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HIERARCHICAL SYSTEM CONCEPT GENERATION

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ABSTRACT
The most important stage in a product life cycle is the conceptual design which involves uncertainty but also opportunity. The SOS (Subjective Objective System) method of generating product design alternatives [1] is expanded here to introduce more information to help reduce uncertainty and explore design solutions to better suite customer requirements, market conditions, and the use of current technology. Hierarchical SOS uses two levels of building blocks: the 1st level contains major building blocks (the same as in regular SOS) and the 2nd level contains slightly more detailed articulations of the building blocks of the 1st level. The product requirements are cascaded to the 2nd level and are translated to secondary targets. The search of the best product design alternatives is done by a genetic algorithm (GA). As expected, the new information introduced and manipulated at the 2nd level turns out to be critical for creating good conceptual designs of systems.

Keywords: conceptual design, subjective objective design, target cascading, genetic algorithm, NSGA-II.

1 INTRODUCTION
The conceptual design stage is crucial since it is the most influential on the success or failure of a product to achieve its target goals. However, information used in this stage is quite uncertain and the space of possibilities is large and could be expanded further. Therefore, it is difficult to develop a systematic approach to generate good design concepts. The classic method of using morphological chart to record the options, and heuristically coming up with solutions is very limited.

There have been different approaches to address this or similar problems, mainly configuration tasks where the concept is known and different options need to be selected for each concept part, such as computer assembly, choosing actuator type and dimensions, or finding a flat [2-5]. Tools suitable for configuration problems are very common on the internet [6-7]. Several studies addressed the issue of evaluating a configuration or a concept [8-10].

Target Cascading [11] and Hierarchical Overlapping Coordination (HOC) [12] are methods for solving a general optimal design problem at the configuration phase. The methods decompose the main targets to several smaller optimization problems in several hierarchical levels. The coordination between the low-level optimization problems is done by means of connecting variables. The coordination between the lower level optimization problems to the upper level optimization problems is done by global variables, results and responses.

Hierarchical Morphological Multicriteria Design (HMMD) [13] is a method suitable for several optimization problem classes: selection of representatives, selection of representatives with compatibility, and re-configuration, to name some. The HMMD iteratively solves the optimization problem taking into account (as inputs) the compatibility between sub-systems Design Alternatives (DAs) and the suitability of each DA for several design criteria on an ordinal scale. HMMD is suitable for finding an optimal configuration but less for concept design due to the vague description of sub-systems and their interconnections.

Two methods [14-15] for automated generation of design concepts for a system’s functional model that were later combined [16] to allow designers generate interactively feasible solutions were also developed. Another interactive hierarchical method for optimizing a design concept incorporating designer's preferences of concepts or sub-concepts is given in [17] and a similar method that considers uncertainties of delayed decisions regarding sub-concept selection, yields a set of robust concepts [18]. An approach involving the use of a genetic algorithm for the optimization of design configuration is described in [19] and a method for optimizing system reliability that could be generalized for design concept optimization is given in [20].

SOS [1] is a method developed to address directly the concept generation stage. The problem solved by SOS is choosing a set of building blocks to produce the best concept to meet customer requirements and manufacturer preferences. SOS can produce results as well as the estimation of the interactions between building blocks, the mutual constraints among them, and the contribution of building blocks to achieving the product requirements.

In order to reduce uncertainty, we expand SOS to introduce additional knowledge to the conceptual design stage via 2nd level building blocks. We also cascade the product requirements to a more refined 2nd level. This additional level increases the resolution of the problem definition and the information used for making design decisions. The extended method presented in this paper is called Hierarchical SOS (HSOS). Since the space of design alternatives grows tremendously, the search for the optimal conceptual design in HSOS is performed by a genetic algorithm. In the solution process, Pareto-optimal product concepts are found including hints to improve sub-optimal design alternatives.

The outline of this article is as follows. Section 2 discusses the hierarchical SOS method followed by an example in section 3. We conclude with main conclusions and further research recommendations.

2 HIERARCHICAL SOS

2.1 A brief overview of SOS

SOS addresses the need for concept generation tool. With little uncertain information, designers face difficulty to combine numerous product building blocks (such as, components, parameters, or technologies) to address conflicting requirements. There are constraints between candidate building blocks that are expected to be known to the product designer, based on her experience and knowledge. In SOS, all such constraints are modeled as linear inequalities, e.g.,

- Mutual exclusiveness: if three components compete to be incorporated in a product concept, the linear constraint $D_1+D_2+D_3=1$, $D_j=0,1$, $j=1,2,3$ makes sure that only one building block will be selected for the design concept.
- Functional necessity: component D_1 must be selected if component D_2 is selected, we get $D_1-D_2\geq 0$. If $D_2=1$ is (selected) then $D_1=1$ to satisfy the equation and therefore is also selected. If $D_2=0$ (not selected) D_1 can assume any value.

