Combining heterogeneous indicators by adopting Adaptive MCDA: dealing with Uncertainty

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Abstract. Adaptive MCDA systematically supports the dynamic combination of heterogeneous indicators to assess overall performance. The method is completely generic and is currently adopted to undertake a number of studies in the area of sustainability. The intrinsic heterogeneity characterizing this kind of analysis leads to a number of biases, which need to be properly considered and understood to correctly interpret computational results in context. While on one side the method provides a comprehensive data-driven analysis framework, on the other side it introduces a number of uncertainties that are object of discussion in this paper. Uncertainty is approached holistically, meaning we address all uncertainty aspects introduced by the computational method to deal with the different biases. As extensively discussed in the paper, by identifying the uncertainty associated with the different phases of the process and by providing metrics to measure it, the interpretation of results can be considered more consistent, transparent and, therefore, reliable.

Keywords: MCDA · Uncertainty · Sustainability.

1 Introduction

There is an intrinsic relationship between decision theory [29] and uncertainty. Indeed, uncertainty often characterises typical decision-making scenarios in different disciplines [34]. Intuitively, more uncertainty in a given context results in a more difficult decision-making process in that context. Depending on the extent in which decision theory is applied (e.g. under ignorance, risk), minimising the uncertainty by adopting the different techniques to inform decision-making may become a key factor for the whole decision-making process.

Such considerations evidently also apply to Multi-Criteria Decision Analysis (MCDA) [30], whose methods are often integrated with explicit mechanisms or models [8] to deal with uncertainty (e.g. [14]). The relevance of the different uncertainty factors often suggests the combined use of MCDA and probablistic approaches [10][33]. In general terms, the different applications of MCDA deal with different kinds of uncertainty. Concrete examples are, among others,

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in the field of energy planning [6], waste-water infrastructure planning [35], assessment of strategic options [23], healthcare [13][19], transport infrastructure appraisal [5], sustainability assessment [7], life-cycle assessment [22] and marine conservation [9].

In this paper we discuss the uncertainty associated with *Adaptive MCDA* [21], which systematically supports the dynamic combination of heterogeneous indicators to assess overall performance. Such a method is completely generic and is currently adopted to undertake a number of studies in the area of sustainability (e.g. [20]). The intrinsic heterogeneity characterizing this kind of analysis leads to a number of biases, which need to be properly considered and understood to correctly interpret computational results in context. While on one side the method provides a comprehensive data-driven analysis framework, on the other side it introduces a number of uncertainties that are object of discussion in this paper. Uncertainty is approached holistically, meaning we address all uncertainty aspects introduced by the computational method to deal with the different biases. As extensively discussed in the paper, by identifying the uncertainty associated with the different phases of the process and by providing metrics to measure it, the interpretation of results can be considered more consistent, transparent and, therefore, reliable.

Previous Work. *Adaptive MCDA* is described in [21], while an application on global sustainable development adopting such a method is proposed in [20]. The proposed contribution is strongly related to previous work as (i) the uncertainty analysis provided refers to *Adaptive MCDA* only and (ii) the case study on sustainable development is used as practical example for uncertainty analysis.

Aims and Scope. This paper focuses on uncertainty analysis in *Adaptive MCDA*. Such a topic is not addressed in previous work. Analysis and considerations in the paper apply only to *Adaptive MCDA*, while a more generic uncertainty analysis along the different MCDA techniques is out of the scope of this paper.

Structure of the paper. The introductory part of the paper follows with Section 2, which briefly addresses MCDA. The core part of the paper (Section 3) deals with the uncertainty analysis in *Adaptive MCDA*, looking at a concrete case study. As usual, the conclusions section provides a concise summary of the contribution both with a brief outline of possible future work.

2 MCDA & Adaptive MCDA

MCDA is a consolidated concept within decision science, where MCDA-based techniques aim to provide a more comprehensive decision framework to contrast decisions based merely on intuition [25]. As many problems can be structured as multi-criteria decision problems [11][18], MCDA proliferated in the past decades by defining a relevant number of different approaches, methods and techniques.

