

Multi-Stakeholder Optimization for Identification of Relevant Life Cycle Assessment Endpoint Indicators

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ABSTRACT

Endpoint indicators provide a concise representation of environmental impacts by aggregating multiple midpoint indicators into a single value. Traditional endpoint weighting systems, however, are often limited by biases introduced through panel reviews and a lack of robustness in scientific process models. Additionally, they typically fail to account for the preferences of key stakeholders, including industry, government, and the public. This work addresses these limitations by developing an endpoint indicator that incorporates stakeholder preferences and minimizes dissatisfaction. A multi-stakeholder optimization framework was formulated to achieve this goal, employing distance, downside risk, and conditional value at risk as objective functions. Stakeholder preferences were derived from emissions data for industry, federal spending on environmental issues for government, and public surveys for societal input. Results highlight regional variations in midpoint indicator weightings across Texas, California, Delaware, and the United States. Furthermore, the influence of public and government preferences reveals a prioritization of human health concerns over environmental impacts. This framework offers a novel approach to creating endpoint indicators that align with stakeholder priorities, promoting more inclusive and collaborative environmental decision-making.

Keywords: Life Cycle Assessment, Multi-Stakeholder Optimization, Risk Assessment

INTRODUCTION

Life Cycle Assessment (LCA) is used to evaluate the environmental effects of products and processes. Several Life Cycle Impact Assessment (LCIA) methods such as TRACI and ReCiPE have been developed to quantify impacts[1, 2]. They employ midpoint indicators that relate the impact of an activity on specific environmental sectors. For example, kg SO₂-eq relates to acidification and kg N-eq for eutrophication in TRACI v2.1[2]. All environmental flows are measured relative to a basis, which serves as the primary causal factor. Additionally, ReCiPE also employs endpoint indicators that are a linear combination of midpoint indicators, with weights assigned based on relative physical impact.

Endpoint indicators aggregate relevant midpoint indicators to reflect broader societal impacts, such as human health, ecosystem quality, and resource depletion. While there is a physical basis for some of these endpoint

indicators, their weights are mostly subjective and may not necessarily align with the interests of stakeholders. One example is the human development index (HDI) of the United Nations where three indicators (life expectancy, education index, and the income per capita) are grouped into the HDI with a fixed weight[3]. These weights can change between regions and the stakeholders' preferences.

Eco-Indicator 99 weighting for endpoint indicator was determined by a panel survey to weigh the importance of human life loss, extinction of plant species, and resource depletion[4]. The authors remarked that this panel is not necessarily reflective of society. The Institute of Environmental Science at Leiden University developed the CML method which does not provide endpoint indicators and states that any aggregation needs to be thoroughly explained[4]. The ReCiPE method provides three types of aggregation for endpoint indicators: individualistic, hierarchist, and egalitarian[5]. These

aggregations are based on Cultural Theory from the work of Thompson and are used to represent certain assumptions[5, 6]. The individualistic approach assumes a 20-year horizon with optimistic developments, the hierarchist approach aligns with current science over 100 years, and the egalitarian approach spans 1000 years with pessimistic assumptions and highest impact damages. The endpoint value varies based on the approach and assumptions made.

There are some limitations in the use of midpoint and endpoint indicators. The weighting for endpoint indicators is often done by an expert panel, which can result in biases and not accurately reflect stakeholder preferences[7]. In other instances when endpoint indicators are based on science modeling, the aggregation for different midpoint categories results in a loss of accuracy due to the lack of robustness of endpoint models[7].

In lieu of expert weighting or model-based aggregation, we propose an endpoint indicator that considers the environmental impacts important to stakeholders. By considering all stakeholders in the evaluation of the metric, we hope the framework would increase buy-in, particularly for policymaking. This metric is essential for setting policy that prevents burden-shifting between different environmental impacts. Consequently, a multi-stakeholder optimization approach with risk objective functions is formulated to develop an LCA endpoint metric. The multi-stakeholder framework allows for every perspective to be considered. Risk metrics are extensively used within the financial industry to minimize and mitigate extreme losses. In this context, they are used to minimize stakeholder dissatisfaction.

A data-driven, multi-stakeholder framework has been developed to enable the creation of LCA endpoint metrics that accommodate the diverse needs of stakeholders, including businesses, governments, and the public.

