Evaluating Design Decisions in Real-Time Using Operations Modelling

Benjamin Schumann[1], James Scanlan[2] and Kenji Takeda[3]
University of Southampton, Southampton, Hampshire, SO17 1BJ, UK

Using operational simulations during the early design phase has been largely neglected within the aerospace industry. This paper suggests that an operational simulation should be used twofold by designers during the design process to improve a product. First, it presents how an operational simulation can be used to react to customer specifications. Second, its active use as a design decision support tool is portrayed. Results are found by means of two case studies recreating the operational life of a Search-and-Rescue Unmanned Air Vehicle developed in parallel at the University of Southampton. The simulation's ability to act as a decision support tool is explored by conducting a fuel weight optimization. Reactive capabilities are explored by calculating the surplus value of using UAVs. This exemplifies the derivation of product specifications as the simulation reveals the value and hence usefulness of supplied customer specifications. It is shown that operational simulations benefit designers and overall product value by analysing product specifications and guiding designers to more informed design decisions.

Nomenclature

MCA	=	Maritime Coastguard Agency
RNLI	=	Royal National Lifeboat Institution
SAR	=	search-and-rescue
UAV	=	unmanned air vehicle
VDD	=	value-driven design present

I. Introduction

In the past, design processes of aerospace products generally focused on customer specifications in order to meet expectations. Life cycle costs, design space exploration and value engineering were neglected, often leading to substantial cost overruns, delivery delays and inferior quality in the final product. Moreover, customer specifications were not scrutinized and design decisions made ignoring potential operational knowledge. Due to these shortcomings, new approaches to product design emerged. Manufacturers are now striving to understand life-cycle costs, explore the design space and focus on the value that a product will generate for the customer and the manufacturer.

In order to obtain a competitive design, it is desirable to understand the life-cycle cost implications from the early concept stage[1]. However, obtaining detailed, trustworthy and useful cost information from early concept geometry is nearly impossible, potentially compromising the whole project[2,3]. A useful cost model needs to address the complexity of costs, the non-objectivity of cost estimates and the cost drivers outside the design[4]. An operational simulation can inform upon the latter early on, improving the quality of the cost model.

A. Value-driven design

Value-driven design is an emerging approach to product design that introduces flexible customer specifications aiming to output the optimal design based on a value-function[5]. It allows system-wide design optimization during the early design phase as well as component optimization during the detailed design phase. A value-driven design is chosen by engineers as the best possible design rather than any design meeting the design requirements[6]. This choice is based on ranking different designs using a value function. Ranking is unambiguous because the value function transparently and consistently assigns unique scores to each design[7]. Value-driven design replaces the need for traditional system requirements like maximum weight or cost because designers

[1] PhD-student, Computational Engineering Design, Benjamin.Schumann@soton.ac.uk.
[2] Professor of Design, Computational Engineering Design, J.P.Scanlan@soton.ac.uk.
[3] Senior Lecturer, Aerodynamics and Flight Mechanics, KTakeda@soton.ac.uk.

aim to optimize overall system value[8]. This increases the chance to find an optimal design by several orders of magnitude[6].

Collopy[9] states that a useful value function must also incorporate operational metrics of a product. So far, this information is usually based on engineering judgement, experience and estimates. A simulation of the anticipated operational life of a product can specify operational metrics and analyse customer specifications.

B. Research question

This research investigates the “active” and “reactive” use of an operational simulation in order to improve cost information and specify operational metrics. The following questions are addressed:

- Can operational knowledge be used to optimize a product? Here, a designer *actively* seeks the optimum design beyond customer requirements.
- Can comprehensible and useful product definitions be derived from operational information? This conforms to a designer *reacting* to given customer specifications.

Both problems are examined using case studies of a real-life Search-and-Rescue (SAR) Unmanned Air Vehicle (UAV). Section II details the operational simulation developed for the case studies. The results are presented in section III followed by a discussion and critical appraisal in section IV.

II. Methods

A. Overview

Aerospace product complexity grows[10] and customer specifications include inherently stochastic variables such as reliability and process consistency[11]. Combining probability distributions even for simple systems either returns unmanageable equation sets or simplified models with low fidelity. In order to simulate complex stochastic operations, numerical modelling is the only viable tool to date that allows uncertainty and discontinuities to be implemented at any stage. The most appropriate simulation technique for the scenario described here is agent-based modelling.

