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A framework for multi-criteria decision support in sustainable through-life management of industrial assets

Stefanie Niekamp[1,2], Ujjwal Bharadwaj[1], Jhuma Sadhukhan[2], Marios Chryssanthopoulos[2]

[1]TWI Ltd, Granta Park, Great Abington, Cambridge CB21 6AL, UK
[2]University of Surrey, Guildford GU2 7XH, UK
stefanie.niekamp@affiliate.twi.co.uk

Abstract The aim of this research is to present rational decision support for sustainable management of industrial assets in situations where there are multiple conflicting objectives. For this purpose, a Multi-Criteria Decision Analysis (MCDA) framework that incorporates sustainability criteria over the whole life cycle has been developed. The basic needs of such a framework are reviewed and an initial concept is presented. Life Cycle Costing (LCC) and Life Cycle Assessment (LCA) criteria are discussed in-depth. These criteria provide a combination of the costs and environmental impacts that occur throughout the life phases of an industrial asset, including initial, operation and maintenance phases, any associated failure and the end of life phase. Moreover, preference weighting and uncertainty are considered explicitly allowing for higher confidence in the results. In order to facilitate stakeholder communication, numerical results are visualised. Contributions and scoring of the chosen criteria are depicted which help to identify most relevant parameters. Finally performance scores can be aggregated with the aid of MCDA techniques.

1. Introduction

In today's increasingly complex interrelated industrial systems there is an ever growing demand for sustainability of products and processes over the whole life cycle. In view of climate change and global population growth the impact of industrial activities on environment and society needs to be considered explicitly in addition to traditionally used economic performance criteria. The goal of asset management is defined as 'the optimum way of managing assets to achieve a desired and sustainable outcome' (BSI, 2008). It is aspired to achieve management excellence by finding an optimal solution in balancing performance quality, cost and risk over the whole life cycle (Campbell et al., 2011). The overall goal in sustainable asset management is to integrate economic, environmental and social factors to enable decision making in the most sustainable way. To identify optimal solutions, rational decision making is required. Different stakeholders may have conflicting objectives and priorities. Although risk assessment is well established in asset management (BSI, 2008), there appears to be very little work how it is incorporated into sustainability frameworks (JRC, 2012).

Complex problems with conflicting objectives can be addressed with Multi-Criteria Decision Analysis (MCDA) that provides formalised methodologies to identify optimum solutions considering preferences of decision makers and stakeholders (Linkov and Moberg 2011). To the author's best knowledge little if any work has been spent on applying MCDA approaches to sustainability evaluations whilst incorporating risk-assessment. This paper presents a review of existing approaches and proposes a framework to address this gap.

2. Review

2.1 Through-life sustainability

Many issues associated with population growth, finite resources and climate change have been pointed out over the recent decades by numerous studies, with the IPCC report on climate change being only the most recent one (IPCC, 2013). This has led to an increasing call for sustainable development with strong governmental push. An example is the European Horizon 2020 framework (EU, 2013) where demand for sustainability evaluation and demonstration can be observed throughout the calls and it is expected to consider the impact of products and processes over the whole life cycle. Two methods to evaluate environmental and economic performance are life cycle assessment (LCA) and life cycle costing (LCC) which are reviewed in the following paragraphs.

2.1.1 Life cycle assessment (LCA)

LCA is one of the most widely applied tools for assessing the environmental impact over the entire life cycle. ISO Standards, such as the ISO 14040 family for Life Cycle Assessment provide an international guideline. It provides a method to analyse and quantify environmental impact of both manufactured and consumed products and services in the different stages of their life cycle. The stages considered include raw material acquisition, production, use, end-of-life treatment, recycling and final disposal. This is commonly called a cradle-to-grave approach. The potential environmental impacts assessed are related to a functional unit as a means to allow comparison between different aspects (ISO, 2006a; ISO, 2006b).

