A Composite Indicators Approach to Assisting Decisions in Ship LCA/LCC

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Abstract: During of the life cycle of ship, multiple decisions concerning design, operation and demolition must be made. The Life Cycle Assessment/Cost (LCA/LCC) framework applied in ships, mandates that such decisions need to encounter dominant economic and environmental aspects about the ship. In this paper we consider these decisions in the context of Multi-Criteria Decision Analysis and present a methodology to construct composite indicators to assist decision making. For the criteria introduced we propose the use of key performance indicators (KPIs) that quantify economic and environmental dimensions. For the construction, aggregation and weighting of the KPIs we present linear programming models that estimate the weights endogenously from the data. The models developed can discriminate the optimum designs, thus assisting decision making.

1 INTRODUCTION

A ship Life Cycle Assessment (LCA) is a framework to evaluating different economic and environmental aspects and impacts, from its design and building from raw materials, through operation, maintenance, end-of-life treatment, recycling and final disposal to its end of lifetime. It is a tool to better understand costs, risks, opportunities, trade-offs and nature of environmental impacts. LCA can assist in identifying opportunities to improve the environmental performance of a ship at various points in its life cycle, in informing decision and policy makers in the maritime industry and in selecting relevant indicators of economic and environmental performance.

The basic theory of LCA (Curran, 1996) is transferred to the field of maritime and shipping from the products and services design throughout their lifespan. For the products, the requirements and the implementing guidelines for LCA is covered by the international standards ISO 14040 and 14044 (ISO 2006). Especially the economic impact of LCA, has been addressed by the concept of Life Cycle Cost (LCC) (Aurich et. al., 2007; Dhillon, 2013). LCC aims to identify factors that affect cost, to quantify them and to evaluate the cost effectiveness of alternative strategies to incur over a specified period of time. LCA/LCC were applied to energy systems, electromobility, buildings and built environment, food and agriculture, biofuels and biomaterials, chemicals, wastewater treatment, solid waste management, etc. (Hauschild et. al, 2018).

Ships, seen as complex systems, integrated in economic, technical and transportation activities, need to be studied in line with the concept of LCA/LCC (Marius, 2014; Angelfoss, 1998). Ships' life cycle is decomposed in three phases: the design and ship building (phase I), the operation & maintenance (phase II), and the end-of-life, demolition and disposal (phase III). During the ships' life, designers, shipowners, executives, and others, are confronted with different decision situations that are complex and involve a large number of options and alternatives. For example, in the ship design/construction phase, shipbuilders -- based on a primitive ship construction (ship reference) that fulfils all the technical, cruising, safety and environmental regulations -- have a large number of options to consider and evaluate as type of fuel and engines, materials for the structure and superstructure, type of generators. Every single combination, if applied to the final ship structure, has economic and environmental consequences.

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During the operation phase of a ship, the LCA/LCC approach may give useful answers to questions such as which technical adjustments are cost /environmental effective so to reduce operating expenses? which are the most beneficial options for ship lay-up or hire out for offshore storage facility? which is the most environmental friendly and cost efficient solution among alternatives such as to burn diesel fuel inside ECA or to install scrubbing technology or even after a costly damage? which alternative decisions (in terms of costs) are the most valuable: repair the vessel? to sell the ship in the second-hand market or to sell ship for scrap?. Finally, in the end-of-life period, the decision whether to dismantle a ship or continue the activity by restructuring it in a retrofit procedure or convert it to another type of maritime mission, requires both technical condition assessment and economic evaluation since a decision may end up in adverse economic results, with a negative impact on the environment.

In this paper we allege that a significant number of problems that arise during the life cycle of a ship with the context of LCA/LCC, can be formulated and considered under the scope of decision-making theory. Accordingly, a decision-maker is called to evaluate alternatives on the basis of two or more criteria so to discriminate the superior in terms of economy and environmental impact. For the criteria, we particularly consider established economic and environmental key performance indicators (KPIs) that measure the performance of each alternative decision in specific aspects (ship building cost, operational expenses, maintenance and repair costs, energy efficiency, NOx/Sox emissions etc.). Then, based on mathematical programming methods, we propose to aggregate the KPIs in composite indicators that express more abstract concepts, understandable by the users thus assisting the decision-making process.

