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HARMONIZATION MODELS FOR DESIGNING COMPOUND SYSTEMS

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Abstract: *A system to be designed and developed is composed of several sub-systems with complex configuration. The relationship between the sub-systems and the system cannot be fully expressed in analytical terms and has a high degree of uncertainty. Each sub-system can be designed and developed independently and is a subject of several possible measurable versions including both the cost of designing and creating the sub-system and its reliability. The problem is to assign reliability and cost requirements in the system design phase to all sub-systems, in order to:*

- *achieve a specified reliability goal for the system, and*
- *minimize the total costs of designing and creating of all the sub-systems.*

The corresponding dual problem is being solved as well. The third problem centers on optimizing the system's structure in order to maximize the system's utility by means of implementing local parametrical reliability and cost values.

Key words: *compound system; engineering design; cost-reliability optimization; harmonization model*

1. Introduction

The solution of engineering design problems generally requires a compromise between several objectives, including a trade-off among cost and reliability parameters. Those problems become extremely actual in cases when an overall compound system is composed of several sub-systems. The objective is to use the reliability model to assign reliability to the sub-systems so as to achieve a specified reliability goal for the system. The optimization model may be to minimize the total costs of developing the sub-systems subject to the condition that the reliability of the system must meet a certain pregiven level (the direct problem) or to maximize the reliability subject to certain cost constraints (the dual problem). However, it can be well-recognized that most of the publications on that area deal with relatively simple system configurations (e.g. for series and parallel systems) where the functional relationship between the sub-systems' failures and the top system failures is well known (see, e.g. [2, 4, 5][3]). In cases when this relationship is complex for other system configurations, e.g. when the linkage between the sub-systems is carried out under random disturbances, the number of such publications remains very scanty.

We will consider a complicated system to be designed which is composed of several sub-systems. The functional relationship between the sub-systems and the system outcome parameters can be formalized only by means of a simulation model which comprises a variety of random parameters. Sub-systems' failures are not independent, and the linkage between sub-systems is carried out via various information signals. Each sub-system can be designed and developed independently and is a subject of several alternative measurable versions, including the cost of designing and creating the sub-system and its reliability.

The problems to be considered are as follows: in the system design phase to assign optimal reliability and cost parameters (versions) to all sub-systems in order to minimize the total costs of designing and creating, subject to the specified reliability target for the system (the direct problem), and to optimize the sub-systems' reliability and cost parameters in order to maximize the system's reliability subject to the restricted total costs (the dual problem).

The solution of both problems is based on a two-level heuristic algorithm. At the upper level a search of optimal sub-systems' parameters is undertaken, while the lower level is faced with numerous realization of the simulation model to obtain representative statistics. The outcome data of the search procedure at the upper level is the input data for the simulation model.

The results obtained are later on considered within the general problem of the designed system standards harmonization. We formulate an optimization problem to assign optimal versions to all sub-systems in order to provide harmonization to the system reliability and cost standards.

2. Notation

Let us introduce the following terms:

S - the system to be designed and created;

$S_i \subset S$ - the i–th sub-system entering S, $1 \le i \le n$;

n - the number of sub-systems;

S_{ij} - the j–th version of designing sub-system S_i, $1 \le j \le m_i$;

m_i - the number of possible versions of designing and creating the sub-system S_i;

C_{ij} - the average cost of designing and developing S_{ij} (pregiven);

R_{ij} - reliability value of sub-system S_{ij} (pregiven);

SM - simulation model with input sub-systems' reliabilities and the outcome system reliability;

$R\{a_i\}$	-	system reliability value obtained by means of simulation, $R\{a_i\} = SM\{a_i\}$, where integer value $a_i = j$, $1 \le a_i \le m_i$, is the ordinal number of version j of sub-system S_{ij}, $1 \le i \le n$;
C	-	the total costs of designing and creating the system, $C = \sum_{i=1}^{n} C_{ia_i}$;
R^*	-	pregiven specified system reliability;
C^*	-	pregiven restricted total cost amount to design and create system S;
ΔC	-	accuracy estimate (pregiven);
α_R	-	parametrical utility "weight" of the system reliability;
α_C	-	parametrical utility "weight" of the system total costs.