Agent-based models have become widespread during the last decade, supporting research in diverse scientific areas. In engineering, agents have been used to model engine fleets[12], airline personnel and airline operations[13]. Agents are implemented as active objects that can act *autonomously*. Each agent is assigned role-specific if-then-else algorithms that determine its behaviour in a given environment. Therefore, agent-models can be created using a bottom-up approach rather than a top-down approach. This allows creating useful system models despite limited system knowledge. The draw-back of agent-based modelling in engineering is its inherent unpredictability regarding complex agent interactions. However, the limited number of agents used here combined with knowledge about the anticipated overall system behaviour avoids these problems.

The Java-based AnyLogic[14] has been chosen due to its integration of agent-based as well as discrete-event modelling. AnyLogic is also able to create user-friendly standalone applications that can be used without specialist knowledge by designers and engineers.

The model recreates a real UAV developed by the DECODE-project at the University of Southampton (Fig. 1). DECODE develops decision environments for complex designs and tests them by designing and building real UAVs. The UAV used for the simulation is the initial version featuring a maximum take-off weight of 10 kg and a wing span of about 2 metres. The operational simulation presented here is part of the DECODE software stack that is used to iteratively design UAVs.

Figure 1. DECODE UAV, first iteration.

B. Model structure

The case studies are conducted using a model of the SAR environment of the Solent, a major shipping and leisure area at the south coast of the UK. The Solent has the highest number of SAR incidents in the UK[15]. It is covered by a dense network of seven Royal National Lifeboat Institution (RNLI) lifeboat stations and a Maritime & Coastguard Agency (MCA) helicopter base, making it an ideal test bed for investigating the influence of

SAR UAVs. The UAV can support search activities by circling an area and communicate a casualty position to other vessels for a quicker recovery.

The simulation model is based on a central agent imitating the coastguard responsible for the Solent-area. It represents the decision-making authority that coordinates rescue resources and activities. The coastguard has authority about the number of vessels to dispatch to a casualty, the type of vessel to dispatch (helicopter, lifeboat or UAV) and which specific agent to be deployed. The coastguard dispatches the nearest available and most appropriate vessel. Depending on the casualty type and the position knowledge (see Appendix), there are five dispatch options available (Table 1).

Table 1. Coastguard dispatch options and conditions

	Dispatch option	Casualty position known?	UAV in range?
1.	Helicopter only	Yes	irrelevant
2.	Lifeboat only	Yes	irrelevant
3.	UAV only	No & no lives threatened	Yes
4.	Helicopter & UAV	No	Yes
5.	Lifeboat & UAV	No	Yes

If the casualty position is known, UAVs are not dispatched for search. Only one UAV can be dispatched to any one casualty. The effect of UAV swarms is not investigated. Moreover, each casualty is rescued by either the helicopter or a lifeboat. In reality, about 20% of all casualties are supported by both types simultaneously but this is neglected here. Some lifeboat stations house multiple lifeboats and the coastguard dispatch decision is based on lifeboat statistics supplied by the RNLI[16]. UAVs are deployed by the coastguard depending on the casualty type and the associated positional knowledge. UAVs are dispatched to about 60 % of lifeboat casualties and 30 % of helicopter casualties where a quick recovery is desired. This reflects the fact that UAVs are unlikely to be used on every possible mission and that helicopter crews will be reluctant to use UAVs in parallel with their own mission. For the minority of missions where there is no danger to lives (beacon searches, etc.), UAVs are dispatched without a helicopter or a lifeboat.

Casualty agents are created according to RNLI statistics[16] and helicopter data supplied by the MCA[17]. Both datasets include a seasonal variation of incidents because summers are generally 3-5 times busier than winters. The day-night distribution of incidents is neglected because additional risks of night-time missions are not known. The MCA assigns 14 different casualty types that have varying certainties of position (see Appendix). Helicopter casualties are distributed across shore, near-shore or sea areas. Lifeboat casualties are distributed around lifeboat stations according to distance information supplied. Each casualty emits a help signal to the coastguard once it appears. Subsequently, it waits passively until a vessel finds and rescues the casualty upon which it is destroyed.

The helicopter used around the Solent is the Agusta-Westland Aw-139 with a top speed of 145 knots and 2.5 hours endurance. Its behaviour is modelled using the general vessel operation cycle depicted in Figure 2.

