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Design space exploration in aircraft conceptual design phase based on system-of-systems simulation

Tian Yifeng*, Liu Hu and Huang Jun*****

School of Aeronautic Science and Engineering, Beihang University, Beijing 100191, China

Abstract

Design space exploration has been much neglected in aircraft conceptual design phase, which often leads to a waste of time and cost in design, manufacture and operation process. It is necessary to explore design space based on operational system-of-systems (SoS) simulation during the early phase for a competitive design. This paper proposes a methodology to analyze aircraft performance parameters in four steps: combination of parameters, object analysis, operational simulation, and key-parameters analysis. Meanwhile, the design space of an unmanned aerial vehicle applied in earthquake search and rescue SoS is explored based on this methodology. The results show that applying SoS simulation into design phase has important reference value for designers on aircraft conceptual design.

Key words: system-of-systems, aircraft conceptual design, design space exploration, modeling and simulation.

1. Introduction

The concept of system-of-systems (SoS) was first brought up in Boulding's work [1] in 1956, but it was not until 1989, with the Strategic Defense Initiative, that SoS was introduced to engineering application [2, 3]. Although this field has been growing significantly in recent years [4], it is still in the primary stage without a common definition [5-7]. Despite this, the basic features of these definitions are that an SoS is composed of a multitude of complex, independent, and heterogeneous systems, which work cooperatively, to achieve more capacities than the sum of individuals. For this reason, decision-makers begin to think and analyze from a higher perspective of SoS. Systems are no longer studied separately but in the SoS environment, with the influence of other systems, which often lead to different or unexpected results in contrast with previous cases. In the field of aerospace, the concept of SoS has been applied to solve different problems, for instance, air strike [8, 9], civilian transportation [10-12], maritime applications [13] and so on. SoS theory also plays an important role in aircraft design [14-16], because it gives aircraft designers new inspiration about aircraft design methods, especially in conceptual design phase.

As we know, the performance parameters in conceptual design phase have a great influence on preliminary design, detail design, life-cycle cost and operation effectiveness. However, previous design processes usually focus on customer specifications in order to meet expectation. Thus design space exploration, life cycle operation and parameter optimization were neglected, often leading to substantially unnecessary time and cost [17, 18]. Unbefitting performance parameters can even lead to commercial flop especially for civil air vehicles. Due to these shortcomings, incorporating the operation phase into the conceptual design phase to explore design space for a preferred design becomes extremely important to solve the contradiction between design and operation. The bridge connecting two aspects is modeling and simulation (M&S).

This paper aims at establishing a design space exploration methodology based on SoS simulation in aircraft conceptual design phase. This approach creates a mapping from aircraft performance to the effectiveness of SoS in order to explore design space for a competitive design in four steps: combination of parameters, object analysis, operational

* Ph. D Student
** Associate Professor
*** Professor, Corresponding author: junh@china.com

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simulation, and key-parameters analysis. Combination of parameters means selecting performance parameters to construct the design space. Every design point represents a combination of parameters. Object analysis means analyzing all existed objects such as component systems, relationship of systems, modeling method and operation logic to establish the SoS model. Operational simulation means obtaining the SoS effectiveness through setting values for inputs and running simulation program based on Design of Experiment (DoE). Key-parameters analysis means analyzing aircraft performance parameters and optimizing design space according to SoS effectiveness data. The frame of COOK model is shown as Fig. 1. The four steps which will be described in details are noted as COOK hereinafter for brevity. Meanwhile, in order to illustrate the procedures and validity of COOK model, a design case of an unmanned aerial vehicle (UAV) applied in earthquake search and rescue SoS is discussed and analyzed in-depth.

2. Methodology of COOK Model

2.1 Key Issues

Comprised of systems or complex systems, SoS has a larger scale and a higher complexity. Its boundary is also fuzzier, which leads to the lack of a uniform definition. But the five characteristics of SoS proposed by Maier [19] have been widely recognized in this field which are emergent behavior, evolutionary development, operational independence of the elements, managerial independence of the elements and geographic distribution. Dealing with these characteristics is also the key issue when designing aircraft in SoS environment. The first two characteristics are easy to understand and are appropriate for systems as well. For instance, aircrafts are designed or modified to achieve some emergent performance. However, it is the latter three which are unique to SoS that make design process more complicated. Take earthquake search and rescue SoS as an example, the geographic extent of component systems like UAVs, helicopters, temporary base, survivors and rescue equipment is large. They operate independently, and keep connecting with each other all the time as well. Their behaviors vary according to real-time interaction. Owing to the reasons above, it is difficult to predict what the results might be. The uncertainty and discontinuities increase challenge on modeling and analysis of SoS. Therefore when designing a new aircraft based on SoS simulation, designers must construct the complex SoS model first.

Moreover, the component systems share limited resource and compete against each other. So the optimum of a certain individual system may not produce the optimum of the SoS [13]. The overall optimum often tends to result from the compromise and trade-off in different aspects. Therefore, the aircraft that customers need is not the one with best performance, but the one that can optimize the whole SoS. If the aircraft with a lower configuration has almost the same impact on the SoS as others, there is no doubt that both designers and customers will choose the former one to save life-cycle cost. So it is necessary to explore design space according to effectiveness of SoS in depth.

