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REDUNDANCY ELIMINATIONS AND PLAUSIBLE ASSUMPTIONS OF DESIGN PARAMETERS FOR EVALUATING DESIGN ALTERNATIVES

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ABSTRACT
Evaluation of design alternatives is an important task for engineering design and its results affect strongly the outcome of decision-making processes and the quality of the artifact being designed. In the present paper, a method is proposed based on representation of alternatives through associative weighted digraphs of design parameters and use of performance variables defined according to evaluation criteria. The method relies on designer-guided eliminations of redundancies of common design parameters among different alternatives and plausible assumptions about value domains of design parameters that take part in the evaluation process. Eliminations of redundancies of common design parameters lead to unified digraphs for all alternatives and the introduction of Plausible Assumptions' Matrix systematizes the process of assigning feasible value domains for all types of all design parameters. Linear approximate calculation formulas pertaining to the unified digraphs are also introduced for evaluating alternatives based on comparable values of performance variables. A case study for two alternatives for a stiffness element exemplifies the proposed approach.

Keywords: design alternatives, representation, evaluation, redundancy eliminations, plausible assumptions

1 INTRODUCTION
Evaluation of design alternatives is an important task that occurs almost in all phases of engineering design process and evaluation results affect strongly the outcome of decision-making processes and the quality of the artifact being designed [0].

During conceptual design, all functions that the artifact should be able to implement are hierarchically determined [2]. For each such function, different concepts are proposed by the design team that constitute different alternatives that should be evaluated via a proper, criteria-based method so that the one that outperforms all the rest is finally chosen. In configuration design, different architectures are created for the dominant concept and finally, during detailed design, the chosen configuration alternative is further elaborated so that, by the end of this phase, a final detailed and documented artifact description is produced.

There is a strong need for continuous evaluation of alternatives throughout the design process that should be done via systematic, reliable and - if possible - problem-independent methods. Apart from the classical textbooks that present the theoretical basis and provide examples and case studies, there are many published journal articles as well as conference papers that discuss various aspects of these methods. Ullman [1] cites several evaluation methods that refer to the conceptual design phase and distinguishes two main categories. In the first category the methods are absolute; every concept is compared with some set of designer-defined requirements. In the second category, relative comparisons are made among the concepts.

The most popular method for concept evaluation and comparison in engineering design is decision-matrix method [3] that performs tabular calculations of scores for the conceptsand locates the best alternative according to the highest score obtained. Morphological analysis [4] may be considered as an alternative to decision-matrix method; it investigates the total set of relationships contained in multi-dimensional, non-quantifiable, problem complexes [5], [6]. The Analytic Hierarchy Process (AHP) consists of multi-criteria decision-making approaches that may be used to reduce the number of design alternatives [7], [8] and may be also used in cases when design knowledge is characterized by uncertainty, imprecision and fuzziness [9].

Recently, various methods and techniques have been proposed, provoked by the latest advances in the field of computational intelligence. They have been applied in order to solve "hard" problems in the field of engineering design [10], [11]. Jiao and Tseng [12] introduce a fuzzy ranking methodology for concept evaluation within the framework of configuration design for mass customization and Wang [13] utilizes a fuzzy outranking model to determine the non-dominating design concepts. In mechatronics, Moulianitis et al. [14] have developed an evaluation model on the basis of fuzzy T-norms and averaging operators. Other soft computing techniques and methods such as Artificial Neural Networks and Genetic Algorithms have been also used either as stand-alone or as hybrid tools in the field of evaluation of different design alternatives [11].

The majority of the referenced methods and techniques use one or more attributes (characteristics) of the alternatives and examine them with respect to design specifications and targets originated from: a. customer requirements and/or design constraints that have been "translated" to engineering "syntax" and have been properly quantified and b. from new decisions made as design evolves.

The attributes of an alternative that are accessible by the designer(s) should act as reference entities for its evaluation. A study of the available evaluation methods leads to the conclusion that, during evaluation, there is not a systematic reference to the relations between these attributes and the internal, "non-visible", yet inherent in the alternative, data. This implies that the reasoning process regarding attribute values is more or less superficial and relies mostly on subjective/empirical estimations.

