INTELLIGENT DECISION-MAKING FOR ENERGY AND ECONOMIC EFFICIENCY OF INNOVATIVE MANUFACTURING PROCESSES BASED ON MULTI-ATTRIBUTE KEY PERFORMANCE INDICATORS

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Abstract: *Production planning for the replacement of conventional manufacturing systems by new automated process chains is a complex activity particularly when it comes to choosing the right processes, materials and technologies. Nowadays those new process chains have to fulfil constraints such as low energy consumption and have to be resource-efficient and cost-efficient at the same time. The decision-making process can be a difficult task for authorities especially when the uncertainty of the input parameter has to be taken into account, such as prices for electricity, raw materials and lot sizes. This paper proposes a new decision-making model based on multidimensional key performance indicators (KPIs) that represent an economic and environmental objective as well as a performance objective.*

Keywords: MANUFACTURING, LEIGHTWEIGHT STRUCTURES, DECISION-MAKING, ENERGY-EFFICIENCY, COST-EFFICIENCY

1. Introduction

The Designing of hybrid lightweight structures are becoming increasingly more interesting in research and industry. New hybrid materials are developed, consisting of multiple materials like e.g. thermoplastic textile composite components made of plastic and glass fibre, for the realization of lightweight construction concepts and allow a significant weight reduction whilst still providing a high mechanical strength and functional density [1] and can lead to reduced operational costs. For example in the automobile sector the use of lightweight structures can lead to energy savings through weight reduction [2] and in return leads to less fuel consumption. Currently developments of those hybrid structures are limited to niche applications and require the need for innovative process chains, technologies, tools, and the use of hybrid materials.

For accomplishing the goal for the construction of hybrid structures, new machines and tools are used, whereby basic technologies are "merged" together to realize new innovative merged process chains. By using those merged process chains in existing manufacturing facilities, the complexity of the whole manufacturing process can be reduced as well as it allows a resource and economic efficient production and development. But the complexity in the planning phase of those new composite constructions leads to long development times, high financially expenditure and detailed expert knowledge.

In manufacturing chains with a wide variety of materials, machines, tools and production levels, evaluation and comparison of various alternative process chains only consider cost aspects [3] or allow only insight to the energy consumption of processes [4]. Rarely an overall evaluation of the ecological *and* economic factors is conducted.

Choosing from multiple alternatives e.g. the best technology, tool and material is a difficult task for decision-makers, manufacturing supervisors or production managers. Furthermore constraints like low energy consumption and resource efficiency are a basis for discussion in the present time and have to be observed taking account of a robust product. A multi-criteria decision-making (MCDM) support for economic and energy efficiency is essential and can help to drastically cut long development times and costs especially in the early phases of planning, especially when only a small amount of series of tests are carried out and therefore minimum data is available.

MCDM can be used to find the "best" alternative under all available options at the same time considering many, often conflicting criteria and making assumption to different constraints. This paper illustrates a simple but effective approach to multi-attribute decision-making of automated process chains for planning and development in the early phases of production.

2. Methodology of MCDM Design

The decision-making process can be divided into the following 5 steps as depicted in Fig. 1:

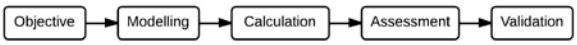

Fig. 1 *General procedure of the multi-criteria decision analysis.*

The first step includes discussion of the current state, formulating the problem to solve and listing comparable process chains or single processes, examining available information (this raises issues about the extent of parameters, which can be measured, approximated or are available) and describing the objective that raising the question: What are the constraints and which goals have to be reached for choosing the best process chain?

The next steps of this procedure model will be illustrated in the following sections.

2.1 Model

The decision matrix M describes the performance of the alternatives (as rows) with respect to selected criteria (as columns) and is defined as set $M = \{\mathbf{A}, \mathbf{C}, \mathbf{W}\}$, where $A_i, i = 1, \dots, n$, denotes the i^{th} process chain, $\mathbf{C} = (c_{ij}),\ j = 1, \dots, m$, the attribute matrix, where every column formally represents a criterion, and $w_j\ (j = 1, \dots, m)$ the corresponding weights:

$$\mathbf{C} = \begin{bmatrix} c_{11} & \cdots & c_{1j} & \cdots & c_{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ c_{i1} & \cdots & c_{ij} & \cdots & c_{im} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nj} & \cdots & c_{nm} \end{bmatrix}, \quad \text{with} \quad c_{\cdot j} \mapsto w_j \tag{1}$$

