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Modeling the Life Cycle Cost Impact of Product Development Decisions in an Aerospace Supply Chain: A Case Study

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Abstract: A dynamic model of the supply chain for an unmanned air vehicle allows assessment of the total life cycle costs of candidate aircraft system architectures. The impact of system redundancy on the cost of ownership can readily be estimated through simulation. In the UAV case study presented here, supply chain simulation early in the design phase enables much better understanding of the interaction between aircraft mission requirements, system failure rates and total cost drivers, including flyaway, maintenance and spares costs. Several spares inventory management policies were also investigated, leading to a hybrid rule based on inventory regulation supplemented by failure replacement ordering during the initial phase of field introduction of the aircraft.

Introduction

Product configuration is a key factor in the total cost of ownership. Design decisions regarding product attributes influence purchase, operating and inventory costs. When such design decisions are made, initial product costs can readily be determined, yet longer term costs, such as maintenance, are more difficult to assess. Dynamic simulation models of the life cycle costs enable understanding of the tradeoffs inherent in the product development phase. This paper investigates these issues through an aerospace example, considering several configurations of the flight control system for an unmanned air vehicle (UAV).

UAVs serve missions once filled only by manned aircraft, or perhaps not filled at all. Communication, control and power supply technology advances enable long term autonomous UAV operation. To date, most applications of UAVs are military. In the future, civil applications will increase, bringing UAVs into closer contact with population centers. Possible civil missions include monitoring of utility distribution systems (e.g. electrical lines, pipelines), highways, forests, farms, ranches, coastlines and borders.

Presented here is a case study of vehicle designs to satisfy a hypothetical mission, requiring a fleet of 50 single-engine UAVs to each fly a 5 hour patrol, twice a day. The focus of this study will be on the aircraft's flight control or vehicle management system. The vehicle management system (VMS) consists of sensing, computing and actuating elements that enable the aircraft to follow a commanded flight path. The UAV's suite of sensors provide information regarding aircraft position, rate and attitude to the flight control computer. The computer commands the appropriate motion of the actuators, positioning flight surfaces (elevator, ailerons, etc...) to modify aircraft trajectory.

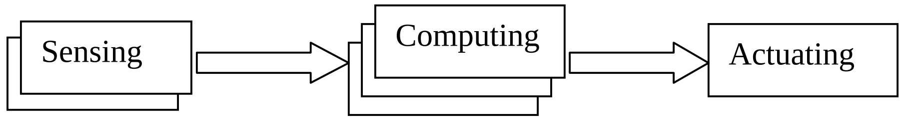

Figure 1: Vehicle Management System Block Diagram

The design decision under consideration is to choose the levels of redundancy of the sensing, computing and actuating functions of the vehicle management system. While in flight, if any of these essential functions ceases to operate, the UAV is uncontrollable, leading to loss of the aircraft. In the block diagram shown in Figure 1 above, each function has different levels of redundancy. To lose the sensing function would require failure of two elements, while losing the actuating function requires only one failure. Another way to express the redundancies pictured above is that there are two sensing channels, three computing channels and one actuating channel.

The higher the redundancy, the greater the reliability. However, higher redundancy requires more components, resulting in greater flyaway and maintenance costs. The principal tradeoff in the redundancy decision is between reliability and life cycle costs.

Reliability

In this simple representation of the vehicle management system, the probability of loss of control of the UAV in flight can be calculated using standard techniques [1] as

$$PLoC = \lambda_S^{n_S} + \lambda_C^{n_C} + \lambda_A^{n_A}$$

where

$$\lambda_S = \text{Sensing failure rate [failures/flight hour]} = \frac{1}{\text{Mean Time Between Failure of Sensing}} = \frac{1}{MTBF_S}$$

$$\lambda_C = \text{Computing failure rate [failures/flight hour]} = \frac{1}{\text{Mean Time Between Failure of Computing}} = \frac{1}{MTBF_C}$$

$$\lambda_A = \text{Actuating failure rate [failures/flight hour]} = \frac{1}{\text{Mean Time Between Failure of Actuating}} = \frac{1}{MTBF_A}$$

n_S = Number of sensing channels

n_C = Number of computing channels

n_A = Number of actuating channels

Other failures can also lead to loss of the aircraft, principally due to engine and airframe malfunctions. For the purposes of this case study, these will be grouped together under the failure rate $\lambda_E = 1/MTBF_E$.

Then the probability of loss of the UAV is

$$\begin{aligned} PLoUAV &= \lambda_E + PLoC \\ &= \lambda_E + \lambda_S^{n_S} + \lambda_C^{n_C} + \lambda_A^{n_A} \end{aligned}$$

To minimize the number of UAVs lost, the redundancy levels of the sensing, computing and actuating functions can be increased. Because the failure rates are much less than one, as the redundancies increase the probability of loss of control will approach zero, and the probability of loss of the UAV will approach the engine and airframe failure rate. Of course, the levels of redundancy are limited by practical considerations of weight, space constraints, integration complexity and cost.