In order to overcome some of the aforementioned problems, a new method is presented for the evaluation of design alternatives. The method is suitable for cases where quantitative estimations of alternative's attributes are required in order to perform its evaluation with respect to a set of criteria. The method is based on designer-guided eliminations of redundancies of common design parameters among different alternatives and plausible assumptions about the value domains of all design parameters that take part in the evaluation process. Eliminations of redundancies of common design parameters diminish their number, lead to unified digraphs for all alternatives and eventually result to less computational effort. Additionally, the introduction of Plausible Assumptions' Matrix systematizes the process of assigning feasible value domains for all types of design parameters and facilitates alternatives' evaluation. Finally, linear approximate calculation formulas of design parameters pertaining to the unified digraphs are introduced as a basis for evaluating alternatives based on comparable values of performance variables.

In section 2, the concepts of redundancy eliminations and plausible assumptions are introduced, design parameters and performance variables are defined and formulas for determining the values of the latter are given. In section 3, a case study is implemented in order to point out the role of redundancy eliminations and plausible assumptions in the representation and evaluation of design alternatives. Finally, in section 4, conclusions are drawn and plans for future work are discussed.

2 REDUNDANCY ELIMINATIONS AND PLAUSIBLE ASSUMPTIONS

A design alternative is a unique formation of interconnected structural elements capable of performing one or more simple or composite functions. Usually, at different design phases and at different abstraction levels, more than one design alternatives are considered. All these alternatives are capable of performing the same function(s), while their differentiation lies on the formation of their structural elements (architecture), the physical principle(s) used for implementing the function(s) and the flows of energy, material and information.

Evaluation of alternatives is a logical process performed with respect to one or more criteria that represent requirements, constraints and specifications. Designers must evaluate the available alternatives and come up with a set of decisions for the most suitable one.

It seems reasonable to assume that there should be a generic mental mechanism activated during evaluation of alternatives that bases its decision-making capability on observations of similarities, commonalities and differentiations among the characteristics of alternatives being evaluated. If there are one or more common characteristics among different alternatives, then it should not be necessary to maintain multiple instances of them. Instead, every common characteristic may appear once and its redundant instances must be eliminated. This elimination will recompose and rearrange the design space and will representatively merge the different alternatives via these common characteristics. As it will be shown later, this transformation will lead: a. to a more efficient - in terms of computational cost - evaluation of the alternatives under consideration and b. to the formation of a common space for representing all design alternatives in a unified way. The process of eliminating all redundant instances of common characteristics among two or more alternatives will be called *redundancy elimination*.

Within the context of the present work, it is assumed that evaluation of alternatives is performed with respect to one or more criteria that can be quantified and get the form of one or more performance variables. The quantification of performance variables is strongly related to the quantification of design parameters (see below for term definitions). Performance variables are defined with respect to one or more design parameters and this dependency is valid also for their values. Under the assumption that it is always possible to calculate the value of a performance variable given the values of all design parameters it depends upon, the designer(s) should be always able to provide the latter. For some cases this may be a trivial task, in the sense that objective restrictions such as standardizations, constraints, etc. may determine strictly these domains. For most of the cases, however, and especially in the early design phases, the designers themselves should make plausible assumptions - within the context of the design problem under consideration - about the possible domains where one or more design parameters may acquire their values from. These value domain definitions are called *plausible value assumptions* (or simply *plausible assumptions*).

2.1 Redundancy Eliminations

At a certain level of abstractness, a design alternative is mapped to a set of design parameters (DPs) that form associative interrelationships which can be represented by directed graphs (digraphs). In these digraphs, nodes represent design parameters and edges between nodes represent the associative relationships (see Figure 1.a for an example).

Design specifications determine the criteria for evaluating design alternatives. According to Otto and Wood [2], design specifications come from requirements and constraints and are always expressed in terms of single values or value ranges accompanied by proper units (where this is applicable). Thus, an evaluation criterion refers always to a design specification and in order to evaluate an alternative according to this criterion, the latter should be somehow formally represented by an entity that: a. may be commonly defined for all alternatives participating in the evaluation process and b. may be mapped to one or more DPs of the alternative's digraph. In the context of the present approach, this entity is the Performance Variable (PV), uniquely defined and equally valid for all alternatives. The value of a PV is usually different for different alternatives because different DPs and - occasionally - different combinations of other PVs (or DPs) may be needed for its calculation. The value of a single PV or a set of PV values provide a quantitative indication about the fulfillment of an evaluation criterion by a certain alternative.

