

Work Package 1 – Shared modelling framework and learnings

D1.2 – Description of scientific methods

Task 1.5- Framework for socio-economic assessment

Stochastic multi-criteria decision analysis

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Acronyms and abbreviations

ABBREVIATIONS	Description
EU	European Union
GHG	Greenhouse emissions
LCA	Life cycle assessment
MCDA	Multi-criteria decision analysis
SMAA	Stochastic multi-attribute analysis
TEA	Techno-economic assessment

Executive summary

This task consists of coordinating a consistent implementation of socio-economic assessment within the ALIGNED project. It consists of three building blocks; (i) economic evaluation (techno-economic assessment), social evaluation (social indicator model), and (iii) multi-criteria decision analysis. In this particular description, the developer focuses on the stochastic multi-criteria decision analysis method based on Prado and Heijungs (2018).

It first sets the basis for assessing the sustainability (economic, environmental, and social dimensions) of technologies, products, or projects through the provided tools and tutorials that can be used by partners and general practitioners. It will then facilitate its application to the case studies in the bio-based sector by providing specific guidelines for modeling and analyzing the economic feasibility.

1. The need for sustainability in the bio-based sectors

The 2030 Agenda for Sustainable Development expresses a dedication to realize sustainable development across economic, social, and environmental domains in a harmonized and cohesive manner (United Nations, 2015). Hence, the European Commission introduced the strategy "European Green Deal". This initiative aims to transform the European Union (EU) into a society that is both fair and prosperous, characterized by a modern, resource-efficient, and competitive economy (European Commission, 2019). In addition to governmental policies and environmental regulations, sustainability is also stimulated by customer's demand and increasing societal and environmental awareness (Leal-Millan et al., 2018). Consequently, companies are faced with the challenge of adopting new strategies, products, and technologies that prioritize sustainability.

Achieving sustainability is closely tied to the implementation of existing and novel innovative technologies and products, ideally with reduced environmental impacts and positive social and economic outcomes. In a world of population growth and increasing environmental challenges (e.g. climate change), the bioeconomy is gaining prominence as it provides an avenue to harmonize economic expansion with environmentally responsible practices, presenting the prospect of a low-carbon economy and the creation of new jobs (Eickhout, 2012). The advancement of the bioeconomy is a key element of the 2020 strategy (Fritsche and Iriarte, 2014). Consequently, the European Commission formulated the Bioeconomy Strategy in 2012 to serve as a guide for research and innovation agendas (European Commission, 2012). An updated version of this strategy was released in 2018, aligning more effectively with contemporary policy priorities (European Commission, 2018).

The development of new or enhanced industrial processes is essential for converting biomass into various energy applications and other products. However, the utilization of organic matter (i.e., biomass) for food, feed, biobased products, and bioenergy carries potential negative impacts, such as land use changes due to deforestation and unsustainable farming practices, as well as increased water use. Consequently, it is crucial to measure and monitor these sustainability-related impacts, preferably already during the developmental phase of new biobased technologies (Van Schoubroeck et al., 2018).

2. Stochastic multi-criteria decision analysis

To evaluate and compare the sustainability of products, processes, or technologies, three domains are essential to be covered; economic, environmental, and social. To do so, multiple methods have been developed. To name a few of them; techno-economic assessment (TEA) for the economic feasibility, social indicator quantification for the social part, and life cycle assessment (LCA) for the environmental part. The usual approach is to conduct these assessments separately and compare the results among the alternatives. This approach is quite straightforward when dealing with single indicators.

However, once the assessments are based on multiple indicators, interpretation becomes challenging usually ending up with no clear single best alternative (Laurin et al., 2016). For instance, in LCA one can choose multiple indicators to evaluate the products. In this case, the user has no other choice than to compare alternatives side by side across all environmental indicators (Prado and Heijungs, 2018). Consequently, multiple indicators assessment can lead to subjectivity/bias when determining the most preferable alternative (Hertwich and Hammitt, 2001).

