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Active mission success estimation through functional modeling

Ada-Rhodes Short¹ · Robert D. D. Hodge² · Douglas L. Van Bossuyt³ · Bryony DuPont¹ Received: 31 May 2017 / Revised: 20 February 2018 / Accepted: 25 February 2018
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Abstract

Through the application of statistical models, the active mission success estimation (AMSE) introduced in this paper can be performed during a rapidly developing unanticipated failure scenario to support decision making. AMSE allows for system operators to make informed management and control decisions by performing analyses on a nested system of functional models that requires low time and computational cost. Existing methods for analyses of mission success such as probabilistic risk assessment or worst case analysis have been applied in the analysis and planning of space missions since the mid-twentieth century. While these methods are effective in analyzing anticipated failure scenarios, they are built on computational models, logical structures, and statistical models that often are difficult and time-intensive to modify, and are computationally inefficient leading to very long calculation times and making their ability to respond to unanticipated or rapidly developing scenarios limited. To demonstrate AMSE, we present a case study of a generalized crewed Martian surface station mission. A crew of four astronauts must perform activities to achieve scientific objectives while surviving for 1070 Martian sols before returning to Earth. A second crew arrives at the same site to add to the settlement midway through the mission. AMSE uses functional models to represent all of the major environments, infrastructure, equipment, consumables, and critical systems of interest (astronauts in the case study presented) in a nested super system framework that is capable of providing rapidly reconfigurable and calculable analysis. This allows for AMSE to be used to make informed mission control decisions when facing rapidly developing or unanticipated scenarios. Additionally, AMSE provides a framework for the inclusion of humans into functional analysis through a systems approach. Application of AMSE is expected to produce informed decision making benefits in a variety of situations where humans and machines work together toward mission goals in uncertain and unpredictable conditions.

Keywords Risk · Functional modeling · Decision making · Mission success

Abbreviations

AI Artificial intelligence
AMSE Active mission success estimation
CDF Cumulative distribution function
DRV Daily recommended valueEMU Extravehicular mobility units
EVA Extravehicular activity
FBED Functional basis for engineering design
FFD Referred to as functional flow diagrams
FFIP Failure flow identification and propagation
ISRU In situ resource utilization
IVA Intra-vehicular activities
PDM Prognostic-enabled decision making
PHM Prognostics and health management
PRA Probabilistic risk assessment
SEV Surface exploration vehicle
WCA Worst case analysis

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1 Introduction

The development of risk analysis has been deeply linked to space exploration, since the formalization of risk analysis methods following the Second World War. Both the era

of space exploration and risk analysis of complex systems spawned from the technological progress of the Second World War and the advent of modern rocketry in the early twentieth century (Goddard 1920). The space race between the USA and the Soviet Union spurred the development of tools such as probabilistic risk assessment (PRA) (Kumamoto and Henley 1996) with the aim to closely examine complex system risk probabilistically and quantitatively. At the same time, prognostics and health management (PHM) began to emerge. As increasing complex systems were developed for space flight and exploration, it became imperative that engineers and operators have the ability to accurately and actively monitor system health and performance. Sensors were developed that could monitor every aspect of system operation, including phenomena that would otherwise have been imperceptible. Taking data from these sensors, models of system operation and health could be constructed that utilize condition-based analysis, laying the groundwork for modern PHM. In recent years, there has been an increased interest in understanding risk and health of systems during the early phase of design of complex systems (Bossuyt Bossuyt and O'Halloran 2015; Van Bossuyt and Dong 2013; Van Bossuyt and Hoyle 2012; Van Bossuyt et al. 2013). However, a gap persists in the development of real-time risk-informed decision support tools for active and ongoing missions. Contemporary mission analysis and risk modeling methodologies require lengthy and extensive adjustment of system models and reanalysis when faced with unforeseen events. The subsequent delay of critical risk information necessary for decisions can lead to rapid development of complex and dangerous scenarios.

This paper presents the active mission success estimation (AMSE) method that provides timely risk information to inform mission decisions being made in crisis during rapidly evolving situations. Through adoption of a modular risk-informed object-oriented approach to mission modeling, health monitoring, and analysis—and active recalculation of risk of mission failure as the mission progresses—a more accurate estimation of the probability of mission success can be developed and mission-critical decisions with many possible options can be analyzed to help inform mission control decision to increase the probability of total mission success.

The performance of AMSE necessitates that all mission-critical components be modeled thoroughly using risk analysis and prognostic techniques, and the models are developed for modularity to enable the rapid rearrangement of the model elements to evaluate available decision outcomes and estimate each outcome's mission success probability. To effectively represent a mission framework, a functional modeling method is presented where environments of interest and relevance can nest within each other and contain the systems of interest within a super system. This nested super systems approach to modeling is used to determine what

environmental hazards are present and if these hazards can cause damage to the system of interest. Modeled mission tasks are analyzed including internal and external system risks, and hazard mitigating factors such as nested functional modeling environments representing protective barriers. The AMSE method presented in this paper is demonstrated on a case study of a crewed multiyear scientific mission on the surface of Mars for the establishment of a permanent scientific base. In the case study, the eight astronauts constitute the systems of interest and their safety and survival are considered the metric for mission success.