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While MCDA can be holistically considered as a completely generic approach, applications within the different domains resulted in a number of more specific and fine-grained methods, as reported by different contributions in literature (e.g. [16] in the area of sustanable and renewable energy and [17] for transportation systems). In [15], the authors reviewed the different techniques and their application within the different disciplines, while an overview from a software perspective is proposed in [32].

Adaptive MCDA is a relatively simple technique that, overall, aims to make the weighting step as simple as possible by adapting computations to available data. Additionally, the method is expected to provide a rich analysis framework by combining multiple assessment metrics and visualizations in presence of heterogeneity. This paper discusses uncertainty factors, metrics and mitigations related to *Adaptive MCDA*, with emphasis on quantitative aspects and their relationship with qualitative ones.

A more holistic discussion of uncertainty along the different MCDA techniques could be complex and very articulated. It is out of the scope of this paper.

3 Uncertainty Analysis in Adaptive MCDA

In this section we discuss the implications of *Adaptive MCDA* in terms of uncertainty. We have identified two main kinds of uncertainty: one of them is associated with the need to weight the considered criteria, while the other one results from the adaptive mechanism for parameter tuning to mitigate the numerical differences among the different indicators. The two categories and the respective metrics will be object of a separate discussion in the next subsections.

The experiments reported belong to the previously mentioned case study in the field of sustainable global development. By adopting multiple configurations that reflect different design decisions for the target case study, we point out the meaning of the uncertainty in context and its quantification according to the proposed metrics. The practical impact of such an uncertainty on final results and interpretations can vary very much depending on the extent and the intent of the considered case study. As the reference method allows customization and largely relies on interpretations in context, understanding uncertainty becomes a critical step for a correct computation set-up and result interpretation. More concretely, the use case object of analysis includes six different indicators: *Temperature Anomaly* [2], *Life Expectancy* [26][4], *GDP x capita* [3], *People living in extreme Poverty* [28][24], *People living in Democracy* [27] and *Terrorist attacks* [1].

3.1 Uncertainty associated with Case Study Design: Indicator Selection and Weighting

The meaning of the weights associated with the different criteria may vary very much from case to case. Generally speaking, the weight set reflects some kind of importance or relevance related to the indicators framework in a given context.

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However, while indicators themselves are somehow objective, yet not always perfect, measures, weighting indicators in a specific context can be a much more volatile and subjective concept. Indeed, depending on the intent and extent of a given study, weights can be simply not relevant (i.e. - "neutral" computations that assume the same weight for all indicators are considered acceptable), can be understood as static parameters estimated, measured or anyway known a priori, as well as they can be considered as variables or their estimation may even be the main purpose of the study (e.g. typical of Participatory Modelling [31][12]).

As weighting plays a very critical and key role to establish holistically the performance of the target system and it can rarely be considered completely objective, we assume an intrinsic uncertainty which reflects the potential variability of weights. *Adaptive MCDA* always proposes final computations taking into account of such an uncertainty. Indeed, the result of a computation $\alpha(t)$ at a given time i, that assumes a weight set from users, is integrated with extreme computations, $\gamma(t)$ and $\beta(t)$, that adopt the weight sets that correspond, respectively, to the best and the worst possible performance at the time i. Thus, at the generic time i, it is always $\beta(t_i) \leq \alpha(t_i) \leq \gamma(t_i)$. The *Uncertainty Range* is defined as $Range(t_i) = \{\beta(t_i), \gamma(t_i)\}$, while the resulting uncertainty Δ is measured as $\Delta(t_i) = |\beta(t_i) - \gamma(t_i)|$.

Looking at the six selected indicators, we consider different combinations of indicators to define the different configurations of the experiment (Table 1).

Table 1: Configuration of the experiment to measure the uncertainty (Δ) associated with weighting.

UC	**Temp.**	**Life Exp.**	**GDP**	**Pov.**	**Dem.**	**Terr.**	***Range***	$\Delta(t_{MAX})$
UC_1.1	✓	✓	✓	x	x	x	-1450/1000	**2450**
UC_1.2	x	x	x	✓	✓	✓	-7000/2550	**9550**
UC_1.3	x	x	✓	✓	✓	x	0/1075	**1075**

For each configuration we have computed the *Uncertainty Range* and Δ. Both metrics are reported in Table 1. As shown, even considering the same number of indicators (3 indicators), the corresponding uncertainty varies notably for the different cases: the second configuration presents a significantly high uncertainty that is almost 5 times higher than in the first configuration and almost 10 times higher than the one associated with the last configuration.

