-down approach, in contrast to a bottom-up one, where employees, experts, or possibly even various political systems promoting specific interests may participate in the decision process as stakeholders.

In the following, the proposed methodology [7,8] will be illustrated using the above-mentioned example from studies on food sustainability [8,9]. In the methodology section, a short introduction to partial ordering and GLA is given.

2. Methodology

2.1. Random Generation of Weight Regimes

Weight regimes were simply generated through random numbers within selected intervals, like [0, 1] or [1, 3], applying the appropriate function in Excel-2021. In all cases described below, three to five different weight regimes were generated.

2.2. Data

The data applied in this study were adopted from the Food Sustainability Index 2021 [9], which has also been used in a recent paper [4] describing the influence of stakeholders on the ranking of the 78 countries based on four indicators (Tables 1 and 2).

Table 1. Indicators of the Food Sustainability Study.

	Indicator	
*r*1	Pct. Of sugar in diets	Percent sugar in the diet
*r*2	Meat consumption levels	The difference in meat consumption (g/capita(day) from the daily recommended intake (90 g/capita/day)
*r*3	Saturated fat consumption	g/capita/day
*r*4	Salt consumption	Average g/day sodium consumption

Table 2. Data matrix of food sustainability. Seventy-eight countries are characterized by the numerical values of four indicators [8,9].

	ID	***r*1**	***r*2**	***r*3**	***r*4**
Algeria	DZA	47.3	86.9	91	24.9
Angola	AGO	65.8	91.2	57.3	72.9
Argentina	ARG	12.2	7.4	14.9	59.2
Australia	AUS	13.3	11.4	6	48
Austria	AUT	22.4	41.1	28.3	33.8
Bangladesh	BGD	84.2	69.4	88.6	44.8

Table 2. *Cont.*

	ID	*r*1	*r*2	*r*3	*r*4
Belgium	BEL	15.7	76.9	31.9	47.2
Brazil	BRA	21.7	26.8	26.2	29.5
Bulgaria	BGR	40.9	70.8	69.4	42.6
Burkina Faso	BFA	78.2	79.4	80.8	62.5
Cameroon	CMR	74.9	78.2	79.8	83.6
Canada	CAN	19.6	35.3	48.8	40.2
China	CHN	84.6	68.2	15	10.2
Colombia	COL	27.5	69.4	30.5	30
Cote d'Ivoire	CIV	77.2	76.1	48	64.6
Croatia	HRV	4.1	48.7	40.2	40.2
Cyprus	CYP	46.8	52.2	58.1	30.8
Czech Republic	CZE	33.9	44.3	43.7	33
Dem. Rep. of Congo	COG	69.4	80.1	79.8	74.8
Denmark	DNK	7.5	49.2	29.8	52
Egypt	EGY	43.8	99.1	90.8	41
Estonia	EST	46.9	60.7	48	33.8
Ethiopia	ETH	77.5	72.5	94.3	78.8
Finland	FIN	40.7	50.6	0	36.5
France	FRA	25.4	49.6	8.3	38.6
Germany	DEU	22.6	49.9	26.1	44.8
Ghana	GHA	78	81.7	95.6	76.7
Greece	GRC	45.9	56.1	71.2	38.6
Hungary	HUN	31.2	44.1	25.8	26.3
India	IND	45.5	69.2	83.4	39.9
Indonesia	IDN	56.8	78.5	73.1	49.6
Ireland	IRE	25.4	50.8	33.9	39.4
Israel	ISL	53.8	28.2	43.9	38.1
Italy	ITA	42.3	46.6	31.4	21.2
Japan	JPN	41.9	82.1	77	8.6
Jordan	JOR	15.8	99.8	64.8	29
Kenya	KEN	49.6	82.1	90.1	100
Latvia	LVA	40.8	58.3	50.9	27.3
Lebanon	LBN	7.3	98.3	88.6	55.8
Lithuania	LTU	28	44.3	33.9	30.6
Luxembourg	LUX	49.1	46.6	11.1	30.6
Madagascar	MDG	74.2	79.5	94.1	80.7
Malawi	MWI	68.6	78.8	95.5	95.2
Mali	MLI	77.2	88	97.6	55.2
Malta	MLT	16.9	50.9	63.6	29.8
Mexico	MEX	10.2	60.6	35.2	65.7
Morocco	MAR	35.9	100	88.1	24.1