The contribution of building blocks toward satisfying product requirements or targets is modeled as *decision layers*. Let us consider the decision layer described in [1]. For each target, the information arrangement is as described in **Error! Reference source not found.**.

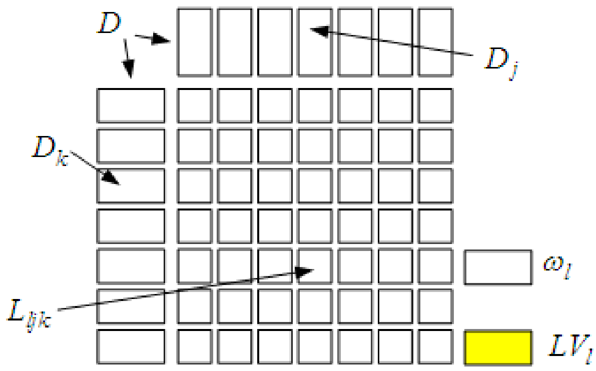


Figure 1: Information organization in a layer for each product target

In general, for the target denoted L_l we collect the contribution of each building block to achieving the target L_l by the entries of the matrix LI (Layer Information). Each entry $LI_{ljk} \in \{-1,0,1\}$ specifies how the incorporation of the building blocks (D_j and D_k) in the design alternative vector assists in attaining the target L_l. For example, positive impact of D_j on L_l is denoted by $LI_{ljj} = 1$ and negative impact of D_j and D_k on L_l is denoted by $LI_{ljk} = -1$. The design alternative (DA) is either a main or a secondary design alternative (see more details later). As mentioned earlier, the DA vector consists of chosen building blocks. For a DA vector, D, evaluating the target L_l is as follows:

$$LV_l = \sum_j D_j \cdot \sum_k LI_{ljk} \cdot D_k \tag{1}$$

Equation 1 is used in HSOS for secondary targets and for the preliminary evaluation of a main design alternative attaining a main target. As will be described later, the calculation of a main target is dependent on the relevant secondary targets, which is dependent on the secondary design alternatives.

2.2 Hierarchical SOS method

The two-level structure of HSOS is described in Figure 2. At level 1, there are M building blocks (main building blocks) and K product requirements (targets). Each main building block i=1,2,..,M has a corresponding set of secondary building blocks of size N_i. There are two types of DAs depicted in Figure 2: main DAs consisting of selected main building blocks and secondary DAs that are DAs of main building blocks consisting of selected secondary building blocks from the relevant set of secondary building blocks. The final product is comprised of both sets. Each target k=1,…,K has a corresponding set of secondary targets of size N_K that need to be satisfied.

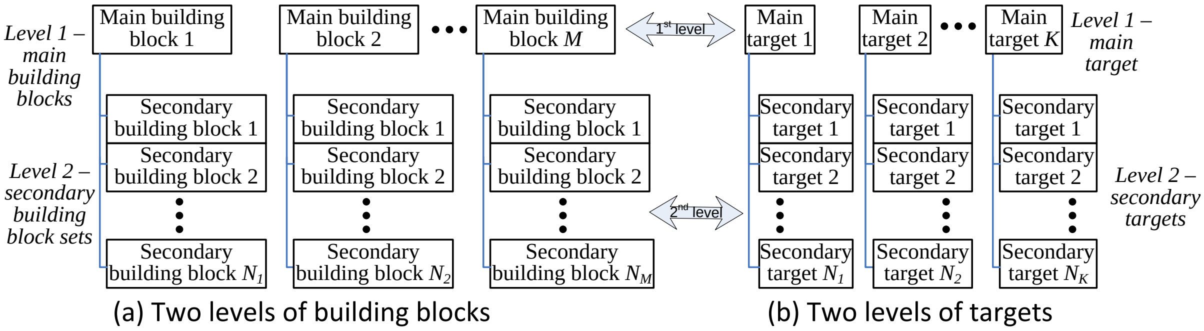


Figure 2: Hierarchical structure of SOS

As in SOS, product requirements (main targets), main building blocks that might attain them, and their mutual constraints are defined. SOS is then used for optimal concept generation related to the main targets. Subsequently, the main targets are decomposed into secondary targets to be satisfied by the level 2 building blocks. It is important to note that achieving the secondary targets is the same as achieving the main targets and that the level 2 building blocks are able to support this achievement.

