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A Simple Method to Construct a Group Composite Indicator with an Application

Davood Nejatpour[a], Abdollah Hadi-Vencheh[a,*] and Ali Jamshidi[a]

[a] *Department of Mathematics, Isfahan (Khorasgan) Branch, Islamic Azad University, Isfahan, Iran.*

Abstract. In this paper, we propose a novel and straightforward nonlinear programming approach for aggregating individual composite indicators (CIs) into a group-level composite indicator (e.g., an aggregate CI for a group of entities). Drawing on performance measurement literature, our model is designed to be both simple and computationally efficient, requiring no specialized solvers for implementation. The proposed approach addresses the growing need for robust and interpretable methods to synthesize multidimensional data, particularly in contexts where policymakers and researchers aim to compare and benchmark the performance of groups or regions. To demonstrate the practical application of our method, we compute an aggregate Human Development Index (HDI) for the European Union (EU) region using HDI sub-indicators from individual EU member states. This case study highlights the model's ability to integrate diverse dimensions of human development—such as health, education, and standard of living—into a single, coherent metric. By doing so, we provide a tool for evaluating the collective progress of the EU region while preserving the unique contributions of each member state. Our approach offers several advantages: (1) it is computationally accessible, making it suitable for a wide range of applications; (2) it allows for flexibility in weighting and aggregation, accommodating diverse policy priorities; and (3) it provides a transparent framework for constructing group-level CIs, enhancing their utility for decision-making and public communication.

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1. Introduction

A composite indicator (CI) is a mathematical aggregation of individual indicators, serving as a valuable tool for performance measurement, benchmarking, policy analysis, and public communication. By providing an aggregated performance index, CIs are widely used in various fields, such as sustainable energy, human development, and environmental performance [10, 12, 2]. Composite indicators should ideally measure multidimensional concepts which cannot be captured by a single indicator. Therefore, a composite indicator is a useful tool for performance comparisons, public communication and decision support in a wide spectrum of fields [13, 15, 16]. According to Saisana and Tarantola [12], a composite indicator combines single indicators that represent different dimensions of a concept, which is the primary objective of the analysis (see also [14] and [8], for detailed discussions). For instance, the Human Development Index (HDI) is one of the most well-known composite indicators. The HDI measures three key dimensions: longevity (a long and healthy life), knowledge (education), and standard of living, reflecting a country's

*Corresponding author. Email: ahadi@khuisf.ac.ir

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growth and development [10].

Composite indicators are particularly effective for evaluating the role of education policies in developing countries within the context of comprehensive economic development. They establish a quantitative relationship between the determinants of human resource development and economic progress. This paper proposes a model for constructing composite indicators and applies this approach to develop a CI for modeling sustainable energy development across eighteen Asia-Pacific Economic Cooperation (APEC) economies. Sustainable energy development encompasses critical elements such as energy supply, energy efficiency, and environmental protection, making it a central concept in sustainable development [3]. Measuring and comparing sustainable energy development across countries or regions is therefore highly significant.

The proposed approach is used to develop a Sustainable Energy Index (SEI) for eighteen APEC economies in 2002, enabling the measurement and comparison of their performance in sustainable energy development. This application study also illustrates the general procedure for constructing CIs and demonstrates how the proposed approach can be practically implemented. Following Esty et al. [2], we select three sub-indicators for constructing the SEI: the Energy Efficiency Indicator (EEI), Renewable Energy Indicator (REI), and Climate Change Indicator (CCI).

In recent years, numerous researchers have explored composite indicators. For example, Zhou et al. [17] proposed two classical Data Envelopment Analysis (DEA)-like models to determine the best and worst sets of weights for underlying sub-indicators, along with a Simple Additive Weighting (SAW) formula for data aggregation. Their approach aggregates the best and worst efficiency scores using an adjusting parameter (λ) to derive final CIs. According to Nardo et al. [9], the number of composite indicators worldwide continues to grow annually, driven by their ability to summarize, focus, and condense the complexity of our dynamic environment. Morais and Camanho [7] developed a composite indicator for quality of life and local management performance using DEA, followed by goal programming to compare the performance of cities and countries. Similarly, Despotis [1] estimated an ideal value of the composite Human Development Index for countries in the Asia-Pacific region using a DEA-like index-maximizing model. He extended this analysis through a goal-programming model to obtain global estimates of human development based on optimal common weights for component indicators.