1.1 Specific contributions

This paper presents the AMSE method for the real-time estimation of risk during a space mission case study through the utilization of risk analysis techniques and functional modeling. The AMSE method provides decision-makers with up-to-date risk information at critical mission decision points. The AMSE method uses a form of nested functional models to analyze the influence of various layers of environmental protection such as space suits, vehicles, or structures. These protective layers can either provide protection to the systems of interest directly, protect mission-critical systems outside of the subject of interest, or protect each other through layering systems in a nested structure. The AMSE functional modeling technique takes a dynamic systems approach to provide a comprehensive picture of the interactions between various mission components. AMSE provides a rapid and active estimation of current mission success, as well as projections of probable total mission success based upon potential decisions. Through active analysis of the probability of mission success at decision points, the probability of total mission success can be optimized allowing for greater mission safety and potentially greater scientific yield. Additionally, the object-oriented modular nature of the AMSE method enables fast adaption to unexpected mission scenarios. Though AMSE was developed for application in risk analysis of a space mission operations case study, AMSE can be easily adapted for use with any complex system and has potential applications for autonomous decision making.

1.2 Assumptions

AMSE depends on the validity of multiple, informed assumptions. The first assumption is that the functional model used is of an appropriate level of detail to be accurate. To ensure this, we have used established functional modeling taxonomy and development standards.

Second, it is assumed that the failure distribution for a mission can be represented by an exponential distribution. The exponential distribution describes processes in which events occur continuously and independently at a constant

average rate (a Poisson process). However, under different missions that we did not consider, there may be a situation in which risk cannot be described as continuous or independent, and in those cases, an alternative distribution should be used.

The third assumption is that failure of individual sub-systems can be considered independent. This should be the case if a system is properly decomposed into a functional model, in which all functions of a system are separated. At this level of decomposition, failures that may be correlated in the whole system are instead connected through flows and failure propagation.

2 Background

AMSE builds on the topics of decision theory, functional modeling, risk analysis, and PHM. Existing mission success estimation methods rely on worst case analysis (WCA) (Ye 1997; Nassif et al. 1986) or Probabilistic Risk Assessment (PRA) (Modarres et al. 2011; Mohaghegh et al. 2009). WCA, PRA, and other related methodologies are adept at analyzing potential foreseeable failure scenarios, but suffer in their ability to perform in situations where rapid reconfiguration of the model is necessary. Such model reconfigurations are needed during rapidly developing situations, such as those faced by in a space mission disaster.

2.1 Functional modeling

Functional modeling encompasses a variety of methods used to represent and model the functionality of a system. Functional models include many sub-functions, representing work performed in the system as flows—the passage of materials, information, and energy—between functions and sub-functions. In addition to flows internal to the system, export flows and import flows enter and exit the system boundary. A popular way to represent a functional model is through flow block diagrams, also often interchangeably referred to as functional flow diagrams (FFD) (Blanchard and Fabrycky 1990; Bohm et al. 2005). FFDs are useful for modeling systems with direct unidirectional flows passing between a variety of functions and clear system inputs and outputs can be defined. One issue with many existing methodologies for functional modeling is that they are difficult to apply to systems that are less linear, resulting in tangled networks of functions and flows that are difficult or impractical to analyze, or must be simplified to the point where they provide an inaccurate representation of the system and its associated dynamics.

The Functional Basis for Engineering Design (FBED) (Bryant et al. 2005; Hirtz et al. 2002; Kurtoglu et al. 2005; Stone and Wood 2000), provides concise definitions of functions and flows that describe all possible engineered systems. Through the use of FBED, we can construct functional models

of complex systems, using a common taxonomy of functions and flows. The process of developing an FBED model is:

1. Generate a Black Box model. This takes the highest-level-possible view of the system and only considers flows into and out of the overarching system model.
2. Create function chains for each input flow and order them with respect to time. This step consists of following a flow from its entrance into the system, through all sub-systems that interact with the flow, and finally exiting the system. All systems that interact with the flow should then be placed into chronological order from the perspective of the flow.
3. Aggregate function chains into a functional model. In Step 3, the final step of FBED, the functional chains are combined to determine the underlying functional structure of the system. FBED is utilized in this paper due to the advanced development of failure analysis methods that are built upon FBED (Jensen et al. 2008; Kurtoglu et al. 2010; O'Halloran et al. 2015; Ramp and Van Bossuyt 2014; Stone et al. 2005).