For example, consider the *Survivability* requirement of an aircraft of any sort; Survivability can be decomposed into the following secondary targets: *active protection*, *passive protection* and *system reliability*. These secondary targets might have the same or different importance levels. A building block that addresses the active protection is “ammunition carrying capability”; passive protection is addressed by “chaff spreading ability” or "stealth"; and system reliability is addressed by introducing “redundancy of critical systems” or “extensive testing” to the aircraft.

Level 2 set of building blocks provides a slightly more detailed concept representation of each main building block. Several groups of constraints (for implementing constraints such as mutual exclusiveness and functional necessity) might be imposed on the composition of the level 2 building blocks:

1. *Within-block constraints* address the composition of two building blocks from the same set.
2. *Between-block constraints* deal with relations between two (or more) level 2 building block sets of different main building blocks.
3. *Multi-level constraints* deal with the influence of selecting main building blocks in the main design alternative (level 1) on the inclusion or exclusion of a level 2 building block associated with one or more main building blocks.

Some *main targets* are relevant only to the main building blocks and are therefore not decomposed and are not subjected to level 2 performance evaluation. The decomposition of the other main targets into secondary targets can be done in one of the following forms, depending on each main target and the definition of level 2 building blocks:

a) Achieving some main targets might depend on some main building blocks whose performance could be influenced by the way they are created from level 2 building blocks. Consider a main target T relevant to a set S of m main building blocks out of M (size(S)=m<M). The main target T is decomposed into a set of secondary targets t_j with relative importance ω_j. The secondary targets depend on the performance of the building blocks selected at level 2. It is possible for each main building block performance to have a different relative importance for achieving the main target T. That relative importance of the i^{th} main building block is denoted as Ω_i. Now, define t_{ji} as level 2 performance towards target t_j of level 2 DA representation of main building block D_i. The evaluation of target T is:

$$T = \sum_{i\in S} \Omega_i \left[\sum_{j=1}^{N} \omega_j t_{ji}\right] \tag{2}$$

For example, the main target T is decomposed into two secondary targets t_1 and t_2 with relative importance of $\omega_1=0.3$ and $\omega_2=0.7$, respectively. There are M=5 main building blocks, but attaining the main target T is done only by building blocks D_1, D_2 and D_4 (m=3). Attaining the main target T depends more on the performance of building block D_2 with relative importance $\Omega_2=0.5$. The relative importance of building blocks D_1 and D_4 is equal: $\Omega_1=\Omega_4=0.25$. For the valid main design alternative *DA=[11011]* (in this case the product consists of four main building blocks - D_1, D_2, D_4 and D_5). The target value of T is calculated using only its three relevant building blocks:

$T=\Omega_1\cdot[\omega_1\cdot t_{11}+\omega_2\cdot t_{21}]+ \Omega_2\cdot[\omega_1\cdot t_{12}+\omega_2\cdot t_{22}]+ \Omega_4\cdot[\omega_1\cdot t_{14}+\omega_2\cdot t_{24}] =$
$0.5\cdot[0.3\cdot t_{11}+0.7\cdot t_{21}]+ 0.25\cdot[0.3\cdot t_{12}+0.7\cdot t_{22}]+ 0.25\cdot[0.3\cdot t_{14}+0.7\cdot t_{24}]$.

b) In case achieving a main target depends on all the main building blocks we get:

$$T = \sum_{i=1}^{M} \Omega_i \left[\sum_{j=1}^{N} \omega_j t_{ji}\right] \tag{3}$$

SOS is used for generating a valid level 2 product representation while evaluating secondary targets. The goal is to find an optimal concept in terms of both levels building blocks that will best attain the main targets, i.e., achieves the highest score attaining all targets. This is a multi-objective optimization problem solved by an iterative process implemented by a genetic algorithm (GA). The GA is used for exploring the large space of valid DAs in both levels representations of the product. The GA used here is inspired by, but slightly different from, the NSGA-II [21].

The Boolean nature of DAs at both levels ("1" means a building block is included in the design concept, "0" means it is not included) makes it appealing for use by GA without further adjustments.

The GA consists of several stages:

- Generating an initial parent population (of size N) and evaluating targets for each population member. For each concept composed of main building blocks, a level 2 representation of building blocks (i.e., an appropriate chromosome) is generated (a combination of 2nd level building blocks for each main building block - Figure 3). In HSOS, this representation is used for evaluating secondary targets (using appropriate 2nd level decision layer matrices) and later, re-evaluating the main targets (equations 2 and 3).