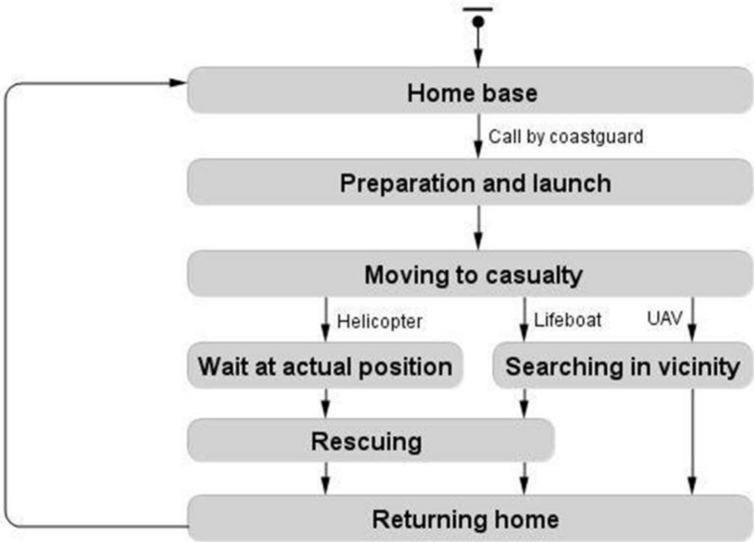

Figure 2. General vessel operations cycle.

Unlike lifeboat and UAV data, the helicopter database includes the durations to search for casualties and rescue them. Therefore, the duration of the varying mission stages dictates the helicopter behaviour directly.

There are nine lifeboat agents spread across seven RNLI-stations. Lifeboat agents vary in cruise speed and number of crew aboard according to their type. Lifeboat agents follow the operation cycle shown in Fig. 2. Once called for dispatch by the coastguard, lifeboats are prepared for launch (time supplied by RNLI-data[16]). Subsequently, the lifeboat moves into the vicinity of the casualty in order to start its search. The distance between the initial search position and the actual casualty position depends on the coastguard knowledge of the casualty position. Therefore, searching for casualties with exact knowledge of position takes less time than searching for lost casualties.

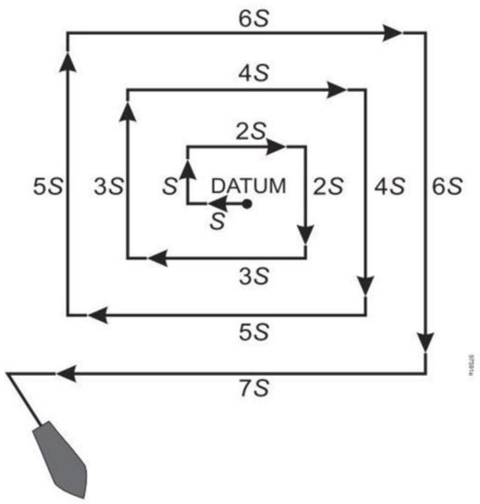

Figure 3. Expanding square pattern[18]

The lifeboat initiates an 'expanding square pattern' search from its initial search datum as in Fig. 3. The path width S depends on the number of crew aboard. In this model, lifeboats never miss a casualty: upon passing a casualty, they spend between 1 and 30 minutes to rescue it (uniformly drawn). This value is estimated as the RNLI does not collect this information. After rescuing, the lifeboat returns to its home base.

UAV agents also follow the vessel operation behaviour depicted in Fig. 2. Preparation time is uniformly drawn between 1 and 15 minutes as is anticipated of future service. Similar to lifeboats, the UAV moves into the vicinity of a casualty (distance depends on the casualty position knowledge) and starts the expanding square pattern search (Fig. 3). The path width S depends on its height and camera sweep angle. The UAV monitors its fuel status and cancels a search if required for a save return journey. Upon crossing a casualty, the UAV discovers the casualty with a probability that depends on its height, camera properties and weather. On average, the success rate of spotting a casualty upon crossing is just below 50 % (Fig. 4). UAVs announce casualty discovery or failure of discovery to the respective rescue vessel directly and return home.

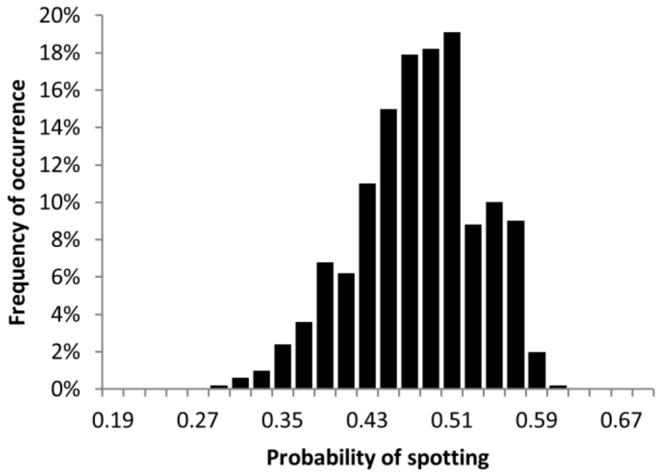

Figure 4. Probability histogram of UAVs spotting a casualty upon crossing

Realistic vessel operations and coastguard-vessel interactions were implemented using a bottom-up approach. Thereby, helicopter missions, lifeboat dispatch scenarios and coastguard decision algorithms could be recreated directly. All agents interact in discrete events in order to keep computation times reasonable.