3. The Problem's Formulation

The direct cost-optimization problem is as follows:

Determine the optimal set of integer values a_i, $1 \le i \le n$, which requires the minimal amount of costs

$$\underset{\{a_i\}}{Min} \sum_{i=1}^{n} C_{ia_i} \tag{1}$$

subject to

$$R\{a_i\} = SM\{a_i\} \ge R^*, \quad 1 \le i \le n, \quad 1 \le a_i \le m_i. \tag{2}$$

The dual problem is as follows:

Determine the optimal set $\{a_i\}$, $1 \le i \le n$, in order to maximize the system reliability by means of simulation

$$R = \underset{\{a_i\}}{Max}\, R\{a_i\} \tag{3}$$

subject to

$$\sum_{i=1}^{n} C_{ia_i} \le C^*. \tag{4}$$

Note that the costs of unifying sub-systems $\{S_i\}$ into a complex system S are assumed to be negligibly small in comparison with the total costs of designing and creating all those sub-systems.

It can be well-recognized that if the number of sub-systems n, as well as the number of alternative options m_i to design sub-systems S_i, is high enough, both problems (1-2) and (3-4) are NP-complete [3]. Thus, an optimal solution can be obtained only by means of a look-over algorithm that checks the feasibility of each of $\prod_{i=1}^{n} m_i$ combinations $\{a_i\}$. If the number of combinations is high enough and taking into account that each combination requires numerous simulation runs, solving both problems by means of precise classical methods meets unavoidable computational difficulties. To avoid this obstacle, we suggest a high-speed two-level approximate heuristic algorithm. At the bottom level a simulation model to realize the functional relationship between reliability values of local sub-systems S_i, is implemented. At the upper level a search procedure to determine optimal values $\{a_i\}$, has to be carried out.

Note, in conclusion, that for any sub-system S_i increasing its version number $a_i = j$ results in increasing both costs C_{ij} and the reliability value R_{ij}. Thus, the m_i–th version has the highest reliability R_{im_i}, as well as requires the highest costs C_{im_i}. If for *each* S_i its <u>highest version has been chosen</u>, it can be well-recognized that the overall system S has the highest possible reliability $R^{**} = SM\left\{a_{m_i}\right\}$, $1 \le i \le n$. Thus, if relation $R^{**} < R^*$ holds, problem (1-2) has no solution.

We will assume henceforth that both relations

$$R\left\{a_{m_i}\right\} = SM\left\{a_{m_i}\right\} \ge R^* \tag{5}$$

and

$$\sum_{i=1}^{n} C_{i1} \le C^* \tag{6}$$

hold.

4. Two-Level Heuristic Algorithm for Solving the Direct Cost-Optimization Problem

As outlined above, the system reliability $R = SM\{a_i\}$ is a complicated non-linear function of values $\{a_i\}$. This enables solution of problem (1-2) by using the cyclic coordinate search algorithm ($CCSA$) with optimized variables $\{a_i\}$ [6]. The justification of using $CCSA$ is outlined in [1]. To solve the problem, SM is implemented to obtain representative statistics for calculating $R = SM\{a_i\}$. The expanded step-by-step procedure of $CCSA$ is as follows:

<u>Step 1</u>. Choose an initial search point $\vec{X}^{(0)} = \{m_1, m_2, \ldots, m_n\}$. According to (5), search point $\vec{X}^{(0)}$ is a feasible solution.

<u>Step 2</u>. Start using $CCSA$ which minimizes value $\sum_{i=1}^{n} C_{ia_i}$ with respect to the coordinate variables. Decrease the first coordinate $x_1^{(0)} = m_1$ by a constant step equal 1, i.e., $x_1^{(0)} - 1 \Rightarrow x_1^{(1)}$, while all other coordinates $x_2 = m_2$, $x_3 = m_3$, ... , $x_n = m_n$ are fixed (see *Step 1*) and remain unchanged. In the course of under-

taking the search steps the feasibility of every routine search point $\vec{X}$ is examined by performing numerous simulation runs by means of the SM in order to check relation

$$SM\left\{\vec{X}\right\} \geq R^{*}. \tag{7}$$

The process of decreasing the first coordinate x_1 terminates in two cases:

- if for a certain value $x_1 = j \geq 1$ relation (7) ceases to hold;
- if for all values $1 \leq x_1 \leq m_1$ relation (7) remains true.

For the first case we set $x_1 = j+1$, while in the second case $x_1 = 1$ is fixed.