Due to the above reasons, when seeking a desirable point in design space, designers must consider about both randomness of SoS and competition of systems. The design process is not a one-time event but an iterative process. The SoS simulation should run repeatedly to provide enough data for the relationship research between combinations of performance parameters and effectiveness of SoS. Different combinations will lead to different effectiveness of SoS, and on the contrary, data analysis of SoS simulation also helps designers to choose the optimal combination. Thus, the new methodology should be a closed-loop process through a bottom-up simulation as well as a top-down analysis.

In view of above analysis, the presented methodology which is also named COOK model must solve four key issues: (1) how to establish design space; (2) how to construct an SoS model; (3) how to operate SoS simulation; (4) how to analyze SoS data. In this paper, the four steps of COOK model realize a one-to-one correspondence with the four issues.

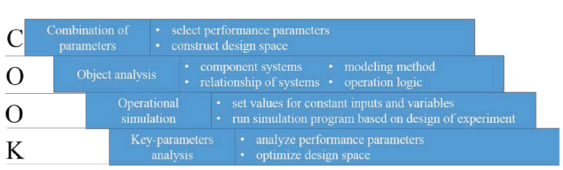

Fig. 1. Frame of COOK Model

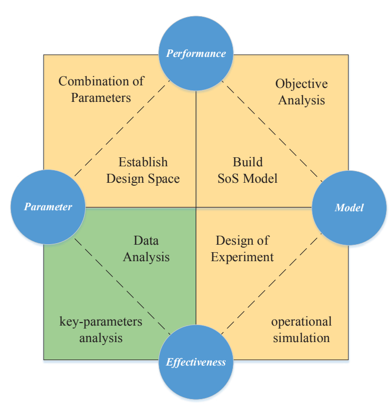

Fig. 2. Architecture of COOK Model

The logic of COOK model is shown as Fig. 2. The four blue circles are the key nodes in design process. The four corners of the square connecting two nodes are the four steps of COOK model: combination of parameters, object analysis, operational simulation and key-parameters analysis. The issue that each step aims at and solves is in the dash square. And the yellow squares represent the bottom-up M&S while the green one represents the top-down analysis. Each step will be described in following sections in-depth.

2.2 Combination of Parameters

This step aims at the establishment of design space. The performance requirements vary a lot in different applications. However, the main performance parameters in conceptual design phase are almost the same, such as gross take-off weight (W_{gtow}), wing area (S_w), cruise speed (V_{cs}), lift-drag ratio (K), thrust-weight ratio (T/W), thrust specific fuel consumption (c_f), thrust efficiency (η), fuel weight (W_{fuel}) and so on. Although the number of parameters and their types become much larger as design process continues, the derived parameters are still set according to the initial performance parameters in conceptual design phase. Thus, combinations of performance parameters have a great impact on the subsequent design process. Exploring design space means seeking better combinations for a competitive product.

The design space is the set of possible design points actually. Each point represents a certain combination of performance parameters which vary in their intervals. The whole design space could be described as parallel coordinates, see Fig. 3. The vertical parallel lines in parallel coordinates represent different performance parameters and the part between upper bound dash line and lower bound dash line represents the value interval of each parameter. A design point is represented as a polyline with vertices on parallel axes. The position of the vertex on axis corresponds to the parameter value in this design. Because designers cannot predict which design point will produce an overall optimum in advance, the combinations should cover the design space as completely as possible. The more types of parameters there are, the larger the number of combinations should be. Just like cutting meat into pieces, it is impossible to predict which piece is the best after cooking, so a large quantity of pieces with different sizes are prepared as samples.

2.3 Object Analysis

In this step, object analysis aims to analyze all existed objects in modeling process, such as component systems, relationship of systems, modeling method and operation logic. Actually, this step is an abstraction and simplification of real SoS, because it is extremely difficult to create all system models or clarify all relationships in real SoS. However, if the research focuses on a certain component system instead of the complete reproduction of real SoS, it is acceptable to remove some systems or relationships that have little impact on operation.

The logic of object analysis is shown as Fig. 4. When analyzing objects, component system selection comes first, which is the basis to build relationships, select modeling method and analyze operation logic. Regarding individual system as a communication node, a decrease in the number of systems means a decrease in the number of communication node, which will lead to a much clearer relationship network. Neglecting some insignificant systems will make the modeling process more easily. After that designers need to select suitable modeling methods for selected systems based on relationship network. In fact, different modeling methods bring different similarities between simulation models and real systems. For instance, agent-based modeling can create most system models despite limited system knowledge. Each agent is applied as an active object that can operate autonomously in simulation environment. They are assigned role-specific operational rules to determine their behaviors according to different conditions. So the aircrafts modeled as agents will have a high similarity, compared with described as empirical formulas.

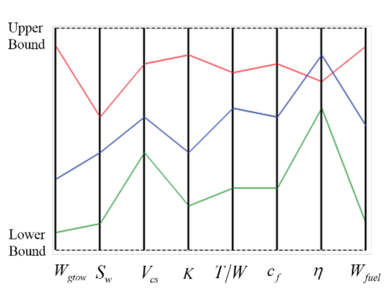

Fig. 3. Parallel Coordinates of Design Space

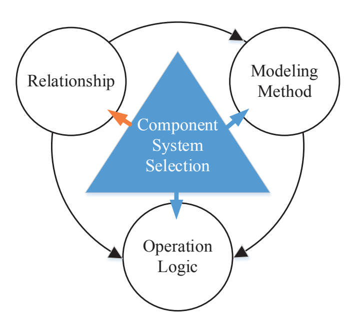

Fig. 4. Logic of Object Analysis

After determining component systems, relationships and modeling methods, the next step is to analyze the operation logic of each system based on the above existing analysis. Many system attributes must be set, such as variables, states, interactive contents, geographic distribution, mission targets and primary behaviors. In summary, object analysis process is to analyze all elements in SoS to create a simulation model. Just as cooking, not only the meat but also vegetables and seasoning should be prepared. In addition, the concrete steps of cooking should be selected before starting to cook.