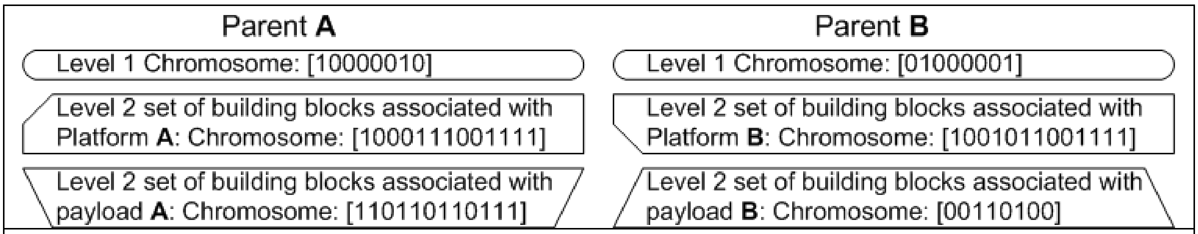


Figure 3 - Two parents Design Alternatives with corresponding representations for both levels (1 & 2 chromosomes). Notice the different lengths of level 2 chromosomes

- Performing a Domination Sort over the parent population. This creates several sets (or Pareto fronts) in which members of one dominate those in the other. The non-dominated DAs are included in the optimal Pareto-front. If those are removed, another front could be created, etc.
- Genetic operators such as selection, crossover (Figure 4) and mutation (Figure 5) are used to produce the children population of DAs from the sorted parent population of DAs. The children DAs are checked for validity (in terms of both levels building blocks and constraints) and their secondary and main targets are evaluated. In order to produce better DAs in the children population, the higher ranked parent DAs are more likely to participate in the genetic operators.
- The parent and children populations of DAs are combined and later are sorted by non-domination. The best N DAs are selected as the parent population for the next generation. In

addition, the lowest-ranked DAs (located on the worst Pareto front) are cleared of repetitions (authors' choice for keeping diversity; in this manner, the GA presented here differs from NSGA-II). This is done to preserve the initial population size *N* (though the population size might decrease) and to guarantee diversity.

- Repeating the search for the optimal DA until a stopping and/or convergence conditions are met. It is common to choose a limit on the number of generations (search iterations) as a stopping condition. Common convergence conditions are decreasing population size that can occur due to many repetitions in a population consisting of DAs located only on the Pareto-optimal front; or an insignificant change in the average performance of the Pareto-optimal DAs.

The population of DAs after the GA has stopped is sorted to Pareto-fronts (optimal, sub-optimal etc.).

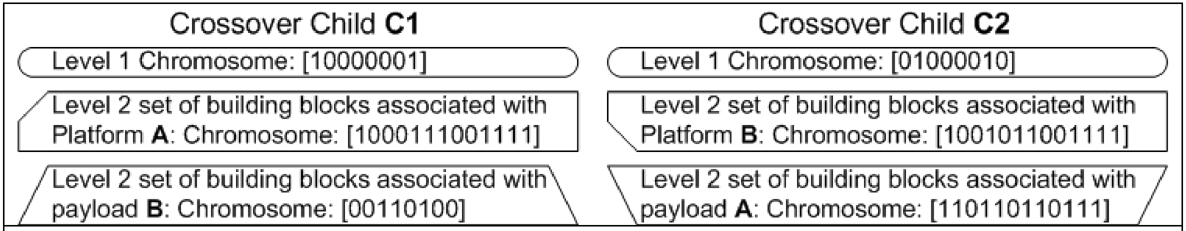


Figure 4 - Two children Design Alternatives resulting from crossover of parent Design Alternatives given in Figure 3. The Crossover operator is applied at Level 1 altering the coupling of Platform-Payload only. Respective Level 2 chromosomes do not change.

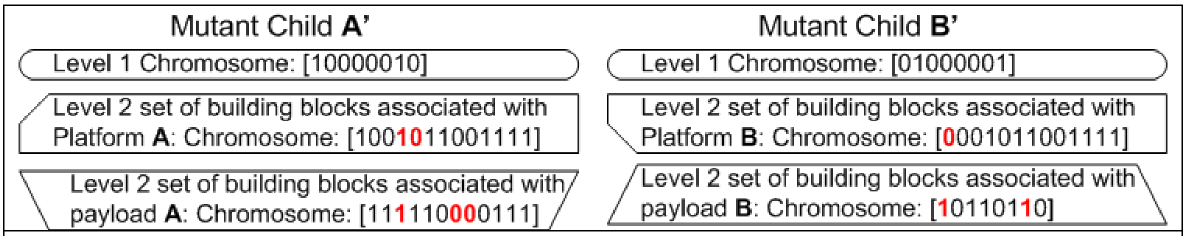


Figure 5 - Two children Design Alternatives resulting from mutation applied to parent Design Alternatives given in Figure 3. The mutation is applied at Level 2 only, altering several bits of Level 2 chromosomes in predefined places (red coloured). The parent concept does not change.