2.2 Space mission risk assessment

Many risk assessment modeling techniques attempt to represent trends of physical failure through the application of various failure distributions. One common method is the use of a hazard rate λ , which describes the expected number of failures over a period of time. The hazard rate can be used in a failure distribution such as an exponential distribution (Eq. 1) to calculate the probability of survival of a system or sub-system at a given time (Wertz et al. 2011):

$$S(t) = e^{-\lambda t}. \quad (1)$$

The expected survival rate can then be subtracted from 1 (Eq. 2) to find the failure rate, or the probability that a system will have survived after time, t :

$$F(t) = 1 - S(t) = 1 - e^{-\lambda t}. \quad (2)$$

The failure rate (or related metrics) appears in a wide variety of risk assessment methods, but many additional and more complex techniques exist for evaluating the risk of failure of a system. One such method for evaluating the risk of failure is failure flow identification and propagation (FFIP) (Kurtoglu et al. 2010; Jensen et al. 2008). FFIP uses a functional modeling approach based in a function block diagram structure (Stone and Wood 2000). FFIP can be enhanced to enable mission control, navigation, and autonomous decision making through the application of failure flow decision functions (FFDF) (Short et al. 2015, 2017). FFDF is a tool that determines an optimal decision when faced with problems of controlling or designing a system to maximize system survivability. Specific to the case study employed

in this paper, space mission risk assessment can also be applied to control of autonomous systems to maximize mission success while minimizing human work hours (Short and Van Bossuyt 2015; Mimplitz et al. 2016; Short et al. 2016; Friedenthal et al. 2014; Mohaghegh et al. 2009; Kumamoto and Henley 1996).

While many of the existing methods are robust, they suffer from lengthy setup and analysis processes. The heavy computational cost of these existing methodologies makes active mission assessment previously infeasible.

2.3 Prognostics and health management

Prognostics and health management (PHM) is a suite of analytical tools and methods used to predict and prevent failures in mechatronic systems (Sheppard et al. 2014). There are diverse approaches to PHM that are typically tuned to specific applications or industries (Hutcheson et al. 2006; Balaban et al. 2013). A common PHM case study for development of models is battery health (Xing et al. 2011). Much research has been conducted on the important issues of battery capacity depletion (Saha and Goebel 2009), optimization of battery life (Saha et al. 2012), generation of battery health data (Saha and Goebel 2007; Widodo et al. 2011), and application of battery PHM analysis (Saha et al. 2011). While battery health is a common case study, partially due to the large quantity of available data (Saha and Goebel 2007) and partially a result of general acceptance within the field, the methods and techniques are generalizable to a wide variety of systems and applications such as electrical actuators (Keller et al. 2006), transmissions and gearboxes (Zhang and Isom 2011), and other components and systems (Pecht 2008).

PHM analysis can be used to inform a decision with the optimum level of risk through prognostic-enabled decision making (PDM) (Sweet et al. 2014; Herr et al. 2014; Nathalie et al. 2016). PDM is a valuable method in health management of complex systems, because it allows a succinct modeling of potential damage caused by the failure of a subsystem or individual part. Some PHM techniques model not only the mechatronic system itself, but also the physical interactions it encounters, such as mobility and environmental interface, control systems, structural actions, and hazards (Balaban et al. 2013; Frost et al. 2013). In this paper, we extend PHM methods to include the consideration of humans as additional sub-systems which to our knowledge has not been done before.

3 Methodology

The AMSE method presented here is based on a nested super system approach to space mission risk assessment that allows for the active estimation of mission success during an

ongoing mission. Using techniques derived from functional modeling of systems, FFIP, and related methods in conjunction with concepts taken from decision theory, risk analysis, and PHM, AMSE is capable of providing useful insights when making mission control decisions by rapidly analyzing potential options when confronted with unanticipated and previously unanalyzed scenarios. In this section, we present the AMSE method using a case study of a Mars mission. First, two pre-steps are presented, then three primary phases (modeling, analysis, and interpretation) are shown.

3.1 Pre-step 1: Mission success definition

To glean insight from AMSE, both a definition of mission success and a quantifiable method for evaluating success must first be established. In many cases, mission success can be defined as a primary system (or systems) of interest surviving the length of the mission. One example of a system of interest surviving the length of a mission is a planetary exploration rover remaining functional for the entire duration of the planned mission. To determine the probability of survival of a primary system of interest and the related probability of mission success, a survival rate must be calculated. A survival rate, $S(t)$, tends to take the form of a cumulative distribution function (CDF) representing the probability that the system of interest will not have experienced a failure by time, t . One common form for a survival rate is the exponential survival rate which is found by subtracting the exponential failure rate, $F(t)$, from 1 as shown in Eq. 5. The exponential failure rate is found by taking the integral of the probability density function (PDF) form of the exponential failure rate, $f(t)$, which determines the probability that a failure will occur at the instant, τ , given a hazard rate, λ , which is the number of expected system failures over time. Equations (3), (4), and (5) define $f(\tau)$, $F(t)$, and $S(t)$, respectively (Pinto and Garvey 2012). These and other forms of failure distributions, such as system-specific PHM models, are an integral part of the AMSE methodology and necessary for the development of failure models:

$$f(\tau) = \lambda e^{-\lambda\tau}, \quad (3)$$

$$F(t) = 1 - e^{-\lambda t} = \int_0^t \lambda e^{-\lambda\tau} d\tau, \quad (4)$$

$$S(t) = e^{-\lambda t} = 1 - (1 - e^{-\lambda t}). \quad (5)$$

3.2 Pre-step 2: Functional model development

The AMSE method requires a series of functional models to represent every major system involved in the mission, as well as their individual behavioral and system health