2.4 Operational Simulation

This step is to obtain the effectiveness of SoS based on operational simulations. Without geometric design, it is hard to get some aerodynamics data. However, different aircraft performance will lead to different SoS mission effectiveness and the other way round aircraft performance could be analyzed according to their corresponding mission effectiveness. Although operational simulations provide a feasible way to analyze system performance, the specific process still needs to be discussed. Because of the randomness and discontinuities in operational simulations, it is hard to get exact solutions. And even if a simulation operates repeatedly with the same input variables under the same initial conditions, the results could be very different. Despite this, it is feasible to gain an approximation to variation trend based on output statistic of all simulations. In order to obtain a relatively accurate approximation, DoE [20] can be used to handle this problem. DoE aims to connect the performance parameters with the effectiveness of SoS simulation. DoE might be different in different simulations. If there is only one input variable, sensitive analysis may be enough to describe the relationship. However, if the object is the whole design space comprised of many input variables, a Monte Carlo or a Latin hypercube [21] might be preferred to populate the design space to capture variation trend. Meanwhile, this step is also an accreditation process. If there are some excessive errors in a certain simulation, DoE will not be conducted before eliminating these errors.

It is an iteration process based on combinations of parameters in design space. The value of input variables should accord with a certain distribution, such as a uniform distribution or a normal distribution. And the results of simulations are also not a certain value or formula, but a probability distribution of effectiveness. This process is similar to real cooking process, in which a large amount of prepared ingredients will be cooked continually under the same initial condition in the same cooking method.

2.5 Key-parameters Analysis

Key-parameters analysis is a filtration process in which a large quantity of statistic data are filtered based on mission requirements. In this step, the statistic are expressed as a probability distribution curve or histogram. The influence of parameters on the effectiveness can be analyzed through the histograms of successful cases and all cases. For an aircraft, not all performance parameters have an evident impact on SoS operation. Thus, through observing the probability variation corresponding to parameter variation, the parameters that SoS operation is sensitive to will be obtained. And these parameters are key-parameters which need to be considered first in design phase. Meanwhile, the analysis results also have important reference value for designers. In the histograms, the points where the probability density has significant changes are the key points that designers should pay more attention to. In summary, this step is similar to getting food with a strainer. The desirable will be selected and the undesirable will be left. And then compared with the sizes of selected food before cooking, the one without great changes in size could be regarded as a template when preparing meat next time.

COOK model actually provides a methodology for designers to design experiments and analyze problems in SoS environment. It helps designers make the M&S process more clear and improve the whole research. For instance, if designers want to gain more accurate performance parameters, from the above four steps there are four ways, i.e., a). increase the number of samples; b). retain more component system; c). choose modeling methods with higher similarity; d). increase constraints. Designers can choose different ways to improve the whole process according to different conditions.

COOK model provides an available method for designers to explore design space based on SoS simulations. For a detailed description of COOK model, a design case of a UAV applied in earthquake search and rescue is discussed in following sections.

3. Earthquake Search and Rescue SoS with UAVs

3.1 Advantage of UAVs and Design Objective

In contrast of normal aircrafts or helicopters, UAVs have the advantages of small size, light weight and high flexibility. In addition, the life-cycle cost is far lower than flight vehicles with pilots. And with the maturing of UAV technology and the application of new technological equipment, UAVs have been widely applied in civil fields. Equipped with GPS and image detection system, they play a significant role in earthquake rescue [22], forest monitoring [23], maritime patrol [24], aerial mapping [25] and so on. For earthquake search and rescue SoS, UAVs can fly to targets immediately without too much preparation after earthquake. They can fly along the search path under the guidance of navigation equipment and search and monitor the allocated area. Once survivors are found by UAVs, the base will dispatch helicopters to rescue survivors. In the process, UAVs have a better performance at low-altitude detection than other types of aircrafts and the costs of operation are also much lower than that of helicopters. So it is necessary to design a UAV used in earthquake search and rescue SoS.

Thus in presented case, the design objective is a small size, inexpensive, portable UAV with a small size piston engine applied in earthquake search and rescue SoS. The mission is that during the allotted time, UAVs search the target areas at a low altitude in order to find survivors and helicopters fly to the coordinates of survivors when receiving messages from UAVs. On one hand, since this type of UAV must detect accidents in complex terrains, it should have a long endurance, enough load capacity for related equipment, and the ability of cruising with a low speed and altitude. On the other hand, not only UAVs but also helicopters have a significant impact on SoS mission. Due to the limit of helicopters, excessive performance of UAVs might not make an evident difference to the effectiveness of SoS. So for the purpose of seeking a suitable and preferable design of UAVs, the performance parameters of required UAVs should fulfill the mission requirement first. Then the corresponding performance requirement should be easy to reach. In other words, the level of parameters should not be set too high from the perspective of saving life-cycle cost. And the design space of UAVs should be explored in conceptual design phase, because the parameters have a great influence on preliminary design and detail design. An efficient way to solve this problem is to apply modeling and simulation based on COOK model to explore the design space before designers begin preliminary design, even if there are no existing systems or UAVs as a reference.