Rogge [10] introduced a procedure for aggregating individual composite indicators into a group. This method is closely related to DEA, specifically an input-oriented model with a single constant input. Its primary advantage lies in generating idiosyncratic weights for aggregating sub-indicators, which vary across both sub-indicators and decision-making units (DMUs) [4]. In general notation, an aggregate group CI is a function that combines and weights the CIs of constituent countries into a single aggregate score. Formally, for a group of $\boldsymbol{K}$ countries, this can be expressed as: $\boldsymbol{CI_G = f(w_1 CI_1, w_2 CI_2, \ldots, w_k CI_k)}$ with $\boldsymbol{CI_G}$ the aggregate CI-score for the group of countries, $\boldsymbol{CI_k}$ $(\boldsymbol{k = 1, 2, \ldots, K})$ the CI-values for the $\boldsymbol{k}$ evaluated countries in the group, $\boldsymbol{w_k}$ the country shares in the aggregate of the group, with $\boldsymbol{w_k \geq 0}$ and $\boldsymbol{\sum_{k=1}^{K} w_k = 1}$ [11].

In recent years, researchers such as [5] have employed a Benefit-of-the-Doubt (BOD) weighting model that incorporates expert opinions to construct a composite indicator evaluating the competitiveness level of Costa Rican counties from 2010 to 2016. Their results demonstrate the superior informative power of the proposed BOD composite indicator compared to models using equal weights or principal component analysis. Similarly, Mergoni et al. [6] measured and benchmarked the environmental performance of Portuguese utilities operating in water supply, wastewater collection, and solid waste management. They proposed a directional distance BOD index, complemented by a robust and conditional approach, revealing significant room for improvement, particularly among small and large urban utilities.

Recent advancements in CI methodology include the work of Xavier [16], who developed a composite indicator to assess the sustainability of urban systems, focusing on energy consumption, waste management, and greenhouse gas emissions. Their study emphasized the importance of integrating environmental and social dimensions into sustainability assessments, providing a holistic framework for evaluating urban sustainability. Additionally, Sánchez et al. [14] proposed a novel approach to constructing composite indicators using machine learning techniques. Their method leverages clustering algorithms to identify patterns in sub-indicators, enabling the creation of more robust and interpretable CIs. This approach represents a significant advancement in CI methodology, offering a data-driven alternative to traditional weighting schemes.Wa ng et al. (2022) explored the use of composite indicators in assessing renewable energy adoption across developing countries. Their study highlighted the role of policy frameworks, technological innovation, and public awareness in driving renewable energy transitions. The findings underscore the potential of CIs to inform policy decisions and track progress toward sustainable energy goals.

By reviewing the above literature, we found that the proposed methods are not easy and needs an advanced mathematics knowledge. The aim of this paper is to present a simple way to compute the CI and then we extend the proposed method for obtaining the group CI. The reminder of this study is organized as follows. In the following section we first review the Zhou model. Section 3 is devoted to the proposed method and then it is illustrated with a real case in section 4. Section 5 includes the conclusion.

2. The Zhou-model

Zhou et al [17] proposed a mathematical programming approach to constructing Cis. The approach requires no prior knowledge the weights for sub-indicators. It produces a CI by using two sets of weights that are generated from data themselves. In the section 4, we apply the proposed approach to developing a CI for modeling sustainable energy development of eighteen Asia Pacific Economic Cooperation (APEC) economics. Suppose there are k entities with M criteria. Also suppose y_{km} denotes the value of entity k with respect to sub-indicator m.Let entity k, be under consideration. A DEA like model is given here for aggregation purpose:

$$\begin{aligned} & gI_k = max \sum_{m=1}^{M} v_m^g y_{km} \\ & \quad \text{s.t} \quad \sum_{m=1}^{M} v_m \, y_{jm} \leq 1 \qquad j = 1, \dots, k \\ & \quad v_m^g \geq 0 \qquad m = 1,2, \dots, M. \end{aligned} \tag{1}$$

Model (1) provides an aggregated performance score for entity k in terms of all the underlying sub-indicators. In virtue of its DEA feature, model (1) can help each entity select the best set of weights for use. It avoids the subjectiveness in determining weights and therefore provides a relatively objective performance score for each entity. However, if an entity has a value dominating other entities in terms of a certain sub-indicator, this entity would always obtain a score of 1 even if it has severely bad values in other more important sub-indicators. Furthermore, only model (1) may lead to the situation that a large number of entities have a performance score of 1 and further ranking among them becomes difficult. To address these issues, we extend model (1) and propose a similar linear programming model as follows:

$$\begin{aligned} & bI_k = min \sum_{m=1}^{M} v_m^b y_{km} \\ & \quad \text{s.t} \sum_{m=1}^{M} v_m \, y_{jm} \geq 1 \qquad j = 1, \dots, k \\ & \quad v_m^b \geq 0 \qquad m = 1,2, \dots, M \end{aligned} \tag{2}$$