In order to fully understand the computation results also considering the associated uncertainty as previously defined, the method's output (Figure 1) is always proposed in context.

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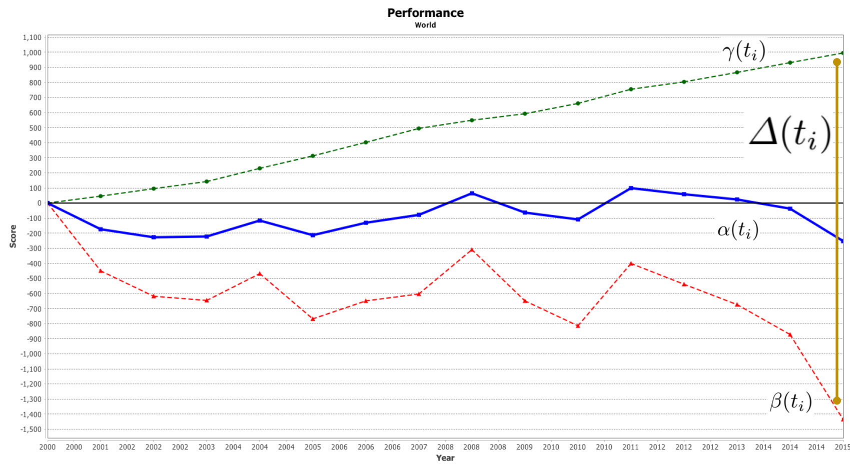
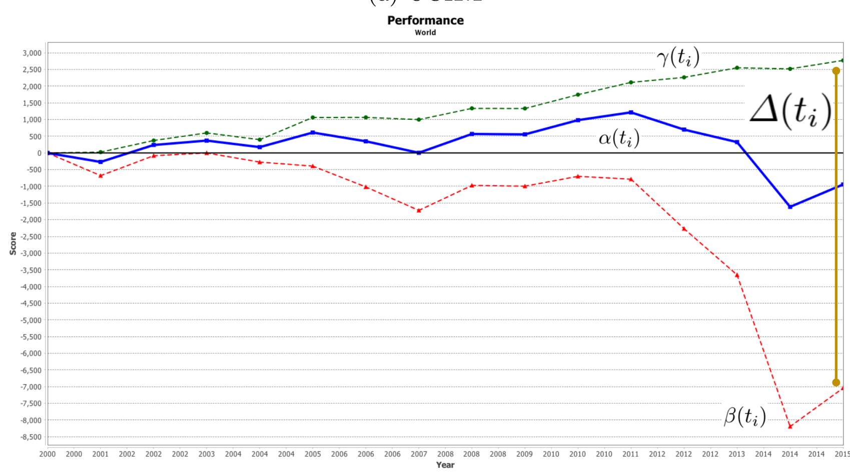
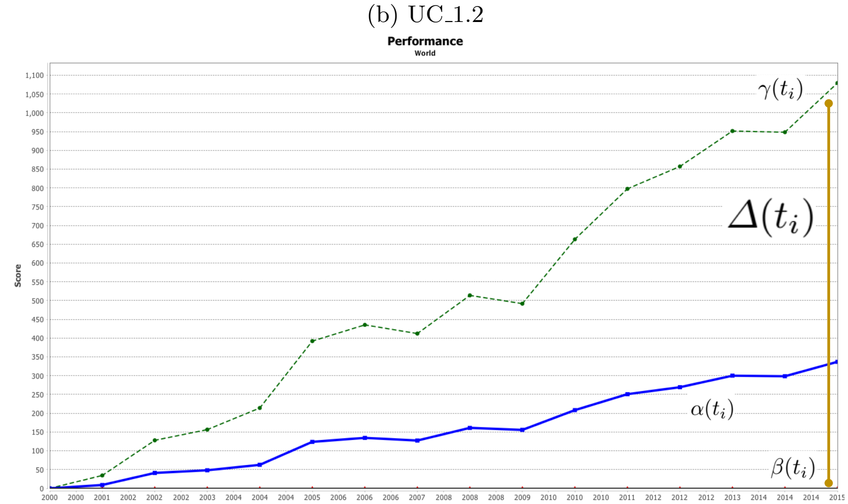


(a) UC_1.1



(b) UC_1.2



(c) UC_1.3

Fig. 1: Visualization of the uncertainty Δ associated with weighting.