3.2 Combination of UAVs' Performance Parameters

As analyzed in section 3.1, designers might consider that a long endurance means much fuel; enough load capacity means high trust-weight ratio; and cruising with a low speed and altitude means high lift-drag ratio. Of course it is a rough and apparent analysis. In fact, these parameters are not isolated. Instead, they follow mathematical relationships.

A major change of UAVs in the mission is fuel consumption (Q_f), so performance parameters, which are selected to form design space, and their relationship will be discussed according to related functions. The weight of UAVs decreases continually due to the increase of fuel consumption when flying with a cruise speed. However, the variation is actually very slow, so in every moment UAVs keep a steady motion. Thus the thrust (T) equals the drag (D) and the lift (L) equals the current weight (W). Meanwhile, the lift-drag ratio (K) represents the value of lift over drag. In consideration of engine efficiency, the engine thrust (T_a) represents the value of T over η. The mechanical relationships are shown as equations (1-3). In the process, there is also a relationship between thrust specific fuel consumption and fuel consumption. If a UAV flies with a speed of V, the time it costs and distance it flies over in this moment is calculated as equation (4, 5). In equation 4, d_m represents the differential of the total mass. According to the initial weight (W_1) and the final weight (W_2), the range (R) and the endurance (T_e) are calculated as equation (6, 7).

$$T = D \tag{1}$$

$$L = W \tag{2}$$

$$T = \eta T_a = \frac{W}{K} \tag{3}$$

$$dt = \frac{dQ_f}{c_f T_a} = -\frac{dm}{c_f T_a} = -\frac{dW}{g c_f T_a} \tag{4}$$

$$dR = V dt = -\frac{V dW}{g c_f T_a} \tag{5}$$

$$T_e = -\int_{W_1}^{W_2} \frac{dW}{g c_f T_a} = \int_{W_2}^{W_1} \frac{K\eta}{g c_f W} dW \tag{6}$$

$$R = -\int_{W_1}^{W_2} \frac{V dW}{g c_f T_a} = \int_{W_2}^{W_1} \frac{V K\eta}{g c_f W} dW \tag{7}$$

In SoS simulations, V and g are often decided by mission requirements and some parameters can be calculated through other parameters, such as W_2, T_e and R. W_2 could be calculated through W_1 minus Q_f. T_e and R could be calculated based on numerical integration. So here just W_1, Q_f, η, K, T/W, c_f are selected as main performance parameters.

3.3 Object Analysis in SoS Mission

3.3.1 Component System Selection

The component systems in earthquake search and rescue SoS include temporary base, UAVs, helicopters, helicopter crews, weather system, survivors and ground rescuers. However, if all elements are included in the SoS environment, modeling process will become very difficult and the relationships of them will also be extremely complex. Some secondary systems need to be removed or simplified. First, the terrain is so varied and complicated in earthquake areas that ground rescuers cannot play an efficient role in a short time, especially in the zones of low population density such as highlands. Then, helicopter crews can be regarded as a part of helicopter systems. They provide rescue capacity for helicopters. After that weather system can also be neglected because of the short mission time. According to the above analysis, there are only four systems left: temporary base, UAVs, helicopters and survivors.

3.3.2 Relationship of Component Systems

The relationship of component systems is shown as Fig. 5. When starting a mission, the temporary base first decides the mission area and plans a path for each UAV. Meanwhile, it provides ground service for UAVs and helicopters. Then UAVs fly to the origin of their paths and search along the path. Helicopters await orders in the base before survivors are found by UAVs. Once UAVs find exceptional cases, they will fly to accident locations and search for survivors. After confirming the coordinates of survivors, the related information will be sent to helicopters and then UAVs fly back to their own paths for the rest of mission areas. At the same time, helicopters will fly to the coordinates of survivors and rescue them. Because helicopters can only carry limited survivors per launch, they must repeat the rescue until all survivors are in safe. When the last survivor is rescued by helicopters, the mission is complete and the time is set as mission time.

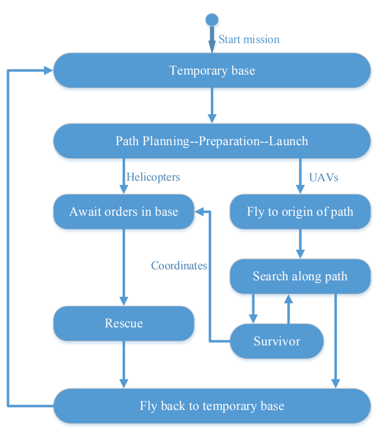

Fig. 5. Relationship of Component Systems

3.3.3 Modeling Method and Operation Logic of Systems

In this case, each component system has a high autonomy and reactivity. Their behaviors are not fixed but alterable according to the complex environment. Compared with other methods, agent-based modeling is chosen to describe each system. The key step of agent-based modeling is to set behavior rules for each agent. The rules might include some variables such as cruise speed, cruise altitude, or some other run-time variables. However, the primary rules are the state-switch rules which drive agents to take different actions based on the information that they received from outside world. The state-switch rules must keep basically the same as the reality so that the behaviors of agents are always logical and acceptable under any external condition. The detailed logic is shown as below. All operation logic must be validated through running and debugging the simulation program repeatedly in different mission conditions. These logic must be accurate enough to conform to the relationship in Fig. 5 in different mission environments after the validation.