Another part of the model is the cost estimation algorithm. In theory, a value model consistently computes numerical scores for different designs in order to compare them. They can be used for trade studies, design optimization, design space exploration and technology evaluation[19]. In this report, a simple value model derives cost data from the operational simulation and is used for technology evaluation ("reactive" use) and optimization ("active" use). The model focuses on the change in cost caused by design changes, rather than absolute cost. Predictive accuracy is secondary because value models cannot be calibrated in the traditional sense. It is more important if the value model can easily differentiate and rank designs[20]. The value model presented here omits expected utility for simplicity. According to Lave and March[21], economic models should be judged according to their truth, beauty and justice by which they mean model accurateness, simplicity and usefulness for progress respectively. The cost model used here is not accurate but simple and justified.

The model sums the costs for each vessel type (helicopter, lifeboats and UAVs) after calculating the individual vessel contributions using a simple divide-and-conquer approach as in Equ. 1. The component costs are estimated from RNLI publications[17,22], MCA data[18] and the engineers that construct the real-life UAV.

$$\begin{aligned} Total\ cost =& (cost\ per\ vessel * number\ of\ vessels) \\ &+ (cost\ per\ launch * number\ of\ launches) \\ &+ (cost\ per\ flight\ hour * number\ of\ flight\ hours) \\ &+ (maintenance\ cost\ per\ year * number\ of\ years) \end{aligned} \tag{1}$$

It is difficult to validate this value model against reality because it is almost impossible to compare. System costs cannot be calculated because the system boundaries are arbitrary. Component costs are difficult to obtain due to company policies. However, the simplicity of the model makes it reasonable to use, transparent and repeatable, the properties required for useful value models by Collopy[19].

As for any useful simulation model, validation was the last major step of model creation. The simulation model recreates the real operational environment of the Solent Search-and-Rescue environment in order to see the effect of introducing UAVs. Therefore, model validation was carried out by comparing the baseline case (no UAVs) to real world data. The model reproduced the distribution of casualties over the year, the time to find and rescue casualties, the distribution of casualties during varying wind speeds and the number of helicopter to lifeboat missions. Repeated model walk-throughs and a graphical representation (Fig. 5) supported validation throughout model construction.

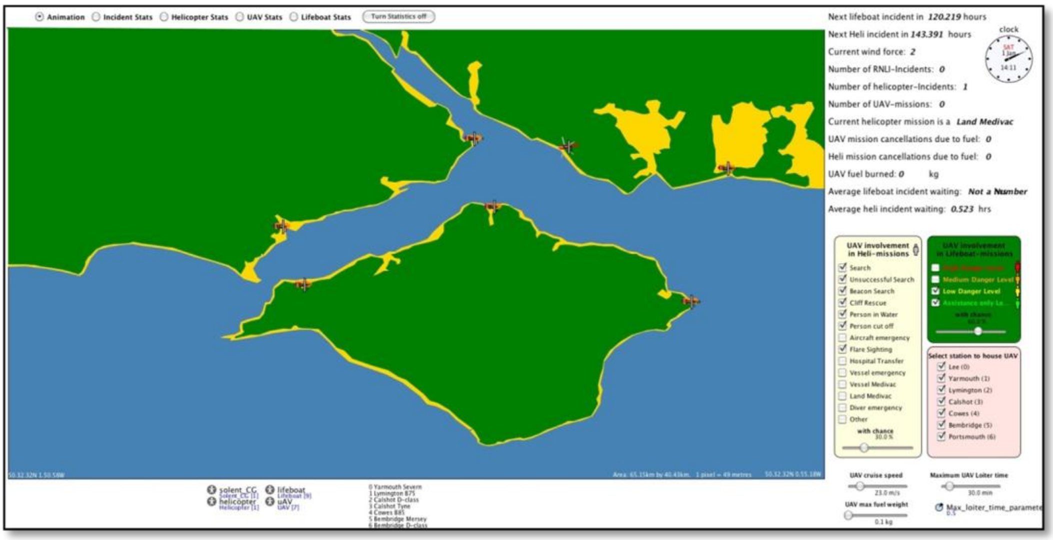

Figure 5. Graphical user interface (part)

III. Setup and Results

A. "Reactive" case study setup

In order to demonstrate product specification derivation using an operational simulation, envisage the following hypothetical situation: A design team is designing a Search-and-Rescue UAV according to the Value-driven design approach. Therefore, no extensive product attributes (such as maximum allowed cost, maximum weight, etc.) are known during the early design phase. The designers need to explore and understand the extensive product specifications in order to evaluate and improve the design. As part of this investigation, the simulation model described above is used to assess the maximum allowed cost of the UAV to be economically feasible. The simulation is setup as follows:

A baseline simulation scenario recreates the operational environment of the SAR-area before the UAV appears on the market. Additional scenarios which include UAVs contrast the baseline scenario. In this case study, seven additional scenarios are created each introducing another UAV to observe the effect on the overall system cost. The reason to choose seven scenarios is based on the assumption that each of the local six lifeboat stations and the helicopter base will house one UAV. It is beyond the scope of this research to observe the effect of multiple UAVs for any one station. Scenario results are averaged across 50 simulation runs including standard errors to judge uncertainty. Each simulation run covers a simulated period of 10 years. Each scenario is setup such that the overall service level remains constant. This ensures comparability of cost between different scenarios. The service level metric used is the time a casualty waits for its rescue. Time-to-rescue directly measures the success of Search-and-Rescue operations because it relates to casualty survival rates[23]. The coastguard could deploy UAVs such that they improve the overall service level at constant system cost. However, the possibility of reducing cost by maintaining satisfactory service levels is more reasonable for government agencies. The total system cost changes due to additional UAV costs and savings accrued in helicopter and lifeboat operations. Savings can be achieved in two ways: (i) the helicopter or lifeboat waits at its base until a UAV has found a casualty not in danger of death, thereby reducing vessel operating time. (ii) Helicopter/lifeboat operating time is reduced because a UAV supports the vessel and the casualty is spotted quicker. Lifeboat and helicopter operating costs are about 2 orders of magnitude higher than operating the UAV. Therefore, any reduction is desirable.

B. "Reactive" case study results

Figure 6 summarises the cost impact of introducing UAVs.

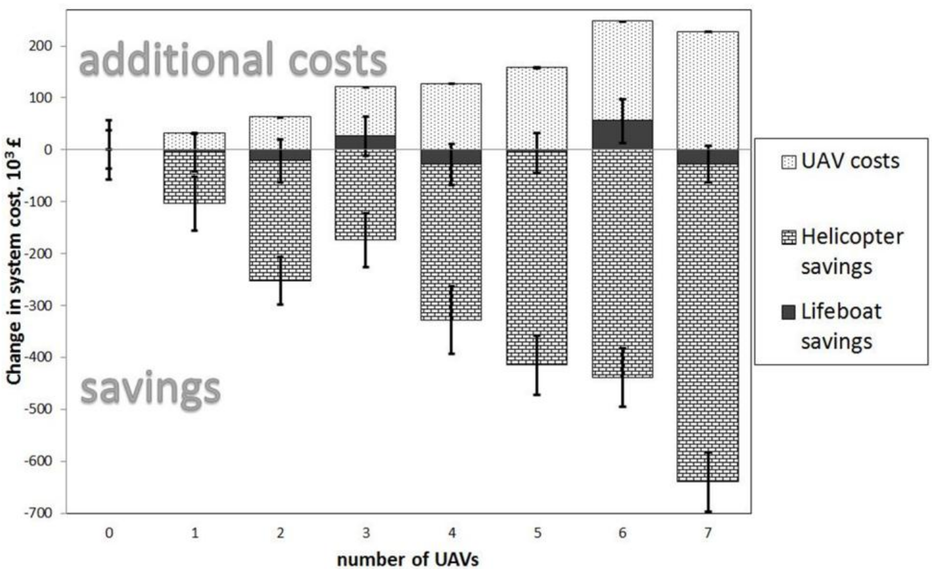

Figure 6. Change in system cost due to introducing UAVs

The overall system cost reduces if one or more UAVs are introduced. Additional costs for UAVs are significantly less than cost savings from reduced helicopter usage. Both cost additions and savings increase linearly with the number of UAVs. On average, the UAV saves 2.3 times compared to what it costs ($\sigma = 0.6$). Lifeboat costs do not change significantly. Lifeboat and helicopter uncertainty is high due to high hourly operational costs amplifying stochastic effects. UAV costs are two orders of magnitude lower constraining random variables to have negligible effects.

C. "Active" case study setup

This case study demonstrates the active use of an operational simulation for a product designer. Assume the designer has an initial UAV design that needs to be optimized for its intended use as a Search-and-Rescue support UAV. As part of this, the fuel tank size is a critical aircraft parameter because it determines the range of the UAV, indicating the proportion of casualties it can support from its home base. If the tank size is too small, the UAV cannot reach enough casualties and becomes ineffective. However, if the fuel tank is too large, the aircraft's structural weight increases together with operational costs. Therefore, an optimum fuel tank size must be found to satisfy these constraints.