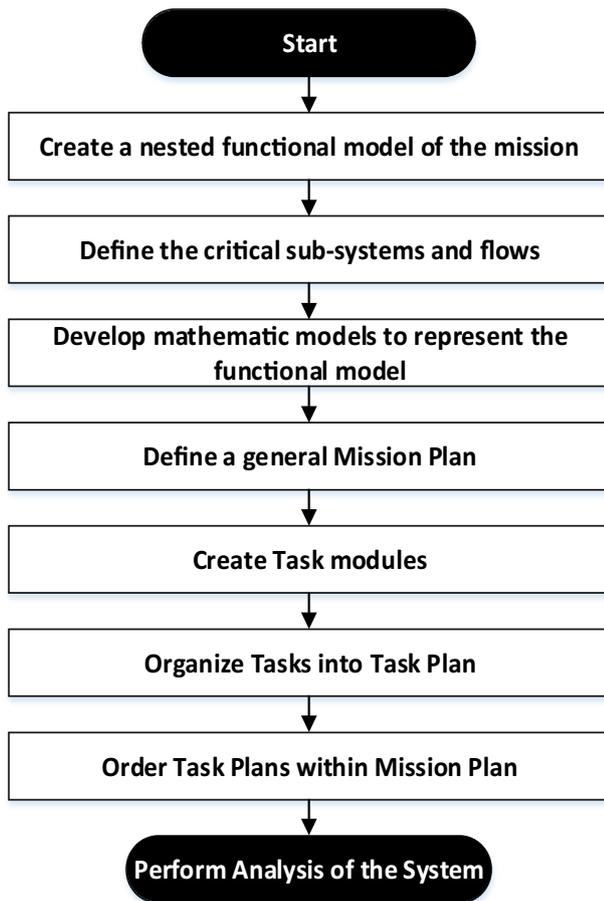


Fig. 1 Phase 1, modeling, process flow

characteristics. We used the FBED method of functional modeling, because it clearly represents energy, material, and data flows. PHM information that can be collected from systems in real-time must be identified in this step built into the functional model where applicable. This information is encoded into the mathematical models developed below.

3.3 Phase 1: Modeling

In Phase 1 of the AMSE method, seven distinct steps are performed to develop the AMSE model. Figure 1 graphically shows the seven steps.

3.3.1 Step 1: Create a nested functional model of the mission

The first step consists of creating a metamodel of all major mission systems (previously modeled in the pre-steps above) within a nested super-system framework. This is performed by first modeling each individual system using traditional FBED methods (pre-step 2), before placing the individual

systems into a nested super systems structure. An example functional model of a surface exploration vehicle (SEV) can be seen in Fig. 2. A graphical representation of the AMSE nested super systems structure for a Mars crewed surface exploration mission can be seen in Fig. 3. In Fig. 3, the outermost “system” is the space environment in the solar system that contains the Sun, Earth, Mars, and a communications satellite. Mission Control is defined as part of the Earth “system”. The SEV, the Martian Surface Habitat, and the EVA suit are located within the “Mars” system. Within the EVA suit, the astronaut is found. Thus, the astronaut (the system of interest in the case study presented in the next section) is inside three larger systems. Under this method, flows can pass between systems, while crossing the boundaries of environmental or protective systems such as an SEV, space suit, or the Martian surface habitat module. This allows for the entire system to be modeled and to represent environmental hazards and various levels of protection that prevent and mitigate system failure. Additionally, the effects of the current health of each layer of protection on the system of interest can be determined through application of PHM and risk analysis models and information (identified in pre-step 2) for each individual system.

3.3.2 Step 2: Define critical system(s) of interest and critical flows

In the case of a functional model of a single system, critical functions and flows are defined as elements of the functional model that must be operational for the system to not be in a failure state (Lucero et al. 2014). In the context of super systems representing a mission framework, the idea of critical functions and flows is extended from the functional level to the system level, and a critical system of interest is defined. A critical system (or systems) of interest is a system that must be functioning in order for the mission to be considered not failed. For example, in the case of a rover mission, the critical system of interest is the rover, and for the case of a crewed space mission, each member of the crew is considered a critical system of interest. Step 2 concludes once the critical system(s) has been identified and defined.