Operation logic of temporary base

Temporary base plays an important role in the SoS. It plans a path and search area for each UAV according to the number of UAVs and the radius of their investigation. The path is set as an expanding square pattern [26]. The path width is little shorter than the diameter of investigation so that the scan circle can cover square search area without dead angle. The cruise altitude and the angle range of detection equipment also have an impact on path width. On the other hand, the mission area could be regarded as the set of single search areas. So the splicing shape and the location of temporary base are different as the number of UAVs increases. Fig. 6 shows the different shapes of search area when the number of

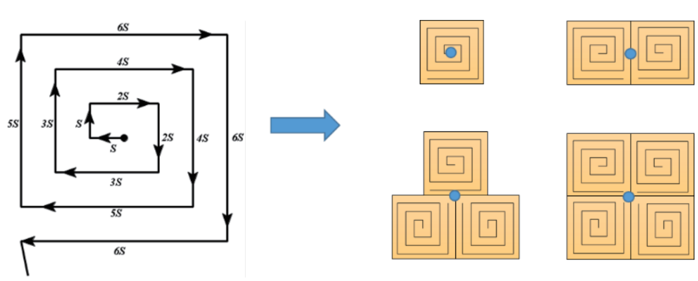

Fig. 6. Search Path of UAVs

UAVs varies from 1 to 4. Different shapes will lead to different locations of the temporary base. The basic principle to set the location is that the sum of distance to the origin of each path should keep the shortest. Another significant principle is that the end point of each path should be set closed to the base as much as possible. Based on this principle, it can be seen that although the calculation methods of each path are the same, there are still some distinctions in the initial direction.

Meanwhile, temporary base also provides ground service for UAVs and helicopters, such as refueling and maintenance. The service duration is described as a distribution, such as a uniform distribution *uniform*(t_{min}, t_{max}) or a normal distribution *normal*(t_{min}, t_{max}, t_{mean}, t_{sigma}), in which t_{min}, t_{max}, t_{mean} and t_{sigma} represent minimum value, maximum value, mean value and standard deviation, respectively.

Operation Logic of UAVs

The operation logic of UAVs is shown as Fig. 7. In the figure, each rounded rectangle represents a certain state of UAVs. The yellow ones represent normal states. The red ones represent unexpected states, such as refueling state in the base. The green one with many states inside represents UAVs in these states have the ability to search for survivors. The connecting lines represent the transitions between states. The lines with a clock icon are activated if the specified amount of time elapses. The lines with a question mark are executed if a certain condition becomes true. The lines with a envelop icon become active if UAVs receives a certain message. The lines with a flag icon are executed when UAVs reach the destination. The figure describes the operation process of UAVs in the mission.

Under initial condition, UAVs stop in the temporary base until they receive the message of starting a mission. After accepting ground service, they fly to the origin of each path. If they find an accident on the way to the origin, they will circle there to search survivors until confirming the coordinates. Afterwards, they continue flying to the origin and then begin searching along the path. When performing a task, they will monitor their fuel consumption all the time. If the fuel weight almost reach the tipping point, which represents the fuel left is just enough for UAVs to fly back to the base, UAVs will stop current mission and fly back for refueling. And even if they find an accident on the way back, they have to neglect it at the moment. However, they are able to search that place after refueling on the way to the breakpoint of the previous launch. There is a special situation that two UAVs might find the same survivor when the survivor is near the boundary of two search areas. In this case, the one that reaches the target first will send message to the other one to prevent it from flying to the same target.

Here some assumptions are made to simplify the logic. In the mission, the cruise speed and altitude always keep the same. Meanwhile, the thrust specific fuel consumption c_f is related to altitude, Mach number and thrust. The first two parameters are fixed here. The last parameter thrust could also be regarded as a constant because the total weight changes little in each launch. So c_f is simplified as a constant in each mission. Under the above assumption, the fuel consumption could also be replaced by endurance. If the endurance left approximates the time of flying back to the base, they will fly back immediately for refueling. Another assumption is that UAVs never miss a survivor.

Operation Logic of Helicopters

The operation logic of helicopters is shown as Fig. 8. When helicopters receive the coordinates of survivors from UAVs, they fly to the targets and rescue survivors. Helicopters can still receive messages about the coordinates of other survivors from UAVs in the rescue task. Once they finish current rescue task, they will fly to next target. If the capacity of helicopters is not enough for another survivor, they will fly back to the base. Each helicopter is allocated to different survivors in order to save resources. Here an assumption is also made to simplify the model. The fuel consumption is not taken into consideration because the research focuses on UAVs. In addition, the whole search area is not large, so the fuel of helicopters is enough to support several launches.

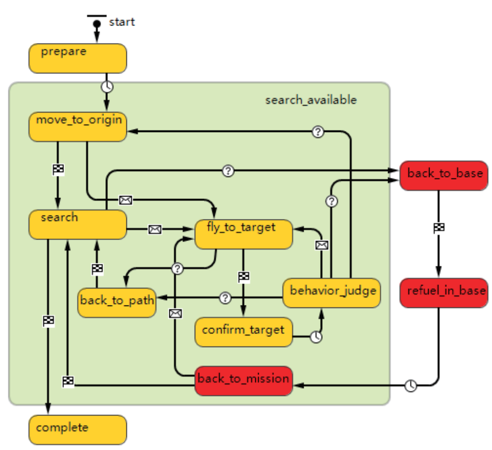

Fig. 7. Operation Logic of UAVs

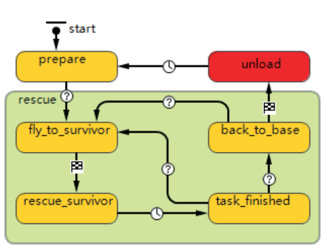

Fig. 8. Operation Logic of Helicopters

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Operation Logic of Survivors

The operation logic of survivors are relatively simple, shown as Fig. 9. Due to the characteristics of survivors, there are three main states which are named helping state, found state and rescued state. The yellow helping state represents that survivors haven't been found by UAVs. Once they are found by UAVs, their states change to the red found state. And then when helicopters reach there, the blue rescued states are active until they are out of danger. After that, survivors disappear from the mission map.