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The first two configurations (Figure 1a and 1b) present classical ranges, meaning that, depending on the weight set adopted, the system may have positive or negative performance. However, the Δ value is much higher for the second configuration that is, therefore, characterised by an higher level of uncertainty. The third configuration (Figure 1c) proposes a completely different pattern, as the performance of the system can only be positive. Additionally, this use case is associated with a significantly lower uncertainty.

Impact on results and interpretations . Weights play a key role in final computations and, therefore, in the whole decision analysis process. Weighting doesn't necessarily raise uncertainty, as well as the potential impact of uncertainty on results and interpretations may vary significantly from case to case. The method discussed in this paper is based on the contextual interpretation of the results computed. The results are always proposed both with extreme computations (Figure 1) in order to provide a clear understanding of the range of possible results as the function of the chosen weights set. The uncertainty associated with the weighting process may also be understood as a possible driver factor to select target criteria, as the minimization of the uncertainty can be, at least in theory, a way to have a more "objective" and transparent analysis.

3.2 Numerical bias

An additional uncertainty is inducted by the *Adaptive MCDA* algorithm used to mitigate numerical differences existing among heterogeneous indicators. Such an adaptive algorithm is not always adopted as it is a user choice. It can be very useful any time the target indicator framework presents strong differences in scale among the different indicators. If not properly addressed by the computational method, this *numerical bias* can make certain criteria as non-relevant in the assessment of overall performance regardless of the weights associated.

Adaptive MCDA adopts a metric, which we refer to as *distance*, to estimate the accuracy of the algorithm, as lower values correspond to higher accuracy. This metric is associated with the *neutral computation*, that is a reference computation which assumes the same weight $w_i = \hat{w}$ for the i target indicators. $\hat{w}$ is normally the average value over the allowed values for weighting (e.g. $\hat{w} = 5$ for the range [0,10]). More concretely, it measures the distance between the neutral computation function and the x-axis. Some visualizations assuming $\hat{w} = 5$ are reported in Figure 3.

We adopt *distance* to assess the uncertainty introduced by the adaptive parameter tuning. In this case, uncertainty is mostly synonymous with precision. Indeed, an ideal parameter tuning assumes *distance* $= 0$, while in fact such a value is normally not null. It introduces an uncertainty in the computation which is estimated by *distance*, which measures the distance between the current parameters tuning for computation and the ideal one.

The experiment proposed consists in the analysis of the four different configurations as reported in Table 2. These configurations include all available

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indicators. The time frame for the analysis is 2000-2015 (16 points). The configurations differ from each other on the number of points considered (Figure 2).

Table 2: Summary of results for uncertainty associated with parameter tuning.

UC	Temp.	Life Exp.	GDP	Pov.	Dem.	Terr.	Period	#Points	*distance*
UC_2.1	✓	✓	✓	✓	✓	✓	2000-2015	**2**	≈ **10**
UC_2.2	✓	✓	✓	✓	✓	✓	2000-2015	**3**	≈ **100**
UC_2.3	✓	✓	✓	✓	✓	✓	2000-2015	**5**	≈ **650**
UC_2.4	✓	✓	✓	✓	✓	✓	2000-2015	**16**	≈ **2000**

In general terms, considering more points contributes to have a more fine grained analysis by providing a clearer and more detailed understanding of trends. Reducing the number of points considered affects the analysis of trends. The proper number of points to consider depends first of all on data availability and can be normally considered very specific of a given case study. We assume that many studies consider all available data so we expect a relatively high number of points.