If A is a set of alternatives proposed for satisfying a set of design specifications, then, for alternative $a_i, a_i \in A$, a set P_i of design parameters together with set of relations H_i among its members will form digraph $G_i = \left(P_i, H_i\right)$. If Q is the set of performance variables used for evaluating the members of A and q_k is a member of Q, then set $G_i^k = \left(P_i^k, H_i^k\right)$ is a sub digraph of G_i. If another alternative a_j is considered, then another such set $G_j^k = \left(P_j^k, H_j^k\right)$ will be formed. The union of these two digraphs will form another graph where all common DPs between the two initial digraphs will appear only once. This is the case for the example shown in Figure 1, where the digraphs of two alternatives a_1 and a_2 (see Figure 1.a) for PV q_k are shown with $G_1^k = \left(\{p_1, p_2, p_3\}, \{(p_2, p_1), (p_3, p_1)\}\right)$ and $G_2^k = \left(\{p_4, p_5, p_6\}, \{(p_5, p_4), (p_6, p_4)\}\right)$

If p_3 is common with p_5 ($p_3 = p_5$), then a new composite digraph is formed by merging G_1^k and G_2^k (see Figure 1.b), given as

$$G_{12}^k = G_1^k \cup G_2^k = \left(\{p_1, p_2, p_3, p_4, p_6\}, \{(p_2, p_1), (p_3, p_1), (p_3, p_4), (p_6, p_4)\}\right)$$

1.a. Six (6) DPs

1.b. Five (5) DPs

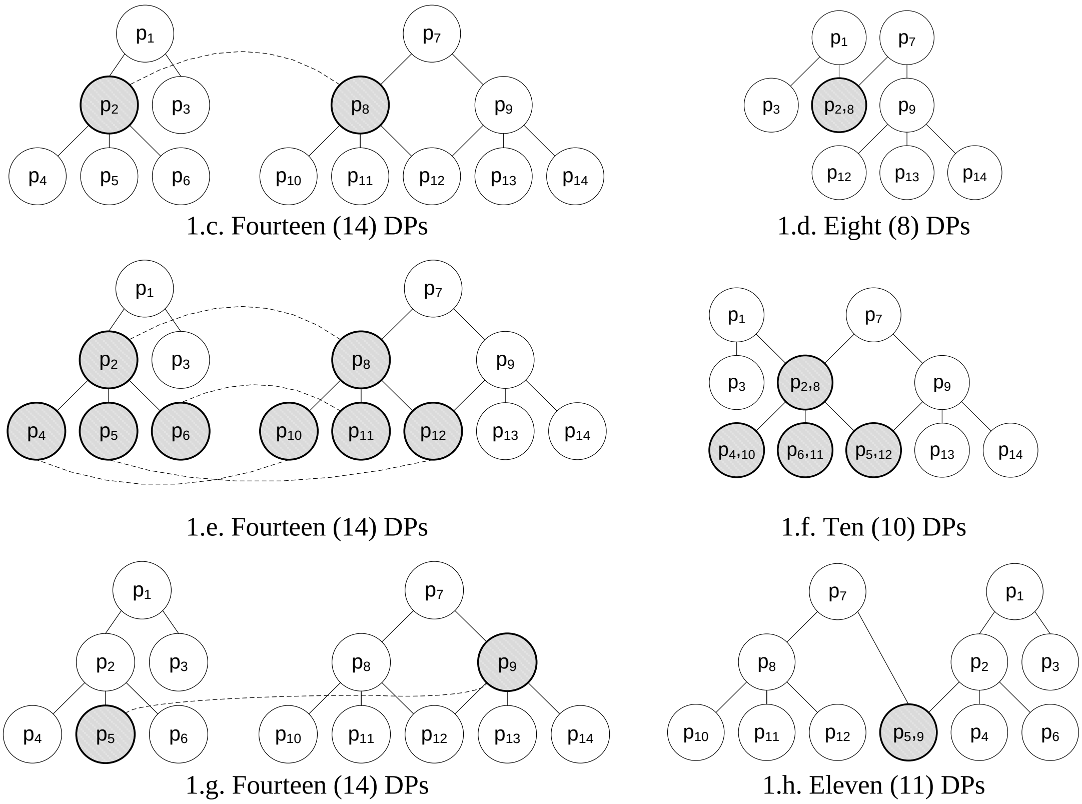


Figure 1. Different cases of redundancy eliminations of DPs and formation of composite digraphs.

Depending on the type of common DP, the following rules are valid when forming the unified digraph:

1. If it is independent, then its dependencies (edges) with its parent DPs in both digraphs will be preserved in the new digraph. This is the case of the example in Figure 1.b
2. If it is dependent, its sub digraphs in initial digraphs should be recursively examined for identity. If there is at least one differentiation in either a child DP or an associative relationship, then the DP will be still considered as common but it will be transformed to primary in the new digraph. Every child DP will be eliminated unless if it affects one or more other DPs in the digraph. This is shown in Figure 1.d where the original digraphs of Figure 1.c are shown merged. Comparison of Figures 1.c and 1.d shows the significant reduction of the total number of DPs
3. If DP is dependent and its sub digraphs are identical (see Figure 1.e), then all children DPs will be considered as common and will appear - each one of them - only once in the new digraph. This is the case in Figure 1.f
4. If it is independent in one digraph and dependent in the other, then the new digraph will be formed by transforming the dependent DP to independent (see Figures 1.g and 1.h above).