3.4 Operational Simulations of SoS Mission

When carrying out a mission, the factors which could affect the SoS effectiveness should be defined as inputs. Some factors are defined as constant inputs because the resources in a certain mission usually keep unchanged. But the performance parameters should be set as variables because the purpose of operational simulations is to find a competitive combination of parameters from design space. The values of constant inputs are usually defined based on specific circumstances of a certain mission. Changing the values means changing the missions, such as number of UAVs. But the values of performance parameters are usually defined based on the type of UAVs and technical experience. They depend on the material of structure, the engine type and other possible design. The bounds should be wide enough to cover possible values.

In this SoS problem, many factors affect the rescue mission and some of them are random. Survivors are distributed in whole search area randomly. The ground service time of UAVs and helicopters are also random. UAVs spend a random time to confirm the coordinates of survivors. Helicopters also spend a random time to rescue survivors. These unpredictable elements have a great influence on the effectiveness of this SoS. In addition, the focus aims to choose a competitive design point from large amount of combinations of performance parameters. The characteristics of this research result in a comprehensive exploration of design space. Thus, just operating the simulation once cannot lead to relatively accurate outputs. It is necessary to apply a DoE to the operational simulations. Here a Monte Carlo is used to populate the design space to capture variation trends. The parameters which form the design space are the input variables, i.e., W_{gtow}, K, T/W, c_f, η and W_{fuel}. Because the structure of a small size UAV is usually made up of wood, fiberglass and carbon fiber and the engine is usually a small size piston engine, the value of W_{gtow} could not be too large, such as 10 to 15 . The low thrust of the engine will lead to a lower T/W, such as 0.4 to 0.8. Thus a higher K is needed, such as 12 to 24. c_f and η could be set as 0.8 to 1.2 $kg/(kg{\cdot}h)$ and 0.7 to 0.9 respectively based on some small size engine characteristics. And then the space for fuel tank is usually not very large, so W_{fuel} is set as 0.6 to 1.4 kg. The distribution of the value of each performance parameter is set as a uniform distribution because designers cannot predict the best combination in advance. Other system parameters are set as constants, such as the number of UAVs and helicopters, radius of detection, cruise speed and so on. However, the above so-called constants can also change into variables if designers want to study their impacts on effectiveness of SoS. Meanwhile some other random system factors are set as a uniform distribution which remains the same in different simulations, such as ground service time. Here the value of constant inputs are set as Table 1, and the value of input variables are set as Table 2.

The operation scenario is shown as Fig. 10. According to the inputs, there are four UAVs and three helicopters in the temporary base. The length and width of the whole

Fig. 9. Operation Logic of Survivors

Table 1. List of Constant Inputs in DOE

Constant	Description	Value	Units
N_{uav}	Number of UAVs	4	
V_{uav}	Cruise Speed of UAVs	80	km/h
H_{uav}	Cruise Altitude of UAVs	100	m
R_{uav}	Radius of Investigation	280	m
g	Gravity Acceleration	9.8	m/s^2
N_{sur}	Number of Survivors	20	
N_{hel}	Number of Helicopters	3	
K_{hel}	Capacity per Launch	3	
V_{uav}	Cruise Speed of Helicopters	210	km/h
L_x	Length of Search Area	16	km
L_y	Width of Search Area	16	km
T_{rt}	Refueling Time of UAVs	Uniform(8,12)	min
T_{gh}	Ground Service Time of Helicopters	Uniform(3,5)	min
T_{ct}	Confirming Time of UAVs	Uniform(1,3)	min
T_{rs}	Rescue Time of Helicopters	Uniform(8,12)	min

Table 2. List of Variables in DOE

Variable	Description	Distribution	Units
W_{gtow}	Gross Take-off Weight	Uniform(10,15)	kg
K	Lift-Drag Ratio	Uniform(12,24)	
T/W	Thrust-Weight Ratio	Uniform(0.4,0.8)	
c_f	Thrust Specific Fuel Consumption	Uniform(0.8,1.2)	$kg/(kg \cdot h)$
η	Thrust Efficiency	Uniform(0.7,0.9)	
W_{fuel}	Fuel Weight	Uniform(0.6,1.4)	kg

search area are both 16 kilometers. The whole mission area is divided into four pieces. The paths of four pieces are a slightly different. The green house in the center represents the temporary base. The light blue circle with an aircraft icon is a UAV. The pink circle near the base with a helicopter icon is a helicopter. The yellow circle with a person icon is a survivor in helping state. The red circle is a survivor in found state. And the dark blue circle is a survivor in rescued state. The red shadows represent the areas which have been searched by UAVs.

Based on a Monte Carlo, 20000, 30000 and 40000 design points are used to capture the stochastic nature in the SoS simulation respectively. The results between 20000 and 30000 are a little different, but the results between 30000 and 40000 are almost the same. So 30000 design points are decided for Monto Carlo simulations from the perspective of computational accuracy and saving time in the following key-parameters analysis step. Each run completes in about one second and the total calculation time lasts about 90 minutes by means of parallel evaluations. In each run, mission time is chosen as the main output because this variable reflects the effectiveness of SoS best and it is also the greatest concern for designers in the simulations. In search and rescue SoS, the shorter mission time is, the better the effectiveness is. The probability distribution of mission time is shown as a histogram which can help designers to find the variation trends.