In this notional UAV design, the following mean time between failures for a single channel are estimated for each function:

Sensing	$MTBF0_S$ = 3570 hours / failure
Computing	$MTBF0_C$ = 4000 hours / failure
Actuating	$MTBF0_A$ = 2500 hours / failure
Engine & Airframe	$MTBF0_E$ = 110,000 hours / failure

For each VMS function, many components contribute to the overall failure rate. For example, the sensing function failure rate includes those of the individual sensors (e.g. pitch, roll, yaw gyros, airspeed, etc..) as well as the signal and power wiring. The engine and airframe failure rate is comprised principally of catastrophic structural defects. The component failure rates comprising the VMS function MTBF are readily found in trade literature [2, 3]. The theoretical basis for combining these component failure rates at a system level is discussed in references such as [1].

The VMS functions' nominal mean time between failure, *MTBF0*, are predictions for mature components. For a newly developed aircraft, the functions' MTBF are less than predicted. As the aircraft fleet accumulates flight hours, the MTBF will increase, as the service experience leads to improvements in design, operating procedures and maintenance methods. This process of reliability growth through the process of "test, analyze and fix" is described in Reference 4. One means of modeling this growth in MTBF as a function of total fleet flight hours, T, is

$$
\begin{aligned}
&MTBF = f(T)MTBF0 \\
&.4 \leq f(T) \leq 1.2 \quad \text{where} \quad f(T) = .002\sqrt{T}
\end{aligned}
$$

The resulting MTBFs for the single channels of the VMS functions are graphed below in Figure 2. Note that the maximum value of the actuation function MTBF is 1.1 $MTBF0_A$ due to the limits in improvements expected with the mechanical, electromechanical and hydraulic components.

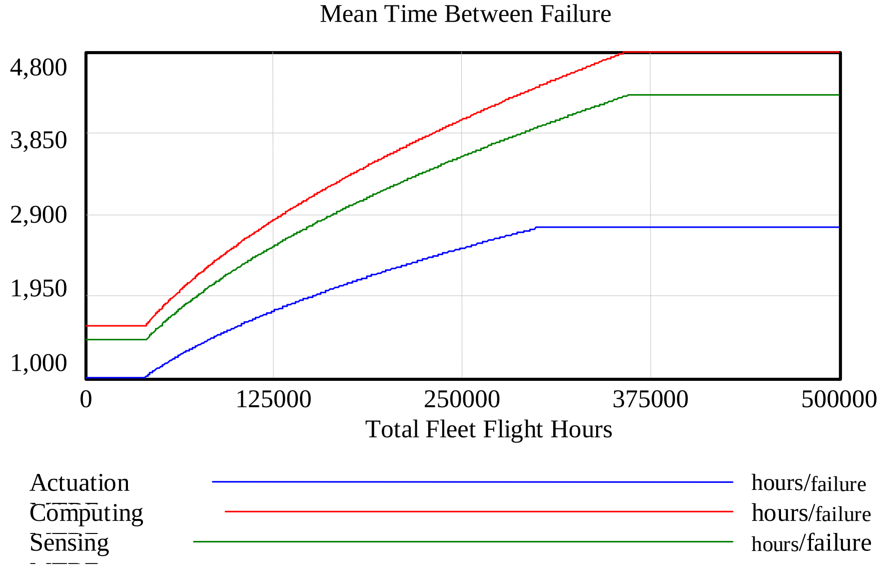

Figure 2: Mean Time Between Failure of VMS Elements

Life Cycle Costs

In this case study, the components of total VMS life cycle costs include development, production, spares, maintenance and holding costs. Also included are the replacement costs for UAV failures due to loss of control, assumed to be $5 million per aircraft. The assumed production cost for a single channel of the VMS functions are:

Sensing	$60,000
Computing	$30,000
Actuating	$100,000

Spares and repair costs are a fraction of the VMS function costs. The development costs include factors for added integration effort inherent with redundant systems. Holding costs equal the inventory value multiplied by a nominal interest rate, 10%.

The maintenance failure rate influences significant contributors to the life cycle cost, including the frequency of troubleshooting and the amount of spares required. As the equation below shows, the greater the redundancy level, the higher the maintenance failure rate

$$MFR = n_S \lambda_S + n_C \lambda_C + n_A \lambda_A$$

The required on-hand spares inventory is influenced by the maintenance failure rate as well as the replacement lead time. While not the central focus of this trade study, several spares ordering policies were considered. The Failure Replacement policy simply places an order for defective components upon their failure. The Desired Inventory Regulation policy orders component spares equal to the desired level less the spares on hand and the spares on order. The desired spares level is computed based on predicted failure rate and lead time as shown below for the actuators:

$$DesiredActuatorSpares = DesiredFlightRate * \frac{n_A}{MTBF0_A} * ActuatorLeadTime * SafetyStockFactor$$

Note that the actuation redundancy level directly affects the desired spares level. The safety stock factor is chosen to achieve a desired service level. Other spares ordering policies evaluated were combinations and modifications of the Failure Replacement and Inventory Regulation policies were also considered. For all policies, the initial spares stock equaled a multiple of the desired spares level.