METHODOLOGY

In this work, we consider the use of the following TRAClv2.1 midpoint indicators: acidification, ecotoxicity, climate change (GWP), human health (cancer and non-cancer), particulate matter (PM), smog formation, and ozone depletion. An endpoint indicator is a linear combination of the midpoint indicators as shown in equation 1, where EP is the endpoint indicator value, p_j is the weight for midpoint indicator j , and f_j is the impact of midpoint indicator j .

$$EP = \sum_j p_j f_j \quad (1)$$

The main contribution of this work is to provide a method for determining the weighting factors of the

midpoint indicators that will satisfy the needs of multiple stakeholders. To do so, first the stakeholder preferences are generated from data. A multi-stakeholder optimization function is generated to determine the optimal weighting function that minimizes stakeholder dissatisfaction.

Stakeholder Preference Generation

There are three stakeholders: Industry, Public, and Government. For the public preferences, the results from a Gallup poll surveying 1,016 adults living in the United States were used[8]. Human health indicators and the remaining environmental indicators were split based on the number of correspondents who indicated that healthcare was a problem they worried about a fair amount or more. The remaining environmental indicator preferences were determined similarly by correlating responses with indicators. For the government preferences, the EPA 2024 Fiscal Year budget was used[9]. The EPA has strategic goals that were correlated with midpoint indicators. The preferences were generated as the fraction of money allocated to each strategic goal. For any indicators that are broken down into additional sub-indicators, such as Ecotoxicity, the weights are allocated uniformly.

For industry stakeholders, their preferences are built based on midpoint indicator impacts as calculated by their point-source air emissions. The point source air releases are obtained from the National Emissions Inventory (NEI), which contains information on point source emissions for every state in the United States[10]. The NEI consists of criteria air pollutants/precursors (CAPs), hazardous air pollutants (HAPs), and greenhouse gas emissions (GHGs). Point sources are facilities that have a large number of emissions from a fixed point. The NEI also reports nonpoint, on-road, nonroad, and fire sources. These alternative sources are smaller in magnitude than the point sources and are harder to attribute a stakeholder to. Consequently, only point sources from the NEI are used in this analysis. The NEI labels all point source data into facility types, which will serve as the basis for the industrial stakeholders. After the emissions for each pollutant type are identified, the midpoint impacts are calculated using the characterization factors from TRAClv2.2[11]. For substances in the NEI that are not found in the TRACI database, surrogate molecules are used as needed. Note that eutrophication is not considered in the optimization. Eutrophication can be calculated according to the spatial characterization factors provided by Henderson et al.; however, this consists of water emissions which can theoretically be determined by the national phosphorus inventory and national nitrogen inventory[12-14]. However, the water inventories do not have information on individual point sources. Therefore, we cannot attribute these emissions to any single stakeholder, and they are on a different basis than the air

emissions.

The stakeholder preferences are calculated from the midpoint impact values in the following way. Consider the matrix with elements $a_{i,j}$ where i is the stakeholder and j is the impact factor. The first transformation normalizes each column with respect to the total midpoint impact value, i.e. $a_{i,j}^1 = \frac{a_{i,j}}{\sum_i a_{i,j}}$. The second transformation consists of normalizing each row with respect to the total TRACI impact across all impact categories, i.e. $a_{i,j}^2 = \frac{a_{i,j}^1}{\sum_j a_{i,j}^1}$. We assume that if each stakeholder were to make an endpoint indicator as outlined in equation (1), then their desired weighting, p_j , will be proportional to their respective midpoint impacts. Therefore, we consider the preferred weightings for stakeholder i , $p_{i,j}$, to be equivalent to $a_{i,j}^2$. The preferred stakeholder weightings serve as parameters in our multi-stakeholder optimization problem.

Multi-Stakeholder Model Formulation

There are three optimization objectives considered in the work, corresponding with Euclidean distance (ED), Conditional Value at Risk (CVaR), and downside risk (DSR) approaches. The three objective functions are different measures of stakeholder dissatisfaction, which should be minimized.

The Euclidean distance approach is equivalent to minimizing the sum of the stakeholder dissatisfaction. The distance approach minimizes the following objective function:

$$ED = \sum_s \sum_j k_s (p_{s,j} - p_j^*)^2 \quad (2)$$

where $p_{s,j}$ is the preference for midpoint indicator $j \in J$ of stakeholder $s \in S$, p_j^* is the optimum preference for midpoint indicator j , and k_s is the stakeholder coefficient. The stakeholder coefficient is used to normalize the weighting between the industry, public, and government sectors. This is required because there are many industry stakeholders and only one public and one government stakeholder considered in this work. The goal of the distance approach is to simply minimize the sum of Euclidean distances between all stakeholders and the optimal preference.