Step 3. After the first coordinate x_1 is optimized in the course of carrying out *Step 2*, we proceed with the $CCSA$ by decreasing the second coordinate x_2 by a constant step, i.e. $x_2^{(0)} - 1 \Rightarrow x_2^{(1)}$, while all other coordinates, namely, x_1 (the new optimized value at *Step 2*), $x_3, \ldots, x_n$ are fixed and remain unchanged. After examining the coordinate x_2 by a step-wise decrease via simulation, its newly obtained value is fixed, similarly to x_1, and we proceed with the third coordinate x_3, and so forth, until x_n is reached and checked by the constant step decreasing procedure.

Step 4. After all coordinates $\{x_i\}$ are checked by means of the $CCSA$ (first iteration), the process is then repeated starting with x_1 again. The $CCSA$ terminates after a current iteration does not succeed in bringing any changes to the search point $\vec{X} = (x_1, x_2, \ldots, x_n)$. Thus, the n-dimensional search point $\vec{X}$ is then taken as the quasi-optimal solution of the direct problem (1-2).

Call henceforth the above algorithm of $CCSA$ to solve the direct problem (1-2) - *Algorithm I*. Note that in the course of implementing *Algorithm I* the total costs $C = \sum_{i=1}^{n} C_{ia_i}$ decrease monotonously at each step $\vec{X} = \{a_i\}$.

After obtaining an approximate solution $\vec{X} = \{a_i\}$ we suggest to undertake a corrective random search procedure designated henceforth as *Algorithm II*. The enlarged step-by-step procedure of *Algorithm II* is as follows:

Step 1. Choose an initial search point $\vec{X}^{(0)} = \{a_i\}$ which has been determined in the course of implementing *Algorithm I*. Denote, in addition, the required total costs to design the system with $\{a_i\}$, by

$$C\left(\vec{X}^{(0)}\right) = \sum_{i=1}^{n} C_{ia_i} . \qquad (8)$$

Step 2. Simulate n random independent values p_i, $1 \le i \le n$, uniformly distributed in the interval $[-1, +1]$.

Step 3. Introduce a random step $\vec{X}^{(1)} = \vec{X}^{(0)} + \Delta\vec{X}$ obtained by

$$\vec{X}^{(1)} = \vec{X}^{(0)} + \vec{\beta}, \qquad \vec{\beta} = (\beta_1, \beta_2, \ldots, \beta_n), \qquad (9)$$

where local steps equal 1 and

$$\beta_i = \begin{cases} +1 & if \quad p_i \ge 0 \\ -1 & if \quad p_i < 0 \end{cases},$$

subject to additional constraints for the i–th coordinate $\vec{X}_i^{(1)}$, $1 \le i \le n$,

$$\vec{X}_i^{(1)} = \begin{cases} m_i & if \quad X_i^{(0)} = m_i \quad and \quad p_i \ge 0 \\ 1 & if \quad X_i^{(0)} = 1 \quad and \quad p_i < 0. \end{cases} \qquad (10)$$

Step 4. Calculate by means of the SM the frequency rate $R\left\{\vec{X}^{(1)}\right\}$ and compare the latter with R^*. If $R\left\{\vec{X}^{(1)}\right\} \ge R^*$ apply the next step. Otherwise go to *Step 6*.

Step 5. Calculate the total costs to design the system with $\vec{X}^{(1)} = \{a_i + \beta_i\}$. If relation

$$C\left(\vec{X}^{(1)}\right) = \sum_{i=1}^{n} C_{i,a_i+\beta_i} < \sum_{i=1}^{n} C_{ia_i} = C\left(\vec{X}^{(0)}\right) \qquad (11)$$

holds, go to *Step 7*. Otherwise apply the next step.

Step 6. Set $C\left(\vec{X}^{(1)}\right)$ equal to K, where K is a very large number (take, e.g. $K = 10^{17}$). Go to the next step.

Step 7. Repeat *Steps* 2-6 Z times, i.e., undertake Z independent steps

$$\vec{X}^{(0)} + \Delta\vec{X} \Rightarrow \vec{X}^{(1)}.$$

Step 8. Determine the minimal cost value $C\left(\vec{X}^{(1)}\right)$ from Z values (11). Denote it by $C^{*(1)}$.