This paper is organized as follows. Section 2 presents the relation of KPIs used as criteria in the decision-making LCA processes. Section 3 presents the construction of composite indicators so to exploit KPIs and assist decision making by identifying the optimized alternative decisions. Section 4 presents an illustrative example for evaluating alternative ship designs. Conclusions appear at the end of this paper.

2 KPIs AND COMPOSITE INDICATORS IN SHIP LIFE CYCLE ASSESSMENT

Key performance indicators (KPIs) within the LCA/LCC framework are quantifiable performance measurements used for specific economic, technical, operational and environmental dimensions of a ship. Common KPIs, potentially used in ship LCA/LCC are the: (1) Building Cost, Capital Expenditure (CAPEX), (2) Operational Expenditure (OPEX), (3) Maintenance and Repair costs (MRC), (4) Average Annual Cost (AAC), (5) Required Freight Rate (RFR), (6) Net Present Value (NPV), (7) Average Annual Benefits (AAB), (8) Earnings Before Interests, Taxes, Depreciation and Amortization (EBITDA), (9) Return on Investment Capital (ROIC), and (10) Energy Efficiency Design Index (EEDI). KPIs like the above, are provided in different units, dollars, number of years etc., may have any scale of measurement, ratio, ordinal etc. and may have positive contribution/utility (e.g., NPV, EBITDA, EEDI) or negative (OPEX, MRC, AAC, NOx/Sox emissions). Such KPIs have been used in past research studies to estimate the ships' performance. For instance, the work of Gratsos & Zachariadis (2009) examines the importance of the Average Annual Cost (AAC) as an indicator to evaluating different ship designs that technically appear as optimized. Furthermore, the Energy Efficiency of Operation (EEO) (Lu et al., 2015) is defined and utilized to predict the operational ship performance.

According to the LCA/LCC, KPIs are used for measuring costs, revenues, energy efficiency, etc., not only for a specific period but for the entire lifecycle of the ship. For example, during the ship design (first phase of LCA), different ship models and configurations are evaluated in terms of operating – maintenance costs, total revenues gained during the operation phase, price at the time of demolition, potential use of recycled materials etc. In this context, the decision-making problem is to identify those alternative designs that have the total optimum performance (minimum costs, maximum revenues, minimum environmental impact). This goal cannot be achieved by only exploiting KPIs, because they are of low-level and measure only partial dimensions. Furthermore, KPIs may usually conflict one another. For example, a ship built with low budget, at the operation stage may have higher maintenance and repair costs.

In this study we propose as more beneficial for the assessment of different alternative decisions the use of composite indicators derived from the aggregation of properly selected KPIs. Composite indicators, in general, are commonly used for benchmarking of entities, summarizing in a single measurement, complex social, economic, environmental etc. concepts by involving several thematically related sub-indicators. According to our approach, composite indicators' that measure abstract concepts such as "economic benefits", "environmental impact" etc., meaningful to a decision-maker, may derive from the aggregation of the values of individual sub-indicators (KPIs).

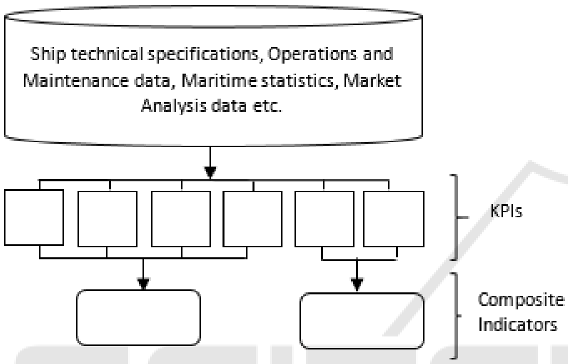


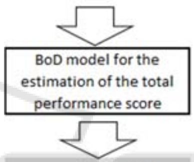
Figure 1: The hierarchy of data processing, from raw data to KPIs and composite indicators.

Figure 1 presents the place of the composite indicators in the hierarchy of data processing, deriving from KPIs regarded as sub-indicators which in turn are estimated from data sources (ship technical specifications, Operations and Maintenance data, Maritime statistics, Market Analysis data etc.).