The simulation is set up as before, recording the overall system cost as the output. However, the number of UAVs is kept constant at seven in order to observe the maximum impact on system cost. The fuel tank size is varied between 0 and 10 kilograms in steps of 0.1 kilograms. Each scenario is averaged across 35 iterations in order to achieve statistically relevant 95% confidence intervals. For each fuel tank size, the overall system cost is recorded. System cost is normalized with regards to the case of UAVs having zero fuel tank capacity.

D. "Active" case study results

Figure 7 shows the results of optimizing the fuel tank size to minimize overall system cost.

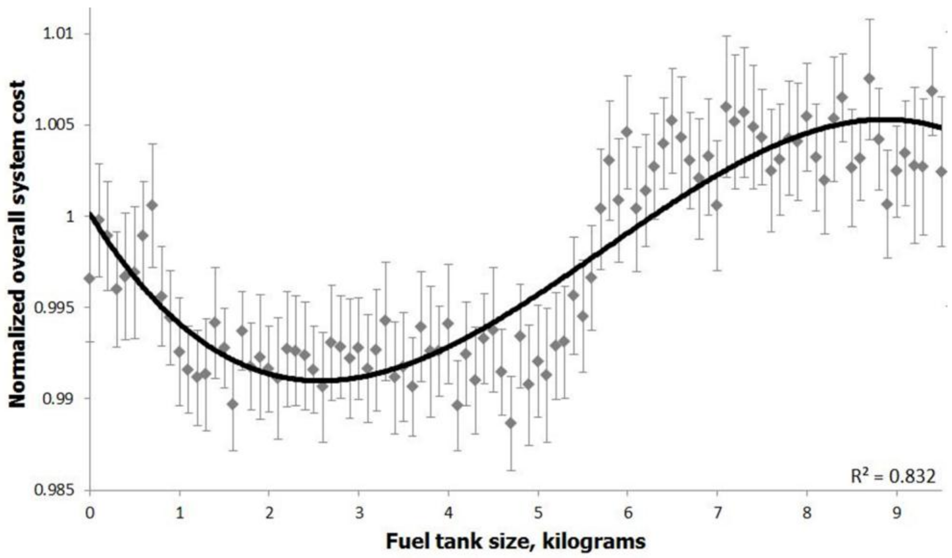

Figure 7. Fuel tank size versus system cost

There appears to be an optimum fuel tank capacity somewhere between one and five kilograms. A third-order polynomial trend-line with $R^2 = 0.832$ suggests an optimum at 2.6 kilograms. Below one kilogram, the system cost rises up to the baseline case with zero fuel capacity. Above five kilograms, the system cost rises sharply to about 0.5% above the baseline cost. Between six and ten kilograms, the system cost stays constant.

IV. Discussion

A. "Reactive" case study

The result (Fig. 6) clearly indicates to the designer that the current UAV would create value during its operational life. This value is predicted based on operational and product performance. The simulation predicts a reduction in helicopter flight hours based on the specific UAV performance. This demonstrates the reactive use of an operational simulation: the designers can now quantify the maximum feasible cost that the UAV may accrue during its life. In this example, the maximum allowable cost to create value would be 2.3 times higher than the current cost. Additional costs can comprise UAV acquisition, maintenance or operational costs. Unlike contemporary approaches, this cost estimate is more complete as it is founded on operational as well as product performance.

Lifeboat costs do not change significantly because it is anticipated that lifeboat crew will dispatch to most casualties even with the support of a UAV. Therefore, lifeboat operation costs will not reduce significantly. The linear increase in value by using more UAVs is finite: at some point, the introduction of additional UAVs will cease to reduce the helicopter usage because the helicopter has to fly a minimum amount of time to actually rescue casualties. It is beyond the scope of this research to investigate how many UAVs would be required to achieve this tipping point.

This case study neglects the influence of other constraints during product design. In reality, the operational simulation would serve as an analysis tool among many to increase the value of a product. Investigating the relationship between the operational simulation and other design tools such as CAD, CFD or advanced cost models is beyond the scope of this research and reserved for future work as part of the DECODE-project.

B. "Active" case study

At the optimum fuel tank size, UAVs can reach enough casualties to reduce lifeboat and helicopter usage as much as possible without excess structural weight. Below the optimum, UAVs increasingly fail to support conventional vessels, thus increasing the overall cost of the system. Above the optimum, UAVs do support all missions but system cost increases due to flight performance penalties such as increased fuel consumption. Note that the UAV modelled here has an empty weigh of about 8 kilograms. In reality, a UAV of this size can accommodate a maximum fuel tank capacity of about 3.2 kilograms on average[24]. Therefore, the upper end scenarios in Fig. 7 are not realistic because fuel tank capacity approaches or equals the empty weight of the aircraft. In this case study, the designer could incorporate the optimum operational fuel tank capacity of 2.6 kilograms because it is within the structural limits of the aircraft.