3.3.3 Step 3: Develop mathematical models to represent graphical functional models, their health, failure distributions, and how failures relate to each other

The third step of the AMSE method consists of developing a mathematical model to represent the graphical functional model, and risk and PHM information developed in the second Pre-Step. This mathematical model serves as the computational basis of analysis of the system. Building on previous work on failure analysis and PHM in functional models,

Fig. 2 Functional model of an SEV

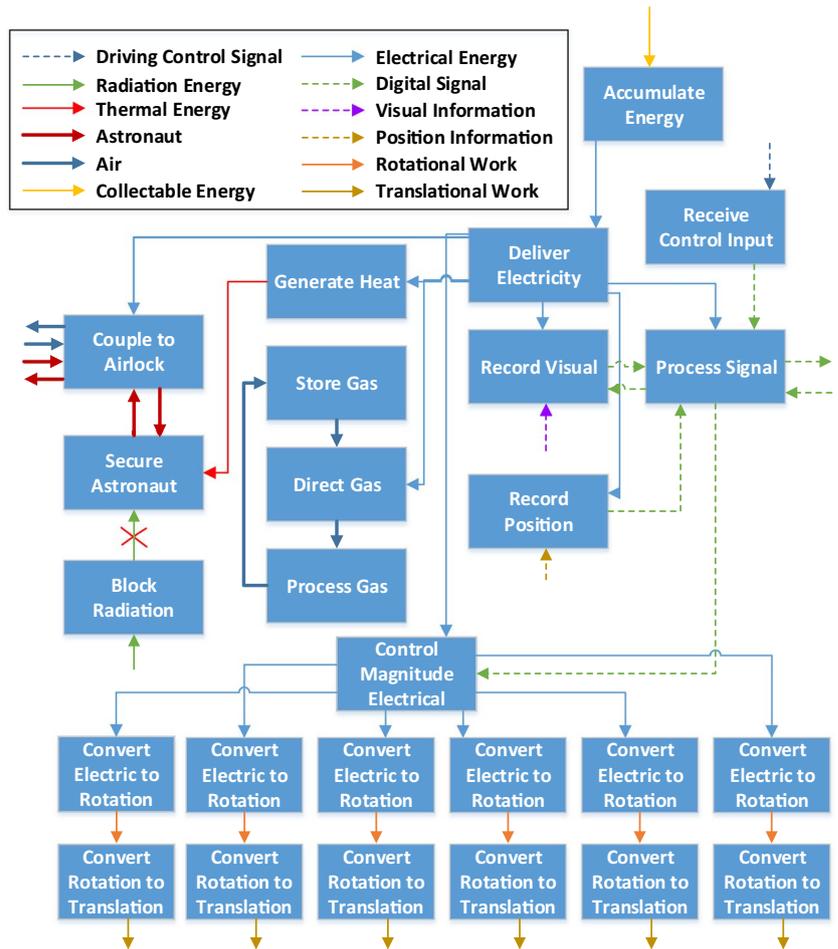
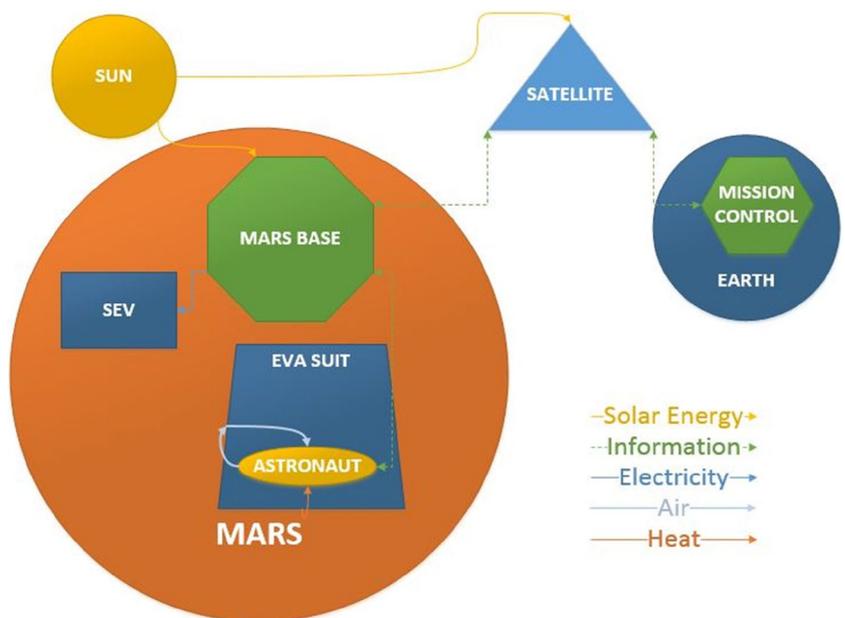


Fig. 3 Nested super systems functional model



the logic by which failure propagates can be described and analyzed (Short et al. 2015, 2017).

In the AMSE method, it is important to assign failure distributions to systems and accurately represent how failure is passed between systems (Upadhyay 2010). These failure distributions will describe the instantaneous hazard rate of the system. PHM condition-based failure distributions must be selected that are dependent on the flows passed into and out of the system, and often are dependent on the time over which the system is utilized (though not exclusively, and could be dependent on resources such as the flow of cooling fluid at appropriate levels or available energy). Additionally, for systems for which PHM models have not been developed, several common forms of failure distributions can be used, such as the Weibull distribution, normal distribution, and the exponential distribution (Upadhyay 2010). However, for many systems, more complex prognostic health models have been developed and can be integrated into the math of the system models (Goebel et al. 2008; Saha et al. 2009; Gao et al. 2002; Daigle et al. 2011).