In the CVaR approach, the expected dissatisfaction of the top $c\%$ dissatisfied stakeholders is minimized. c is an arbitrary cutoff value, which is selected as 2.5 in this work. This objective function attempts to reduce the dissatisfaction of the stakeholders who will be most affected by the new endpoint metric [12]. The Conditional Value at Risk approach minimizes the following objective function:

$$CVaR = \frac{1}{(1-c)|S|} \sum_{s \in S} \psi_s + VaR \quad (3)$$

where $\sum_j ((p_{s,j} - p_j^*)^2 - VaR) \leq \psi_s$ and ψ_s is the amount of dissatisfaction above the VaR, $p_{s,j}$ is the preference for midpoint indicator $j \in J$ of stakeholder $s \in S$ and p_j^* is the optimum preference for midpoint indicator j . Both ψ_s and VaR are positive continuous variables. The Value at Risk, VaR, which represents $(1-c)$ percentile of dissatisfaction.

Downside Risk specifies a specific dissatisfaction level L . All stakeholder dissatisfaction greater than L is summed into the metric. The objective minimizes all stakeholder dissatisfaction above a specific level. The downside risk is given the following objective function:

$$DSR = \sum_s \phi_s \quad (4)$$

where $\sum_j ((p_{s,j} - p_j^*)^2 - L) \leq \phi_s$ and ϕ_s is the amount of dissatisfaction above L , $p_{s,j}$ is the preference for midpoint indicator $j \in J$ of stakeholder $s \in S$ and p_j^* is the optimum preference for midpoint indicator j .

The full optimization problem is formulated as follows:

$$\begin{aligned} \min f(p_j^*) \\ \text{s.t. } \sum_j p_j^* = 1 \end{aligned} \quad (5)$$

where $f(p_j^*)$ corresponds to the corresponding objective function and p_j^* are positive continuous variables corresponding to the ideal endpoint indicator weightings, that sum to 1. Additional inequalities are required for the CVaR and DSR approaches and are added as needed.

CASE STUDY DESCRIPTION

The optimization problem was formulated and solved in Excel as an NLP using the Excel Solver plug-in with the GRG Nonlinear method. All computations were performed on a Mac M1 Pro @ 3.2 GHz CPU and 16.0 GB of RAM. The case study considers solving for endpoint indicator weights using the three objective functions described above. First, the state of Delaware is studied in depth. The endpoint indicators, risk by sector, and a sensitivity analysis on risk level are performed. To assess the effect of geography, the differences between the weightings are calculated from data for Texas, California, and Delaware, as well as the entire United States. These states were chosen as Texas and California have the largest GDP and large manufacturing sectors, while Delaware is a smaller state with manufacturing capacities. This is compared against the United States in aggregate. These results do not consider the effect of the public and of the government as stakeholders in the model. Finally, the effect of non-industry participants is considered by

increasing the stakeholder coefficients for these entities.

RESULTS

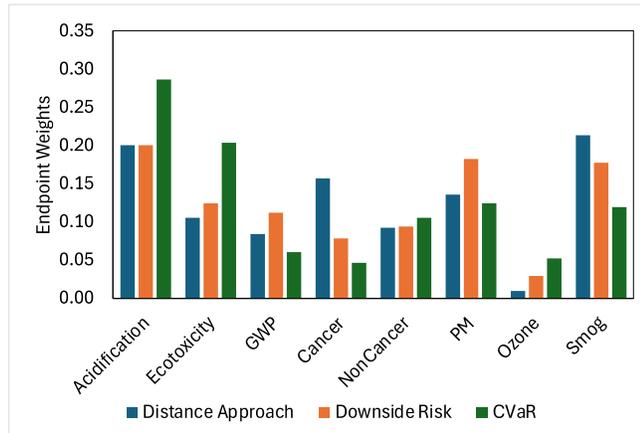


Figure 1. Endpoint indicator weights for the distance, downside risk ($L = .15$), and CVaR ($c = 2.5\%$) objective functions for the state of Delaware.

The weights for the state of Delaware using distance, downside risk, and CVaR are obtained solving the optimization problem given in Equation 5. The resulting values p_j^* are presented in Figure 1. The CVaR approach has higher weighting for acidification, ecotoxicity, and ozone depletion compared to the downside risk and distance approaches. CVaR has lower weighting for global warming potential (GWP), cancer, and smog. The downside risk approach with a dissatisfaction level of 0.15 has weights in between the distance approach and CVaR for a majority of indicator values. This effect is due in part to the low risk tolerance and medium risk tolerance set for CVaR, and downside risk, respectively. Additionally, the distance approach does not consider risk and therefore has the highest risk tolerance. Global warming potential and particulate matter (PM) are exceptions where downside risk has higher weighting.