The above analysis may be easily extended to include cases where more than two alternatives are considered. For all participating alternatives and for a certain PV, a unified digraph will represent uniquely and cohesively the necessary information - in terms of DPs and associative relationships among DPs. This digraph may be considered also as an optimized representation scheme for the considered alternatives, because all redundancies regarding DPs and associative relationships among DPs will have been eliminated.

2.2 Representation and Calculation of Performance Variables

Each digraph depicts directed associative relationships and dependencies among the different DPs for each represented alternative. Dependencies have to do with intensity and increasing/decreasing effect that DPs exert on the values of other DPs and may be represented by analytical expressions and formulas. During initial design phases, the deduction of these dependencies may be quite complicated due to partial or even total absence of analytical knowledge and it might be necessary to add subjective estimations, based – among other – to empirical knowledge, about the dependency intensity and the increasing/decreasing effect. Additionally, it should be taken into account that, for the majority of the design problems, different types of DPs (real with continuous or discrete value ranges, linguistic, etc) will be concurrently involved in the same alternative.

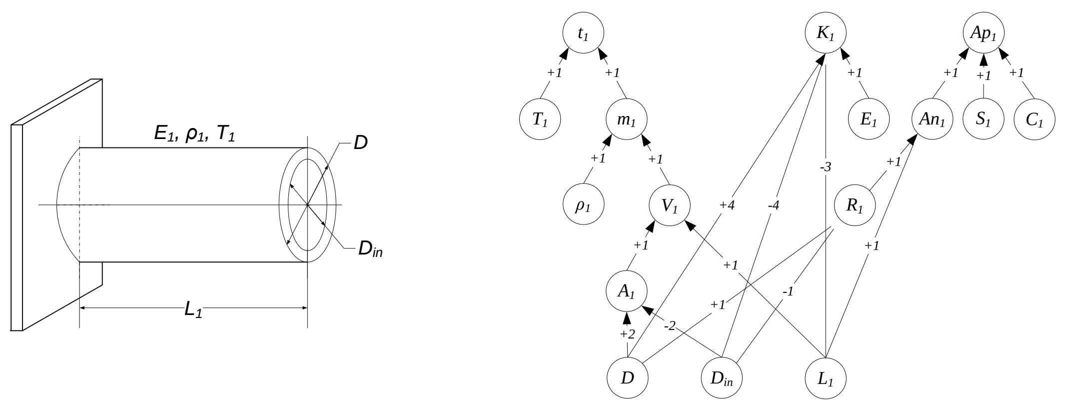
In order to resolve the aforementioned issues, the edges of digraphs defined in section 2.1 are weighted. These Associative Weighted Digraphs (AWDs) can now represent the intensity and increasing/decreasing effect that children DPs exert on their parental DPs [15]. In Figure 2, a structural embodiment (design alternative) for a stiffness element is shown (fig. 2.a) together with its AWD (fig. 2.b)

In order to compensate for the need of representing formally and within the same representation scheme different types of design knowledge, simple linear calculation formulas for approximating associatively the values of parental DPs are introduced. The process for structuring these formulas is generic (problem-independent) and could be based upon an AWD.

Each such formula is a simplified representation of the overall available knowledge for a DP and may be used for an approximate calculation of its value. In its turn, a PV may be either a single entity or composite. In the first case, the PV is defined with respect to a certain DP, while in the second it may be considered as a synthesis of one or more DPs and/or one or more other simple PVs. As a consequence, two cases of calculation of PV values may be distinguished. In the first case, the value of a simple PV may be determined recursively through an AWD-based formula as follows [15]:

$$q^k_{i.norm} \to p^k_i \cong \sum_{m=1}^{\left|P^k_i\right|} (\pm)\, {}^k w^i_m \, p^k_{m.norm}, k = 1, 2, ..., |Q| \tag{1}$$

where q^k_i is the value of q_k for *i*-alternative, $p^k_{i.norm}$ is the corresponding dimensionless DP that provides its value to q^k_i, $p^k_{m.norm}$ is the dimensionless normalized value of any other DP p^k_m that belongs to P^k_i and ${}^k w^i_m$ is the signed relative weight value for that DP. Since q^k_i always results from a certain DP, the value for ${}^k w^i_m$ is "relative" with respect to the rest of the weights of the edges that connect that DP with its children.



a. b.