LCA is especially useful for comparative studies or to assess potential improvement through scenario changes. It can thus help in a decision making process, where the environmental impact is an important criterion, such as comparing energy alternatives. Application of LCA as a tool for assessing the whole system sustainability for bioenergy and chemical process design is shown by Sadhukhan et al. (2014). Careful interpretation of results of LCA studies is crucial as decision making tools deliver complex system insights. Trade-offs between different criteria should be explored explicitly within a decision making process (Elghali et al., 2008). Due to significant costs and effort associated with a full LCA study it is debatable whether it is always feasible to implement. To overcome this issue, simplified approaches may be used (e.g. Padey, 2013) but their implications must be well understood.

2.1.2 Life cycle costing (LCC)

LCC is used to calculate the value of a product or service throughout the entire life cycle while fulfilling its required performance (ISO, 2008). This includes initial costs, costs for maintenance and repair as well as costs for disposal or recycling activities respectively. The decreasing monetary value over time is considered by discounting the cash flows to convert all costs and benefits to net present values (NPV). Discount rates for public investment for instance are determined by national agencies, such as HM treasury's green book in the UK. An application of LCC for decision making in through-life management of offshore structures was presented by Bharadwaj (2011).

2.1.3 Combination of LCC and LCA

The different approaches for obtaining LCC values in contrast to LCA values already show that a combination can be complicated. Gluch and Baumann (2004) studied LCC-orientated environmental accounting tools. They judged LCC as insufficient and advocated for the use of integrated decision support tools. These would not only provide a combination of different tools, but also focus on better understanding of the decision making process itself. According to Jin (2007) the traditional approaches of combining LCC and LCA performance scores can be grouped into three categories: 1. Determination of an overall performance score as a combination of costs and environmental impact. 2. Showing the cost and environmental impact scores together without calculating an overall score. 3. Translating LCA outcomes into costs and use as input for LCC. Each of them has their own merits. Considering the viewpoint of Gluch and Baumann, none of the categories may provide an ideal solution. MCDA methods in contrast offer more formalised approaches for combining different criteria. It is within the scope of this research to determine how these can be ideally exploited for any given application.

2.2 Multi-criteria decision analysis (MCDA)

MCDA approaches provide methodologies to systematically evaluate all options regarding a number of criteria and help to identify a preferred option or a ranking. Ranking between a number of alternatives with different competing objectives may not be straight-forward. The optimum solution for a decision maker facing a multi-objective problem may not even exist (Turskis and Zavadskas, 2011). MCDA approaches are also capable of addressing high uncertainty, multi-interests and perspectives (Wang et al., 2009). Therefore, multi-criteria analysis (MCA) approaches in general have become increasingly popular, particularly in energy decision making (Kowalski et al., 2009). For an MCDA approach the alternatives with their different criteria can be expressed with the aid of an $m \times n$ decision matrix as in equation 1. Wang et al. (2009) reviewed MCDA approaches for renewable energy. They identified four different steps in the MCDA process which are discussed in the next paragraph, namely: 1. criteria selection, 2. weighting of criteria, 3. execution of MCDA, 4. aggregation of different MCDA methods.

$$
\begin{array}{lc}
\text{criteria} & C_1 \quad C_2 \quad \ldots \quad C_n \\
\text{(weights} & w_1 \quad w_2 \quad \ldots \quad w_n\ ) \\
\text{alternatives} & \\
X = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}
\end{array}
\qquad (1)
$$

2.2.1 Criteria and categories

Sustainability criteria generally include economic, environmental and social aspects. These can be augmented by adding a context specific fourth category, such as 'institutional' criteria (e.g. Singh et al., 2012) or 'technical' criteria (e.g. Wang et al., 2009). The most commonly used criteria for energy decision making were efficiency (in the technical category), investment cost (economic), CO_2 emissions (environmental) and job creation (social) (Wang et al., 2009). Although categorisation of criteria is popular, classification may not be very clear (Bachmann, 2013). The UN has removed categorisation completely from their most recent sustainability guidelines in order to emphasise the multi-dimensional focus of sustainable development (UN, 2007). In view of this, it seems plausible that a focus should be placed on ensuring that indicators provide an appropriate representation of the overall goal rather then forcing them into distinct categories.