Hence, in case of trade-offs, studies often focus only on a single environmental indicator (e.g. carbon footprint) leaving the user to interpret multiple environmental factors without clear guidance or to come up with a single score using either random or standard weight factors (Prado and Heijungs, 2018). Although quantifying different environmental impacts provides valuable insights, the complexity of the results makes it difficult to make profound decisions.

To resolve these challenges, it is advised to use multi-criteria decision analysis (MCDA) which considers mutual differences. MCDA is a decision-supporting method addressing complex problems with high uncertainties, conflicting goals, different forms of information, and different interests and viewpoints (Wang et al., 2009).

To better balance different impact categories and view them more objectively, the stochastic multi-attribute analysis (SMAA) has been introduced by Prado-Lopez et al. (2014). It uses internal normalization and sets the weights randomly, without giving special preference to any specific category. Van Schoubroeck et al. (2021) extended the idea of SMAA by applying it to all dimension of sustainability. Hence, the guideline the tool of Prado and Heijungs (2018) will be used to create a **stochastic multi-criteria decision analysis** for different indicators within all three sustainable domains (see guideline).

3. Guide to use the Excel file tool ‘Stochastic multi-criteria decision analysis for ALIGNED’

To conduct a stochastic multi-criteria decision analysis, University of Antwerp (ANTW) provides a Excel file tool named: ‘Stochastic multi-criteria decision analysis for ALIGNED’. It consists of the following worksheets:

- **ReadMe**
- **Input parameters & results**
- **Products indicator value (h)**

- **Pairwise difference (d)**
- **Thresholds**
- **Outranking score (theta)**
- **Net flows (π)**
- **Weights (w)**
- **Overall score (z)**
- **Rank (R)**

This guide provides an explanatory tutorial of how to conduct a stochastic multi-criteria decision analysis based on the Prado and Heijungs (2018).

Before using the ‘stochastic multi-criteria decision analysis’, the user is advised to pay attention to the legend which indicates which values needs to be (i) inserted, (ii) are calculated automatically, or (iii) represent the results, illustrated in Figure 1:

LEGEND (color indication)
Value to be inserted by the user
Value calculated automatically
Results

Figure 1. Color-based legend.

3.1 ReadMe

This sheet provides a general overview of all worksheets and their purposes within the Excel file ‘Stochastic multi-criteria decision analysis for ALIGNED’. Moreover, it describes the utilization of the different sources within the datasheets.

3.2 Input parameters & results

Inputs:

The worksheet ‘Input parameters & results’ represents the starting point of the calculation method. To illustrate how the stochastic multi-criteria decision analysis works, a hypothetical comparative case study is used consisting of 3 alternatives (e.g. products A, B, and C) and 3 indicators (X, Y, and Z). Note, that the indicators can be from the same domain (e.g. environmental indicators), or three indicators from 3 different domains (e.g. economic, environmental, and social).

Action required: First, the user needs to insert the mean values (*mean*) and the standard deviations (*sigma*), representing the uncertainty, for each product’s indicator to run a randomized Monte Carlo simulation.

Let’s assume that we are comparing the GHG emissions (indicator X) for 3 different products (A, B, and C,) that have the same functionality (e.g. different chairs but the same functionality = seating). Each product has different GHG emissions and different uncertainty levels of the outcome. The same applies to the indicator Y and Z, see Table 1.

Table 1: Mean value and standard deviation of indicators X, Y, and Z for products A, B, and C.

Indicators	Product A		Product B		Product C	
	mean_A	sigma_A	mean_B	sigma_B	mean_C	sigma_C
X	44	6	59	8	41	5
Y	49	14	81	10	99	12
Z	54	9	31	11	45	10

Results:

For users who do not have any experience

Once all parameters are chosen, the excel file runs its iterations automatically (enter any random number => activates the Monte Carlo simulation) and provides the results, see Figure 2. This is perfect for users who immediately want to use the tool without diving into the internal mechanism and calculations of the stochastic multi-criteria decision analysis and are fine with 3 products and 3 indicators.