If spares inventory proves insufficient to replace a UAV's defective component, the aircraft will remain on-ground (AOG) until a new part is delivered. AOG UAVs decrease the number aircraft available to fulfill the mission. Of course, UAVs lost to in-flight failures cannot perform future missions and must be replaced. UAV ordering policies follow rules similar to those for component spares.

Selecting Redundancy Level

A system dynamics model of the UAV supply chain developed using Vensim software [5], provides the means to evaluate the life cycle cost impact of VMS redundancy. The full model is pictorially described in the appendix.

Comparing different combinations of VMS redundancies leads to the following graph of total cost after 48 months of fleet operation. The legend denotes each VMS function's redundancy. For example a3c2s3 indicates that the number of actuating, computing and sensing channels were 3, 2 and 3 respectively. As the graph in Figure 3 shows, the lowest total cost is for an aircraft with all VMS functions dually redundant. UAV configurations with single channel VMS functions suffer from frequent aircraft losses, causing high replacement costs and therefore total costs.

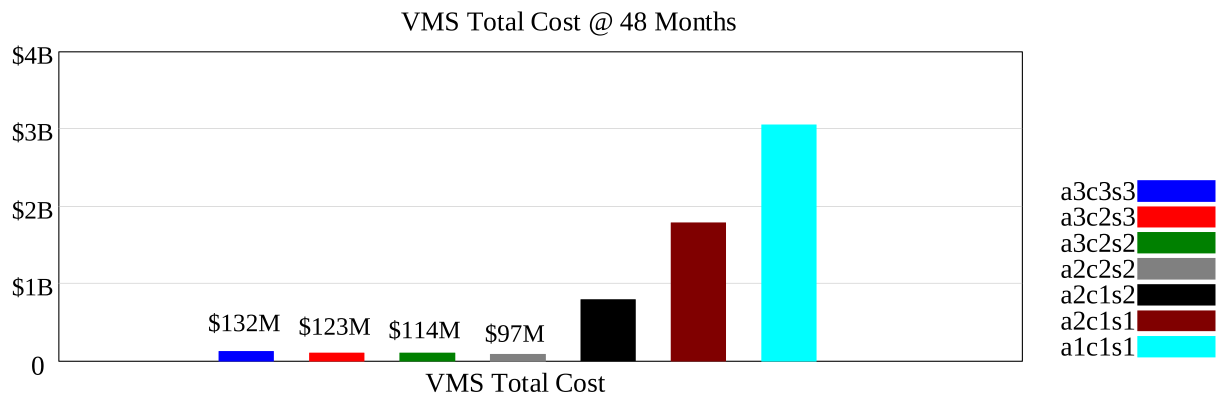

Figure 3: VMS Total Cost after 48 Months

Configurations with at least dual redundant functions have much lower frequency of UAV losses, as shown on the graphs below in Figure 4. For VMS system redundancy of 2 and greater, the probability of loss of aircraft approaches the failure rate of the engine and the airframe.

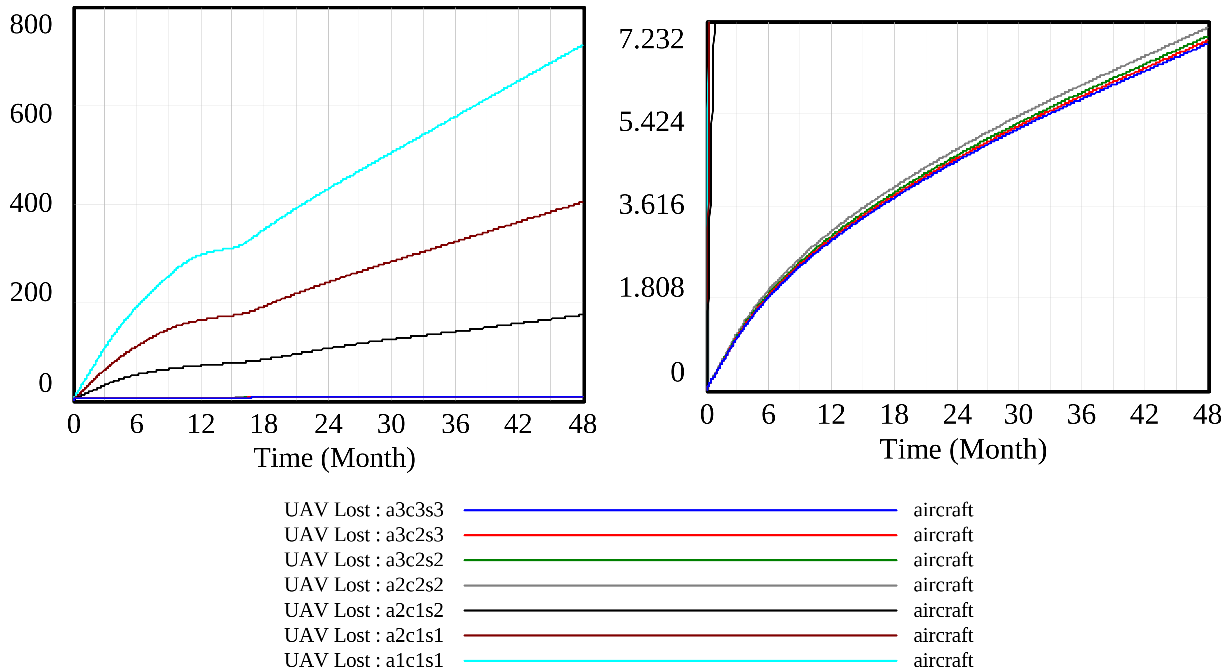

Figure 4: UAV Lost

Eliminating the single channel configurations from consideration, the following plots in Figure 5 show the key contributors to total cost after 48 months of operation. Because of the fewer number of components, the dual redundant configuration has lower maintenance, holding and build costs. These relative savings offset the slightly higher UAV loss cost.