2.2.2 Weighting

Regarding weighting of different criteria several methods have been presented by Wang et al. (2009). They distinguish between equal weights, subjective and objective weighting methods. Equal weights became popular since Dawes and Corrigan (1974) argued that they often produce results that are nearly as good as ones produced by an optimal weighting method. Moreover, they require the least input. Subjective weighting methods on the other hand allow decision makers to assign priorities. Objective methods use the given data and determine weighting factors according to the consistency and sensitivity of the data. If certain factors are conflicting or appear to have very little impact on the results, lower weights are applied to them. Equal weights and subjective weighting methods are more popular for energy decision making than objective weighting methods (Wang et al., 2009).

Yager (1988) proposed the Ordered Weighted Averaging (OWA) as a new class of operators for aggregating multi-criteria for decision making. This concept was expanded further for example by Merigó and Casanovas (2011) to include weights on each criterion (WOWA) or other high level policies such as the induced aggregator (IOWA) to be applicable to more specific decision making cases. Amongst others it was used in the context of MCDA by Zarghami and Szidarovszky (2009) to account for uncertainty and minimise risks.

2.2.3 MCDA tools and techniques

Since the first formal decision theory for MCDA by Keeney and Raiffa (1976) a large number of tools and techniques have been developed and applied in different contexts. An overview of the currently prevalent MCDA tools and techniques and their application to environmental case studies has been presented by Linkov and Moberg (2011). They presented Multi-Attribute Utility Theory (MAUT), Analytical Hierarchy Process (AHP) and Outranking models as the three basic categories. MAUT translates different units into a common utility or value to allow comparison. It was judged as a powerful method, based on the assumption of a rational decision maker. AHP on the other hand requires pair-wise comparison for each criterion, including relative weighting of importance, at the data entry stage. Hence it captures inconsistencies of the decision maker through data analysis. Outranking also applies pairwise comparison but with the aim to identify options that outperform or dominate the others. It is less optimisation, but rather a comparative approach. Fuzzy set approaches may be used to better capture qualitative and imprecise data. How to select the most appropriate Multi-Criteria Analysis (MCA) has been suggested by Kurka and Blackwood (2013).

Sometimes a number of MCDA methods are carried out which may lead to different preference rankings, whose results can be aggregated. This can be done by voting or through mathematical aggregation, either with or without involvement of the decision maker. For energy decision making there have however been very few applications of aggregation methods (Wang et al., 2009).

2.3 Risk & Uncertainty

Risk is defined as ‘the probability that a particular adverse event occurs’ (Royal Society, 1992). The API Recommended Practice, an example of an operational guidance, defines risk as the ‘combination of the probability of an event and its consequence’ (API, 2009). Inclusion of risk assessment in LCA has been discussed by Bachmann (2013). Although it was deemed important they found no particular consideration of risks in the respective ISO norms. Guinée et al. (2010) proposed to include risk assessment for ‘certain sustainability questions’. This was confirmed in the ILCD handbook, stating that risk assessments can complement LCA studies since integrated assessments are not yet available (JRC, 2012). Badurdeen et al. (2012) suggested a framework for sustainable asset management which includes consideration of risk and sustainability principles over the whole life cycle. The description of the framework is however relatively brief and stresses the need for considering the issues rather than presenting solutions. Another framework for integrating risk assessment into MCDA was proposed by Catrinu and Nordgård (2011). They studied the criteria ‘potential to reduce safety risk’ and ‘investment and maintenance costs’ to achieve risk reduction and combined them in a hypothetical MCDA case. Although these are important criteria, the limitation to just these two can be judged as insufficient for addressing the whole complexity of risk-informed sustainable asset management. Little work has been done on formally integrating risk into decision support for sustainable asset management, a gap that is being addressed in the current research.

Risk in asset management is intimately connected to the inevitable presence of uncertainty. According to Ang and Tang (2007) uncertainty can be classified into the aleatory and the epistemic type. Epistemic uncertainty arises from limited knowledge and lack of accuracy in predicting a given system. Aleatory uncertainty on the other hand reflects the natural variability and randomness occurring within a system. In order to address the effects of uncertainty in decision making the significance of each type needs to be evaluated separately. Regardless of the type of uncertainty, probability and statistics provide suitable tools which help to increase confidence in calculated values and enable better estimation for decision making. In the context of Bayesian theory, the two types can be treated in a unified way, though a distinction helps to identify sources of uncertainty that can be reduced further (Kiureghian and Ditlevsen, 2009).