Step 9. If $C^{*(1)} \geq C\left(\vec{X}^{(0)}\right)$ the search process terminates. That means that search point $\vec{X}^{(0)}$ cannot be improved. Go to *Step 11*. In case $C^{*(1)} < C\left(\vec{X}^{(0)}\right)$ apply the next step.

Step 10. Set $\vec{X}^{(1)} \Rightarrow \vec{X}^{(0)}$, $C^{*(1)} \Rightarrow C\left(\vec{X}^{(0)}\right)$, and go to *Step 2*.

Step 11. Take $\vec{X}^{(0)}$, together with its corresponding budget value $C\left(\vec{X}^{(0)}\right)$, as the quasi-optimal solution of *Algorithm II*.

Note that since using a search step of pregiven length in the n-dimensional space with a finite number of feasible solutions cannot result in an infinite monotonic convergence, the random search process always terminates.

As outlined above, we suggest to use *Algorithm II* on condition that the initial search point $\vec{X}^{(0)}$ is determined by using *Algorithm I*.

5. The Dual Cost-Optimization Problem

The step-by-step algorithm to solve problem (3-4) (call it henceforth *Algorithm III*) is based on the bisection method [8] and runs as follows:

Step 1. Calculate reliability values by means of the SM

$$R_{min} = SM\{1, 1, \dots, 1\}, \tag{12}$$

$$R_{max} = SM\{m_1, m_2, \dots, m_n\}. \tag{13}$$

Step 2. Calculate cost values

$$C_{min} = \sum_{i=1}^{n} C_{i1}, \tag{14}$$

$$C_{max} = \sum_{i=1}^{n} C_{im_i} \ . \tag{15}$$

Note that relation $C_{min} \le C^*$ holds, otherwise problem (3-4) has no solution. In case $C^* \ge C_{max}$ there is a trivial solution: $\{a_i\} = \{m_i\}$. Thus, we will assume that a reasonable relation

$$C_{min} \le C^* \le C_{max} \tag{16}$$

holds.

Step 3. Calculate

$$R' = 0.5 \cdot \left(R_{min} + R_{max} \right). \tag{17}$$

Step 4. Solve direct cost-optimization problem (1-2) with $R' = R^*$. Denote the minimal cost objective value obtained in the course of implementing *Algorithms I-II*, by C'.

Step 5. Compare values C' and C^*. If $\left| C^* - C' \right| < \Delta C$, go to *Step 9*. Otherwise go to *Step 6*. Here $\Delta C > 0$ designates the pregiven problem's solution accuracy as outlined in *Section 2*.

Step 6. Examine relation $C_{min} \le C' < C^*$. In case it holds, go to *Step 7*. Otherwise, i.e., in case $C^* \le C' \le C_{max}$, go to *Step 8*.

Step 7. Set $R' \Rightarrow R_{min}$. Go to *Step 3*.

Step 8. Set $R' \Rightarrow R_{max}$. Go to *Step 3*.

Step 9. Solution $\{a_i\}$ of the direct problem (1-2) obtained at *Step 4*, is taken as the quasi-optimal solution of problem (3-4).

6. Harmonization Models in Designing Compound Engineering Systems

As outlined above, in *Section 1*, engineering design problems generally require a compromise between certain parameters of the system to be designed, e.g. a compromise between cost and quality parameters. If a system to be designed and created is compound in nature and consists of several local sub-systems with complex configuration, such a compromise may be realized by means of certain optimization problems. Let us describe two different situations which lead to a "compromise optimization":

Strategy A

A company is faced with designing and creating a new complicated technical system which consists of several sub-systems. The latter have to be designed and further on created at the company's design office. Each sub-system may be created in several technical versions, as outlined above. The problem is to determine optimal versions for each sub-system to be designed, in order to:

- meet the system reliability restriction from below;
- meet the system total cost restriction from above;
- optimize a trade-off function between reliability and cost parameters.

Both restrictions can be formalized by relations (2) and (4).

Strategy B

A highly complicated compound technical system has to be created (e.g. a new aircraft). The system comprises several sub-systems (with complex configuration) which are *already manufactured* by several different companies (and, quite possible, in different countries). Each company manufactures only one version of a certain sub-system while other companies may produce other versions. Thus, each sub-system is available in several alternative versions provided to the international market with pregiven cost and reliability parameters. The compromise optimization problem is similar to that outlined above for *Strategy A*.