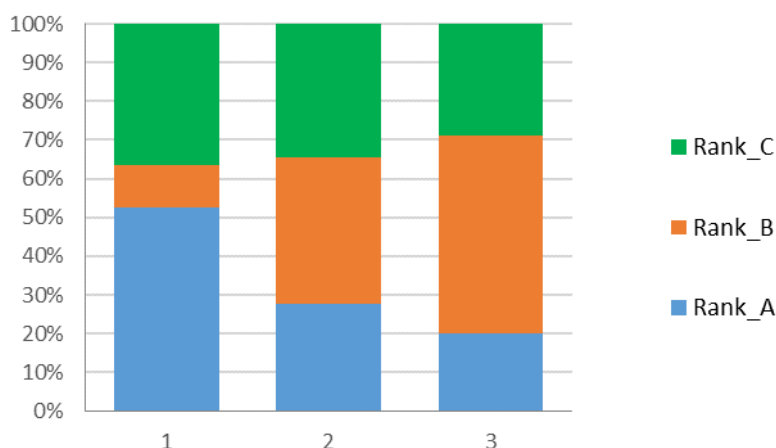


Figure 2. Rank acceptability indices for products A, B, and C. The x-axis shows the rank position, and the y-axis, the rank acceptability for each product for every rank.

For experienced users:

For those who want to further understand, adjust, extend, and tailor-made the tool according to the condition of their products, it is advised to go over all the following worksheets (Section 3.3 – 3.10) and consult the guideline of Prado and Heijungs (2018) for further insights.

To extend the tool to more than 3 products and 3 indicators, additional columns need to be added. It is quite straightforward. To extend the structure in each worksheet, the user needs to copy and paste the columns, rows, and Excel-based equations. Hence, no further explanation is needed.

3.3 Products indicator value (h)

The first step is to calculate the difference (d_{ijk}) between alternative pairs (e.g. product A vs B) on a specific impact category (e.g. X = GHG emissions) for a pre-defined number of Monte Carlo iterations.

To do so, first, we need to calculate the randomized values for each alternative (h_{ijr}) based on the parameters (*mean and sigma*) in ‘Input parameters and results’, see Table 2:

Table 2: Randomized values for each alternative (h_{ijr}).

Iteration r	Hard copy								
	h_XAr	h_YAr	h_ZAr	h_XBr	h_YBr	h_ZBr	h_XCr	h_YCr	h_ZCr
1	45.87	35.03	43.94	71.18	75.85	17.11	42.10	114.11	45.72
2	41.09	55.43	82.96	58.54	88.93	21.74	30.13	100.51	41.26

The stochastic outcome of the alternatives A, B, and C based on the indicator X for 1000 iterations r is displayed as follows (Figure 3):