3 DERIVATION OF THE COMPOSITE INDICATORS

In the derivation process of composite indicators, the aggregation and the weighting are the most important steps and for them, a number of alternative methodologies (Nardo et al. 2005, OECD 2008) have been proposed to substitute the common approach of using additive or multiplicative average formulas in conjunction with constant, predetermined values for the weights: Principal components/Factor analysis, Benefit of the doubt approach, Unobserved components model, Budget allocation process, Analytic hierarchy process, Conjoint analysis etc. Among them, the Benefit of the doubt (BoD) modelling (Melyn and Moesen, 1991; Cherchye, 2007) uses linear programming and an additive weighted-based form to estimate the scores of the composite indicator. Advantage of the method is that it arranges so the weights of the sub-indicators to derive directly from that data, endogenously, as result of an optimization process. BoD is inspired by the multiplier formulation of Data Envelopment Analysis (DEA) (Charnes et. al, 1978) as it estimates different weights for each unit (alternative design) under assessment, choosing the most favourable values so to let them reach the highest possible score. BoD modelling can discriminate alternative decisions to superior and non-superior. Figure 2 depicts the estimation process.

	KPIs			
Alternative scenarios	KPI_1	KPI_2	.....	KPI_m
#1	0.25	1250	.....	55.3
#2	0.48	1750	.....	48.18
#3	1.32	1950	.....	23.45
.....	.....	.....	.....	.....
#n	0.99	980	.....	60.15



Alternative scenarios	Total Performance score
#1	0.751
#2	1
#3	0.955
.....	.....
#n	0.487

Figure 2: The estimation of the superiority index from the decision matrix.

BoD linear programming models are applied to the decision matrix composed of alternative decision scenarios and the KPIs (criteria) to obtain a total performance score. Alternative decisions with score equal to 1 are regarded as superior. The mathematical background of this method is briefly described in the following sub-sections.

3.1 Optimization Models for the Aggregation and the Weighting of KPIs

Assume that in a typical assessment in the ship design /building phase I, n alternative designs have to be assessed in terms of m KPIs so to derive scores of a composite indicator. The decision matrix of the problem is composed of a set of n alternative designs $A=\{a_1,a_2,\dots,a_n\}$ and of m individual KPIs

$X_1, X_2, ..., X_m$, $X_i = (x_{i1}, x_{i2}, ..., x_{in})$ $i = 1,..,m$. The values $x_{ij}, i = 1,..,m, j = 1,..,n$ denote the performance score of the alternatives a_j on the KPIs X_i .For any alternative a_j , the contribution of a the i-th KPI to the total value of the composite indicator, is expressed by the factor $w_i x_{ij}$, with the weight w_i to be unknown, under estimation. In such a setting, the value of the composite indicator for an alternative j derive by the additive linear form $I_j = \sum_{i=1}^{m} w_i x_{ij}$. The value I_j expresses the total performance of the alternative a_j on all the involved KPIs. Consequently if for two alternatives j_1, j_2 holds $I_{j_1} > I_{j_2}$, the conclusion is that alternative j_1 , is superior (has better performance) than alternative j_2. It is important to note that this additive form function designates a compensatory approach (OECD 2008, Bandura 2011) according to which, any possible disadvantage (low value) of a particular alternative design in a specific KPI can be counterbalanced by the advantage (high value) in other KPIs.

For the estimation of the values of the weights w_i , the BoD model (1) is proposed.

$$Max \ \mathrm{I}_{j_0} = \sum_{i=1}^{m} w_i x_{ij_0}$$

$$I_j = \sum_{i=1}^{m} w_i x_{ij} \le 1, \ j = 1,..,n \tag{1}$$

$$w_i \ge \varepsilon, i = 1,..,m$$

Model (1) is solved *n* times, once for each alternative design j_0 and estimates the optimal values $w_i^*, i = 1,...,m$ of the weights so to maximize its total performance score. Let this score be $I_{j_0}^*$. The constraints $\sum_{i=1}^{m} w_i x_{ij} \le 1, \ j = 1,..,n$ ensure a comparative assessment and set maximum attainable score $I_{j_0}^*$ equal to 1. The factor ε in the constraint $w_i \ge \varepsilon, i = 1,..,m$, seen as a parameter, is assigned small values (approximately $\varepsilon = 10^{-6}$) and prevents the weights to accept zero values. Model (1) is able to discriminate alternative designs to superior and non-superior. Superior are those that, in the comparative process, achieved to reach the upper bound score 1 by selecting the proper optimal values w_i^* (superior alternatives={ $j : I_j^* = 1$ }) and non-superior are those that did not succeeded to do so (non-Superior alternatives ={ $j : I_j^* < 1$ }).