Once the individual systems have been analyzed to determine how failure will propagate (Jensen et al. 2009; Kurtoglu and Tumer 2007; Short et al. 2017), the entire nested super system assembled in Step 1 can be modeled. The super system model is constructed in the same manner as a single functional model, but with systems in the place of sub-systems. The end product is a mathematic representation of a risk-informed functional model that can track the passage of flows between all mission systems and actively reported an estimated system health.

3.3.4 Step 4: Define a mission plan

A mission plan is used in AMSE to develop future scenarios for automatic mission success probability calculation. The mission plan includes the planned operations and objectives to be completed over the course of a mission. We suggest that the mission plan start loosely with only primary mission objectives and milestones defined at first, and then the secondary objectives and operations that must be completed to facilitate the performance of objectives can be developed. For use with AMSE, the mission plan is then broken down further into actionable items that can be completed by systems in the mission. These actionable items are referred to as “tasks” for the rest of this paper. Examples of tasks for a rover include driving a specific distance, performing a scientific operation, or performing communication with Earth. For the case of a crewed space mission, tasks may include EVAs, the performance of experiments, or health-related tasks such as eating and sleeping.

3.3.5 Step 5: Develop task modules

Task modules are important to develop for the AMSE method, because AMSE uses tasks to automatically plan how mission objectives can be completed when analyzing potential decision choices. Tasks modules include the duration that a task is to be performed, all systems and resources used during the task, and any fatiguing or consumption of systems affecting the health of systems that may occur during completion of the task. This information will be necessary for analyzing the mission in Phase 2 of AMSE. “Appendix 1” lists several typical mission tasks, and associated resource and system health cost parameters.

3.3.6 Step 6: Organize tasks into a task plan

Using the task modules generated in Step 5, the next step is to organize the task modules into a task plan that defines typical operations or schedules that are to be followed within the mission plan. For example, a task plan can represent all of the tasks to be completed on a particular type of day, such as a day that an EVA is to be performed by a crew member. Additionally, a typical week can be assembled from task plans for days and made into a larger meta-task plan. The bundling of task modules into task plans allows for more rapid reconfiguration of the system model for analysis by AMSE by allowing the mission controller or astronaut performing the analysis to quickly assemble a typical period of time to include into the analysis.

3.3.7 Step 7: Arrange task plans to align with the mission plan

The general mission plan defined in Step 4 is now filled in with task plans developed in Step 6. This enables the analysis of the mission using AMSE by providing a time-discretized list of all of the actions and systems that are to be used for completion of the mission as a whole. Figure 4 shows how task modules are assembled into task plans and then arranged to align with the mission plan.

While each of the seven steps of Phase 1 must be completed prior to using AMSE, and the initial modeling can involve a large time investment, though once many of these steps have been performed, they do not have to be performed again. If the model needs to be reconfigured to account for an unforeseen circumstance or to iterate on the mission design (in the case of using AMSE for mission design rather than mission operations), adjustment of the models developed in Step 3 or reconfiguration of the Task Plans in Step 6 can account for the majority of changes that may need to occur to the mission plan and its constituent parts. Due to the ease of configurability enabled by initial up-front investment of time and resources in model building, AMSE models are

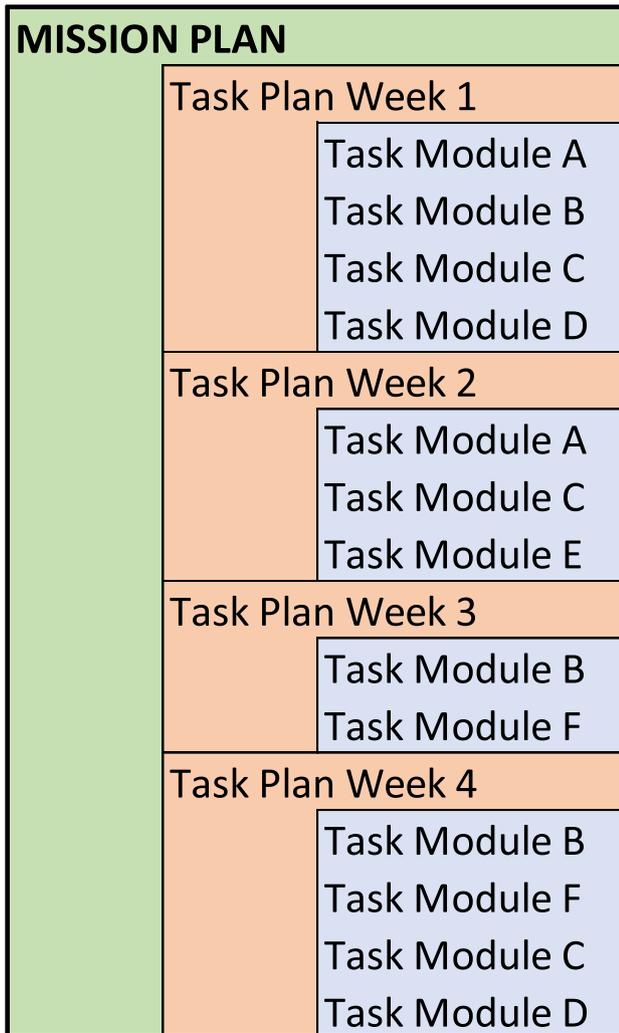


Fig. 4 Organization structure of tasks

able to be reconfigured rapidly to adjust to unforeseen circumstance or examine a variety of options to inform a mission control decision.