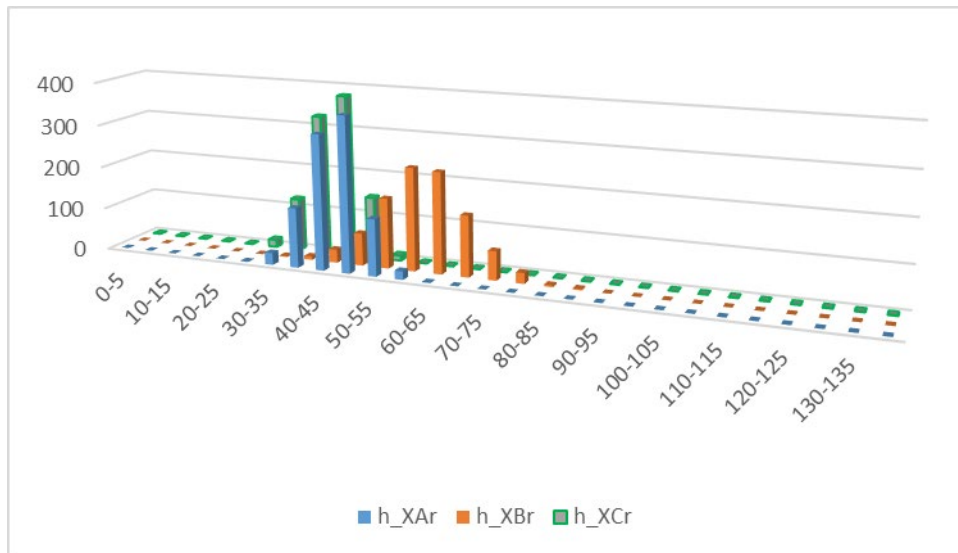


Figure 3: The stochastic outcome of the alternatives A, B, and C based on the indicator X for 1000 iterations r.

3.4. Pairwise difference (d)

Next, the pairwise difference is calculated. Here, the difference between product A and B value for iteration $r = 1$ ($44.87 - 71.18 = -25.31$) are calculated using the following Equation 1:

$$d_{ijk r} = h_{ijr} - h_{ikr} \quad (i = 1, \dots, m; j, k = 1, \dots, n; r = 1, \dots, R) \quad (1)$$

The results are illustrated in Table 3:

Table 3: Pairwise differences.

r	d_XABr	d_XACr	d_XBCr	d_XBAr	d_XCAr
1	-25.31	3.77	29.08	25.31	-3.77

3.5. Thresholds

In the next step, the thresholds are calculated. Thresholds are established criteria for decision-making based on the preferences and priorities of the user. Prado and Heijungs (2018) considered an automatic uncertainty-generated thresholds to avoid subjective information.

Using the following Equations (2, 3, and 4):

$$P_i = \frac{-1}{n} \sum_{j=1}^n S_{ij} \quad (i = 1, \dots, m) \quad (2)$$

$$Q_i = \frac{1}{2} P_i \quad (i = 1, \dots, m) \quad (3)$$

$$S_i = \sqrt{\frac{1}{R-1} + \sum_{r=1}^R (h_{ijr} - \bar{h}_{ij})^2} \quad (i = 1, \dots, m; j = 1, \dots, n) \quad (4)$$

The preference threshold (P_i) and indifference threshold (Q_i) are generated based on $r = 1000$ (iterations), illustrated in Table 4:

Table 4: Preference threshold (P_i) and indifference threshold (Q_i).

P_X	Q_X
-6.26	-3.13

For P the threshold level is the average of all standard deviation (s) and for (Q_i) it is (P_i) divided by 2.

3.6. Outranking score (Θ_{ijk_r})

In next the step, the relative performance of alternatives A, B, and C are measured using the outranking score Θ_{ijk_r} . These values range between 0 to 1 defined by Equation 5 and visualized in Figure 4:

$$\Theta_{ijk_r} = \begin{cases} 0 & \text{if } d_{ijk_r} \geq Q_i \text{ (indifference)} \\ 1 & \text{if } d_{ijk_r} \leq P_i \text{ (complete preference)} \\ \frac{Q_i - d_{ijk_r}}{Q_i - P_i} & \text{if } P_i \leq d_{ijk_r} \leq Q_i \text{ (partial preference)} \end{cases} \quad (i) \quad (5)$$