About the meaning of the weights w_i and the values that can be assigned to them, it is necessary to point out that they must not be considered as importance coefficients that reflect the contribution of a KPI to the value I_j^* but rather as the "trade-off" factors expressing the marginal rate of substitution between two alternatives (Decancq and Lugo 2013). In sub-section 3.4 the issue of restricting them according to the users' opinion will be discussed.

Despite the flexibility of Model (1) to choose the weight values directly from the data, there are certain drawbacks: it provides unrealistic weight values, it privileges the alternatives with high performance to only few sub-indicators, it is not capable to discriminate those that achieve the highest score 1 and due to different set of weights, lacks a common cross-alternative comparison (Zhou et al. 2007). The latter can be resolved by a model variation that uses common set of weight values. The issue of common weights in BoD has been transferred again from the similar DEA context (see Kao (2010), Bernini et al. (2013), Koronakos et al (2019)). The modified extension of model (1) with common weights is formulated as follows.

For an alternative *j*, let d_j be the difference between the sum $\sum_{i=1}^{m} w_i x_{ij}$ and the 1 (the deviation factor from the absolute attainable score 1), i.e. $d_j = 1 - \sum_{i=1}^{m} w_i x_{ij}$. By its definition, d_j is a positive number $d_j \ge 0$, while the sum $\sum_{j=1}^{n} d_j$ denotes the total deviation of all the alternatives from the absolute score 1. The basic idea behind the common assessment is to let alternatives cooperate in order to get as close as possible to the absolute score 1. This approach can be characterized as fair and democratic since all the alternatives, collectively and equally, participate to the generation of the optimal set of common weights that yield the composite index. In terms of linear programming, this is translated as a goal to minimize the total deviation expressed by the sum $\sum_{j=1}^{n} d_j$. Model (2) achieves to do so.

$$Min \ \sum_{j=1}^{n} d_j$$
$$\sum_{i=1}^{m} w_i x_{ij} + d_j = 1, \ j = 1,..,n \qquad (2)$$
$$w_i \geq \varepsilon, i = 1,..,m$$
$$d_j \geq 0, j = 1,..,n$$

In model (2), the objective function minimizes the sum of the deviations (distance of L_1 norm) of all alternatives between the performance that they can achieve using the common multipliers and their ideal rating. Compared to model (1), model (2) requires less computational effort as it is solved only once and it produces lower scores from model (1), thus providing higher discrimination.

3.2 Controlling the Number of Superior Alternatives

About the parameter ε, it is important to notice that higher values than ε =10-6 reduce the number of superior alternatives and thus affect the discriminating power of the method (Cook et al. 1996). Large enough values may result to infeasibility of model (1). The greatest unique value of ε, say ε* that makes model (1) feasible, ensures that only one superior, the best, alternative is obtained from the process (Toloo & Tavana 2016). Such a value ε* can be estimated by model (1) when its objective function is replaced by $Max \ \varepsilon$ and the rest of the constraints remain unchanged.

3.3 Normalization

Models (1)-(2) are capable to incorporate data from KPIs that are expressed in different measurement units (dollars, years of ship operation, etc.). However, normalization of the data in KPIs is needed before applying the aggregation step. The main reason is to convert the data so all KPIs to have a positive contribution or utility – higher values are more desirable (for example Operational Expenditure - OPEX). Another reason is that models (1)-(2) are sensitive to outliers and to highly skewed data. The normalization can be achieved with different methodologies for example min-max, z-score etc.

3.4 Implementation of Decision-Makers' Preferences

Models (1)-(2) give freedom to the alternative designs to assign such weight values so to appear as superior as possible. This means that any design can appear as excellent performer by overestimating those KPIs that has advantage over the rest. However, this situation may give results that contradict to prior common views and overestimate KPIs that are insignificant to the decision-maker. Fortunately, BoD models are able to incorporate prior information by imposing additional weight restrictions that express the common value judgments of the decision maker. The most important are those of type "pie-share", initially proposed by Wong and Beasley (1990) and classified by Cherchye et al. (2007), that affect the contribution of each KPI to the total indicator score.