The attributes represent the model values against which the alternatives will be evaluated (cf. [5, p. 52]) and are partitioned in two levels with $M = 3$ upper level criteria, representing the three indicators $I\ (I = 1, .., M)$, which we will describe shortly, and overall $m = 12$ lower level criteria (see section 2.2). Let L_I be the set of the lower level criteria for the first indicator $(I = 1)$, namely the economic objective then $L_1 = \{1,2,3,4\}$; the environmental objective with $I = 2$ is formulated as $L_2 = \{5,6,7,8,9\}$, and the performance objective with $I = 3$ is represented by $L_3 = \{10,11,12\}$. The model values for the alternative A_i can then be formulated as vector $A_i = \{c_{i1}, c_{i2}, c_{i3}, c_{i4}, c_{i5}, c_{i6}, c_{i7}, c_{i8,} c_{i9}, c_{i10}, c_{i11}, c_{i12}\}$ with the corresponding weights $w_j = \{w_1, \dots, w_{12}\}$.

2.2 Model Values

The model values are based on three different multidimensional key performance indicators (KPIs) as already mentioned above, which represent an (i) **economic**, (ii) **environmental** and

(iii) **performance** objective. The term indicator and upper level criterion will be used as synonyms for KPI throughout the paper. The KPIs are calculated from real data of first series of tests or can be approximated. At the same moment they have the same function like constraints (see section 2.3). The criteria are arranged in two hierarchical levels with three upper level criteria (the KPIs) and overall 12 lower level criteria. An attribute is a property of an alternative to be evaluated. That means $I = 1$ has four lower level criteria, $I = 2$ has five sub-criteria, and three other lower level criteria belonging to upper level criterion $I = 3$. As mentioned before the attributes are evaluated against the alternatives, so that they are also called criteria, because of the one-to-one correspondence, concerning the evaluation of an alternative. Table 1 shows the KPIs with their related sub-attributes, the unit of measurement, and the direction in which they should be optimized.

Table 1: *The criteria represented by the three KPIs are displayed and subdivided into their related attributes which form the corresponding KPI. The unit of measurement is listed as well. The direction of the optimization for the decision-making is displayed in the last column for every attribute. Component is abbreviated with comp.*

KPI	Sub-attribute	Unit	Direction
Economic			
	Production Overhead	[€/Comp.]	Min
	Material Costs	[€/Comp.]	Min
	Personnel Costs	[€/Comp.]	Min
	Total Costs of Process Chain	[€/Comp.]	Min
Environmental			
	Energy Costs	[€/day]	Min
	Energy Costs	[€/month]	Min
	Energy Costs	[€/year]	Min
	CO2 Emissions	[CO2 of kg /year]	Min
	% of Renewable E.	[%]	Max
Performance			
	Production Volume	[Comp./day]	Max
		[Comp./month]	Max
		[Comp./year]	Max

Even though the KPIs are formed by different attributes with different unit of measurements the strength of MCDM is shown here, because it can handle the hybrid nature of the unit of measurements of various attributes. For example *material costs* is measured by euro per component, and *production volume* has the unit components per day. Also qualitative and quantitative attributes can be mixed.

Suppose we have two process chains, Q and C, of length n and m, respectively, where

$$Q = q_1, q_2, \dots, q_n, \tag{2}$$

$$P = p_1, p_2, \dots, p_m, \tag{3}$$

and q_i and p_i represent one process with their related machine, tool or material. The decision model is designed with its KPIs to compare different kind of process chains, no matter of what length they are or of which machines and tools they consist of. Each KPI is firstly calculated independently for every process in the chain before they get merged to one value as illustrated in (Fig. 2). That approach has the advantage that also numerous new features can be introduced into the model. Statistical values can be calculated (e.g. averages, standard deviations etc). For example this was done to introduce the attribute "total costs of the process chain" from the values *personnel*, *material*, and *production overhead costs* **(**Table 1**)**. As next their calculation will be briefly discussed in this section.