In general, the statistic of all cases can surely provide useful information of overall operational simulations. However, designers might care more about some special cases. For example, the purpose is to finish the mission in two to three hours which are acceptable in reality for earthquake search and rescue. So the scenarios in which mission time is shorter than two hours or longer than three hours will be neglected. In the first scenarios a higher performance requirement of UAVs will increase the life-cycle cost. And in the second scenarios the UAVs with a lower performance are undesirable. In addition, in the selected scenarios, designers are more interested in how to decrease the performance of UAVs without losing much effectiveness of SoS for the purpose of reducing difficulties and saving cost. So the quantitative relationship between performance parameters and effectiveness of SoS should also be output.

3.5 Key-parameters Analysis of Simulation Results

In this step, designers focus on analyzing the data of chosen cases. First, a constraint is set to filter eligible cases. The upper bound is set as 180 minutes and the lower bound is set as 120 minutes. Among 30000 cases, 20656 cases is in the interval. The histogram of probability distribution is shown as Fig. 11. The histogram in blue represents all 30000 cases. The histogram in yellow represents the selected 20656 cases. Some blue bars are invisible because they are covered by yellow bars. The statistics such as the mean and the standard deviation, are shown in the right side of Fig. 11. However, the contribution of them is limited in analyzing the relationship between the performance parameters and the effectiveness. Thus, the data should be analyzed from the view of each performance parameter in depth.

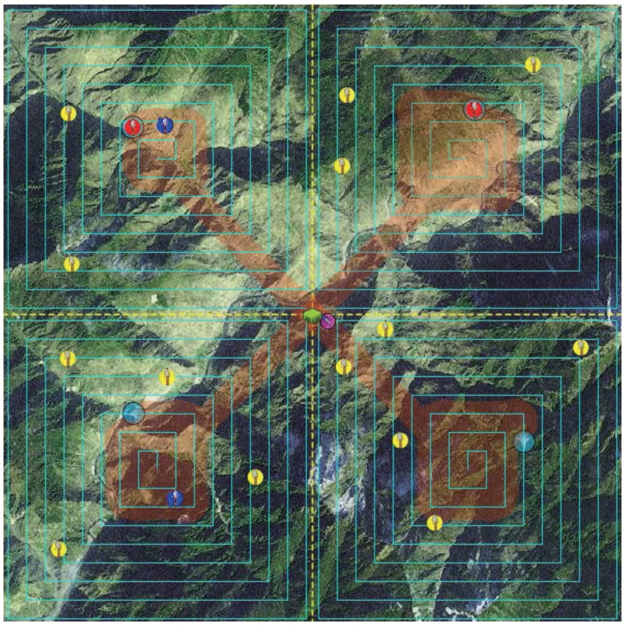


Fig. 10. Operation Scenario of Earthquake Search and Rescue SoS

The histograms about the variation of performance parameters are shown in Fig. 12. The x axis represents each parameter in design space: gross take-off weight, lift-drag ratio, thrust-weight ratio, thrust specific fuel consumption, thrust efficiency and fuel weight. The y axis represents the percentage of the number of cases. The light blue bars represent the piecewise probabilities of all 30000 cases within the range of all the inputs. It is easy to see that the probability distribution of all cases is uniform because the input parameters are set as equally probable on their value intervals. The blue bars represent the piecewise probabilities of the selected cases with a constraint. The comparison of their probability distributions provide some valuable information. Through analyzing the probability variation of the selected cases corresponding to parameter variation, the key-parameters that the effectiveness are sensitive to can be obtained.

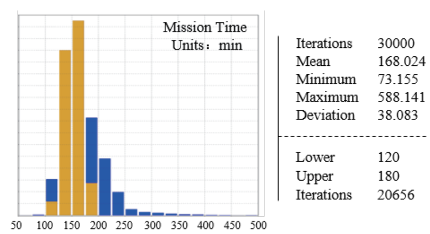
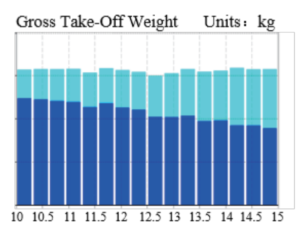


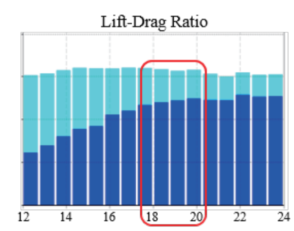
Fig. 11. Histogram of All Cases and Selected Cases

Figure 12(a) shows the relationship between gross take-off weight and the effectiveness of SoS. The probability of eligible cases decreases slowly as gross take-off weight increases, because the fuel consumption increases as the total weight increases. Thus, UAVs have to fly back to the base for refueling more frequently. However, the variation is not evident if adding one more kilogram payloads to current UAVs. So gross take-off weight is not the key-parameter which should be taken into account first. When designing a new UAV, the total weight could be set as 11 kilograms to 12 kilograms.