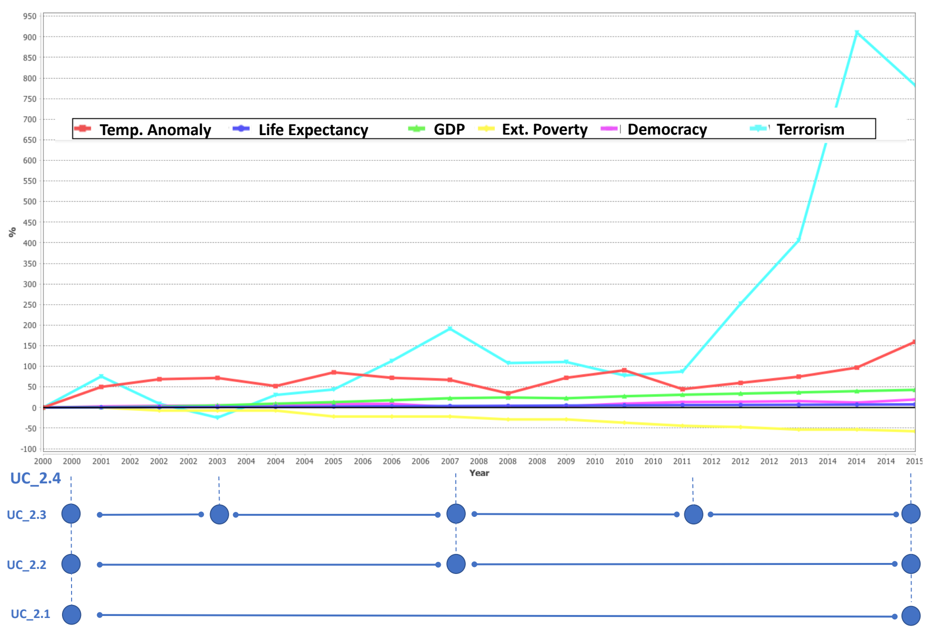

Fig. 2: Configuration of the experiment to measure the uncertainty associated with parameter tuning.

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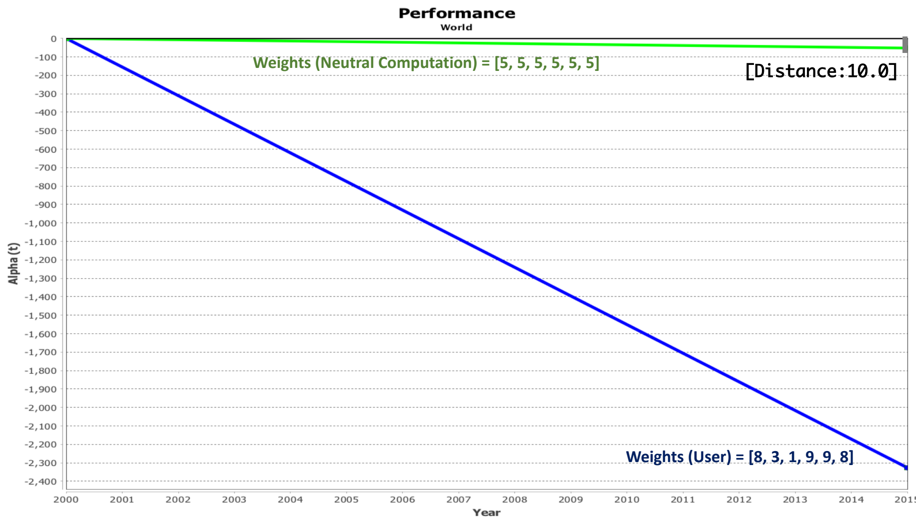