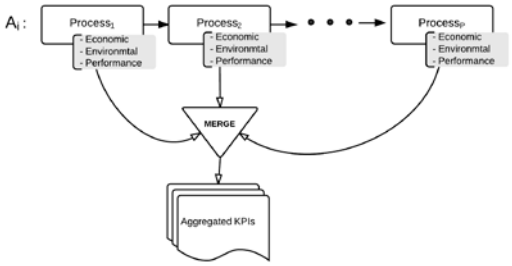

Fig. 2 *Illustration of the calculation for the three KPIs. Every sub-attribute is computed separately for every process before they get merged (accumulated) together to represent the sub-attributes which build up the hierarchical structure to represent the specific KPI for the whole process chain.*

At first, boundary conditions have to be made, because they are necessary for the calculation. They include the following factors: (i) number of work shifts, (ii) working hours per shift [h], (iii) working days per year [d], (iv) pay rate for personnel [€/h], (v) material costs [€/unit], and (vi) energy costs [€/kWh]

The **first indicator** and its sub-attributes are calculated through cost accounting like implemented in [3]. Important sub-attributes are *production overhead*, *personnel costs* and *material costs*, and the sum of all as value *process chain costs* **(**Table 1**).** All these values have the unit [€/component]. This has the advantage that the costs can be taken into causal consideration [3], this means that every cost attribute is calculated separately for every process in one process chain and are accumulated to form this KPI with its sub-attributes (Fig. 2). The values can be approximated or can come from accounting reports or other data sheets.

The **second indicator** represents information such as energy costs and environmental issues like the percentage of use of renewable energy sources. The values can be actually measured or can come from data sheets from machines or tools. In early stages of production planning only the energy consumption may be available so that for every process the energy costs could be calculated and then accumulated in the end for the whole process chain:

$$E = E_1 + E_2 + E_3 + \cdots + E_p. \tag{4}$$

Here E_1 formally represents the sub-attribute *energy costs* of the environmental objective (Table 1) for process$_1$ of the process chain A_i (Fig. 2). In the end every sub-attribute is accumulated for one process chain to get an overall value for the alternative. This is done for *energy costs* in all three unit of measurements (days/month/year).

The performance is measured through the **third indicator**. It is subdivided into *production volume* and is covered in three units of measurements (Table 1). The production volume per day can come from first test series or can be approximated if the cycle time for every process is available. The production volume per day, month and year can also be calculated roughly with the global assumptions. For every process the sub-attributes are calculated separately and accumulated in the end to get a value for the whole alternative.

2.3 Prioritizing the KPIs by Weighting

Weighting is an important and essential issue in this process because it reflects the preferences of a decision-maker and depends on different factors [6, 7]. For example production managers tend to rate technical and economic criterion and profitability higher than environmental issues like energy, fuel or gas consumption or the use of renewable energy sources, whereas operators of industrial robots might rate security at the working place and personnel loan higher than production volume. Through the different subjective perception of those authorities and operators the importance of those factors is different.

The preference (importance) of one attribute in comparison to another is modeled through weights. For each attribute $c_{.j}$ a weight w_j is assigned independently from one alternative as described earlier in section 2.1. The weights are standardized to 0 at the most un-

important and to 1 at the most preferred. Assigning weights to attributes is a way to prioritize the criteria that are considered the most important for decision makers or stakeholders. Let W_I the weight for the indicator I than for every low level criterion a weight w_j is assigned, so that they sum up to W_I:

$$\sum_{j \in L_I} w_j = W_I, \text{ with } 0 \leq W_I \leq 1, \sum_{I=1}^{M} W_I \leq \mathrm{M}. \quad (5)$$

The weights of all indicators can add up to 3 (see constraint in Eq. (5)) and each KPI must have a value in the interval [0,1]. The low level criteria $c_{\cdot j}, j \in L_I$ are dependent of the weight from their parent indicator I. The weights of each group of indicator I add up to W_I. The assignment of the weights is independent from the alternatives, however; they relate to the attributes in general and not to a specific value.

2.4 Assessment

To ensure that the calculated criteria are comparable the attribute matrix $\mathbf{C}$ is normalized between the interval [0,1] with the min-max-normalization rule [8]. Even if MCDM methods are suited dealing with large scales and the hybrid nature of attributes, works like [9] showed that normalization of all attributes may change the outcome and lead to a different assessment. If extreme values are present in the data set one attribute may get prioritized, but with scaling the assessment is not shifted towards possible outliers.

We use the value measurement approach to produce a preference order among all alternative (cf. [5, p. 85]). For that the utility (value) function $U(\cdot)$ is formulated and associated with an alternative in such a way that an alternative is represented as a value. If A_i is preferred over A_{i+1} then $U(A_i) > \mathrm{U}(A_{i+1})$, if both alternatives are indifferent then $U(A_i) = \mathrm{U}(A_{i+1})$. To calculate the utility (or use value) of an alternative A_i, **weighted additive aggregation** is used that takes the level hierarchy into account (cf. [5, 6, 9]):

$$U(A_i) = \sum_{I=1}^{M} W_I * \sum_{j \in L_I} w_j * c_{ij}. \quad (6)$$

Where:
$U -$ is the overall "score" (utility) for the alternative A_i,
$W_I -$ is the weight for the upper level criterion I (the I^{th} KPI),
$c_{ij} -$ is the normalized attribute j for the alternative A_i,
$w_j -$ is the weight corresponding to the attribute j in the attribute matrix C, and
$L_I -$ is the set of indices that represent all attributes for the indicator I.