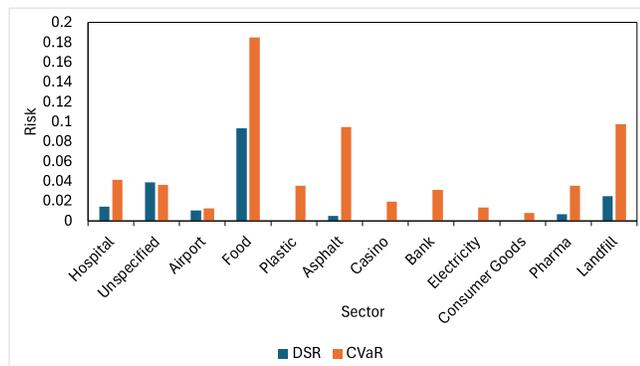


Figure 2. Risk levels for the downside risk and CVaR approach for unsatisfied sectors for the state of Delaware

There are 23 sectors considered in Delaware. At the prescribed dissatisfaction level, there are a number of sectors with dissatisfaction levels above the enforced limit. This is equivalent to risk. In the downside risk approach, there are 7 unsatisfied stakeholders with dissatisfaction levels above the dissatisfaction limit. In the CVaR approach, there are 12 unsatisfied stakeholders. The sectors' risks are shown in Figure 2. The lower risk tolerance in the CVaR approach accounts for the higher number of stakeholders and higher overall risk per sector compared to the downside risk approach.

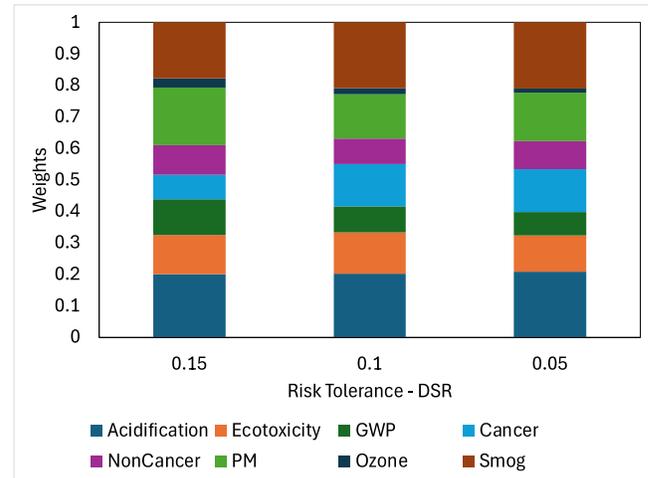


Figure 3. Endpoint indicator weights as a function of risk tolerance level for downside risk in the state of Delaware

A sensitivity analysis was performed on the risk tolerance level to understand the impact on endpoint indicator weights as shown in Figure 3. Decreasing the risk tolerance level results in smog, and cancer weights to increase. In contrast, global warming potential, particulate matter, and ozone decrease. Particulate matter and smog have the greatest contribution towards the total dissatisfaction. For particulate matter, there are two stakeholders with high dissatisfaction, food and asphalt. In contrast, smog affects a larger number of stakeholders but with relatively lower levels of dissatisfaction. Adjusting the weight of smog will result in higher cumulative stakeholder satisfaction than for particulate matter. For ecotoxicity, 0.1 relative to 0.15 risk tolerance has higher weights; however, 0.05 relative to 0.15 has a lower risk tolerance. The weighting for ecotoxicity is summed from several sub-indicators consisting of air, water, and soil emissions to water, resulting in no clear trend. When the risk tolerance was set above 0.2, there was no risk. Because there is no unique solution in this case, those results are omitted as there are multiple solutions.