It can be well-recognized, however, that both from the point of logical assumptions and considering the solution method, those optimization problems are different. *Strategy A* is based on the assumption that for each sub-system S_i reducing the costs C_{ij} results in reducing its reliability level R_{ij}, and vice versa. This simplifies essentially the solution method.

However, for *Strategy B* the relation between cost and reliability parameters for different competing versions may be entirely different, since certain sub-systems may be produced and purchased in different countries and thus affected by their domestic policies in business and standardization.

A detailed description of different strategies (there may be more than two of them), together with developing optimization problems and the corresponding methods of solution, do not lie within the framework of this *Appendix*. However, we will show the nature of the "compromise optimization" by an example of *Strategy A*.

We suggest to formalize the "compromise optimization" problem as follows:

Determine optimal integer values (versions) a_i to maximize a "system priority value" which is composed of local priority functions $\alpha_R(R)$ and $\alpha_C(C)$

$$\underset{\{a_i\}}{Max}\left(\alpha_R\left[R\{a_i\}\right]+\alpha_C\left[C\{a_i\}\right]\right) \tag{18}$$

subject to (2) and (4).

It goes without saying that decreasing the total cost C increases the corresponding priority function $\alpha_C(C)$, while decreasing reliability value R decreases value $\alpha_R(R)$.

Thus, we suggest to introduce the concept of harmonization by means of a compromise, trade-off optimization. Finally, we obtain:

$$\underset{\{a_i\}}{Max}\left(\alpha_R\left[R\{a_i\}\right]+\alpha_C\left[C\{a_i\}\right]\right) \tag{19}$$

subject to

$$R\{a_i\} \geq R^*, \tag{20}$$

$$C\{a_i\} \leq C^*. \tag{21}$$

This is a complicated stochastic optimization problem since value $R\{a_i\}$ is calculated through a simulation model and can be determined in frequency terms only. As to functions α_R and α_C, we suggest to assume they are deterministic.

7. Monte-Carlo Algorithm for the Harmonization Model

The enlarged step-wise procedure of the suggested problem's solution is as follows:

Step 1. Solve cost-optimization problem (1-2) by means of *Algorithms I-II*. Denote the quasi-optimal solution as $a_1^*, a_2^*, \dots, a_n^*$.

Step 2. Solve cost-optimization problem (3-4) by means of *Algorithm III*. Denote the quasi-optimal solution by $a_1^{**}, a_2^{**}, \dots, a_n^{**}$.

Step 3. Calculate $C' = \sum_{i=1}^{n} C_{ia_i^{**}}$.

Step 4. If relation $C' > C^*$ holds, problem (19-21) has no solution. Otherwise apply the next step.

Step 5. Determine three n-dimensional areas:

- area *I* which comprises n-dimensional points $\vec{X} = \{a_i\}$ between $\vec{X}^{(1)} = \{1, 1, \dots, 1\}$ and $\vec{X}^{(2)} = \{a_i^*\}$;

- area *II* which comprises n-dimensional points $\vec{X} = \{a_i\}$ between $\vec{X}^{(2)} = \{a_i^*\}$ and $\{a_i^{**}\} = \vec{X}^{(3)}$;

- area *III* which comprises n-dimensional points $\vec{X} = \{a_i\}$ between $\vec{X}^{(3)} = \{a_i^{**}\}$ and $\{a_{m_i}\} = \vec{X}^{(4)}$.

Step 6. Note that solution $\{a_i^*\}$ of problem (1-2), as well as solution $\{a_i^{**}\}$, are approximate ones. However, it can be well-recognized that:

- an overwhelming majority of n-dimensional points $\vec{X}$ entering area *I* does not meet reliability level R^*;
-
- an overwhelming majority of n-dimensional points $\vec{X}$ entering area *III* does not meet total cost restriction C^*.

Both assertions can be easily checked by simulating points $\vec{X}$ by means of the Monte-Carlo method in areas *I* and *III* with coordinates $X_i^{(1)}$ and $X_i^{(3)}$ as follows:

$$X_i^{(1)} = \left[a_i^* \cdot \beta_i \right] + 1, \quad 1 \le i \le n, \quad \beta_i \in U(0,1),$$

$$X_i^{(3)} = \left[a_i^{**} + \left(m_i - a_i^{**} \right) \cdot \alpha_i \right] + 1, \quad 1 \le i \le n, \quad \alpha_i \in U(0,1),$$

where $[x]$ denotes the whole part of x and α_i, β_i are random values uniformly distributed in $[0,1]$.