The maximum system cost reduction of 1% is significant. Using the simple cost model described above, the estimated cost of maintaining the Search-and-Rescue system around the Solent is £ 5.8 million per year. The cost savings from an optimal fuel tank capacity could amount to £ 50,000 per year for the Solent alone. Similarly, a non-optimum fuel tank could increase overall system cost by up to £ 25,000 per year. Therefore, using an operational simulation to optimize design parameters is important.

In reality, product designers would optimize many more design parameters for the intended operations, potentially reducing operational costs further. Combining traditional product optimization with operational optimization could yield further cost reductions and prevent unrealistic cost estimates.

C. Criticism

The case studies demonstrate the feasibility of product specification estimation and optimization through operations modelling. It is not an absolute measure of truth. The simulation model is based on real SAR procedures captured through interviews. Several simplifying assumptions were incorporated throughout model development to keep results tractable:

- The complex dispatch decision network of lifeboat crews, the MCA and local coastguards was condensed into a simple decision tree based on casualty type and UAV-status.
- Vessel cooperation is limited to UAVs plus one vessel. Helicopter and lifeboat missions are strictly separated.
- UAVs and vessels can only serve one casualty at a time. Search patterns are restricted to the "Expanding Square"-type.
- Operations are not constrained by visibility, wind or temperature.

The cost model is very simple but relies on engineering rationales. However, its simplicity causes high uncertainty regarding the quantitative results in this work.

The quality of data used for this simulation varies. The RNLI provides very detailed statistics on casualties and service levels. However, it lacks certain core information (the time to rescue casualties) that were estimated using operational simulation. The MCA-data for helicopters offered the rescue times but covered one year only, potentially skewing the helicopter performance. UAV-data was provided by the DECODE-team designing the real UAV.

V. Conclusion and future work

It has been shown that an operational simulation can be beneficial for product designers during the early design phase. Using the simulation "actively" as an optimization tool reveals designs that are fit for the product environment. A "reactive" use is presented that yields information about extensive product attributes such as maximum cost. This information is especially useful in systems engineering environments that divert from fixed product specifications in order to find optimal designs.

Future work will focus on developing a more generic operational simulation. It is important to understand how a simulation can incorporate a variety of product utilization scenarios so that designers can estimate the impact of their product for potential uses early on. The aim is to find a trade-off between sufficient model fidelity and maximum model generality. Another important aspect of future research is to incorporate the simulation into a Value-driven design workflow within the DECODE project. The aim is to utilize the simulation in a real test case to see how designers can best profit from such a tool.

Appendix

This table lists the helicopter casualty types as used by the MCA and their frequency of occurrence according to data gathered during 2009 for Lee-on-Solent. The 'position' column indicates the knowledge about casualty positions assumed in this model. This determines the dispatch of UAVs for these casualty types.

Table 2. Helicopter casualty types and UAV deployment

SAR-type	Likelihood (%)	Position	UAV-deployment
Search	21.5	Unknown	Yes
Beacon search	4.3	Unknown	Yes
Unsuccessful Search	2.4	Unknown	Yes
Person in water	12	Partly unknown	Yes
Cliff rescue	6.2	Partly unknown	Yes
Person cut off	2.4	Partly unknown	Yes
Aircraft emergency	1.4	Partly unknown	Yes
Flare sighting	0.5	Partly unknown	Yes
Hospital transfer	17.2	Known	No
Land evacuation	12	Known	No
Vessel evacuation	8.1	Known	No
Diver emergency	4.3	Known	No
Vessel emergency	3.3	Known	No
Other	4.3	N.A.	Yes

Acknowledgments

This research was funded by the EPSRC Doctoral Training Centre grant EP/G03690X/1 and the EPSRC grant EP/H007431/1 for the DECODE-project. The authors would also like to thank the RNLI-crew at Calshot and the MCA-crew at Lee-on-Solent for their valuable feedback and criticism.

References

[1]Collopy, P. D., and Eames, D. J. H. "Aerospace Manufacturing Cost Prediction from a Measure of Part Definition," *World Aviation Congress and Exposition*, Society of Automotive Engineers, Seattle, USA, 2001.

[2]El-Diraby, T. E., "Web-services Environment for Collaborative Management of Product Life-Cycles," *Journal of Construction Engineering and Management*, Vol. 132, No. 3, 2006, pp. 300.