Contrary to model (1), model (2) seeks the worst set of weights for each entity which are used to aggregate the sub-indicators into a performance score. Since the two indexes are based on weights that are most favorable and least favorable for each entity, they could only reflect partial aspects of an entity in terms of its aggregated performance. It is logical and reasonable to combine them into an overall index. Therefore, they combine the two indexes to form a CI in the following way:

$$CI_k(\lambda) = \lambda \frac{gI_k - gI^-}{gI^* - gI^-} + (1-\lambda)\frac{bI_k - bI^-}{bI^* - bI^-} \quad (3)$$

Where

$$gI^* = max\{gI_k, k = 1, \dots, K\} \qquad bI^* = max\{bI_k, k = 1, \dots, K\}$$

$$gI^- = min\{gI_k, k = 1, \dots, K\} bI^- = min\{bI_k, k = 1, \dots, K\}$$

$0 \le \lambda \le 1$ Is a control parameter which may reflect the preference of decision maker on the good and bad indexes. Choosing appropriate value for this parameter is crucial and depends on DM's preferences on two aforementioned extreme cases. If ƛ=1, CI_k will become a normalized version of, gI_k. If ƛ=0, CI_k will become a normalized version ofbI_k. For other cases model (5) makes a compromise between the two indexes. If inventory managers have no strong preference ƛ=0.5 would be a fairly neutral and reasonable choice.

3. The proposed model

Suppose there are k entities with M criteria. Also suppose y_{km}denotes the measurement of sub-indicator m with respect to entity k. We would like to convert the multiple measures into a single score of an entity. We firstly transform all measures to comparable base. using transformation $\frac{y_{km}}{max_{k=1,2,\dots,K}\{y_{km}\}}$ can be adopted to convert all measurement in a $0-1$ scale for all entities. To facilitate the construction of CI, we define a non-negative weight $w_m$which is the weight of contribution of performance of the kth entity under mth criteria. Besides, we assume the criteria are ranked in a descending order such that $w_1 \ge w_2 \ge \dots 0 \ge w_M$for all entities. The proposed model is as follows:

$$\begin{aligned} & CI_k = \max \textstyle\sum_{m=1}^{M} w_m\, y_{km} \\ s.t \quad & \textstyle\sum_{m=1}^{M} {w_m}^2 = 1 \\ & w_m \ge w_{m+1} \ge 0 \qquad \forall \; m = 1,2,\dots,M-1 \\ & w_m \ge 0 \qquad m = 1,2,\dots,M \end{aligned} \quad (4)$$

The model (4) is a nonlinear programming model, which determines, the most favorable weights within the feasible region

$$W = \left\{ w | w = (w_1, \dots \;, w_M). w_1 \ge w_2 \ge \dots \ge w_M \ge 0, \sum_{m=1}^{M} w_m^2 = 1 \right\}$$

For each entity. Now, if we remove the weightsconstraint in model (4), we can see the analytical solution of this model even without using the software as follows.

$$w_m^* = \frac{y_{km}}{\sqrt{\sum_{m=1}^{M} y_{km}^2}}, m = 1,2,\dots,M \quad (5)$$

Due to presence of the ordering constraint $w_1 \ge w_2 \ge \cdots \ge w_m \ge 0$, the model (4) cannot usually be solved analytically. But with the software these solutions can be easily achieved. At the end, we compute CI_G is as follows:

$$CI_G = \frac{\sum_{k=1}^{K} CI_k}{k} \quad (6)$$

In the next section using a numerical example for the Human development index of the European Union the proposed model is compared with those published in the literature.