Fig. 3: UC_2.1

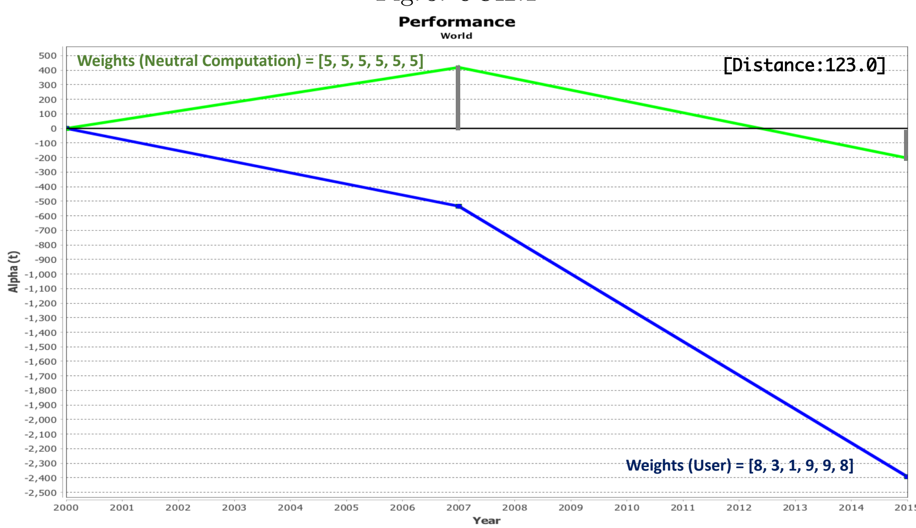

Fig. 3: UC_2.2

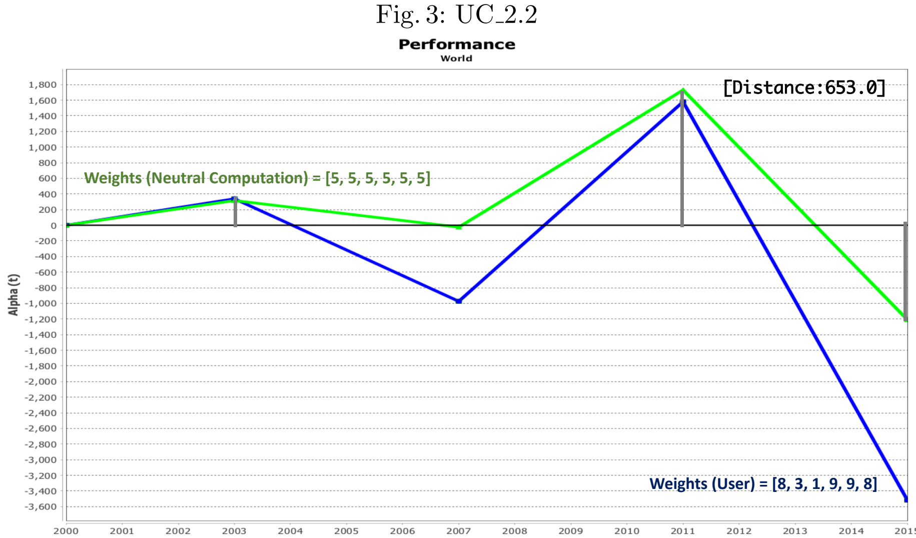

Fig. 3: UC_2.3

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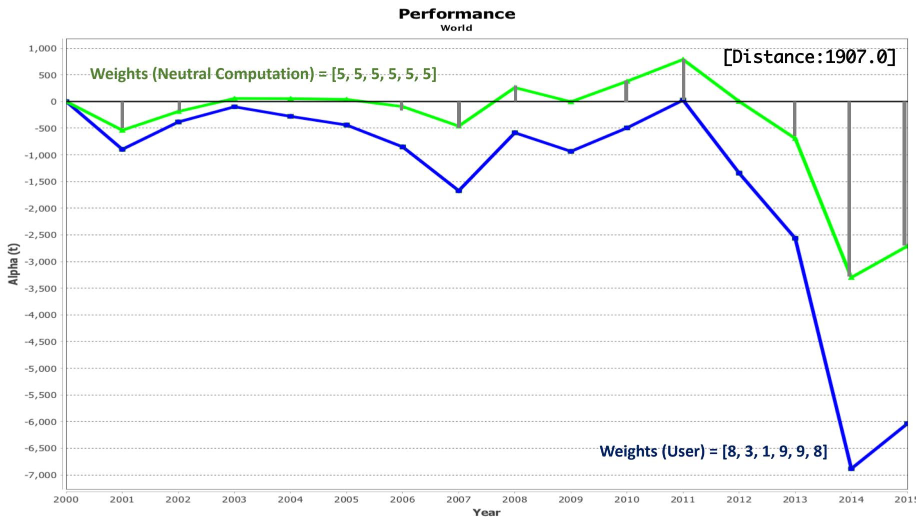

Fig. 3: UC_2.4

Fig. 3: Visualization of the uncertainty (*distance*) introduced by the parameter tuning algorithm.