Figure 2. An alternative for a structural element: a. Cantilever beam of circular hollow section, b. AWD of design parameters.

Regarding DP p^k_m, if it is real, then its domain may be either continuous and in that case:

$$p^k_{m.norm} = \frac{p^k_m - p^k_{m.\min}}{p^k_{m.\max} - p^k_{m.\min}}, p^k_{m.norm} \in [0,1] \tag{2}$$

with $\left[p^k_{m.\min}, p^k_{m.\max} \right]$ being the domain for p^k_m, or real discrete and its domain will be given as $\left\{ p^k_{1.norm}, p^k_{2.norm}, ..., p^k_{q.norm} \right\}$. In that case, it must be always ensured that the value of p^k_m is equal to one of the discrete values of its domain.

If p^k_m is linguistic, two distinct cases should be considered:

1. Suppose that p_m^{k} gets its values from list $\Lambda = \{\lambda_1, \lambda_2, ..., \lambda_n\}$ where $\lambda_i, i = 1, 2, ..., n$ are meaningful linguistic terms such as “soft”, “hard”, etc. It is assumed that these terms describe a gradation of the characteristic that p_m^{k} represents. Then these terms may be rearranged in either descending or ascending order thus reflecting the decreasing or increasing trend in this gradation. By mapping proper real - preferably integer - values to each linguistic list term, a new numerical list will be formed that should be also rearranged in order to reflect this trend. The list so formed could be subsequently used as a new domain for p_m^{k} and in that case the latter will be considered as real discrete
2. Suppose again p_m^{k} gets its values from list $\Lambda = \{\lambda_1, \lambda_2, ..., \lambda_n\}$ where $\lambda_i, i = 1, 2, ..., n$. Now the values in the list do not provide any additional information that could form a basis for common treatment and gradation forming for a characteristic of DP. This fact poses a serious problem because there is no objective way to map values to Λ. In this case, knowledge about how these values affect the PV under consideration should be available. Based on this knowledge, the designer may form scalable qualitative domains and then, as described in case 1 above, respective quantitative domains.

There are cases when two or more simple PVs and - occasionally - DPs may be combined in order to provide a composite PV. In that case, for the aggregation of contributing PVs and DPs, a proper method should be used. Non-weighted Euclidean norm seems to be suitable for this task. The components in the norm are the individual PVs that may be easily calculated through proper expressions formed according to expression (1). So, for a certain “composite” PV ${}^{c}q_i^{\mathrm{k}}$ (the left superscript signifies compositeness), its value will be given as:

$$\left\| {}^{c}q_i^{\mathrm{k}} \right\| = \left[\sum_{m=1}^{|Q|} \left(\frac{q_m^k - q_{m.\max/\min}^k}{q_{m.\max}^k - q_{m.\min}^k} \right)^2 \right]^{1/2} \tag{3}$$

where $q_{m.\max/\min}^k$ is a term that may exclusively get a value from the two-values set $\left\{ q_{m.\min}^k, q_{m.\max}^k \right\}$ depending on whether maximization or minimization of q_m^k is required. The dimensionless normalized value of ${}^{c}q_m^k$ will get its values within the domain $\left[0, \sqrt{n_c} \right]$, where n_c is the number of PVs used for its definition.

2.3 Plausible Assumptions and Plausible Assumptions Matrix

The formulas introduced in previous section may provide exploitable results only if feasible values are assigned to their DPs. Therefore, the designers should provide these values by making plausible assumptions for value domains, based on their experience and – perhaps - to the available specific design knowledge. These assignments are necessary for evaluating quantitatively the alternatives with respect to the design specifications under consideration. Values from those domains may be used in expressions 1 or 3 to calculate the dimensionless normalized values of the respective PV for each alternative. These domains are considered as valuable information that should be retained, classified, recalled and applied in the evaluation of future akin concepts.

As stated in section 2.2, design parameters may be either real or linguistic. Making plausible assumptions raises the question of systematic representation of the respective information. Such a representation is shown in matrix form in Table 1 below. The first column contains DPs’ names, while the rest six columns contain values for different attributes of the DPs. In this manner, a *plausible assumptions matrix* (PAM) is formed. In order to comprehend the way (PAM) is formed, consider, as an example, alternative a_1 and set $P_1^k = \left\{ p_1^k, p_2^k, p_3^k \right\}$ of DPs that are necessary for determining PV q_1^k.