Later on, by means of the SM, the outlined above assertions can be easily verified. Practically speaking, points $\vec{X}$ in areas *I* and *III* do not meet restrictions (20) and (21).

Step 7. A Monte-Carlo sub-algorithm (call it henceforth *Algorithm IV*) is suggested to solve problem (19-21) for area *II*. The sub-steps of *Algorithm IV* are as follows:

Step 7.1. Simulate by means of the Monte-Carlo method points $\overrightarrow{X}$ in area *II* with co-ordinates $X_i^{(2)}$,

$$X_i^{(2)} = \left[\left(a_i^{**} - a_i^{*} \right) \cdot \beta_i + a_i^{*} \right] + 1, \quad 1 \le i \le n, \quad \beta_i \in U\left(0,1\right).$$

Step 7.2. Check by means of SM and $C' = \sum_{i=1}^{n} C_{ia_i^*}$ restrictions (20-21). If at least one restriction does not hold apply *sub-Step 7.1* . Otherwise go to the next sub-step.

Step 7.3. Calculate for point $X_i^{(2)}$, by means of the SM and $C = \sum_{i=1}^{n} C_{ia_i}$, system priority value $\alpha_R \left(SM \left\{ a_{ia_i} \right\} \right) + \alpha_C \left(\sum_{i=1}^{n} C_{ia_i} \right)$.

Step 7.4. Undertake a random search outlined in *Algorithm II*, by substituting maximization for minimization. Take the local optimum obtained in the course of the random search, as a local solution.

Step 7.5. Check the number of local solutions generated in the course of implementing the optimum trial random search method. If the number of such solutions exceeds N, go to the next sub-step. Otherwise apply *Step 7.1* .

Step 7.6. Choose the maximum of local solutions obtained at *Steps 7.1-7.5*. The result should be taken as the approximate solution of the trade-off problem (19-21).

Note that the above global random search method is highly recommended in [7] and can be considered as an effective one for solving harmonization problems of type (19-21).

As for harmonization problems related to *Strategy B*, using the global random search method is less effective. This is because optimization methods for *Strategy B* may deal with a lot of isolated n-dimensional points in both areas *I* and *II* (see *Algorithm IV*). It normally causes much computational troubles to detect those points.

8. Conclusions and Future Research

1. The problem of multi-parametrical optimization, i.e., harmonization models, can be applied to design an optimal structure for compound engineering systems. Practical achievements in that area are outlined in [1].

2. For single network projects harmonization may be effective by analyzing a PERT-COST type project with random activity durations. The project comprises several essential parameters which practically define the quality of the project as a whole:
   - the budget assigned to the project (*C*);
   - the project's due date (*D*);
   - the project's reliability, i.e., the probability of meeting the project's due date on time (*R*).

   To establish the utility of the project, the concept of the project's utility may be introduced. In order to maximize the project's utility, a three-parametric harmonization model is developed [1]. The model results in a certain trade-off between essential project's parameters and is, thus, a compromise optimization model. The model's algorithm is a unification of a cyclic coordinate search algorithm in the two-dimensional area (cost- and time values) and a harmonization model to maximize the project's reliability subject to the preset budget and due date values. The model comprises a heuristic procedure to reassign the budget among project's activities, and a simulation model of the project's realization.

3. Harmonization approaches in Reliability and Safety Engineering can be successfully used to develop various cost – reliability optimization models. The latter are applicable to a broad spectrum of hierarchical technical systems with a possibility of hazardous failure at the top level and a pregiven multi-linkage of failure elements at different levels.

4. The newly developed harmonization models in Reliability and Safety Engineering cannot be compared with any similar research outlined in former publications in the regarded area. The existing references do not cover multi-parametrical optimization for hierarchical production plants with the possibility of hazardous failures at the top level.

5. The results of our research can be expanded in future for a broad spectrum of other parameters - attributes which actually form both the utility and marketability values of the newly developed product. Besides the area of product marketing, harmonization models can be applied as well to unique technical devices which function under random disturbances and may trigger hazardous failures. Thus, the developed models can be applied to various hierarchical organization systems, e.g. industrial systems, project management systems, creating new urban areas, developing various service systems, etc.

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