Table 2. *Cont.*

	ID	*r*1	*r*2	*r*3	*r*4
Mozambique	MOZ	60.2	75.4	60.5	79.6
Netherlands	NLD	32.3	60.7	34.7	50.7
Niger	NER	100	74.3	92.4	61.4
Nigeria	NGA	74	73	69.4	64.1
Pakistan	PAK	37.8	82.8	41.1	34.9
Philippines	PHL	43.7	96.8	48.2	24.7
Poland	POL	18.7	39	7.2	36.7
Portugal	PRT	52.3	32	30.4	26
Romania	ROU	50.4	65.5	63.8	29.2
Russia	RUS	19.8	53.4	57.9	27.9
Rwanda	RWA	70.4	73.3	80.4	96.8
Saudi Arabia	SAU	42.4	87.3	22.3	53.9
Senegal	SEN	54.2	81.4	74.8	55.2
Sierra Leone	SLE	84.9	74.4	52	72.4
Slovakia	SVK	29.1	73.9	65.1	26.3
Slovenia	SVN	45.3	60.2	64.1	26.3
South Africa	ZAF	30.4	66.4	57	73.2
South Korea	KOR	31.3	58.5	33.1	0
Spain	ESP	39	27.4	54.9	31.9
Sudan	SDN	23.8	88.3	95.5	76.1
Sweden	SWE	27.8	56.2	4.1	41.8
Tanzania	TZA	70	76.6	82.1	66
Tunisia	TUN	36	96.5	80.5	20.9
Turkey	TUR	46.9	94.1	43.4	29.8
United Arab Emirates	ARE	29.3	61.8	68.1	41.3
Uganda	UGA	62.7	78	69.2	83.1
United Kingdom	GBR	40.9	51.6	31.7	42.9
United States	USA	0	0	41.5	43.2
Vietnam	VNM	75.6	65.2	24.6	16.6
Zambia	ZMB	66	85.7	87.1	78.8
Zimbabwe	ZWE	27.9	85.3	100	56.6

It should be emphasized that "all indicator scores are normalized to a 0 to 100 scale, where 100 indicates the highest sustainability and greatest progress towards meeting environmental, social, and economic key performance indicators (KPI), and 0 represents the lowest" [9] (cf. Excel Workbook: Methodology), i.e., for all 4 indicators, the higher the indicator value, the better. Hence, no further treatment of the indicator values was necessary (cf. discussion about normalization in [7,8]).

2.3. Partial Ordering

Partial ordering is a relation between objects (here, the 78 countries, cf. Table 2). The method allows the analysis of the data without any pretreatments, e.g., aggregation of the data into one single indicator. In mathematical terms, partial ordering is based on the "$\leq$" relation (cf. e.g., [10,11]). Considering two objects, x and y, where object x is characterized by a set of indicators r_s(x), s = 1, . . ., m (in the present case m = 4, cf. Table 1) is comparable to the object y, which is characterized by an identical set of indicators r_s(y), if and only if the relation x $\leq$ y holds (see below, Equation (1)):

$$r_s(\mathrm{x}) \leq r_s(\mathrm{y}) \text{ for all } s = 1, \ldots, m. \tag{1}$$

The application of Equation (1) needs a convention about the orientation of the single indicators, i.e., the larger the value of an indicator, the better. In cases where indicators do not have the same orientation, this will initially be remedied by multiplying these indicator values by -1 to secure the common orientation. Since the single indicator values are not numerically aggregated, the method excludes, by default, possible compensation problems, i.e., a "good" value of an indicator may compensate a "bad" one of another indicator. [1,10]. A graphical representation of Equation (1) is the so-called Hasse diagram [2,11], visually displaying the partial ordering of the objects.

The Hasse Diagram

In the Hasse diagram, comparable objects are connected through a sequence of lines [2,11]. If Equation (1) is not fulfilled for some objects x, y, then x is incomparable with y, denoted by x $\|$ y. Such incomparabilities point to the data leading to conflicts between the objects, e.g., x < y for some indicator(s) and y < x for other(s). If, for a subset of the data x, y, the $\leq$ - relation (Equation (1)) holds for all elements, this set will be denoted as a chain. On the other hand, if for a given subset, x $\|$ y for all x, y, this set is called an antichain.