The types of these three (3) DPs are real, linguistic with gradation and linguistic with no gradation respectively.

Parameter names are shown in column *Design Parameter* of Table 1. Their types, stated in column *Class of DP*, are *Quantitative* meaning real, *Qualitative gradated*, that is linguistic with gradation, and *Qualitative non-gradated* meaning linguistic with no gradation respectively.

For the first two types of DPs, mapping of value domains to continuous - or discrete real values domain is a trivial task. In case of a qualitative non-gradated DP, knowledge about how its set of values reflects the respective PV should be available and this knowledge could be obtained with respect to that PV. Since such DPs represent linguistic and non-gradated values (e.g. color, type of electric motor, etc), designers should substitute - if possible - the DP with one or more others equivalent DPs of the other two manageable types. If this is not possible, feasible values of that DP should be mapped to a scale of discrete real values by taking into account the intensity with which each mapped value affects the corresponding PV. Then the set of values is transformed to a *Qualitative gradated* one. Therefore, for reasons of traceability in the alternatives' evaluation process, this function is declared in the (PAM) through column *Performance*. For the other two types of DPs declaring the related performance is considered as excess.
The domains of the linguistic DPs are denoted in the column *Qualitative values* for both gradated and non-gradated values, whereas their transformation in sets of real values and the real values of the quantitative DPs are imported in column *Quantitative values*. Finally, the units and the constraints applied on the DPs are registered in the homonymous columns of the PAM.

Table 1. PAM – a systematic representation of plausible assumptions for DPs

Design Parameter	***Class of DP***	***Performance***	***Qualitative values***	***Quantitative values***	***Units***	***Constraints***
p_1^k	Quantitative	No	No	$\left[p_{1.\min}^{k}, p_{1.\max}^{k}\right]$	Yes	Yes
p_2^k	Qualitative gradated	No	$\left\{\lambda_1^k, \lambda_2^k, ..., \lambda_n^k\right\}$	[*1, 2,…,n*]	No	Yes
p_3^k	Qualitative non- gradated	Declared	$\left\{\lambda_1^k, \lambda_2^k, ..., \lambda_q^k\right\}$	[*1, 2,…,q*]	No	Yes

3. CASE STUDY

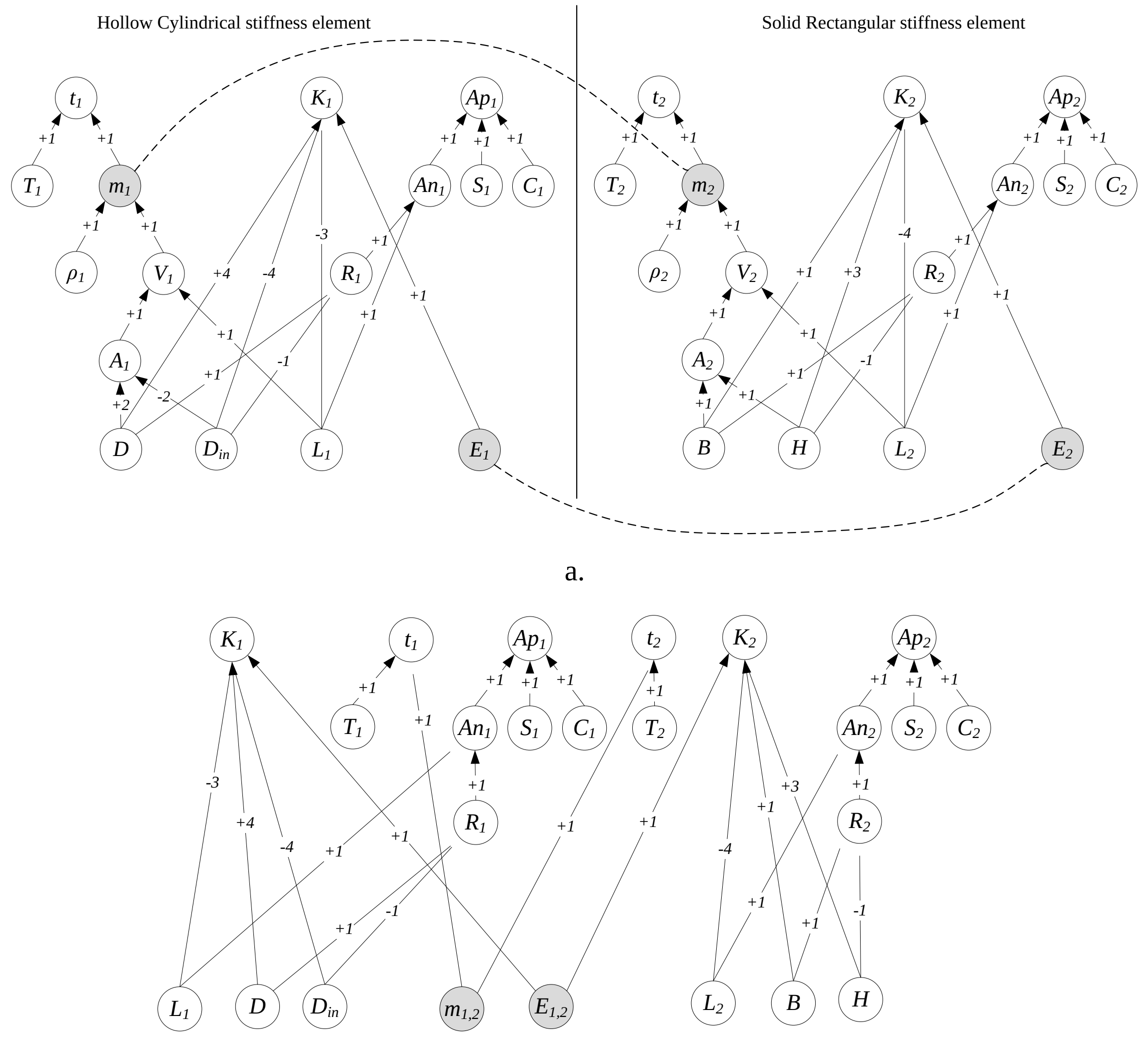
In the context of the current work, the concepts of redundancy eliminations and plausible assumptions are implemented for two alternatives of a stiffness element. The graphical representation and the AWD of the first alternative (hollow cylindrical cantilever beam) are shown in Figures 2.a and 2.b, whereas the AWD of parameters of the second one (solid rectangular cantilever beam) are shown in Figure 3.a. The graphical representation of the solid rectangular stiffness element is not represented for reasons of brevity.