4. Illustrative example

The proposed model has been used for 28 countries in the EU region, where the results are compared with the results of the Rogge-model [10] and Zhou et al-model (2006). Four sub-indicators are used to construct countries HDI-score (1) y_1: life expectancy at birth (years), (2) y_2: expected years of schooling (years), (3) y_3: mean years of schooling (years), and (4) y_4: gross national income (GNI). Information on the human development sub-indicators of the EU region is given in Table 1 [10]. The development of the human dimension in the region of the EU is of particular importance, and the composite indicators of human development for the EU region are satisfactory. As shown in Table 2, in the proposed model, the five countries of Denmark, the Netherlands, Luxembourg, Germany and Ireland have the highest CI scores (marked with stars in the table).the following results of the proposed model are compared with the results of the Zhou et al and Rogge models: in the both proposed model and the Rogge -model, seven countries of Denmark, Ireland, Netherlands, Germany, Sweden, United Kingdom and Luxembourg, have seven first places and this ranking is not unpredictable as the seven countries are almost in most criteria have had a very good performance. Denmark has the first rank in both models. On the one hand, it is observed that Denmark, Belgium, Austria, France, Finland, Slovenia, Czech-Republic, Spain, Slovakia, Latvia, Croatia, Portugal, Romania and Bulgaria in these ratings remain unchanged. Romania and Bulgaria stand at last places, which are also far from not expected because the two countries have had a poor performance in all four criteria for the human development index. Also we compare the proposed model with Zhou et al-model: in the both proposed model and the Zhou et al -models, six countries of Denmark, Ireland, Netherlands, Germany, Sweden and United kingdom, have seven first places and this ranking is not unpredictable as the six countries are almost in most criteria have had a very good performance. But the differences that can be mentioned here that, for example, Luxembourg has dramatic change in their ranking, because in the proposed model, rank 3 and in the Zhou et al model ranked 17th. It is observed that the countries Netherlands, Romania and Bulgaria in these ratings remain unchanged. The countries of Romania and Bulgaria have not changed in all three models and are located at places 27 and 28. Finally, in the proposed model $CI_G = 0.8920$, in the R-model $CI_G = 0.9230$ and in the Zhou et al model $CI_G = 0.5887$, a general observation is the Northern European Member States are doing better in promoting human development as compared to Southern European and central and eastern European Member States. Also, we apply the proposed approach to developing a CI for modeling sustainable energy development of eighteen Asia Pacific Economic Cooperation (APEC) economics. We compared the results of our model with the results of the Zhou model. Considering the results obtained from the proposed model it can be seen that in the proposed model, such as the Zhou model, the Peru, Philippines, Papua New Guinea, New Zealand and Vietnam ranked first to fifth. In the proposed model, Chile ranked sixth And Canada ranked seventh but in the Zhou model, Chile ranked seventh and Canada ranked sixth. It is also seen that in the proposed model, China and Thailand are ranked 11th and 12th respectively, and in the Zhou model, respectively, ranked 12th and 11th. It is observed in the Zhou model, SEI for Russia is zero and in the proposed model, value is 0.181. And in the end, according to the proposed method the $CI_G = 0.483$ and according to the Zhou model $CI_G = 0.373$.

Table 1. HDI sub-indicator data.

Country	$\mathbf{y_1}$	$\mathbf{y_2}$	$\mathbf{y_3}$	$\mathbf{y_4}$	$\mathbf{y_1}$ transformed	$\mathbf{y_2}$ transformed	$\mathbf{y_3}$ transformed	$\mathbf{y_4}$ transformed
SWEDEN	82.2	15.8	12.1	45636	0.98916967	0.84491978	0.92366412	0.77729897
Netherlands	81.6	17.9	11.9	45435	0.98194945	0.95721925	0.90839694	0.77387542
Germany	80.9	16.5	13.1	43919	0.97352587	0.88235294	1	0.74805402
Ireland	80.9	18.6	12.2	39568	0.97352587	0.99465240	0.9312977	0.67394525
United kingdom	80.7	16.2	13.1	39967	0.97111913	0.86631016	1	0.68074125
Denmark	80.2	18.7	12.7	44025	0.96510228	1	0.9694656	0.74985948
France	82.2	16	11.1	38056	0.98916967	0.85561497	0.84732824	0.64819199
Slovenia	80.4	16.8	11.9	27852	0.96750902	0.89839572	0.90839694	0.47439151
Belgium	80.8	16.3	11.3	41187	0.97232250	0.87165775	0.86259542	0.70152101
Italy	83.1	16	10.1	33030	1	0.85561497	0.77099236	0.56258622
Austria	81.4	15.7	10.8	43869	0.9795427	0.83957219	0.82442748	0.74720239
Spain	82.6	17.3	9.6	32045	0.99398315	0.92513369	0.73282442	0.54580913
Greece	80.9	17.6	10.3	24524	0.97352587	0.94117647	0.78625954	0.41770707
Finland	80.8	17.1	10.3	38695	0.97232250	0.91443850	0.78625954	0.65907581
Czech-republic	78.6	16.4	12.3	26660	0.94584837	0.87700534	0.93893129	0.45408867
Estonia	76.8	16.5	12.5	25214	0.92418772	0.88235294	0.95419847	0.42945955
Luxembourg	81.7	13.9	11.7	58711	0.98315282	0.74331550	0.89312977	1
Poland	77.4	15.5	11.8	23177	0.93140794	0.82887700	0.90076335	0.39476418
Portugal	80.9	16.3	8.2	25757	0.97352587	0.87165775	0.62595419	0.43870824
Cyprus	80.2	14	11.6	28633	0.96510228	0.74866310	0.88549618	0.48769395
Malta	80.6	14.4	10.3	27930	0.96991576	0.77005347	0.78625954	0.47572005
Croatia	77.3	14.8	11	19409	0.93020457	0.79144385	0.83969465	0.33058541
Slovakia	76.3	15.1	12.2	25845	0.91817087	0.80748663	0.93129771	0.44020711
Lithuania	73.3	16.4	12.4	24500	0.88206979	0.87700534	0.94656488	0.41729829
Hungary	75.2	15.4	11.6	22916	0.90493381	0.82352941	0.88549618	0.39031868
Latvia	74.2	15.2	11.5	22281	0.89290012	0.81283422	0.87786259	0.37950298
Romania	74.7	14.2	10.8	18108	0.89891696	0.75935828	0.82442748	0.30842601
Bulgaria	74.2	14.4	10.6	15596	0.8929001	0.77005347	0.80916030	0.26564017