2.4. Generalized Linear Aggregation (GLA)

Although the GLA procedure has been explained in detail previously [7,8], a brief explanation is given here.

When the original multi-indicator system (MIS) (denoted as "MIS(old)" to emphasize the role of the aggregation process) is written in the form where r_r are the indicators and e_i the studied elements:

$$MIS(old) = \begin{array}{c c} & \begin{array}{cccc} r_1 & r_2 & \cdots & r_n \end{array} \\ e_1 e_2 \cdots e_m & \left[\begin{array}{cccc} \; & \; & \; & \; \end{array} \right] \end{array} \tag{2}$$

If only the opinion of one single stakeholder is introduced, i.e., applying one single weight scheme, only the aggregation to a single scalar, CI (composite indicator), that subsequently may serve as a ranking index can be formulated using (Equation (3)):

$$\mathrm{CI} = (\mathrm{g}_1\ \mathrm{g}_2 \ldots \mathrm{g}_\mathrm{m}) \cdot \mathrm{MIS(old)}, \text{ i.e., } \mathrm{CI} = \sum \mathrm{g}_\mathrm{i} \cdot \mathrm{r}_\mathrm{i}^{\mathrm{old}}, \tag{3}$$

where the selection of weights, g_i, is responsible for the composite indicator CI but is based on a system of indicator values r_i^{old}, where r_i^{old} refers to the MIS(old).

The result of the matrix multiplication, where a row of m entries is acting on each column of matrix MIS, leads to the traditional weighted sum expressing the aggregation process. The difficulty in Equation (3) is not its mathematics, but the way how the weights can be found cf. [3–6].

If several stakeholders, s_1, s_2, . . ., s_t, are considered, the corresponding weight scheme can be summarized in a matrix G (Equation (4)):

$$G = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ g_{t1} & g_{t1} & \cdots & g_{tn} \end{bmatrix} \tag{4}$$

The weights bear important information concerning the roles played through the single indicators of an original MIS. The aggregation to a set of single scalars can be formulated as follows:

$$\hat{G} \cdot MIS(old) = MIS(new). \quad (5)$$

Equation (5) describes the calculation of a new MIS through matrix multiplication of the weight matrix G (Equation (4)), where each row of G corresponds to a weight regime. In Equation (5), the role of G as an operator $\hat{G}$ is stressed; $\hat{G}$ denotes the transformed G matrix. Application of Equation (5) is more convenient as it accepts any number of weight regimes/stakeholder opinions.

Following the GLA procedure, a highly enriched Hasse diagram is obtained, i.e., a diagram with a much higher number of comparisons and, simultaneously, a significantly reduced number of incomparisons, U, as a consequence of including all stakeholder opinions, i.e., weight regimes, simultaneously. In general, the procedure will not lead to a strict linear order, as would the result of taking only one weight regime/stakeholder into account.

2.5. Average Ranks

The level structure of the Hasse diagram offers a first approximation to an order. However, as all objects on a level automatically will be assigned identical orders, such an order will cause many tied orders. It is desirable that the degree of tiedness is as low as possible, i.e., a ranking with a low number of incomparabilities, ideally a linear ordering of the single objects. However, since a certain portion of incomparable objects are present, this is not immediately obtainable. Partial order methodology provides a weak order, i.e., where tied orders are not excluded—an average ranking—as described by Bruggemann and Carlsen [12] and Bruggemann and Annoni [13]. The above-described GLA procedure significantly enriches the Hasse diagram, thus decreasing U and eventually leading to an average ranking closer to the single linear order.

2.6. Software

All partial-order analyses were carried out using the PyHasse software [14]. PyHasse is programmed using the interpreter language Python (version 2.6). Today, the software package contains around 140 more or less specialized modules. Selected modules are available from the author.