3 EXAMPLE

A simple design problem demonstrates HSOS: optimally combining a payload and an aerial carrying platform. HSOS generates design concepts and searches for, and selects the optimal design concept(s). We compared the optimal designs generated by a single level SOS and HSOS.

3.1 1st level definitions

The definitions of main building blocks and main targets are given in Table 1. The main building blocks are divided into two groups: "platform-type" and "payload-type". The constraints are simple: a main design alternative is a combination of one platform-type building block and one payload-type building block. Additional constraints address the platform carrying ability: only "manned plane" and "large UAV (unmanned aerial vehicle)" are capable of carrying SAR (synthetic aperture radar) and dual payloads (dual payload is any combination of two of the three available payloads). The 12 valid main design alternatives are shown in Table 2.

3.2 2nd level definitions

Decomposition of the main targets to secondary targets and their relative weights is presented in **Error! Reference source not found.**. Attaining some main targets may be associated with the performance of a single main building type (platform or payload) and some others might depend on the combined performance of both types of main building blocks. This division of dependency is also described in **Error! Reference source not found.**. For main targets depending on the performance of both main building types, one type of the main building block types might contribute more strongly to attaining these main targets. This stronger contribution is captured by a relative importance weight.

Next, each main building block is decomposed into a set of level 2 building blocks. This could benefit from the influence of the secondary targets and the relevancy of each type of main building block (platform, payload or both) to the main target. The sizes of the sets might differ even among main building blocks of the same type.
Sets of secondary building blocks relevant to platform-type main building blocks contain, in general, building blocks related to propulsion type, communications, structure and geometry, operational parameters, etc. Sets of secondary building blocks relevant to payload-type main building blocks contain, in general, building blocks regarding stabilization of payload, recording ability, data transmission and compression, etc. The dual payload set of secondary building blocks contains the three combinations of main payloads (FLIR+CCD cameras, FLIR camera + SAR and CCD camera + SAR) in addition to the above described payload-type secondary building blocks typical sets.

Table 1: Main targets and building blocks

Main building blocks		**Main targets**
Platform-type	Payload-type	Survivability Cost Resolution Simplicity Mission Duration Risk Area Coverage
Manned Plane Large UAV Medium UAV Blimp	FLIR camera CCD camera SAR Dual payload	

Nomenclature:

CCD - Coherent Change Detection
FLIR - Forward Looking Infra Red
SAR - Synthetic Aperture Radar
UAV - Unmanned Aerial Vehicle

Table 2: Main valid DAs

# of DA	**Main DA**	
	Platform	Payload
1	Blimp	CCD camera
2	Blimp	FLIR camera
3	Medium UAV	CCD camera
4	Medium UAV	FLIR camera
5	Large UAV	Dual Payload
6	Large UAV	SAR
7	Large UAV	CCD camera
8	Large UAV	FLIR camera
9	Manned Plane	Dual Payload
10	Manned Plane	SAR
11	Manned Plane	CCD camera
12	Manned Plane	FLIR camera

Table 3: Relevancy of building block type and decomposition to secondary targets and relative weights of secondary targets

Main Target	Secondary Targets		Relative Importance	
	Platform	Payload	Platform	Payload
Survivability	Active Protection - 0.4 Passive Protection - 0.2 System Reliability - 0.4	Irrelevant	1.00	0.00
Project Risk	Evaluated through main building blocks. Not decomposed into secondary targets			
Area Coverage	High Velocity - 0.9 Multi-Payload Carrying Ability - 0.1	High Altitude - 0.6 Recording Ability - 0.25 Bore sight Accuracy - 0.15	0.50	0.50
Mission Duration	Fuel Capacity - 0.8 High Endurance - 0.2	Irrelevant	1.00	0.00
Cost	Irrelevant	Single Unit - 0.5 Simple Technology - 0.5	0.00	1.00
Resolution	Irrelevant	Low Altitude - 0.7 High Sensitivity - 0.3	0.00	1.00
Simplicity	Simple Design - 1	Simple Design - 1	0.50	0.50

3.3 Evaluation of Main targets: Single level SOS

The main targets were evaluated based on the performance of the main DAs shown in Table 2. The results are presented in Table 4: Performance of main DAs and 3.4.2 Type 1 Simulations - single targets - results The GA conducts a search in the space of valid level 2 DAs. The GA did not always converge to the global maximum target value and required repeating the simulations to gather statistics.