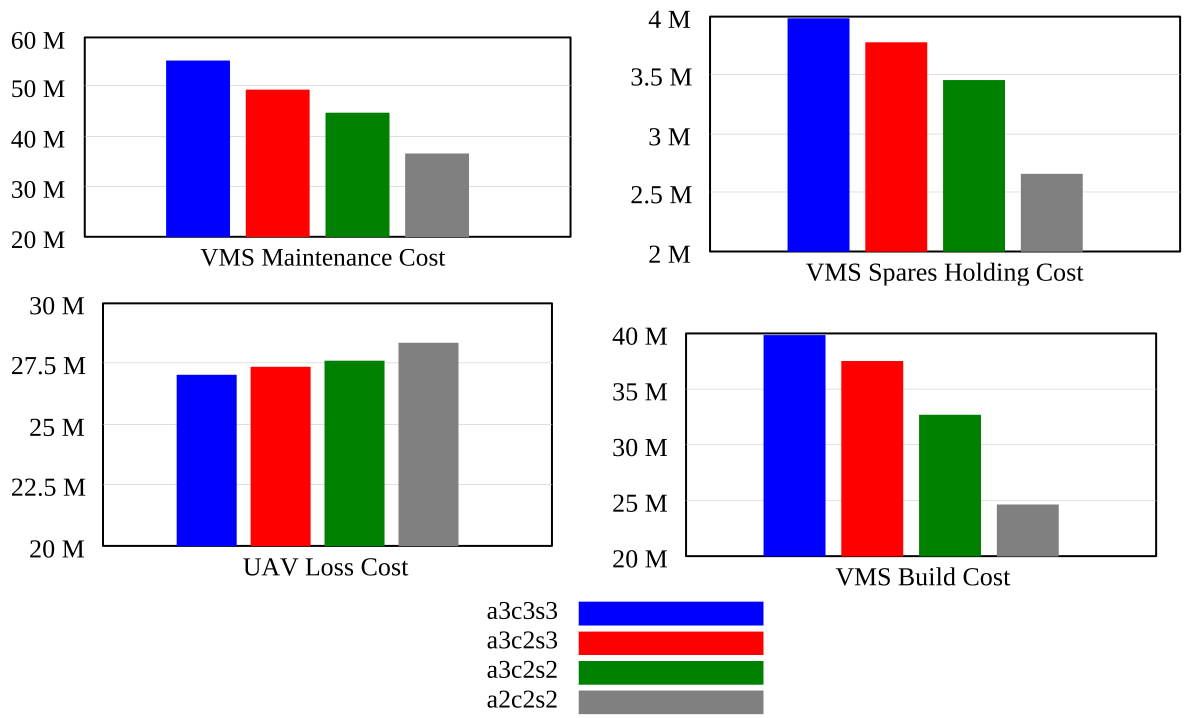

Figure 5: VMS Costs ($) at 48 Months

From the total life cycle cost perspective, the most attractive VMS configuration has two channels for each function - sensing, computing and actuating. This evaluation balanced development, production, maintenance and replacement expenditures, reflecting the total cost of ownership. Selection of the dual channel architecture would not be immediately obvious to the system designer. When designing the system, the VMS engineer trades flyaway cost, weight and flight safety reliability, with greatest emphasis on reliability. Maintenance costs typically do not factor into the system architecture decisions. Indeed, maintenance and operating costs often are estimated after the architecture is determined.

Without a means to assess total life cycle costs, the VMS configuration studies for an unmanned air vehicle could place too much emphasis on reliability. Even for unmanned vehicles, VMS engineers naturally tend to the cautious, high reliability approach. Using a dynamic simulation model that captures the costs of the relevant decision variables enables a balanced assessment of candidate architectures. Of the candidates considered in this case study, the triple channel functions had the best reliability – the favorite of the cautious VMS engineer. As the system dynamics model showed, the triple channel design has significantly higher maintenance costs, far exceeding those of the dual architecture. Based on total cost of ownership, the dual channel configuration for all VMS functions provides the most attractive solution. Additional redundancy beyond the dual architecture cannot be justified for an unmanned aircraft due to the added total cost, not to mention weight and complexity.