For example the constraint $a \leq \frac{w_i x_{ij}}{\sum_{i=1}^{m} w_i x_{ij}} \leq b$, imposes that the proportion /share of the i-th KPI will vary between the constants a, b . In the same manner, ordinal constraints of the "share" type can be adopted to prioritize the contribution of a KPI over others. This type of restrictions overcome the difficulty on the interpretation of the weights and shift the focus to KPI shares which are completely independent of measurement units and easily understandable by the decision makers.

4 ILLUSTRATIVE EXAMPLE

Assume that in the design /building phase of a new 40,000 DWT (Handymax) bulk carrier ship, the basic technical specifications have been decided so to consist the basic ship reference. Based on that, 18 alternative designs are considered as feasible for implementation. These derive as distinct combinations of different types of superstructure materials (steel of various strength), of engines (2-4 strokes DE, Gas turbine etc) and equipment (scrubber, ballast water treatment system, etc). The problem under consideration is, which set of the alternative designs achieve the best performance in terms of economy and environmental impact, considering the whole life of the ship, from its first day of operation to its last. The proposed approach of this paper is to define two composite indicators, say ECO for economy and ENV for the environment, estimate their values for all the alternative designs and by comparing them, identify the most optimised designs, the ones candidate for implementation.

For this problem, a number of KPIs may be selected to describe both the economic and environmental dimensions. In this example, we further assume that a decision maker selects as the most appropriate for the ship economy three KPIs, namely the CAPEX, OPEX to represent costs and AAB for the revenues. CAPEX measures, in thousand $, the funds that a ship owner uses to purchase a vessel from a shipyard, OPEX accounts in thousand $ per year, the ongoing costs that a ship owner pays to run the ship over a specific period, e.g. typical year of operation, while AAB represents the revenues and is the average annual benefits form the ship, measured in thousand $ per year. The details (formulas, data parameters) for the estimation of these KPIs are not mentioned here due to the limited size of the paper. Accordingly, the environmental savings are described by EEDI (Energy Efficiency Design Index) and the NOx and Sox emissions calculated from the technical specifications of each alternative design.

The values of the above mentioned KPIs appear in Table 1. In this table, the first design, indicated as REF, corresponds to the basic ship reference that participates in the assessment equally with the rest of the alternative designs.

Table 1: The basic data set.

Desgin	CAPEX	OPEX	AAB	EEDI	NOx	SOx
REF	6582	1.454	5.836	6.8	13.81	3.45
d1	5377.1	1.447	3.494	7.7	12.3	2.26
d2	5751.8	1.507	3.613	3.6	11.46	1.25
d3	5924.2	1.362	5.284	4.5	11.99	2.92
d4	6914.8	1.61	3.856	4.2	11.14	1.96
d5	5432.2	1.328	5.397	4	12.09	3.74
d6	5754.8	1.567	4.728	3.9	14.37	1.98
d7	5650.4	1.6	6.023	3.1	11.01	1.5
d8	5524.8	1.362	3.863	2.9	12.9	2.21
d9	6718.6	1.61	3.8	4	12.09	3.74
d10	7180.9	1.328	3.893	4.4	11.39	1.81
d11	5944.9	1.424	3.875	5.6	14.44	3.75
d12	7056.5	1.575	4.388	4	12.09	3.74
d13	5360.7	1.338	5.879	3.2	11.35	4.98
d14	5412.5	1.297	4.691	6.8	13.99	2.48
d15	6247.4	1.547	3.474	7.7	11.66	3.76
d16	6526.3	1.61	5.157	4	12.09	3.74
d17	5337.8	1.328	4.058	3.4	12.51	2.6
d18	6260.3	1.435	5.165	7.9	11.03	4.43

From inspecting the data in Table 1, we may notice that a number of alternatives (e.g. d2) have adequate performance on economy and poor in the environmental KPIs while for others (e.g. d14) is vice-versa.

In order to estimate the values of the composite indicators ECO, ENV, models (1), (2) are applied to the data set. Before that, a normalization process (see Section 3.3) eliminates the differences in the scales of measurement and reverses to positive the values for the indicators with negative utility such as CAPEX, OPEX, NOx, SOx. In such an arrangement the two composite indicators ECO, ENV appear both with positive utility (the higher the values, the better is the design). Moreover, for the estimation of the economy indicator ECO, we considered as most important the AAB sub-indicator, giving emphasis to the revenues. Accordingly, for the ENV indicator, the most important sub-indicator is considered EEDI. This initial information is implemented to the modelling as ordinal weight restrictions of type "share" (see Section 3.2). The values resulted from the model application for the composite indicators ECO and ENV, appear in the last four columns of Table 1.