We propose the new function $\hat{U}(\cdot)$ by using the basic utility function in Eq. (6) to turn the results in the positive direction, and extending the function with the parameter θ:

$$\hat{U}(A_i, \theta) = 2 * \mathrm{s}\left(1 - \frac{U(A_i)}{\theta}\right)^{-1}, \text{ with } s(x) = (1 + \exp(-a\,(x-b)))^{-1}. \quad (7)$$

The function allows an optimal representation of the results. The use values will not be negative when evaluating the performance of the alternatives: The higher the value the better the alternative performs compared to the others. The factor θ represents the "strength of effect" or "uncertainty" of the result and is a positive value ($\theta > 0$). The new utility function in Eq. (7) has the following property

$$\lim_{\theta \to \infty} \hat{U}(A_i, \theta) = 1, \text{ if } a = b = 1. \quad (8)$$

The parameter can be varied to well-mark the difference of the evaluated alternatives. The higher the value θ the smaller the gaps between the results and the more difficult the decision will be. If θ becomes extremely large then all alternatives will not be discriminable, because the output will be one. The decision-maker can use this knowledge if there is a high uncertainty in the future. The value can be set smaller if more series of test are conducted and set higher if only rough approximations are available or the values are expectations. An optimization of the parameter is a research base in another paper based on the current available information and the progress of the production planning.

With Eq. (7) the final assessment is then conducted with the maximum rule

$$\max_{i=1,\ldots,n} \hat{U}(A_i, \theta), \quad (9)$$

which states that the alternative process chain A_i with the highest utility value is chosen. It is important here to note that the alternative with the largest value will be selected as the "best" choice for the decision. That means that e.g. high production volumes will be favored as well as high production costs. If criteria like costs or energy consumption should be minimized it is necessary to mark those values in the attribute matrix $\mathbf{C}$ (see Eq. (1)) as negative ones (Table 1).[1]

3 Discussion

To get insight of the effects of the model the following analyses were conducted and afterwards discussed. This helps the decision-maker to understand how the model behaves in a changed environment. For the example three random artificial alternatives are generated with the following relationships:

a) $(C_1 \geq C_2) \wedge (C_2 > C_3)$

b) $(E_1 \leq E_2) \wedge (E_2 \ll E_3)$

c) $(P_1 < P_2) \wedge (P_3 \leftrightarrow 2\,P_2)$

The expressions of the cost (C), energy (E) and performance (P) among the alternatives can be interpreted as follows: a) The costs of A_1 are greater or equal than A_2, but nearly the same, where A_3 has the lowest costs for the production; b) Both A_1 and A_2 have much lower energy consumption than A_3, but A_1 consumes less energy than A_2; c) A_1 has the lowest production volume and A_3 produces twice as much than A_2. The relationships are intentionally simplified for a easier understanding of the results of the model.

3.1 Uni-Criterion Analysis

To begin the analysis of the model we ran a "uni-criterion" analysis to have an overview of the technical performance of each alternative for each criterion independently to measure the influence of the weights. This was done using Eq. (7), by steadily increasing the weight of the selected criterion $W_I (I = 1, .., M)$ by 0.1 beginning from 0 to 1 and settings the weights of all other KPIs to zero with W_K $(K \neq I)$. That is done for all three KPIs separately to prioritize each indicator once. The results are presented in Fig. 3.

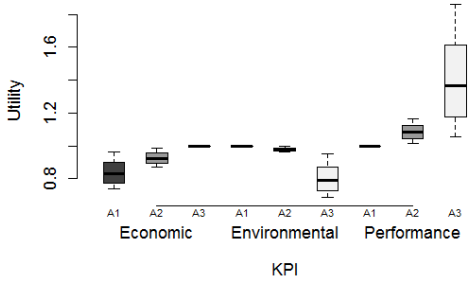

Fig. 3 *Representation of the variation of the outcomes if the importance of the KPIs is changing.*

If only the *economic objective* is considered then A_3 is always the best option. But an outlier from A_1 can be seen that performed nearly as well as the results around the median from A_3. That happened if low weights like 0.1 were used (that means no importance for that indicator). For the *environmental objective* one can say that A_1 and A_2 are the best options. Changing the weighting has no significant influence at the outcome for both (the variation in the data is small). Only for A_3 a high variation in the data can be seen. The