3. Results and Discussion

In a recent study [4], the advantageous effect of applying the GLA method was demonstrated. This study included four "stakeholders" denoted as Expert, Political, Outcome, and Uniform (cf. Table 3), each giving rise to a weighting scheme, with the single weights ranging from 0 to 1. Subsequently, this weighting scheme (Table 3) was applied to give an average ranking of the countries shown in Table 2 [8]. The results of the GLA, i.e., the resulting Hasse diagram and the average ranking are shown and discussed in detail previously [8].

Table 3. Four weighting schemes, as defined within the food sustainability study [8].

Indicators	Expert	Political	Outcome	Uniform
i1: Percentage of sugar in diets	0.375	0.143	0.400	0.250
i2: Meat consumption levels	0.250	0.286	0.200	0.250
i3: Saturated fat consumption	0.163	0.286	0.200	0.250
i4: Salt consumption	0.213	0.286	0.200	0.250

The question now arises: if a random generation of weighting schemes would lead to an identical ranking of the 78 countries, thereby making a significant reduction in the use of resources required to achieve the weighting schemes from the single stakeholders.

A ranking based on a single randomly generated weighting scheme may well result in a quite different ranking than the one shown in Table 3 [8]. To circumvent this, a series of GLA calculations were performed, with the eventual ranking generated as an average of rankings generated through the individual GLAs. In the present case, five randomly generated weighting schemes were applied. The resulting average rankings are shown in Table 4, together with the average and the standard deviation (std).

Table 4. Average ranking of the 78 countries following five GLA based on randomly generated weighting schemes.

ID	Rank_a	Rank_b	Rank_c	Rank_d	Rank_e	Average	Std
AGO	19	16	16	17	13.5	16.3	1.987
ARE	42	45	40	38	42	41.4	2.608
ARG	75	76	75	72	76	74.8	1.643
AUS	78	78	78	76	77.5	77.5	0.866
AUT	69	71	72	70	73	71	1.581
BEL	56.5	51	50	43	51	50.3	4.817
BFA	11	9	11	13	12	11.2	1.483
BGD	13	12	13	20	21	15.8	4.324
BGR	29	32	32	29	32	30.8	1.643
BRA	74	74	74	75	74	74.2	0.447
CAN	61	66	68	60	64.5	63.9	3.362
CHN	43	36	46	55	44	44.8	6.834
CIV	23	27.5	25	21	23	23.9	2.460
CMR	9	8	8	7	10	8.4	1.140
COG	12	13	12	11	11	11.8	0.837
COL	60	55	52	57	53	55.4	3.209
CYP	37	46.5	47	45	47	44.5	4.272
CZE	54	54	58	58	56	56	2.000
DEU	64	65	59	53	59	60	4.796
DNK	66	72	67	56	66	65.4	5.814
DZA	26	21	24	30	28	25.8	3.493
EGY	21	11	15	24	17	17.6	5.079
ESP	52	60	62	61	61	59.2	4.087
EST	45	46.5	44	44	46	45.1	1.140
ETH	5	6	7	5.5	9	6.5	1.581
FIN	68	67	64	63	67	65.8	2.168
FRA	72	73	73	68	71	71.4	2.074
GBR	51	52	51	47	52	50.6	2.074
GHA	1.5	2	1	5.5	2	2.4	1.782
GRC	31	38	37	33	36	35	2.915
HRV	71	70	70	67	69	69.4	1.517
HUN	67	68	71	73	72	70.2	2.588