$= 1, \dots, m; j, k = 1, \dots, n; r = 1, \dots, R$

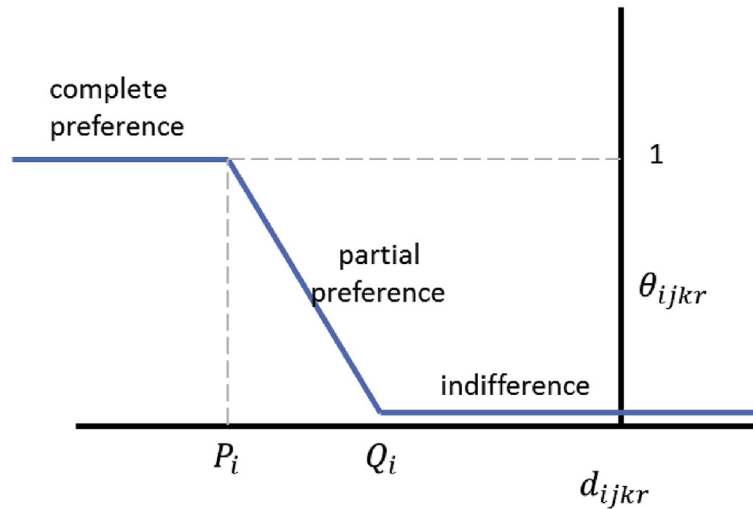


Figure 4: Outranking preference function where lower environmental impact is preferred. Based on Prado and Heijungs (2018).

Indifference ($\Theta_{ijk} = 0$)

If the first condition is met then, the difference between products is negligible. Hence, there is not sufficient evidence of the superiority of a product. This is called a tie. Hence, the number zero is given, see Table 5:

Table 5: Indifference ($\Theta_{ijk} = 0$).

theta_XACr
0

Partial preference ($0 < \Theta_{ijk} < 1$)

If the third condition of the equation is met, then the outranking score will be between $0 < \Theta_{ijk} < 1$, see Table 6:

Table 6: Partial preference ($0 < \Theta_{ijk} < 1$).

theta_XACr
0.26237933

Complete preference ($\Theta_{ijk} = 1$)

To give an example: The outranking score theta '1' for impact X (e.g. GHG emissions) between product A and B for iteration 1 shows that product A performs better than product B. Hence, the value 1 is given, see Table 7:

Table 7: Complete preference ($\Theta_{ijk} = 1$).

r	theta_XABr
1	1

Here lower values (e.g. GHG emissions) are preferred over higher values. Product A (45.87) performs better than product B (71.18) resulting in $d = -25.31$. Looking at the equation above the pairwise comparison between products A and B fulfills the second condition of

the equation, the requirement of threshold P (-5.98) of having a lower value. Hence, it means that Product A is completely preferable over product B, which results in the number '1'.

3.7. Net flows (π)

For each pairwise comparison, there are two ways to compare; (i) product A with B and (ii) product B with A which creates positive and negative values. For instance, positive value indicates how much product A outperforms product B and negative values indicate how much product A is outperformed by product B. Hence, both values need to be considered by using Equation 6:

$$\pi_{ijr} = \sum_{\substack{j=1 \\ k \neq j}}^n (\theta_{ijk} - \theta_{ikj}) \quad (i = 1, \dots, m; j = 1, \dots, n, r = 1, \dots, R) \quad (6)$$

Considering the following values in worksheet 'Outranking score (theta):

- for $\Theta_{XAB} = 1$
- and $\Theta_{XBA} = 0$
- and $\Theta_{XAC} = 0$
- and $\Theta_{XCA} = 0.26$

the number **0.737** = $((1-0)+(0-0.26))$ is calculated, shown in Table 8:

Table 8: Outranking score.

r	pi_XAr
1	0.737621

Note, that this number is important to calculate the overall score in the worksheet 'Overall score'.

3.8. Weights (w)

To prioritize the importance of impacts in the entire evaluation, weights need to be applied. In this approach 'importance weights' are applied (see Prado and Heijungs (2018)). The importance weight reflects the relative importance of impacts according to the user's chosen values and does not depend on the performance of the alternative.