Spares Ordering Policy

With the VMS configuration set to dual channels for the sensing, computing and actuating functions, further study of spares ordering policies was conducted. Examples of the primary rules are shown for computer ordering:

Failure Replacement

Computer Ordering = max(Computer Spares Depletion Rate,0)

Inventory Regulation

Computer Ordering
= max((Desired Computer Spares -Computer Spares-Computers on Order),0)/time to order

The Failure Replacement policy simply initiates an order at the time of discovery of defects. The dynamic model implements this rule by setting the ordering rate equal to the failure rate of the component. As seen on the graphs on the next page in Figure 6, the Failure Replacement policy leads to insufficient computer spares in the later months. This causes UAV Available to drop below 50 aircraft as seen in Figure 7 on page 9.

The Inventory Regulation policy attempts to keep the sum of spares on hand and spares on order equal to a predetermined amount, selected to achieve an appropriate service level. This policy results in a shortage of computer spares early in the program, resulting in a temporary dip in UAV Available below the required 50 aircraft as shown on Figure 8 on the next page.

Both Policies

A combination of both the Inventory Regulation and Failure Replacement policies achieves acceptable results. In the approach investigated here, the Inventory Regulation policy is active at all times. When the observed failure rate is greater than the predicted failure rate, or in other words the *MTBF* < *MTBF0*, the Failure Replacement policy is also in effect. Therefore, early in the program, when the failure rate is relatively high, replacements are ordered as defects occur, replenishing inventory after the manufacturing lead time has elapsed. Later, after the aircraft systems reach maturity, the failure rate stabilizes at or above the expected rate. Then, the Failure Replacement policy is disengaged. This combination provides sufficient spares coverage. As the graphs above illustrate, the combined policy maintains the computer spares on-hand at sufficient levels to avoid an aircraft-on-ground condition.

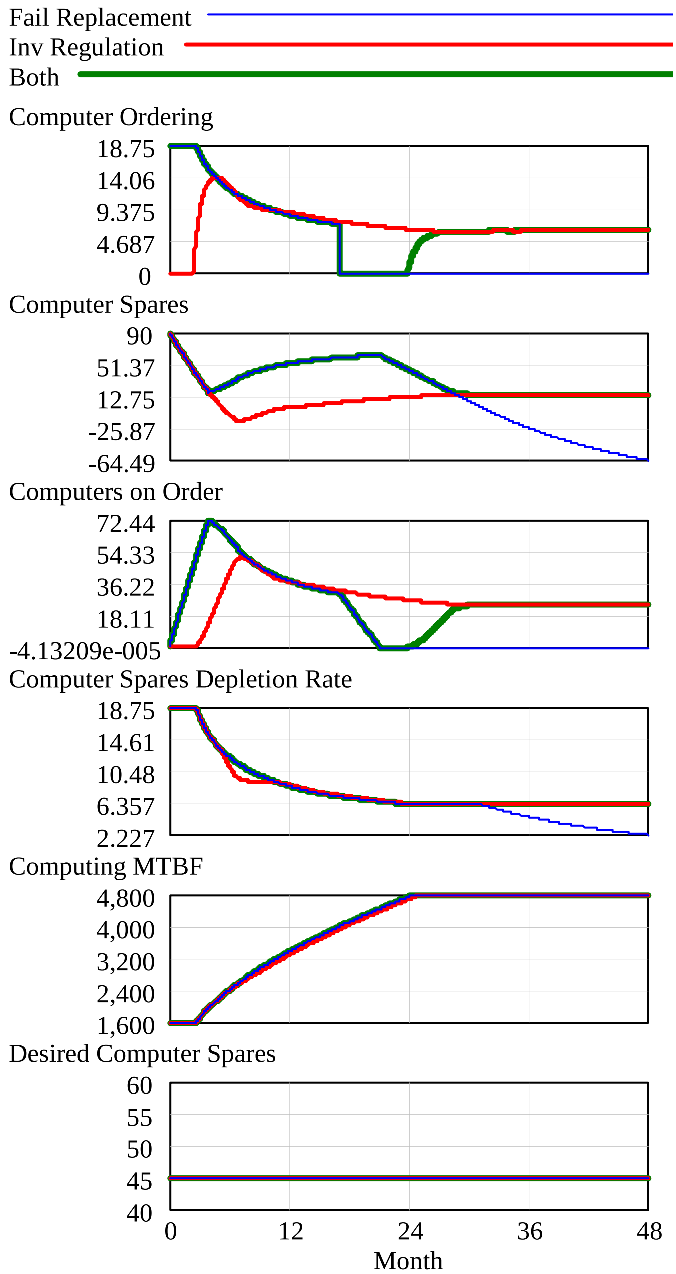

Figure 6: Spares Ordering Policies

The graphs below in Figures 7, 8 and 9 show the actuator, computer and sensor spares on-hand, along with the resulting UAV available for each of the ordering policies discussed.