Average values for *distance* resulting by computing the different configurations are reported in Table 2, as well as a visualization is reported in Figure 3. As expected, a lower number of points is associated with a lower uncertainty, which indeed increases with the amount of data considered.

Impact on results and interpretations . This second uncertainty factor is introduced by the computational method when the adaptive features to mitigate numerical biases are used. The method reflects an analysis framework which always considers computations adopting user weights in relation to neutral computations (Figure 3). When the target case study addresses a single system (e.g. global development, or a single country or city), the concrete impact of this kind of uncertainty on results and interpretations is normally limited and the neutral computation is adopted just to establish how "optimistic"/"pessimistic" a given weights set is. However, when multiple systems/scenarios are considered (e.g. some comparison based on a number of criteria among multiple countries or cities), the uncertainty introduced by the adaptive algorithm becomes much more relevant. In such kind of study, the final analysis needs to be conducted looking at the distance between the user computation and the neutral computation. Indeed absolute values could be misleading as scales could be different because of the algorithm.

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4 Conclusions and Future Work

In this paper we have analysed the uncertainty associated with *Adaptive MCDA*, a method to systematically and dynamically combine heterogeneous indicators to assess overall performance.

We have identified two main kinds of uncertainty related to the weighting of criteria and to the mitigation of numerical bias. The former uncertainty factor is a direct consequence of the weights relevance within the method, while the latter is introduced by the adaptive features of the method.

As extensively discussed, such an uncertainty can be measured and computational results are always proposed in the context of the metrics associated. Uncertainty can be understood in two possible ways: on one side, a clear understanding and quantification of uncertainty makes the analysis framework richer, more accurate and transparent; on the other side, the minimization of uncertainty can be considered as a valuable driver factor to design reasonable case studies in terms of amount of data and heterogeneity.

Future work is still in the field of sustainability and aims at a more fine-grained analysis. More concretely, *Adaptive MCDA* will be used to measure expected country resilience to situations of pandemic (e.g. COVID-19). Because of the notable heterogeneity of criteria, we expect uncertainty to be even more relevant than in the cases approached so far (global development).

References

1. Global terrorism database (gtd). university of maryland.
2. Temperature anomalies - Met Office Hadley Centre. https://www.metoffice.gov.uk/hadobs/hadcrut4/index.html, online; accessed: 11 June 2020
3. World Development Indicators, The World Bank. http://data.worldbank.org/data-catalog/world-development-indicators
4. Zijdeman, Richard and Ribeira da Silva, Filipa, Life Expectancy at Birth (Total), ISH Data Collection, V1, 2005. https://hdl.handle.net/10622/LKYT53
5. Ambrasaite, I., Barfod, M.B., Salling, K.B.: Mcda and risk analysis in transport infrastructure appraisals: The rail baltica case. Procedia-Social and Behavioral Sciences **20**, 944–953 (2011)
6. Diakoulaki, D., Antunes, C.H., Martins, A.G.: Mcda and energy planning. In: Multiple criteria decision analysis: state of the art surveys, pp. 859–890. Springer (2005)
7. Dorini, G., Kapelan, Z., Azapagic, A.: Managing uncertainty in multiple-criteria decision making related to sustainability assessment. Clean Technologies and Environmental Policy **13**(1), 133–139 (2011)
8. Durbach, I.N., Stewart, T.J.: Modeling uncertainty in multi-criteria decision analysis. European journal of operational research **223**(1), 1–14 (2012)
9. Estévez, R.A., Gelcich, S.: Participative multi-criteria decision analysis in marine management and conservation: Research progress and the challenge of integrating value judgments and uncertainty. Marine Policy **61**, 1–7 (2015)
10. Fenton, N., Neil, M.: Making decisions: using bayesian nets and mcda. Knowledge-Based Systems **14**(7), 307–325 (2001)