Table 4. *Cont.*

ID	Rank_a	Rank_b	Rank_c	Rank_d	Rank_e	Average	Std
IDN	25	25	27	27	26	26	1.000
IND	27	29	30	28	30	28.8	1.304
IRE	59	62	57	54	58	58	2.915
ISL	44	50	53	48	54	49.8	4.025
ITA	62	57	60	71	60	62	5.339
JOR	48	43	38	40	39	41.6	4.037
JPN	36	33	34	51	38	38.4	7.301
KEN	10	14	9	4	5	8.4	4.037
KOR	73	63	69	77	70	70.4	5.177
LBN	33	30	28	26	25	28.4	3.209
LTU	65	64	65	66	64.5	64.9	0.742
LUX	63	61	61	64	62	62.2	1.304
LVA	49	48	49	52	49	49.4	1.517
MAR	28	18	22	32	27	25.4	5.459
MDG	4	4.5	3	3	3	3.5	0.707
MEX	53	58	54	37	50	50.4	8.019
MLI	7	3	4.5	12	6	6.5	3.428
MLT	56.5	56	55	59	55	56.3	1.643
MOZ	20	27.5	26	18	20	22.3	4.177
MWI	1.5	4.5	2	1	1	2	1.458
NER	3	1	4.5	9	8	5.1	3.362
NGA	18	19.5	19	19	19	18.9	0.548
NLD	50	49	48	41	48	47.2	3.564
PAK	46	42	41	42	40	42.2	2.280
PHL	38	34	31	39	34	35.2	3.271
POL	76	75	76	74	75	75.2	0.837
PRT	55	59	66	69	68	63.4	6.107
ROU	34	35	36	35	35	35	0.707
RUS	58	53	56	65	57	57.8	4.438
RWA	6	10	10	2	7	7	3.317
SAU	39	39	39	31	37	37	3.464
SDN	17	24	18	15	16	18	3.536
SEN	24	22	23	23	22	22.8	0.837
SLE	15	17	20	14	18	16.8	2.387
SVK	47	44	43	50	45	45.8	2.775
SVN	41	41	42	46	41	42.2	2.168
SWE	70	69	63	62	63	65.4	3.782
TUN	32	26	29	36	29	30.4	3.782
TUR	35	31	33	34	33	33.2	1.483
TZA	14	15	14	16	15	14.8	0.837

Table 4. *Cont.*

ID	Rank_a	Rank_b	Rank_c	Rank_d	Rank_e	Average	Std
UGA	16	19.5	17	10	13.5	15.2	3.616
USA	77	77	77	78	77.5	77.3	0.447
VNM	40	40	45	49	43	43.4	3.782
ZAF	30	37	35	25	31	31.6	4.669
ZMB	8	7	6	8	4	6.6	1.673
ZWE	22	23	21	22	24	22.4	1.140

It is immediately noted that the single average ranking from the five GLAs does not appear identical but still quite similar, which itself appears somewhat surprising. This is further verified through the relatively small standard deviations obtained by averaging the five rankings. In Table 5, the randomly generated weight regime leading to rank a (Table 4) is shown. In Figure 1, the original Hasse diagram based on the data in Table 2 (A) is shown together with the diagram based on the GLA a (B), and for comparison, the diagram following the GLA applying the original weights [4], as given in Table 3 (C). Figure 1A,C is adopted from [8].

Table 5. Randomly generated weight scheme for the GLA process leading to rank a.

Indicators:	R1	R2	R3	R4
i1: Percentage of sugar in diets	0.193	0.165	0.352	0.29
i2: Meat consumption levels	0.494	0.044	0.167	0.294
i3: Saturated fat consumption	0.265	0.258	0.29	0.186
i4: Salt consumption	0.445	0.087	0.229	0.24

The enrichment of the diagram (Figure 1B,C) compared to the original (Figure 1A) is immediately apparent. Thus, the original Hasse diagram has only 1048 comparisons and 1955 incomparisons, whereas the diagram in Figure 1B displays 2602 comparisons and only 401 incomparisons. The diagram in Figure 1C displays 2718 comparisons and 285 incomparisons, which for the two diagrams in Figure 1B,C are further visualized through much slimmer and higher diagrams. The similarity between the diagrams in Figure 1B,C is striking, although there are differences. However, it must be remembered that this is only an exemplary case. Hence, the average rankings obtained through the five GLAs based on randomly generated weighting schemes remain to be discussed, compared to the rankings obtained by applying the original fixed ranking (cf. Table 3). In Table 5, the top 10 and bottom 10 ranked countries are summarized and compared to the ranking previously obtained [8] (Table 6).

Looking at the data given in Table 5, it is obvious that some variations between the original raking and that based on the randomly generated weighting schemes prevail. However, taking into account the standard deviations, a surprisingly good agreement between the two sets of data is immediately noted.

An obvious question now arises: how many randomly generated weighting schemes and subsequent GLAs are necessary to obtain reliable results? To answer this question, a series of weighting schemes were randomly generated, allowing integer values of 1, 2, and 3 for four 'stakeholders' (cf. Table 1). The original dataset (Table 2) was applied, and the combined average rankings for the GLAs were generated following three, five, and seven GLAs. It should be noted that all weighing schemes, i.e., in total fifteen, were different, meaning that, e.g., for the series of five weighting schemes, none of the weighting schemes for the series of three were reused.