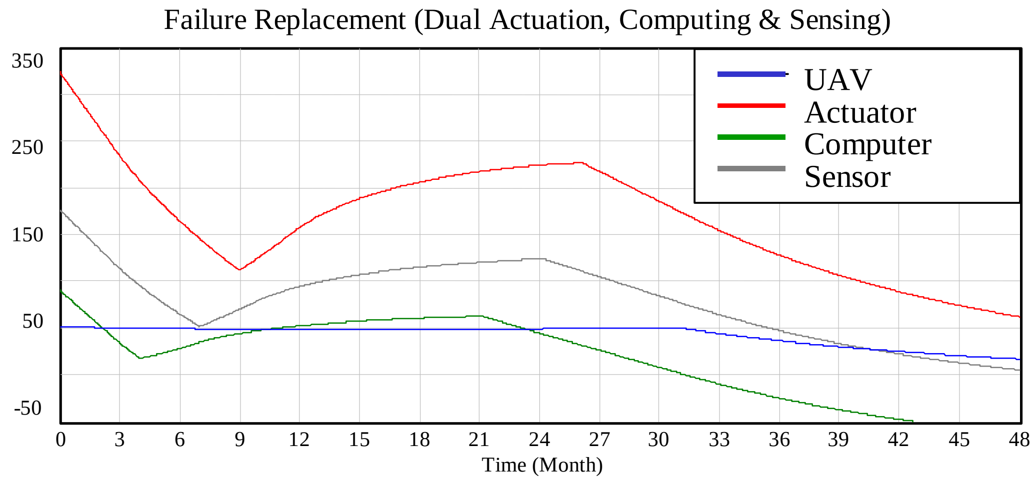

Figure 7: Spares and UAV Available with a Failure Replacement Policy

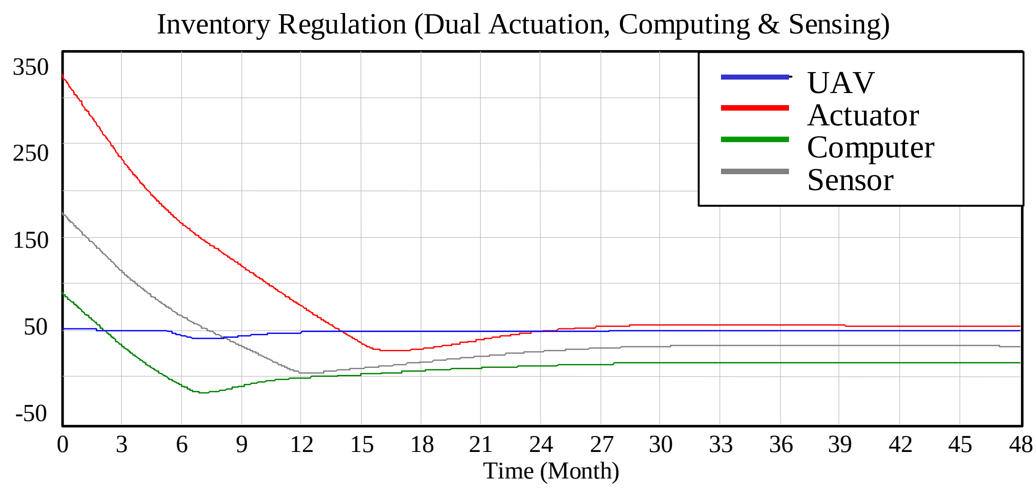

Figure 8: Spares and UAV Available with an Inventory Regulation Policy

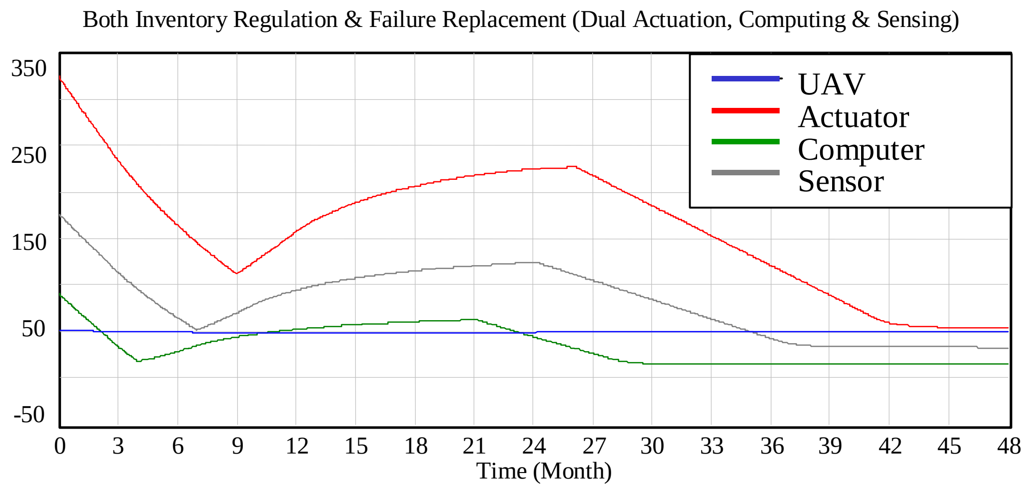

Figure 9: Spares and UAV Available with a Composite Policy

Conclusion

A system dynamics model of an aerospace supply chain provided insight into the impact of system redundancy on life cycle costs. Due to the complex interaction between mission requirements, failure rates and spares ordering policies, a dynamic simulation model is essential to properly assess long term effects of product architecture decisions. In the case study presented here, dual redundant vehicle management functions for a UAV provided the lowest cost solution with acceptable flight reliability. Spares ordering polices investigated led to a rule based on inventory regulation augmented by additional replenishment during periods of high failure rate early in the product life.