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11. Franco, L.A., Montibeller, G.: Problem structuring for multicriteria decision analysis interventions. Wiley encyclopedia of operations research and management science (2010)
12. Gray, S., Jordan, R., Crall, A., Newman, G., Hmelo-Silver, C., Huang, J., Novak, W., Mellor, D., Frensley, T., Prysby, M., et al.: Combining participatory modelling and citizen science to support volunteer conservation action. Biological conservation **208**, 76–86 (2017)
13. Hansen, P., Devlin, N.: Multi-criteria decision analysis (mcda) in healthcare decision-making. In: Oxford Research Encyclopedia of Economics and Finance (2019)
14. Hyde, K., Maier, H.R., Colby, C.: Incorporating uncertainty in the promethee mcda method. Journal of Multi-Criteria Decision Analysis **12**(4-5), 245–259 (2003)
15. Mardani, A., Jusoh, A., Nor, K., Khalifah, Z., Zakwan, N., Valipour, A.: Multiple criteria decision-making techniques and their applications–a review of the literature from 2000 to 2014. Economic research-Ekonomska istraživanja **28**(1), 516–571 (2015)
16. Mardani, A., Jusoh, A., Zavadskas, E.K., Cavallaro, F., Khalifah, Z.: Sustainable and renewable energy: An overview of the application of multiple criteria decision making techniques and approaches. Sustainability **7**(10), 13947–13984 (2015)
17. Mardani, A., Zavadskas, E.K., Khalifah, Z., Jusoh, A., Nor, K.M.: Multiple criteria decision-making techniques in transportation systems: A systematic review of the state of the art literature. Transport **31**(3), 359–385 (2016)
18. Marttunen, M., Lienert, J., Belton, V.: Structuring problems for multi-criteria decision analysis in practice: A literature review of method combinations. European Journal of Operational Research **263**(1), 1–17 (2017)
19. Mühlbacher, A.C., Kaczynski, A.: Making good decisions in healthcare with multi-criteria decision analysis: the use, current research and future development of mcda. Applied health economics and health policy **14**(1), 29–40 (2016)
20. Pileggi, S.F.: Life before COVID-19: how was the World actually performing? Quality and Quantity https://doi.org/10.1007/s11135-020-01091-6
21. Pileggi, S.F.: Is the World Becoming a Better or a Worse Place? A Data-Driven Analysis. Sustainability **12**(1), 1–24 (2019)
22. Prado, V., Rogers, K., Seager, T.P.: Integration of mcda tools in valuation of comparative life cycle assessment. Life cycle assessment handbook: a guide for environmentally sustainable products pp. 413–432 (2012)
23. Ram, C., Montibeller, G., Morton, A.: Extending the use of scenario planning and mcda for the evaluation of strategic options. Journal of the Operational Research Society **62**(5), 817–829 (2011)
24. Ravallion, M.: The economics of poverty: History, measurement, and policy. Oxford University Press (2015)
25. Rew, L.: Intuition in decision-making. Image: The Journal of Nursing Scholarship **20**(3), 150–154 (1988)
26. Riley, J.C.: Estimates of regional and global life expectancy, 1800–2001. Population and development review **31**(3), 537–543 (2005)
27. Roser, M.: Democracy. Our World in Data (2013), https://ourworldindata.org/democracy
28. Roser, M., Ortiz-Ospina, E.: Global extreme poverty. Our World in Data (2013), https://ourworldindata.org/extreme-poverty
29. Steele, K., Stefánsson, H.O.: Decision theory (2015)
30. Stewart, T.J.: Dealing with uncertainties in mcda. In: Multiple criteria decision analysis: state of the art surveys, pp. 445–466. Springer (2005)

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31. Videira, N., Antunes, P., Santos, R., Lopes, R.: A participatory modelling approach to support integrated sustainability assessment processes. Systems Research and Behavioral Science **27**(4), 446–460 (2010)
32. Weistroffer, H.R., Li, Y.: Multiple criteria decision analysis software. In: Multiple Criteria Decision Analysis, pp. 1301–1341. Springer (2016)
33. Yang, A., Huang, G., Qin, X., Fan, Y.: Evaluation of remedial options for a benzene-contaminated site through a simulation-based fuzzy-mcda approach. Journal of hazardous materials **213**, 421–433 (2012)
34. Zarghami, M., Szidarovszky, F.: Mcda problems under uncertainty. In: Multicriteria Analysis, pp. 113–147. Springer (2011)
35. Zheng, J., Egger, C., Lienert, J.: A scenario-based mcda framework for wastewater infrastructure planning under uncertainty. Journal of environmental management **183**, 895–908 (2016)

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