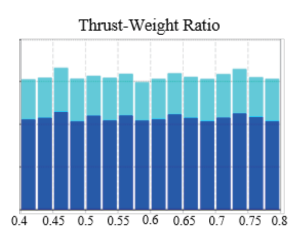
Figure 12(b) shows the relationship between lift-drag ratio and the effectiveness of SoS. It can be seen from the histograms that the height of blue bars increases sharply when the lift-drag ratio changes from 12 to 18. And then the height becomes steady. This is because the thrust decreases as the lift-drag ratio increases, which leads to less fuel consumption and longer endurance. However, once the lift-drag ratio is enough, it doesn't improve the effectiveness further even with a higher lift-drag ratio. It can be speculated that in these cases, it is no longer UAVs but other component



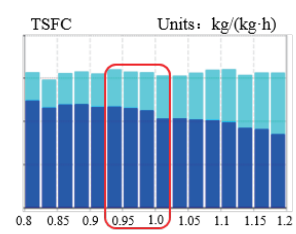
(a) Probability Distribution of



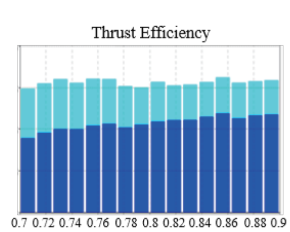
(b) Probability Distribution of



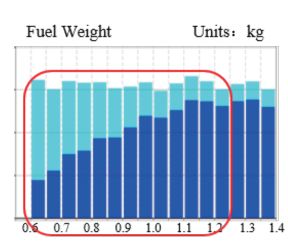
(c) Probability Distribution of



(d) Probability Distribution of



(e) Probability Distribution of



(f) Probability Distribution of

Fig. 12. Histograms of Cases from the View of Parameters

systems that begin to affect the effectiveness. However, lift-drag ratio is still a key-parameter which should be paid more attention to, especially the area in the red rounded rectangle. If designers want to design a competitive UAV, the lift-drag ratio might be set as 19 to 20, a value easy to achieve. The benefit is that designers can choose more conventional airfoils which can be processed more easily.

The effect of thrust-weight ratio is shown in Fig. 12(c). The thrust-weight ratio is also not a key-parameter. It can be seen that the height of blue bars remains relatively stable as thrust-weight ratio increases. This is because the thrust is not required too much under the condition of a relatively high lift-drag ratio and a relatively light total weight. That is to say, designers can actually choose a cheap and low-thrust engine, such as with a reference thrust-weight ratio 0.4 or 0.5.

The effect of thrust specific fuel consumption is shown in Fig. 12(d). Thrust specific fuel consumption has an impact on the effectiveness of SoS. It can be seen that the height of blue bars first keeps relatively flat but falls steady after 1.0. Thrust specific fuel consumption is also a key-parameter. Some engines with low thrust specific fuel consumption are more expensive because their manufacturing and processing are more precise. So this parameter could be set a litter higher from the perspective of saving cost. The reference value might be in the red rounded rectangle, such as 0.95 to 1.0.

According to Fig. 12(e), thrust efficiency is not a key-parameter as well. Although the height of blue bars increases as the thrust efficiency increases, the variation is very slow. To some degree, it is unnecessary for designers to spend too much time and cost in improving thrust efficiency. A conventional thrust subsystem is enough for UAVs, such as with a reference value 0.76 to 0.8.

According to Fig. 12(f), fuel weight is also a key-parameter which have a great impact on the effectiveness of SoS. It can be seen that the height of blue bars increases sharply from 0.6 kilograms to 1.1 kilograms and then levels off. The transition happens in the red rounded rectangle. It is because the UAVs with more fuel can search for a longer time per launch. Once the fuel weight reaches a certain point, more fuel doesn't really help much. Instead the redundant fuel will increase the total

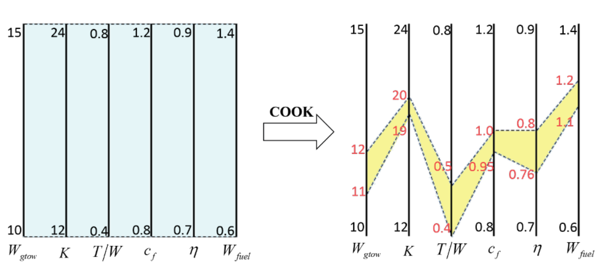


Fig. 13. Comparison of Design Space before and after Exploration

weight. However, the fuel weight should be set bigger than critical value in case of accidents. Thus the fuel weight could be set as 1.1 kilograms to 1.2 kilograms. On the other hand, less fuel weight is conducive to structure design. The smaller the fuel tank is, the more space is available for other elements.

After the key-parameter analysis, the comparison between the initial design space and the one after exploration is shown as Fig. 13. It is easy to see that the size of design space is largely reduced after exploration based on SoS simulations. According to the modified design space, designers will have a clearer objective in the next design phase.

4. Conclusion

From the earthquake search and rescue SoS, it can be seen that the methodology named COOK provides a feasible and logical analysis process on exploring design space in aircraft conceptual design phase. And it can be seen from the example that the design phase of UAVs is well connected with the operational phase through the above four steps. It helps designers to achieve a competitive design based on SoS simulations from the perspective of SoS optimum.

The results show that in complicated SoS environment, aircrafts which produce an SoS optimum might not be the aircrafts with best performance parameters. Instead, preferred aircrafts should cooperate with other systems excellently and meanwhile they are not expensive and are easy to design, manufacture, operate and maintain. This exploration relies on SoS simulations.

However, the methodology still needs continuous improvement. For instance, design or operation cost could be taken into account in future researches and more detailed performance parameters could be analyzed based on SoS simulations.

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