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[3] Honeywell International, Inc., Morristown, NJ 07962. URL: www.Honeywell.com

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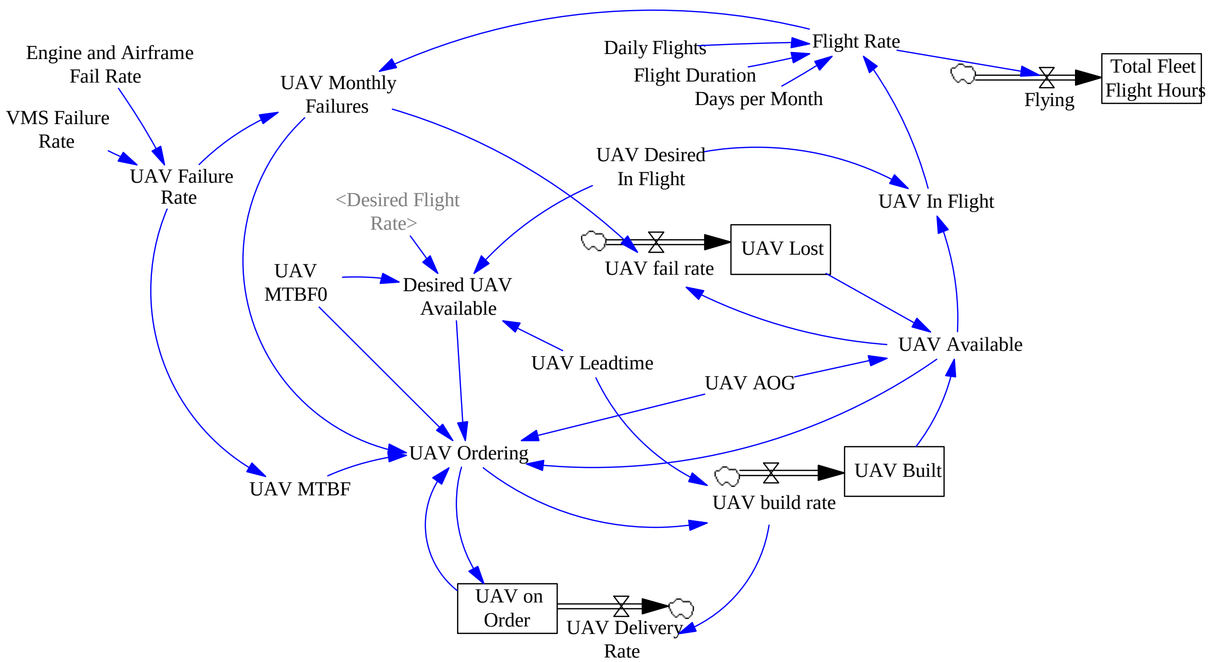
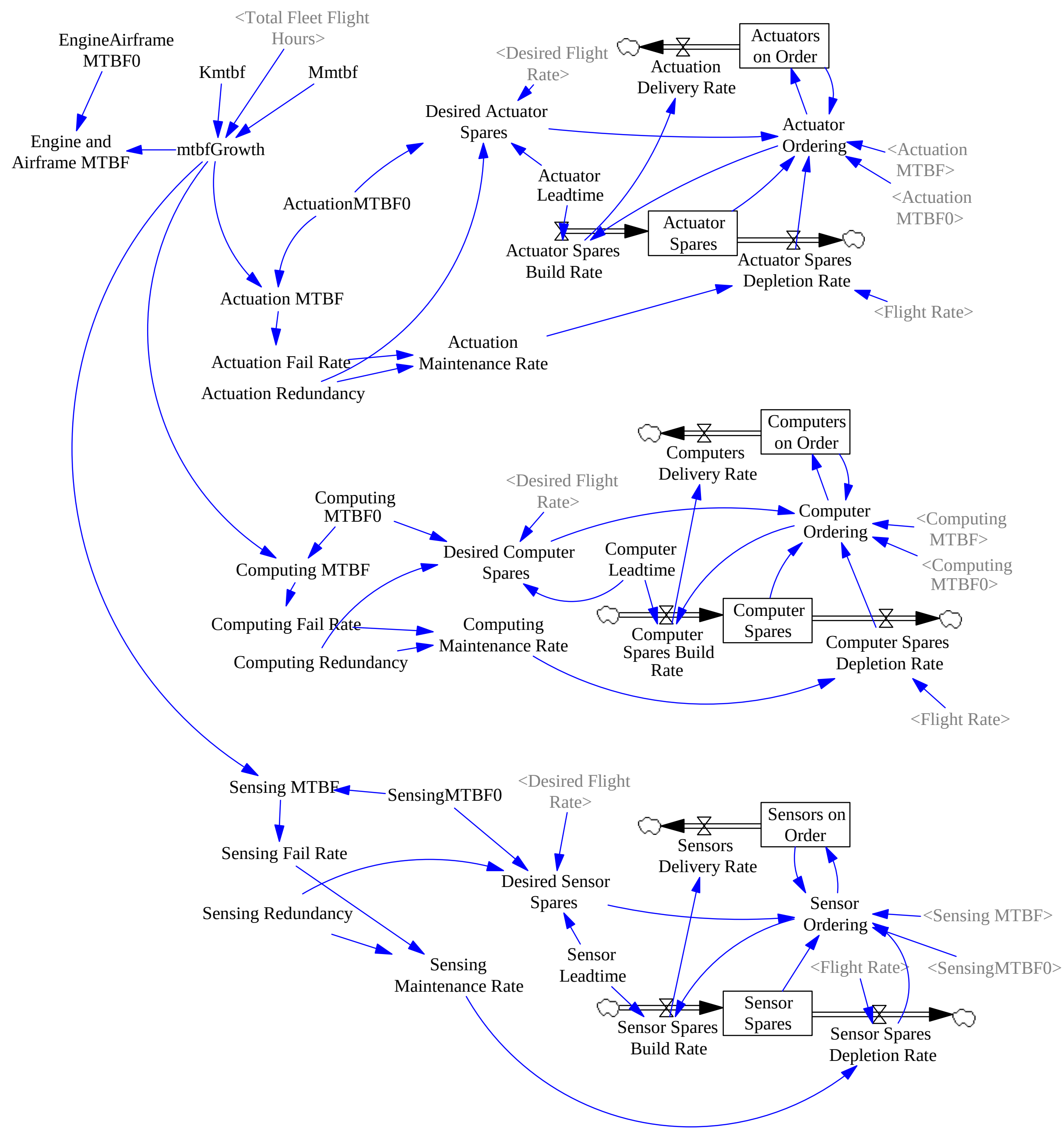
Appendix: *Model Description*