For some main targets, HSOS simulation results did not agree with the single level SOS target evaluation. This disagreement is associated with the additional information introduced in the HSOS level 2 building blocks. This new information might relax or limit the incorporation of building blocks, implementation characteristics, etc., that were not consistent with the *a-priori* evaluation of the single level SOS. In all these cases, we verified that the concept generated by HSOS was correct from an engineering standpoint.
The Pareto-optimal concepts displayed few variations, expressed in different chromosomes describing level 2 DAs. The difference between the chromosomes was in several bits (i.e., selecting a secondary building block for one DA and not selecting it for the other DA). This result is not surprising, taking into account the single level SOS evaluation results for each target independently, showing that for each target there is a limited number of DAs scoring the maximum target value.
Table 5. For each main target, the performance of each main DA was evaluated. We look for product concepts achieving maximum score for all targets. The DAs are divided into three fronts by domination: Pareto-optimal front, sub-optimal front #1 and sub-optimal front #2 (this front contains the DAs with worst performance towards all targets). The fronts are numbered 1, 2, and 3, respectively.
The single level SOS simulation suggests that there are eight optimal concepts. These concepts are the non-dominated concepts and are located at the Pareto-optimal front. The Pareto-optimal concepts achieve the maximum score for at least one main target (concepts 1, 3, 5, 6, 7, 9, 10, 11). Some concepts achieving maximum score of main targets are dominated by other solutions and therefore are located at the sub-optimal front. The worst concept is dominated by a sub-optimal concept.

3.4 Hierarchical SOS

3.4.1 Simulations performed

Several simulation types were performed in order to analyze the design concepts generated by HSOS:

- Type 1: Repeated simulations for each single target. Each optimal concept was checked for variations (e.g., how many level 2 DAs exist for each optimal concept). Disagreements between the single level SOS and HSOS were also analyzed. The population size for these simulations was 400 and the number of iterations (generations in terms of GA) was limited to 10.
- Type 2: Repeated simulations for couples of targets (selecting 2 out of 7 main targets). These simulations were used to view the performance of the GA and variations in level 2 DAs. The population size for these simulations was 400 and the number of iterations (generations in terms of GA) was limited to the maximum of 10.
- Type 3: Repeated simulations for all 7 main targets. These simulations were used to check the Pareto-optimal generated concepts for variety and for comparison with the single level SOS Pareto-optimal designs. The population size for these simulations was 4000 and the number of iterations (generations in terms of GA) was limited to the maximum of 10.

For all simulations performed, the sensibility of the optimal design concepts generated was checked.

Table 4: Performance of main DAs

DA #	**Main Targets**						
	Survivability	Cost	Area Coverage	Resolution	Simplicity	Duration	Risk
1	1	4	-1	2	4	4	1
2	-1	0	-1	-1	0	2	1
3	2	4	1	2	2	3	3
4	0	4	1	-1	2	1	3
5	-3	-4	4	3	-2	-2	-4
6	0	-2	3	3	0	-2	2
7	2	2	1	0	2	4	1
8	2	0	1	-1	2	2	1
9	-2	-3	4	3	-2	-4	-2
10	1	-1	3	3	0	-4	4

11	3	3	1	0	2	2	3
12	3	3	1	-1	2	0	3

3.4.2 Type 1 Simulations - single targets - results

The GA conducts a search in the space of valid level 2 DAs. The GA did not always converge to the global maximum target value and required repeating the simulations to gather statistics.

For some main targets, HSOS simulation results did not agree with the single level SOS target evaluation. This disagreement is associated with the additional information introduced in the HSOS level 2 building blocks. This new information might relax or limit the incorporation of building blocks, implementation characteristics, etc., that were not consistent with the *a-priori* evaluation of the single level SOS. In all these cases, we verified that the concept generated by HSOS was correct from an engineering standpoint.

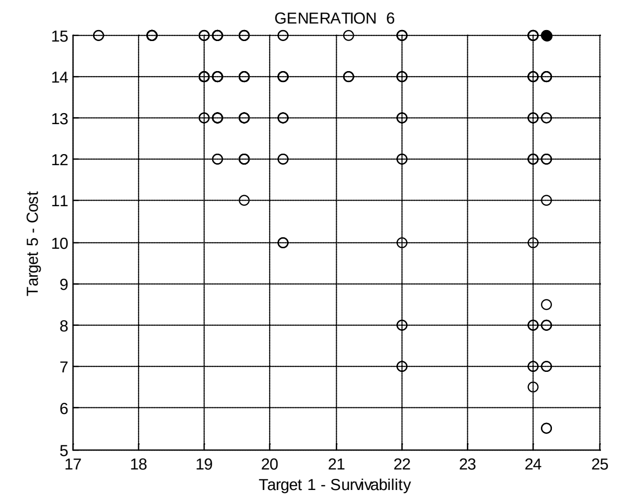
The Pareto-optimal concepts displayed few variations, expressed in different chromosomes describing level 2 DAs. The difference between the chromosomes was in several bits (i.e., selecting a secondary building block for one DA and not selecting it for the other DA). This result is not surprising, taking into account the single level SOS evaluation results for each target independently, showing that for each target there is a limited number of DAs scoring the maximum target value.