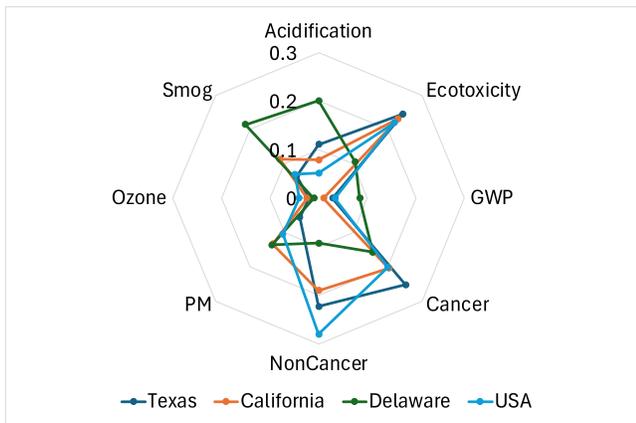


Figure 4. Endpoint indicator weights for Texas, California, Delaware, and the entire United States of America using the Euclidean distance approach

The endpoint indicator weights were calculated for Texas, California, Delaware, and the entire United States as a whole, as shown in Figure 4. The results reveal distinct regional variations in environmental impacts across Texas, California, Delaware, and the United States as a whole. Particulate matter impacts were notably lower in Texas compared to other regions. Delaware exhibited the lowest ecotoxicity values but had the highest acidification and smog endpoint weights. While ozone depletion and global warming potential carried relatively smaller weights across all regions, Delaware recorded a higher GWP weighting compared to the other states. Notably, the United States aggregated values were generally lower than those of individual states across most indicators, with the exception of non-carcinogenic effects, which were higher in the national assessment. These results highlight the spatial heterogeneity of environmental impacts and the importance of location-specific considerations in chemical engineering applications and policy-making.

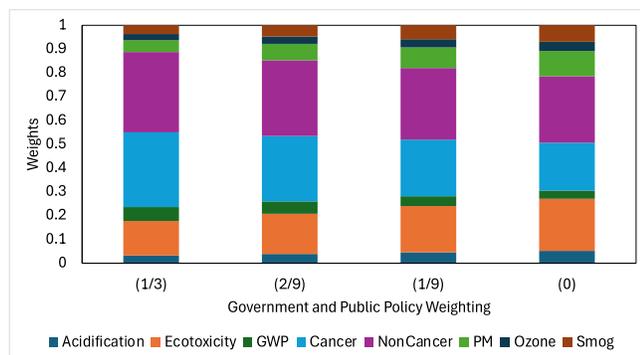


Figure 5. Endpoint indicator weights as a function of government and public policy stakeholder influence for the United States using the Euclidean distance approach

Figure 5 highlights the impact of varying public and

government influence on endpoint indicators coefficients as determined using the Euclidean distance approach. As the influence of public and government preferences increases, the emphasis on cancer and non-cancer health risks increases significantly. This trend reflects the strong prioritization of these indicators, as supported by EPA spending and public survey data—92% of EPA spending is allocated to protecting public health and ensuring safe drinking water[9]. Similarly, the weighting of GWP rises with greater public and government influence, while the importance of other categories diminishes. Under the scenario with one-third weighting, each for the government and public, cancer and non-cancer health indicators account for 65% of the total weight. Even without government and public policy intervention, these indicators remain the most significant, representing 48% of the weight. This somewhat unexpected result underscores the dominant influence of regulatory compliance and societal priorities, which favor human health outcomes over broader environmental emissions.

CONCLUSIONS

This work formulated a multi-stakeholder optimization problem to determine optimal midpoint indicator weightings for the creation of an endpoint indicator that minimizes dissatisfaction between all stakeholders. The Euclidean distance, downside risk, and conditional value at risk objective functions were minimized to do so. Industry, government, and public environmental impact preferences were generated from national emissions data, EPA funding, and public opinion data, respectively. The framework develops a unifying metric that can facilitate collaboration among stakeholders, promoting collective action towards environmental protection. It must be noted that the preference generation procedure in this work results in an inherently dynamic endpoint indicator. Emissions data, EPA fiscal budgets, and public opinion are constantly changing with time. The multi-stakeholder approach aims to minimize dissatisfaction between all stakeholders which optimizes agreement at the present time period. In context of policymaking, time inconsistency refers to the tendency for the optimal solution to any policy problem will be unlikely to remain the optimal solution throughout time, requiring new policies to be created. This is, in part, due to the dynamic nature of people's preferences.

Future work will focus on integrating this framework into policy-driven optimization models, such as cap-and-trade systems, where midpoint indicator impacts can be exchanged among stakeholders. This model will develop a pareto frontier of profits and environmental impacts with the goal of encouraging synergies between stakeholders via the novel endpoint indicator. Additional efforts will include refining the methodology for

determining preferences for midpoint indicators and tailoring the framework to capture regional variations by developing state-specific preferences. These advancements aim to further enhance the applicability and impact of this approach in fostering sustainable decision-making and environmental stewardship.

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