To quantify uncertainty, sensitivity analysis can be used. Certain input parameters of a given system are varied and the impact of this variation on the results is obtained. This allows assessing to which extent output parameters are dependent on the input values. Sensitivity analysis are widely used for scenario-modelling, i.e. for environmental impact assessment such as LCA (Heijungs, 2010). Often a few components can be identified that significantly influence the whole system. This stresses the importance of sensitivity analysis to identify parameters that actually have an impact, even if the original choice of parameters may be challenged.

3. Approach

To address sustainable through-life management a conceptual framework is discussed. It it is possible to include any number of criteria that are deemed important for the decision making process. For each criterion decision makers can assign weights to the scores to prioritise according to their degree of belief about importance and certainty. One unique characteristic of the current approach is the incorporated visualisation. Scores are depicted on a spider chart, both for ‘raw’ as well as weighted scores. Uncertainties can be depicted, too. This shall facilitate communication amongst stakeholders which is crucial to reach optimum decisions.

3.1 Criteria

As highlighted in section 2, the choice of suitable application-specific criteria is a crucial step in the MCDA process. For the sustainability assessment of engineering solutions there should be at least some consideration of the three sustainability aspects economic, environmental and social, alongside technical matters. As discussed before, it is less important that the criteria fit specific categories; they should rather represent the overall goal as holistically as possible. To address this aim, criteria with integrative attributes, either temporally or spatially (in the context of combining products and/or processes) are judged as most appropriate. In order to demonstrate the current approach, the aforementioned LCC and LCA approaches are discussed in greater detail. Both incorporate the whole life cycle which distinguishes them from many others. Incorporation of social and technical aspects over the whole life cycle is envisaged, including consideration of risk assessment. The framework itself is capable of dealing with any additional criteria.

3.1.1 Life Cycle Costing (LCC)

The total life cycle costs C_T can be obtained as a combination of the costs that occur throughout the life of an industrial asset. The following stages of spending costs have been identified: Initial costs C_I, maintenance costs C_M, *c*osts associated with a failure as a combination of the probability that a failure will occur *p(F)*, multiplied with the consequences associated with the failure, namely the repair/replacement costs C_R plus other consequential costs of failure C_F (e.g. production loss) and finally costs associated with the end of life C_{EoL} (e.g. recycling and/or disposal costs). Costs associated with distribution activities are usually included within the other components and thus will not be considered explicitly. Hence, the total costs C_T can be obtained as

$$C_T = C_I + C_M + p(F) \times (C_R + C_F) + C_{EOL} \tag{2}$$

Subsequently the net present value (NPV) is calculated according to equation 3, to find the total through-life costs that include initial costs, maintenance costs, the consequential costs of failure and end of life costs. Both discount rate *r* and time t_i may vary according to the type of asset and the estimated time scale.

$$NPV = \sum_{i=1}^{n} \frac{C_i}{(1+r)^{t_i}} \tag{3}$$

3.1.2 Life Cycle Assessment (LCA):

Analogous to the total costs, the total environmental impact E_T can be calculated to

$$E_T = E_I + E_M + p(E \mid F) \times p(F) \times (E_R + E_F) + E_{EOL} \tag{4}$$

The term *p(E|F)* represents the conditional probability of having an environmental impact given the case that a failure occurs. To determine the resulting statistical environmental impact of a failure, this term is multiplied with the estimated environmental impact per failure E_F and the probability that a failure occurs *p(F)*. It has to be noted that the measure ‘environmental impact’ consists of a number of components. According to the application, relevant criteria have to be chosen and possibly aggregated. Potential categories include global warming potential (GWP), acidification, eutrophication potential etc. The choice depends on the relevant transmission ways (e.g. gaseous releases or liquid substances) as well as the magnitude of their impact. The latter can be obtained through sensitivity analysis and Monte Carlo simulation (Sadhukhan, 2013) which helps to identify critical categories where reduction of the environmental impact is possible.