3.4 Phase 2: AMSE analysis

As with Phase 1 of AMSE, the second phase, analysis, requires the investment of time and resources to generate the mission models for analysis. Unlike Phase 1, Phase 2 only must only be setup once and will be run whenever the evaluation of a new mission model is desired. The majority of the math necessary for Phase 2 was already developed from Step 3 of Phase 1 where the mathematical representation of the mission was developed. The performance of Phase 2 takes the form of execution of an algorithm consisting of eight individual steps. The eight steps that comprise the Phase 2 algorithm are detailed below. A flowchart of Phase 2 algorithm can be seen in Fig. 5.

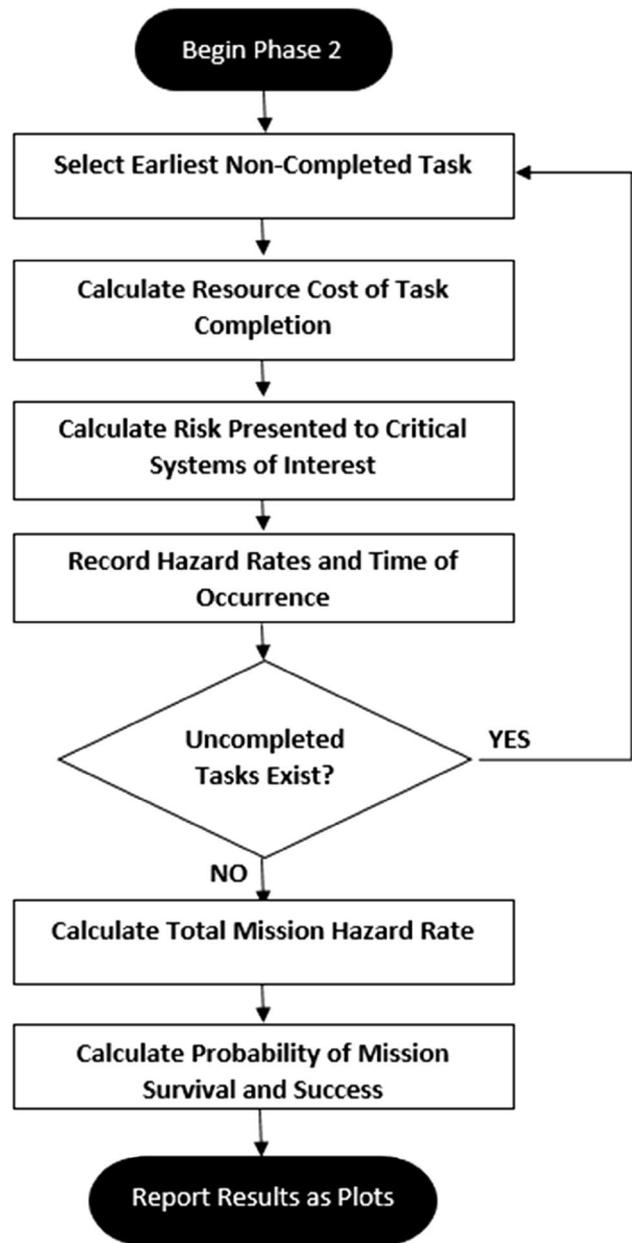


Fig. 5 Phase 2, analysis, process flow

3.4.1 Step 1: Step through mission plan

Starting with the earliest task that has not yet been analyzed, select each task and then perform Steps 2 through 5 on them. This is necessary to analyze how the success rate of the mission develops over time.

3.4.2 Step 2: Calculate resource cost of task and PHM effects

Any resources consumed or systems fatigued by the completion of the task must be accounted for. One implementation

of this is a resource matrix that contains how much of each resource is available, and subtract from the matrix as resources are consumed. A similar approach can be utilized for the tracking of system health from mechanical wear, environmental conditions, or energy usage.

As an example of Step 2 of the algorithm, the model for kilocalories used by an astronaut during the performance of a task is displayed in Eq. (6), where k represents kilocalories used, p represents physical exertion required to perform a task on a scale of 0 to 10, where sleep is a 0.5 and vigorous exercise is a 9.5, d represents the duration of the task in hours, and w represents the astronaut's current weight in kilograms (Appendix 2. Estimated Calorie Needs per Day, by Age, Sex, and Physical Activity Level-2015–2020 Dietary Guidelines-Health.Gov 2016).

$$k = (p \cdot 0.8556 + 0.5622) \cdot w \cdot d. \quad (6)$$

3.4.3 Step 3: Calculate hazard rates presented to critical system of interest

Utilizing the mathematical system model with health information developed in Phase 1, calculate what the risk of system failure is for completion of the task. We recommend calculating the risk in the form of an instantaneous hazard rate, $\lambda(\tau)$, representing the number of system failures expected at the instant τ .