[1] Alternatively it is possible to use the *minimize* function in Eq. (9) instead so that only the attributes of the performance indicator has to be negative.

outliers from A_3 were created due to using a low weight like 0.1 which means that the KPI should be considered unimportant—through that fact a suboptimal alternative can perform as well as another in terms of a KPI if it is not considered important. If only the *performance indicator* is regarded then A_3 clearly is the best option between the other alternatives. Because A_1 and A_2 have the worst production volumes (see expression c) above) the weighting has not much influence on both. As explained before the same applies here: A low weight like 0.1 creates an outlier for A_3, which means that even the other two alternatives perform similar although A_3 has the highest production volume.

The results from the "uni-criterion" analysis were averaged for every alternative and depicted in Fig. 4.

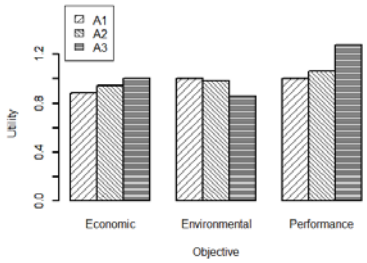

Fig. 4 *Average results in each group for every alternative if different weights are used in the "uni-criterion" analysis. Only one objective is considered at a time by setting the weights of the other objectives to zero.*

It can be seen that the model correctly interprets the relation between the three alternatives. Disadvantages from alternatives can be compensated through low weights and may also lead to false conclusions.

3.2 Considering the Strength of Effect

In next analysis a variation of the factor θ was introduced and analyzed, where a neutral weight distribution of one was used for every KPI. Fig. 5 shows therefore a visual comparison of various values. In this case θ is set to $\theta = \{0.1, 0.5, 1, 4\}$. It can be seen that the higher the value the greater the differences between the three alternatives are. In early stages of production it is useful to set this factor greater or equal one. This can be used as a risk factor to avoid false decisions. In the case for $\theta = 0.1$ the results of the three alternatives are very wide apart (Fig. 5, left plot). The more precise data is available and the more progress in the manufacturing planning is made the lower this factor can be set to be more certain with the decision. For $\theta = 4$ the outcomes are nearly the same (Fig. 5, right plot). It is up to the authority to determine the best value and will be discussed in further research.

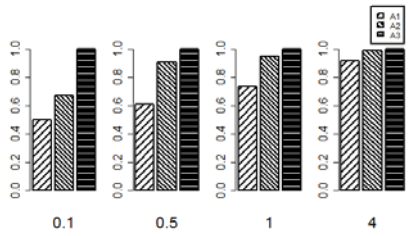

Fig. 5 *Variation of the factor* $\boldsymbol{\theta}$ *("strength of effect") to illustrate the influence on the decision.*

The evaluation of usefulness of an assessment depends on context and requires critical judgment of production manager and decision-makers. The assessment can only evaluate the current state of the environmental factors. Normally there is a high uncertainty in the future for factors like energy prices, new technologies, material or infrastructure, laws etc. that may heavily change the outcome.

4 Conclusions

In this paper a prototype of a new decision-making model is proposed that can be used in the early stages of planning and production for new manufacturing chains. For the assessment three base KPIs with a hierarchical attribute structure were determined to represent an economic, environmental and a performance objective. A modified additive weighting aggregation approach from the classical value measurement theory was used in combination with additional factors that can be parameterized to change to outcome which is not common yet in literature.

It can be updated if new information are available and can then be compared to the previous assessments to evaluate the improvement. Furthermore the global boundaries can be changed to create "scenarios" like increasing production volume or energy prices. Maybe an alternative is favorable if the global boundaries are different.

Further work is dedicated to the integration of more environmental factors (e.g. carbon-footprint) and extending the performance objective by adding methods from data envelopment analysis (DEA). Additionally the goal is to provide simulation capabilities in the model and adding support for conducting multiple decisions at the same time and aggregating the results in an appropriate form. Decision-making under uncertainty will be further considered in the model as well. It is proposed to add an error term ϵ to the model, where ϵ reflects the uncertainty of the future assumed independently and normally distributed with $\epsilon \sim N(0, \sigma_\epsilon^2)$.

5 Acknowledgements

This work was performed within the Federal Cluster of Excellence EXC 1075 "MERGE Technologies for Multifunctional Lightweight Structures" and supported by the German Research Foundation (DFG). Financial support is gratefully acknowledged.

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