LCA is meant to provide long term impact potentials. 100 years are commonly considered based on the life span of an industrial system. It is possible to transform these impact potentials over shorter term by incorporating NPV concept as described above for LCC. To the author's best knowledge, little if any work has been devoted in including the effects of a potential failure into LCA studies. This aspect may be worth exploring further.

3.2 Weighting and Normalisation

Firstly it is important to consider the 'direction of scoring'. In the presented framework the scores are chosen in a way that a more positive score means a higher impact, hence a less preferable option. In case of criteria where this relationship is the other way round (e.g. many technical criteria), their scales have to be inverted to obtain a proportional relationship between scoring and value. Since all criteria may have a different range of values, normalisation is carried out to adjust all criteria scores S_i to a common scale from 0 to 100:

$$S_{i,norm} = \frac{S_i}{S_{i,\max} - S_{i,\min}} \times 100 \tag{5}$$

In order to credit expert opinion and experience and to obtain acceptance of decision makers, weights are applied to the criteria to reflect preferences. As described in section 2.2 this can either be done by choosing subjective weights or by using objective methods based on the given data. These preference weights w_{pref} are multiplied with the criteria scores to obtain weighted scores.

To account for the perceived influence of epistemic (knowledge based) uncertainty, confidence in the performance of each criterion w_{conf} is used as a further multiplicator in the weighting process. The weighted score $S_{i,weight}$ are obtained by multiplying the normalised scores with their respective weighting factors according to equation 7.

$$w_i = w_{pref} \times w_{conf} \tag{6}$$

$$S_{i,weight} = S_i \times w_i \tag{7}$$

It is possible to analyse the consistency of subjective weights which are applied by decision makers. If inconsistencies are identified, the respective weighting factors can be reduced. Likewise, if several independent stakeholders consistently apply high weights to certain criteria, their importance may be stressed by an additional weighting factor. More sophisticated analysis regarding the consistency of weighting factors is envisaged for the future.

Monte Carlo simulations are carried out to assess the sensitivity of input parameters to the chosen criteria. Even if certain criteria are believed to be important but do not have a concomitant impact on the final result, they can be classified as less important. This offers an objective method to reduce the complexity for decision makers to a certain extent. Instead of fixed values, it is also possible to assign distributions to the scores to reflect aleatory (data based) uncertainty. In doing so, uncertainty of the input values is transferred to the results which are presented in the form of statistical distributions. The described operations remain the same. In the future it is envisaged to use suitable OWA operators and Bayesian Belief models which provide algorithms for systematically incorporating uncertainty and dealing with updating and learning procedures.

3.3 Visualisation

One goal which is inexorably linked to sustainability evaluation is the communication of results. These have to be presented in a clear way to all stakeholders. There appears to be very little research in this field. In view of its importance, a way is proposed for visualising performance of impacts, including weighting and uncertainty. Performance scores are depicted in a spider diagram as demonstrated in figure 1.

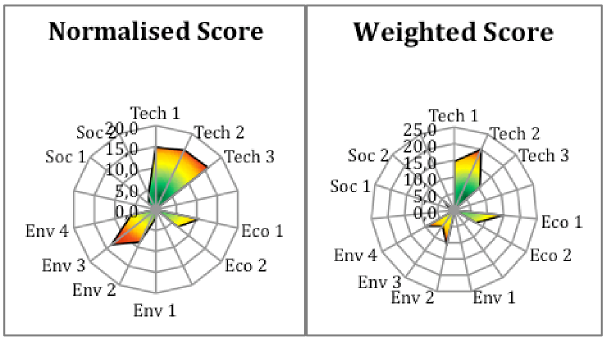

Figure 1: Normalised and weighted performance scores for each indicator

It can be observed that the scores may change significantly when weights are applied. This observation stresses the importance of choosing appropriate weighting factors, both for the confidence level as well as for the preference weights. The contribution of the life cycle stages to each indicator can be depicted through bar charts in order to identify hotspots as displayed in figure 2a. The area of the spider webs for each category provides an indication of the relative contribution of this set of criteria in each life cycle stage as depicted in figure 2b.