3.1 Performance Variables and Redundancy Eliminations

For the current case, three (3) simple PVs are considered. The first simple PV is "cost", the second is "stiffness" and the third is "appearance". The DPs that correspond to these PVs are *t, k* and *Ap* and their corresponding AWDs are shown in Figure 3.a.
Two redundancy eliminations are valid for the current evaluation process; a. mass m_1 is common (equals) with m_2 and b. the modulus of elasticity E_1 is common (equals to) to E_2. In other words, alternatives have equal masses and are made of materials of equal Young moduli. As for the first redundancy elimination ($m_1=m_2$), the two DPs are common and dependent. The new DP $m_{1,2}$ is transformed to primary in the new digraph and the child DPs D, D_{in}, L_1, B, H and L_2 still exist to the new AWD because they affect other DPs (k_1, k_2, Ap_1, Ap_2) in the digraph (see Figure 3.b.). For the second redundancy elimination ($E_1=E_2$), the two DPs are common and independent, so the new and still independent DP $E_{1,2}$ is transferred to the new common AWD with all its dependencies (k_1, k_2) preserved. After performing redundancy eliminations, the total number of the DPs is reduced from thirty two (32) to twenty four (24) DPs. Moreover, the new common AWD forms a common representation space for both alternatives, where the two (2) common primary DPs playing central role.
The dimensionless values of the PVs may be calculated with the help of expressions (1) that are automatically produced from the common AWD via an exhaustive depth first search (see Figure 3.b). All expressions so deduced are shown in Table 2 below.

Table 2. Expressions for dimensionless values of PVs cost, stiffness and appearance

PVs	Dimensionless equations
t_1	$q_1^{\,1} = +1\nu(T_1) + 1\nu(m_{1,2})$
t_2	$q_1^{\,2} = +1\nu(T_2) + 1\nu(m_{1,2})$
k_1	$q_2^{\,1} = +1\nu(E_{1,2}) - 3\nu(L_1) + 4\nu(D) - 4\nu(D_{in})$
k_2	$q_2^{\,2} = +1\nu(E_{1,2}) - 4\nu(L_2) + 1\nu(B) + 3\nu(H)$
Ap_1	$q_3^{\,1} = +1\nu(L_1) + 1\nu(D) - 1\nu(D_{in}) + 1\nu(C_1) + 1\nu(S_1)$
Ap_2	$q_3^{\,2} = +1\nu(L_2) + 1\nu(B) - 1\nu(H) + 1\nu(C_2) + 1\nu(S_2)$



a.

b.