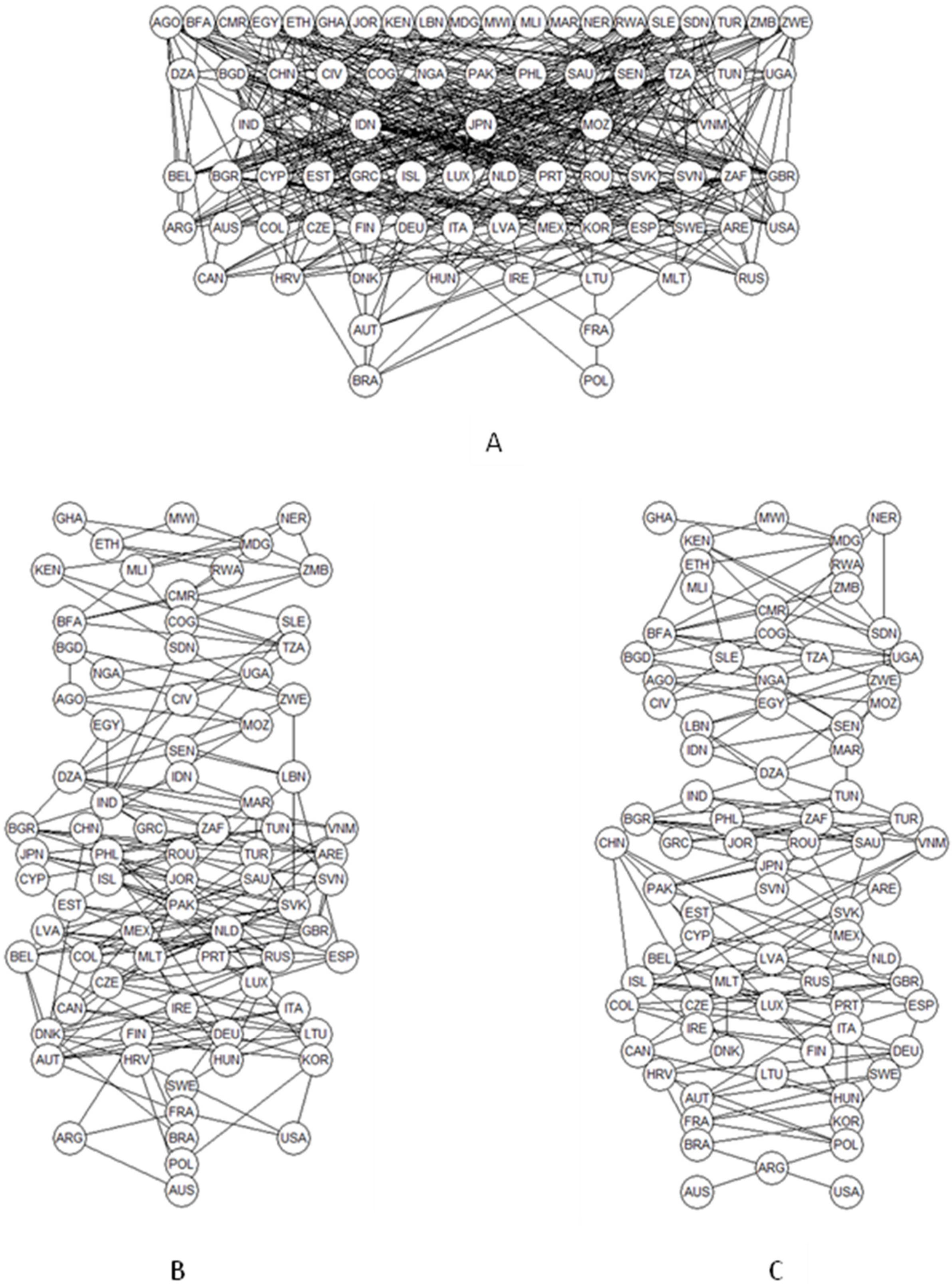

Figure 1. (**A**) The original Hasse diagram based on the data in Table 2, (**B**) the Hasse diagram based on the GLA a, and (**C**) the Hasse diagram following the GLA applying the original weights [4] as given in Table 3.