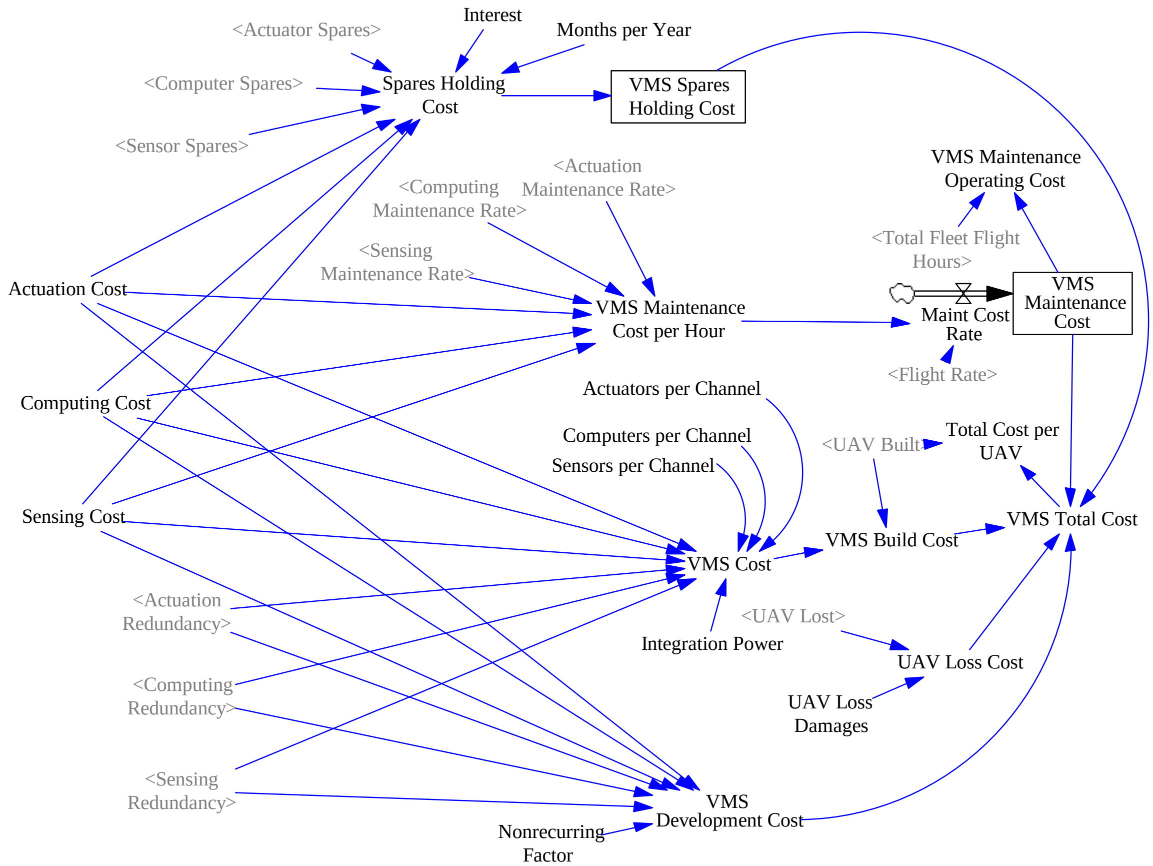
UAV Operation



Spares Ordering



Costs



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