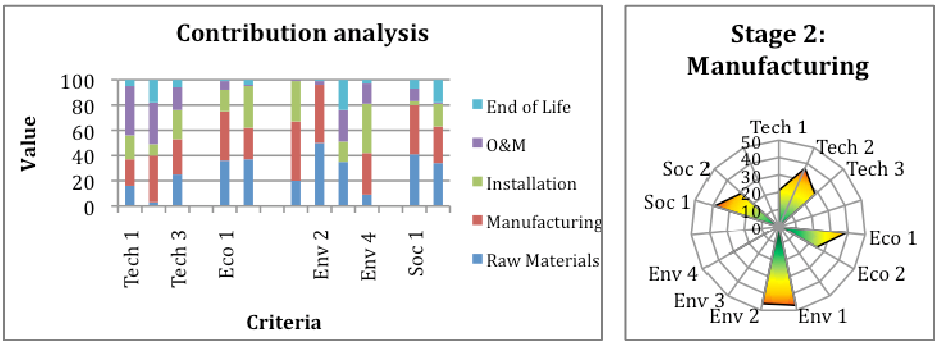

Figure 2: (a) Contribution analysis of performance in different life cycle stages
(b) Visualisation of weighted performance score for one life cycle stage

In this way it is possible to analyse the performance scores for each of the criteria in every category. This allows identification of hotspots and detailed comparison of alternatives. In case of probabilistic values, confidence bands can be displayed.

3.4 Application of MCDA

In order to demonstrate the feasibility of the current framework, the simplest MCDA method, the weighted sum method (WSM) is chosen to determine an overall score. The overall score per alternative is calculated as the sum of the scores for all criteria multiplied by their weighting factors. It is important that all alternatives are normalised to the same common scale for a meaningful comparison.

$$S_{total} = \sum_{i=1}^{n} (w_i \times S_i) \qquad (8)$$

The alternatives can be compared and ranked according to their total scores. Therefore, a clear picture can be obtained with regard to the whole life sustainability scoring of each option. Other MCDA methods could be applied within the current framework, such as outranking, MAUT or AHP, including fuzzy set approaches. Each method applies different principles for weighting, prioritising and scoring. According to the method it is possible to score, sort or rank the given alternatives. Application and comparison of the results allows more detailed and objective judgement of alternatives. Moreover, it is possible to aggregate the results from different methods as a means to obtain even more discerning analyses and results.

4. Conclusions and Recommendations

Approaches for rational decision support for sustainable management of industrial assets with multiple conflicting objectives have been reviewed in this paper. A multi-criteria framework for sustainable asset management including risk considerations has been developed whose basic concept and main features have been presented. The suggested framework incorporates sustainability criteria over the whole life cycle including preference weighting and uncertainty considerations. Additionally, results are visualised in order to facilitate communication among stakeholders. In the following some recommendations are provided.

It is most important that all chosen criteria address the overall goal for sustainable through-life management; hence a whole life cycle perspective should be aimed for wherever possible. Criteria have to be chosen to cover both multiple perspectives as well as and the complexity of interactions. Once a systematic choice of criteria is established, the weighting process has to be reconsidered. Sensitivity analyses can be carried out to determine the effect of varying input criteria. In this way criteria with maximum impact can be identified. Moreover, inconsistencies in subjective weights can be addressed by reducing their weights. As soon as the criteria choice and weighting mechanisms are refined, different MCDA methods will be applied. This allows to compare and contrast results and to identify optimal methods. Aggregation of different methods will be considered alongside.

As pointed out in the literature review, the inclusion of risk assessment and uncertainty considerations is believed to be important but has not yet been fully incorporated into sustainability assessment. Hence it is envisaged to create a stochastic model rather than a predictive one. Extensive sensitivity analysis using Monte Carlo simulations help to model and quantify uncertainty. Thus it can be distinguished between effects of the aleatory (data based) and the epistemic (knowledge based) type of uncertainty. Through explicit consideration of the latter one, limitations of predictive models can be shown and communicated to stakeholders. Increased confidence is obtained about the most likely range of results, expressed as confidence intervals. Together this can provide a much clearer appreciation of capabilities of the suggested model.

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