Table 6. Combined average rankings (top 10 and bottom 10) of the 78 countries following the five GLAs based on the above (Table 4) randomly generated weighting schemes.

Objects	Average	Std	[8]
	Top 10		
MWI	2	1.458	MWI
GHA	2.4	1.782	GHA
MDG	3.5	0.707	MDG
NER	5.1	3.362	NER
ETH	6.5	1.581	ETH
MLI	6.5	3.428	RWA
ZMB	6.6	1.673	KEN
RWA	7	3.317	MLI
CMR	8.4	1.140	ZMB
KEN	8.4	4.037	CMR
	Bottom 10		
HRV	69.4	1.517	HUN
HUN	70.2	2.588	HRV
KOR	70.4	5.177	AUT
AUT	71	1.581	FRA
FRA	71.4	2.074	KOR
BRA	74.2	0.447	BRA
ARG	74.8	1.643	POL
POL	75.2	0.837	ARG
USA	77.3	0.447	AUS
AUS	77.5	0.866	USA

In Figure 2, the comparison of three series, SH3: ●, SH5: ♦, and SH7: ▲, is visualized. It is immediately clear that a good agreement between the three series prevails. However, a somewhat better agreement between SH5 and SH7 than the agreement with SH3 is noted—although not spectacular. Hence, it is suggested that SH5 appears sufficient and should be the preferred choice in general.

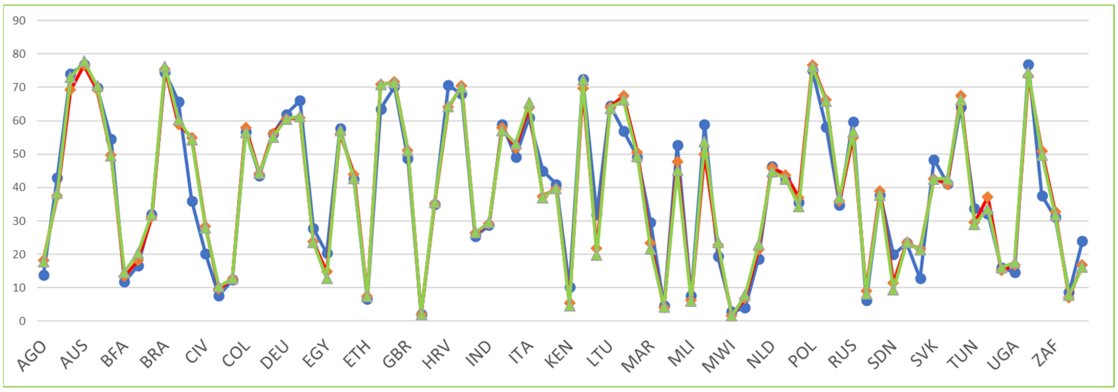

Figure 2. Combined average ranks following GLA applying three (●), five (♦), and seven (▲) randomly generated weighting schemes, respectively.

A further obvious question to ask is to what extent the proposed method can be used and what the possible limitations are. Here, it should initially be noted that a satisfactory agreement between the ranking based on random data and those from real stakeholder opinions is striking. However, despite the fact that the method a priori does not suffer from specific limitations, in cases where real stakeholders' opinions are available, they obviously should be applied.

4. Conclusions and Outlook

The present paper answers the question: Are stakeholders' opinions redundant? To answer the question, partial order-based methods, generalized linear aggregation (GLA) combined with average ranking, were applied. To simulate—here four—stakeholders' opinions, randomly generated weight regimes were brought into play, and using GLA, the combined effect of the stakeholders was calculated. The overall effect was retrieved by averaging the outcome of the individual GLAs. The result is compared to that of a previous study applying real stakeholders' weight regimes, demonstrating close agreement.

In a further study, the effect of the number of simulations was disclosed using three, five, and seven sets of weight regimes for the ranking of the data. Based on these calculations, it is suggested that applying five sets of weight regimes satisfactorily leads to a result that closely mimics what was obtained based on real stakeholders' opinions.