Figure 3. Redundancy eliminations and new common AWD: a. thirty two (32) DPs represented in two separate AWDs, b. twenty four (24) DPs represented in a common AWD

3.2 Plausible Assumptions

For the aforementioned equations to be useful during evaluation phase, value domains should be defined for the primary DPs. These domains are registered in the respective (PAM (see Table 3). Ten (10) DPs, namely T_1, T_2, $m_{1,2}$, $E_{1,2}$, L_1, L_2, D, D_{in}, B *and* H are classified as quantitative with certain value ranges. D_{in} is constrained in relation to D. Two (2) DPs, namely S_1 and S_2, are classified as qualitative gradated. As for the DPs C_1 and C_2 their value lists are {black, white, green} and {black, brown, green} respectively. Even if all list members are candidate values for the DPs, they cannot be directly interrelated meaningfully. Then the designer should arrange the values of these two (2) DPs according their effect on the PV under consideration. Let the values domains be {black, yellow, red} and {black, green, white} respectively. Then, by applying subjective/empirical knowledge, they can be transformed to the non-linguistic domains {1, 10, 5} and {1, 8, 3} respectively and, after rearrangement, to {1, 5, 10} and {1, 3, 8} (the original domains should be also rearranged as {black, red, yellow} and {black, white, green} respectively).

Table 3. PAM for primary DPs of the new common AWD for the two design alternatives

Design Parameter	***DP Class***	***Performance***	***Qualitative values***	***Quantitative values***	***Units***	***Constraints***
T_1	Quantitative	No		[0.70–0.98]	(€/kgr)	
T_2	Quantitative	No		[0.90–1.10]	(€/kgr)	
$m_{1,2}$	Quantitative	No		[8 - 14]	(kgr)	
$E_{1,2}$	Quantitative	No		[160 – 180]	(GPa)	
L_1	Quantitative	No		[1 – 2]	(m)	
L_2	Quantitative	No		[0.6 – 1.4]	(m)	
D	Quantitative	No		[0.01-0.05]	(m)	
D_{in}	Quantitative	No		[0.0099-0.0499]	(m)	$D_{in} \leq D-0.0001$
B	Quantitative	No		[0.008-0.04]	(m)	
H	Quantitative	No		[0.007-0.05]	(m)	
S_1	Qualitative gradated	No	{very rough, rough, normal, smooth, very smooth}	{1, 2, 3, 4, 5}		
S_2	Qualitative gradated	No	{very rough, rough, normal, smooth, very smooth}	{1, 2, 3, 4, 5}		
C_1	Qualitative non-gradated	Appearance	{black, red, yellow}	{1, 5, 10}		
C_2	Qualitative non-gradated	Appearance	{black, white, green}	{1, 3 , 8}		

Now the expressions of Table 3 may be used in order to proceed with the evaluation of the alternatives. This task is the subject of research being currently implemented. Genetic algorithms have been chosen as optimization tool and partial results, obtained so far, provide good prognosis for the success and efficiency of the proposed method.

4. CONCLUSIONS - FUTURE WORK

The analysis has shown that an alternative may be systematically and independently represented via hierarchical associative structures of DPs in the form of weighted digraphs, irrespectively of the chosen level of abstractness and the nature of the available design knowledge.

Two major contributions of the present work are the elimination of redundancies among common DPs and the systematic assignment of value domains for the remaining of them. The first task is guided by set of domain-independent simple rules that eliminate, preserve or change the positions of these common DPs and lead always to composite associative weight digraphs that represent optimally – in terms of participating DPs - in a unified manner the engaged alternatives. The task may have a systematic implementation in a computer environment.

The second task is devoted to assignment of value domains to DPs. All different DP types were examined in depth and it was concluded that it is always possible to map the two major value types (real, linguistic) to either continuous or discrete value domains which may be subsequently used by any optimization method. In order to systematize the task, the Matrix of Plausible Assumptions' was introduced.

The validity of the above two tasks was tested and confirmed in the considered case study (see previous section). The present study considers performance variables as key elements for the evaluation process. Thus, going a step further, the introduced extension of the method for evaluating the alternatives according to the values of simple or composite PVs via linear approximate formulas will provide comparable values - for each one of them – with respect to one or more evaluation criteria. Further work, whose first part has already commenced, includes, among others, the implementation of computations according to the aforementioned approximate linear formulas and the use of genetic algorithms for obtaining optimal values for the performance variables.

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