There are two ways to apply the weights:

1. In case the user has knowledge about the weights, the user can manually include pre-defined weights to each impact category (e.g. impact X = 20% impact Y = 50% and impact Z = 30%),
 - a. **Action required:** The user, must pre-define the weights and insert them for 1000 iterations, see Table 9:

Table 9: Sum of pre-defined weights for 10 iterations

r	wXr	wYr	wZr
1	20.00	50.00	30.00
2	20.00	50.00	30.00
3	20.00	50.00	30.00
4	20.00	50.00	30.00
5	20.00	50.00	30.00
6	20.00	50.00	30.00
7	20.00	50.00	30.00
8	20.00	50.00	30.00
9	20.00	50.00	30.00
10	20.00	50.00	30.00

- In case of lack of knowledge, the user can generate randomized stochastic weights. The stochastic weights are generated which have a range between 0 and 100, where the sum of weights for (impact X, Y, and Z) equals 100, see Table 10:

Table 10: Sum of stochastically generated weights for 10 iterations.

r	wXr	wYr	wZr
1	1.94	51.11	46.95
2	16.40	8.32	75.28
3	0.83	18.44	80.73
4	29.95	50.17	19.88
5	8.57	80.69	10.74
6	44.82	29.52	25.66
7	83.10	3.74	13.16
8	69.55	23.36	7.09
9	32.35	23.97	43.68
10	15.42	31.34	53.24

Note, that the option is chosen for the tool ‘Stochastic multi-criteria analysis.

3.9. Overall score (z)

The overall score is calculated by the following equation:

$$z_{jr} = \sum_{i=1}^m w_{ir} * \pi_{ijr} \quad (j = 1, \dots, n, r = 1, \dots, R) \quad (7)$$

where the weights (w_{ir}) are multiplied by the net flows (π_{ijr}), creating a ranking for each of the 1000 iterations (Table 11):

Table 11: Overall score for 1000 iterations.

r	z_Ar	z_Br	z_Cr	zeta_Ar	zeta_Br	zeta_Cr
1	56.6994	43.0757	-99.7751	1	2	3
2	-133.9169	41.3201	92.5967	3	2	1
3	-43.8497	49.4580	-5.6082	3	1	2

3.10. Rank (R)

In the last worksheet, 'Rank (R)' the result of the stochastic multi-criteria decision analysis are shown. All rankings from 1000 iterations are accounted for, see Table 12.

Table 12: Ranking of Product A, B, and C based on the Indicators X, Y, Z.

Rank	R_A	R_B	R_C
1	456	126	418
2	318	368	314
3	226	506	268

resulting in the following probability distribution, illustrated in Figure 5:

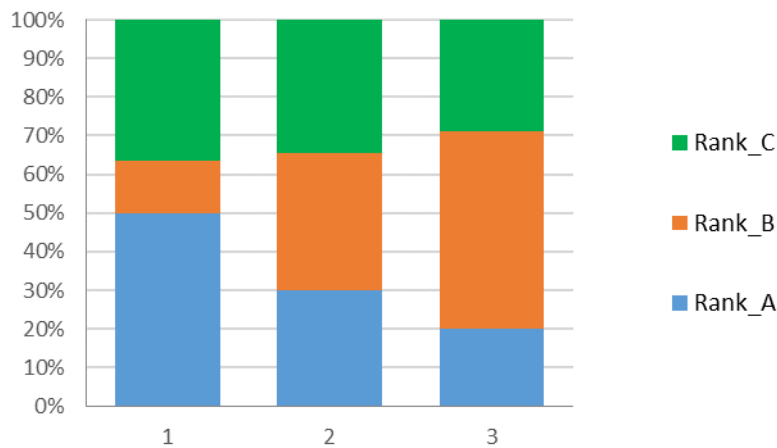


Figure 5: Rank acceptability indices for products A, B, and C. The x-axis shows the rank position, and the y-axis, the rank acceptability for each product for every rank.

Interpretation:

Product A and product C have similar chances of being ranked first, with a 50% likelihood for A and 35% for C. They also have similar chances of being ranked second and third. Product B, on the other hand, is most likely to be the third-best option, with a 50% likelihood. Looking at the performance of the indicators, product A performs better in indicator Y, while product C performs slightly better in indicators X and Z. Deciding between product A and C depends on how important each indicator is. Currently, all indicators have the same priority. If we prioritize indicators X and/or Z more, it would benefit product C, while if we prioritize indicator Y more, it would benefit product A.

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