Table 5: Composition of main DAs and their relative performance

#	DA Platform	DA Payload	Domination	Dominated by	Front
1	Blimp	CCD	Non-Dominated		1
2	Blimp	FLIR	Dominated Solution	3, 11, 1, 7, 8	3
3	Small UAV	CCD	Non-Dominated		1
4	Small UAV	FLIR	Dominated Solution	3	2
5	Large UAV	DUAL SENSOR	Non-Dominated		1
6	Large UAV	SAR	Non-Dominated		1
7	Large UAV	CCD	Non-Dominated		1
8	Large UAV	FLIR	Dominated Solution	11, 7, 3	2
9	Manned Plane	DUAL SENSOR	Non-Dominated		1
10	Manned Plane	SAR	Non-Dominated		1
11	Manned Plane	CCD	Non-Dominated		1
12	Manned Plane	FLIR	Dominated Solution	11	2

3.4.3 Type 2 simulations - two targets - results

Several simulation results for different couples of main targets are shown in Figure 6 to Figure 9: Extreme values for Survivability target of Pareto-optimal main design concepts . The results shown are taken before the final convergence to show different types of Pareto-optimal fronts. Pareto-optimal design concepts are marked with black dots. As can be seen, 400 design alternatives converged to a small number of points on the Pareto-optimal front. These concepts have “close siblings” (concepts with the same main building blocks and a small variation in level 2 building blocks) in the population. For example, the Manned Plane + Dual Payload main DA appearing in the Pareto-optimal design concept set in Figure 9: Extreme values for Survivability target of Pareto-optimal main design concepts , has several sibling level 2 DAs that differ by a slight choice of level 2 building blocks. Increasing the total number of DAs in a population from 400 to 1000 does not change the Pareto-optimal main design concept set but increases level 2 variations of those main concepts.



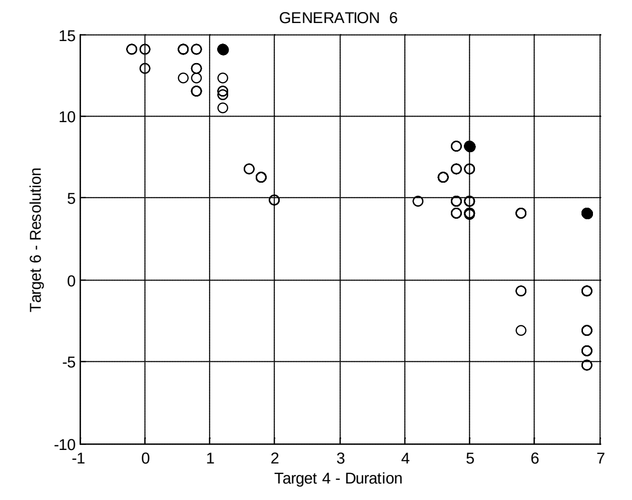
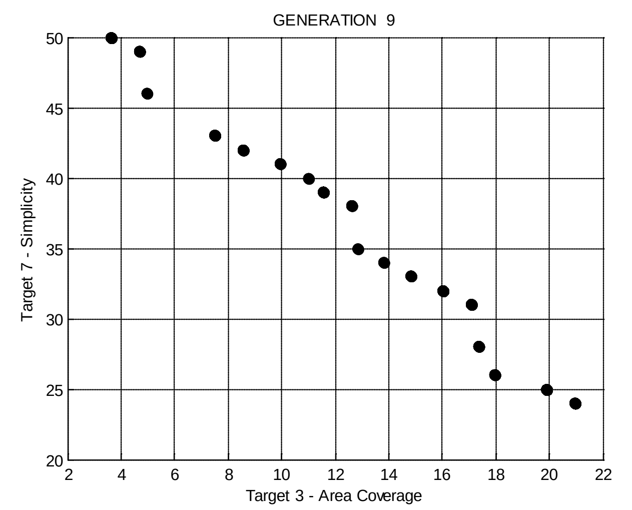


Figure 6: Pareto-optimal front consisting of a single point for cost-survivability targets

Figure 7: Pareto optimal front consisting of three points

An interesting finding is that for certain combinations of main targets, close siblings of some of the main design concepts on the Pareto-optimal front are in the nearest suboptimal front. This suggests the robustness of these main design concepts - a small change in the relative weight of the secondary targets might turn several suboptimal representations of a main design concept into Pareto-optimal designs, or a slight change in the optimal concept would not deteriorate the performance significantly.