Table 2. The compare ours model and other models.

Country	$\mathbf{CI_K}$ Rogge model	$\mathbf{CI_K}$ Zhou et al model	$\mathbf{CI_K}$ Proposed model
Denmark*	0.9949	0.9341	1
Ireland*	0.9716	0.9520	0.9742
Netherlands*	0.9841	0.9851	0.9811
Germany*	0.9862	0.9540	0.9773
Sweden	0.9744	1	0.9574

United kingdom	0.9664	0.9341	0.9576
Luxembourg*	0.9931	0.5	0.9780
France	0.9305	0.9041	0.9109
Spain	0.8923	0.7588	0.8833
Belgium	0.9394	0.8073	0.9256
Slovenia	0.9073	0.8310	0.9020
Italy	0.8978	0.7683	0.8774
Austria	0.9383	0.7607	0.9194
Finland	0.9174	0.6821	0.9086
Greece	0.8729	0.7075	0.8746
Czech-republic	0.8985	0.6553	0.8949
Estonia	0.8878	0.5213	0.8909
Portugal	0.8261	0.3814	0.8170
Cyprus	0.8796	0.3711	0.8541
Malta	0.8573	0.3604	0.8323
Poland	0.8623	0.4561	0.8566
Slovakia	0.8702	0.3443	0.8616
Lithuania	0.8637	0.2735	0.8726
Hungary	0.8452	0.1997	0.8416
Croatia	0.8273	0.3451	0.8194
Latvia	0.8332	0.0755	0.8309
Romania	0.7988	0.0317	0.7927
Bulgaria	0.7844	0	0.7848

Table 3. Three sub-indicators and the SEI values of eighteenAPEC in 2002.

Economies	EEI (10^3US$/toe)	REI (10^3US$/toe)	CCI (10^3US$/toe)	SEI (Zhou model for λ=0.5)	SEI (proposed model)
Peru	13.825	53.6	4.510	1	1
Philippines	17.758	44.6	4.136	0.997	0.999
Papua New Guinea	12.381	23.5	5.039	0.810	0.801
New Zealand	5.473	56.9	2.281	0.648	0.688
Vietnam	10.790	30	2.478	0.529	0.623
Canada	4.286	46.8	1.608	0.477	0.547
Chile	6.950	32.2	2.542	0.463	0.0.559
Japan	8.647	8.2	2.522	0.353	0.437
Mexico	8.424	9.5	2.059	0.278	0.410
Indonesia	8.516	7.8	1.784	0.240	0.388
Thailand	8.204	4.8	1.891	0.220	0.370
China	8.178	11.1	1.372	0.214	0.373
United states	5.901	6.0	1.614	0.144	0.294
Australia	6.208	5.6	1.425	0.116	0.289
Malaysia	5.767	4.0	1.442	0.101	0.269
Taiwan, China	5.539	2.6	1.391	0.081	0.253
Korea	4.683	0.6	1.437	0.064	0.220
Russia	2.453	11.5	0.652	0.000	0.181

Conclusion

In this study, we propose a simple nonlinear programming approach to aggregate individual composite indicators into a group CI. The model is easy to understand. A transformation is then applied on and which induces a simple solution mechanism for calculating a unified measurement of overall score of an entity. If we do not consider the condition of declining weights, then a simple analytic analysis can be obtained without solving the problem and solving the model. To solve this model, k problems must be solved. This feature reduces the complexity of the model. With respect to countries rankings, most countries are in their actual position (compared to the Rogge-model and Zhou et al- model). An illustrative example is presented to compare our model with the Rogge-model and Zhou et al-model.

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