Application of the suggested method discloses that stakeholders' opinions may well be redundant and that a combined inclusion of a series of randomly generated weight regimes to substitute opinions of real stakeholders is assumed to be a highly resource-reducing decision-supporting process. It must, however, be stressed that this obviously top-down method excludes advantages possibly obtained through the involvement of employees in the decision process through a bottom-up process. However, obviously, employees may well be stakeholders. In such a situation, obviously 'real' data, e.g., the weighting based on employee opinions, will be used.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are openly available in reference [9].

Conflicts of Interest: There are no conflicts of interest.

References

1. Munda, G. *Social Multi-Criteria Evaluation for a Sustainable Economy*; Springer: Berlin/Heidelberg, Germany, 2008. Available online: https://www.springer.com/la/book/9783540737025 (accessed on 12 September 2023).
2. Bruggemann, R.; Patil, G.P. *Ranking and Prioritization for Multi-Indicator Systems—Introduction to Partial Order Applications*; Springer: New York, NY, USA, 2011. Available online: https://www.springer.com/gp/book/9781441984760 (accessed on 12 September 2023).
3. Smith, L.W. Stakeholder Analysis: A Pivotal Practice of Successful Projects. In Proceedings of the Project Management Institute Annual Seminars & Symposium, Houston, TX, USA, 7–16 September 2000; Project Management Institute: Newtown Square, PA, USA, 2000. Available online: https://www.pmi.org/learning/library/stakeholder-analysis-pivotal-practice-projects-8905 (accessed on 12 December 2023).
4. Stakeholder Influence. Available online: https://www.stakeholdermap.com/stakeholder-influence.html (accessed on 1 December 2023).
5. Lienert, J. Stakeholder Importance and Influence. 2020. Available online: https://sswm.info/es/humanitarian-crises/prolonged-encampments/planning-process-tools/exploring-tools/stakeholder-importance-and-influence (accessed on 1 December 2023).
6. Greany, K. 4 Fresh Strategies to Transform Your Stakeholder Relationships and Influence Change. eLearning Industry. 2021. Available online: https://elearningindustry.com/fresh-strategies-transform-stakeholder-relationships-and-influence-change (accessed on 1 December 2023).
7. Carlsen, L.; Bruggemann, R. Partial Order as Decision Support Between Statistics and Multicriteria Decision Analyses. *Standards* **2022**, *2*, 306–328. [CrossRef]

8. Carlsen, L.; Bruggemann, R. Combining different stakeholders' opinions in multi-criteria decision analyses applying partial order methodology. *Standards* **2022**, *2*, 503–521. [CrossRef]
9. Food Sustainability Index. See also the Associated Workbook: Food_Sustainability_Index_2021.xlsm. 2021. Available online: https://impact.economist.com/projects/foodsustainability/ (accessed on 12 September 2023).
10. Nardo, M.; Saisana, M.; Saltelli, A.; Tarantola, S.; Hoffman, A.; Giovannini, E. *Handbook on Constructing Composite Indicators: Methodology and User Guide*; OECD: Ispra, Italy, 2008. Available online: https://www.oecd.org/sdd/42495745.pdf (accessed on 12 September 2023).
11. Brüggemann, R.; Carlsen, L. Introduction to partial order theory exemplified by the Evaluation of Sampling Sites. In *Partial Order in Environmental Sciences and Chemistry*; Bruggemann, R., Carlsen, L., Eds.; Springer: Berlin/Heidelberg, Germany, 2006; pp. 61–110. [CrossRef]
12. Brüggemann, R.; Carlsen, L. An Improved Estimation of Averaged Ranks of Partial Orders. *MATCH Commun. Math. Comput. Chem.* **2011**, *65*, 383–414.
13. Bruggemann, R.; Annoni, P. Average Heights in Partially Ordered Sets. *MATCH Commun. Math. Comput. Chem.* **2014**, *71*, 117–142.
14. Bruggemann, R.; Carlsen, L.; Voigt, K.; Wieland, R. PyHasse Software for Partial Order Analysis. In *Multi-Indicator Systems and Modelling in Partial Order*; Bruggemann, R., Carlsen, L., Wittmann, J., Eds.; Springer: New York, NY, USA, 2014; pp. 389–423. [CrossRef]