[3]Park, J. H., and Seo, K. K., "Incorporating Life-Cycle Cost into early Product Development," *Journal of Engineering Manufacture*, Vol. 218, 2004, pp. 1059-1066.

[4]Collopy, P. D. "The Challenge of Modelling Cost: The Problem," *1st International Conference on Innovation and Integration in Aerospace Sciences*, CEIAT, Queen's University Belfast, Belfast, Northern Ireland, 2005.

[5]Cheung, J. M. W., Scanlan, J. P., and Wiseall, S. S., "An Aerospace Component Cost Modelling Study for Value-driven Design," *CIRP IPS2 Conference*, University of Cranfield, UK, 2009.

[6]Collopy, P. D., and Hollingsworth, P., "Value-driven Design," *9th AIAA Aviation, Technology, Integration and Operations Conference*, AIAA, Reston, VA, 2009.

[7]Collopy, P. D., "Assigning Value to Reliability in Satellite Constellations," AIAA, Technical Report 2003-6214, Reston, VA, 2003.

[8]Collopy, P. D., "Economic-based Distributed Optimal Design," AIAA, Technical Report 2001-4675, Reston, VA, 2001.

[9]Collopy, P. D., and Horton, R., "Value Modelling for Technology Evaluation," AIAA, Technical Report 2002-3622, Reston, VA, 2002.

[10]Murman, E. M., Walton, M., and Rebentisch, E., "Challenges in the Better, Faster, Cheaper Era of Aeronautical Design, Engineering and Manufacturing," *Aeronautical Journal*, Vol. 104, No. 1040, 2000, pp. 481-489.

[11]Yu, T. T., "The Development of a Hybrid Simulation Modelling Approach based on Agents and Discrete-event Modelling," Ph.D. Dissertation, School of Engineering Sciences, Univ. of Southampton, Southampton, UK, 2008.

[12]Stranjak, A., Dutta, P. S., and Edden, M., "A Multi-agent Simulation System for Prediction and Scheduling of Aero Engine Overhaul," *7th Int. Conf. on Autonomous Agents and Multi-agent Systems – Industry and Applications Track*, Vol. 1, International Foundation for Autonomous Agents and Multi-agent Systems, Richland, SC, 2008, pp. 81-88.

[13]Castro, A., and Oliveira, E., "A Multi-agent System for Intelligent Monitoring of Airline Operations," *Third European Workshop on Multi-Agent Systems*, Brussels, Belgium, 2005, pp. 91-102.

[14]AnyLogic, Software Package, Ver. 6.5.1, XJ Technologies, St. Petersburg, Russia, 2000-2011.

[15]MacDonald, A., Burr, J., and Roberts, G. D., "Review of the UK Search & Rescue Helicopter Provision and Coverage Criteria," Maritime & Coastguard Agency, Doc. no. ST-8860-RA-1-Rev 01, Southampton, UK, 2001.

[16]Vlasto, M., "RNLI Annual Operational Statistics Report," Royal National Lifeboat Institution, Poole, UK, 2009.

[17]Norris, R., "Helicopter Sortie Reports," Maritime & Coastguard Agency, Lee-on-Solent, UK, 2009.

[18]Benjamin, R., "International Aeronautical and Maritime Search and Rescue Manual," Volume III, Sixth edition, Doc 9731-AN/958, International Maritime Organisation, London, 2007, p. 3-22.

[19]Collopy, P. D., and Curran, R., "Aerospace System Value Models: A Survey and Observations," *AIAA SPACE Conference & Exposition*, 2009-6560, AIAA, Reston, VA, 2009, p. 18.

[20]Collopy, P. D., and Curran, R., "The Challenge of Modelling Cost: Steps towards a Solution," *1st International Conference on Innovation and Integration in Aerospace Sciences*, CEIAT, Queen's University Belfast, Belfast, Northern Ireland, 2009, p. 3.

[21]Lave, C. A., and March, J. G., *An Introduction to Models in the Social Sciences*, University Press of America, Lanham, MD, 1993, pp. 52-79.

[22]Vlasto, M., "RNLI Annual Reports and Accounts," Royal National Lifeboat Institution, Poole, UK, 2008.

[23]Bierens, J. J., Knape, J. T. A., and Gelissen, H. P., "Drowning," *Current Opinion in Critical Care*, Vol. 8, No. 6, 2002, pp. 578-586.

[24]Sóbester, A., Keane, A. J., Scanlan, J. P., and Bressloff, N. W., "Conceptual Design of UAV Airframes Using a Generic Geometry Service," *Infotech@Aerospace Online Proceedings*, AIAA 2005-7079, 2005.