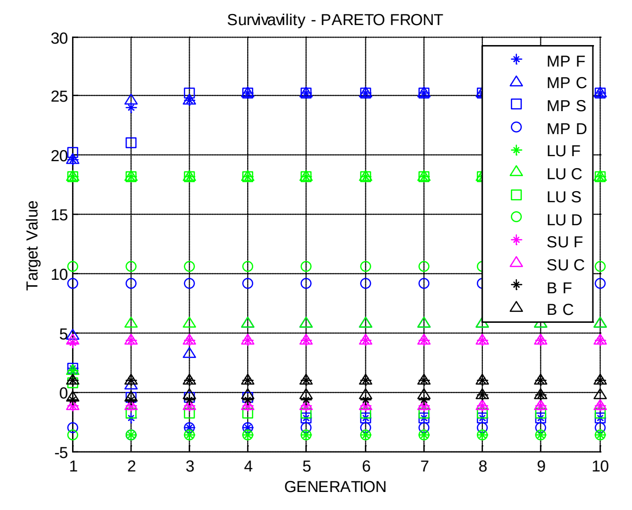


Figure 8: Pareto-optimal front consisting of multiple points

Figure 9: Extreme values for Survivability target of Pareto-optimal main design concepts

3.4.4 Type 3 simulations - all targets - results

These simulations yielded the optimal design concepts taking into consideration all seven targets. Shown in **Error! Reference source not found.**, the minimum and maximum values for the Survivability main target of the Pareto-optimal design concept set, for each generation. As can be seen, all twelve main design concepts (Table 2) are present and are therefore included in the Pareto-optimal set in contrast to the single level SOS where only eight main design concepts are included in the Pareto-optimal set. This disagreement is associated with the addition of information introduced in HSOS that caused inferior design concepts to become relevant optimal design candidates.

Since the Pareto-optimal set is large (4000 DAs consisting of all twelve main design concepts) filtering to ease selection is needed. The filter criteria require some minimum value of targets to pass it. One of the filters with particular minimal values (i.e., Risk≥2, Duration≥2 Simplicity≥10, Area Coverage≥0, Resolution≥0) resulted in narrowing the size of the relevant Pareto-optimal main design concepts to 3 out of the 12 main design concepts: Manned Plane + FLIR Camera (116 variants), Manned Plane + SAR (10 variants) and Large UAV + SAR (only 2 variants). The large number of population members (4000) contributed to finding many variations for the Manned Plane + FLIR main design concept and to preserve the other main design concepts members of the Pareto-optimal set.

4 CONCLUSIONS

This paper presented the Hierarchical SOS method for generating optimal design concepts. HSOS introduces additional design information concerning the incorporation of building blocks towards attaining product requirements. This new information that is used by HSOS turns out to be important: it sometimes causes inferior designs according to single level SOS to become members of the Pareto-optimal concept designs set created by HSOS. In addition, sometimes the relationships between main building blocks might become clearer through level 2 sets of building blocks.

Obtaining the optimal design concepts is a challenging task, especially with large search-space, such as provided by the level 2 space of design alternatives. Searching this space is made possible by a GA. However, the optimal designs obtained by the GA might not be the global optimal designs and repeating the simulations is needed to gather enough data for statistical analysis. The size of the population might have impact upon the amount of variants (different level 2 representations) of the same main design concept appearing in the Pareto-optimal set. HSOS assists in finding different design alternatives for the same design concept. This provides a basis for assessing the robustness of design concepts. If the Pareto set of optimal concepts created by HSOS is large, filtering it by requesting that each target achieves some minimal value can be used to reduce it, hence providing a better basis for concept selection.

HSOS could be used to address the well defined problem of configuration by having users input their preferences concerning each existing building block. With further investigation, HSOS could be used for robust concept generation. Concepts at level 1 that are represented well in level 2 Pareto front seem to be robust. This intuition needs to be transformed into precise definition and procedure. HSOS could also be used to trigger creativity: when using HSOS, it becomes clear that constraints between building blocks prevent their use in a single concept that would lead to better user satisfaction. In such case, creativity methods such as TRIZ or ASIT could be used to resolve the constraint.

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