The values of composite indicators ECO, ENV derived from models (1)-(2) appear in Table 2.

Table 2: The values of the two composite indicators ECO, ENV obtained by Models (1), (2).

	Model (1)		Model (2)	
Design	ECO	ENV	ECO	ENV
REF	0.949	0.708	0.935	0.644
d1	0.796	0.766	0.806	0.797
d2	0.784	0.935	0.788	0.802
d3	0.934	0.858	0.941	0.747
d4	0.747	0.923	0.757	0.894
d5	0.969	0.875	0.970	0.695
d6	0.863	0.788	0.844	0.763
d7	1.000	1.000	0.923	1.000
d8	0.840	1.000	0.855	0.780
d9	0.749	0.875	0.756	0.695
d10	0.791	0.898	0.842	0.908
d11	0.813	0.708	0.827	0.609
d12	0.790	0.875	0.799	0.695
d13	1.000	0.970	1.000	0.687
d14	0.928	0.700	0.936	0.710
d15	0.747	0.802	0.758	0.713
d16	0.863	0.875	0.848	0.695
d17	0.873	0.902	0.885	0.752
d18	0.898	0.839	0.902	0.719

Based on the results presented in Table 2, a number of remarks are possible. First, focusing on the results of model (1), several designs appear as superior (score equal to 1) in one of the two dimensions. This is the case for designs d7 and d13 on economy (ECO indicator) and d7 and d8 on the environment (ENV indicator). Only design d7 is the best in both economics and environment and presumably this design is suggested as the optimum that achieves reduction of costs and the best environmental protection. Scores obtained from model (2) with common weights are lower that those from model (1). Consequently, alternative d8 loses its superiority classification and only d7 and d13 are superior in ENV and ECO, respectively. Note that in this model, no alternatives are optimum in both composite indicators.

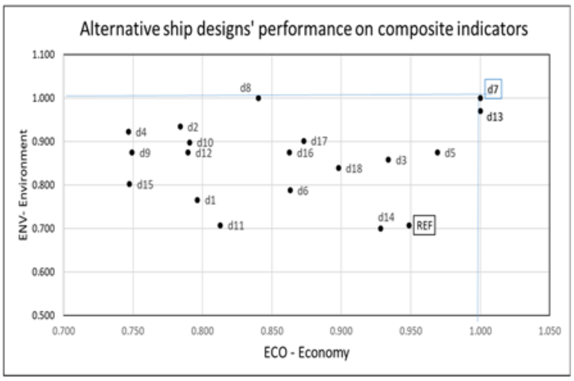


Figure 3: Graph of the values ENV, ECO composite indicators derived from models (1)-(2).

Figure 3 presents the scores of designs in two axes ENV and ECO, as obtained from model (1). Design d7 located at the upper right corner with score 1 on both ECO, ENV indicators is the best alternative. Other alternatives that lie on the horizontal and vertical boundaries (score 1) are superior in only one dimension. Note that the basic reference design (REF), being in an intermediate position, did not achieved to reach superiority as other designs have been proved better than this.

5 CONCLUSIONS

This study contributes to the ship LCA/LCC concept by suggesting composite indicators to assist decision making. Decision situations are formulated as multi-criteria decision making/analysis problems in which, key performance indicators-KPIs are considered as economic and environmental criteria while the different decisions to be made consists the alternatives. The composite indicators use simple, additive weighting sum to aggregate the KPIs so to obtain scores for the alternative decisions. The aggregation and the weighting of the KPIs is based to linear programming models and the weights are estimated endogenously from the data. The proposed models are able to reveals the optimum performance alternatives, those that minimize costs, maximize revenues and minimize environmental impact.

The proposed methodology is simple to use and implement without needing the user interaction. It is flexible to accept initial information as user preferences in order to access alternatives by a specific priority on KPIs. Furthermore, the modelling presented can be easily expanded to cover cases when the KPIs are expressed in ordinal form or include uncertainty, being expressed with intervals with constant bounds. We hope you find the information in this template useful in the preparation of your submission.

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