3.4.4 Step 4: Record hazard rates

A matrix containing hazard rates for the systems of interest and the time at which the hazard rate was reached should be generated. This will be necessary for the calculation of a total mission failure and success rate in later steps. The matrix values for the first three sols spent on Mars for one of the astronauts in the case study presented in this paper is reported in "Appendix 2".

3.4.5 Step 5: Repeat until complete

If tasks still exist in the mission plan that have not yet been analyzed, return to Step 1 of Phase 2. If all tasks in the mission plan have been completed, then continue on to Step 6 of Phase 2.

3.4.6 Step 6: Calculate total mission hazard rate

The mission hazard, $\Lambda_a(t)$, rate defines how often failure is to be expected while executing a mission. For the case study presented, failure is defined as the loss of human life during a space mission. However, for a manufacturing process, it could be shutting down the production line or the generation of product that does not meet quality standards.

Taking the instantaneous hazard rates generated from the functional models and real-time PHM information developed in Steps 2 and 3, calculate the total hazard rate for the remainder of the mission time as a function of time over the entire length of the mission. Like the instantaneous rate, $\lambda_a(\tau)$, the total mission hazard rate, $\Lambda_a(t)$, describes the number of expected system failures per unit of time. While this can be found using integration of continuous data, for the purpose of discretized data generated in completing the AMSE method, a weighted average can find the total mission hazard rate. This is found by summing the product of the instantaneous hazard rate for a task and the duration of a task, $\Delta\tau$, and then dividing by the total mission length, T , minus the current time of the mission (Eq. 9).

3.4.6.1 Formulation 1: $\Lambda_a(t)$, formulation of hazard rate Here we provide the mathematical formulation for $\Lambda_a(t)$, the hazard total rate presented to a critical system of interest from an environmental or internal hazard over the remaining course of the mission $\left[\frac{\text{Losses of System}}{\text{mission}} \right]$.

3.4.6.2 Formulation 1.1: Sets $\epsilon \in E$: set of all Tasks in a Task Plan.

$\epsilon \in E_t$: set of all uncompleted tasks in the task plan after time, t .

$h \in H$: set of all hazards faced by the system of interest.

$h \in H_\epsilon$: set of all hazards presented to a critical system of interest, s , in the completion of task, ϵ .

$a \in A$: set of all critical systems of interest in a system.

$p_{ah} \in P$: set of all parameters used to calculate hazard rates in PHM-based failure distribution, R , for system, a [various units].

3.4.6.3 Formulation 1.2: Parameters T = Total planned mission length (h).

$\Delta\tau_\epsilon$ = Time elapsed during the completion of a task, ϵ (h).

3.4.6.4 Formulation 1.3: Variables τ = Instantaneous time in the mission (h).

t = Time elapsed since mission start (h).

3.4.6.5 Formulation 1.4: Calculation The hazard rate for an individual hazard, h , is found by inputting the appropriate parameters into the PHM-based failure distribution, R .

$$\lambda_{ah} = R(p_{h(i)}) \left[\frac{\text{Losses of System}}{\text{hour exposed to hazard}} \right]. \quad (7)$$

The total hazard rate presented to a critical system of interest, s , during a task, ϵ , is:

$$\lambda_a(\epsilon) = \sum_{h \in H_\epsilon} \lambda_{ah} \left[\frac{\text{Losses of System}}{\text{hour}} \right]. \quad (8)$$

The combined hazard rate presented to all critical systems of interest, s , for the remainder of the mission, is given by:

$$\Lambda_a(t) = \frac{\sum_{\epsilon \in E^t} \lambda_a(\epsilon) \cdot \Delta \tau_\epsilon}{T - t} \left[\frac{\text{Losses of System}}{\text{Mission}} \right]. \quad (9)$$

3.4.7 Step 7: Calculate probability of mission survival over time

In this step, calculate the probability of mission survival over time, $S_a(t)$, for a critical system of interest, a , using the total mission hazard rate as shown in Eq. (10). In the case of a single critical system of interest, $S_a(t)$, is equivalent to the total mission probability of success, P^{success} . However, in the case of multiple critical systems of interest, P^{success} is equivalent to the intersection of the probability of mission survival, $S_a(t)$, for all systems as shown in Eq. (11) Formulation 2 below.

3.4.7.1 Formulation 2: (P^{success}) formulation of probability of mission success Here we provide the mathematical formulation for (P^{success}), the probability of total mission success [Successful Missions per Attempt].

3.4.7.2 Formulation 2.1: Sets $a \in A$: Set of all critical systems of interest in a system.

3.4.7.3 Formulation 2.2: Parameters T = Total planned mission length (h).

3.4.7.4 Formulation 2.3: Variables t = Time elapsed in the mission so far (h).

3.4.7.5 Formulation 2.4: Calculation The probability of survival for a single critical of interest, s , is calculated for planned mission time remaining, $T - t$

$$S_a(t) = e^{-\Lambda_a(t) \cdot (T-t)} \left[\frac{\text{Systems Survive Mission}}{\text{Attempt}} \right]. \quad (10)$$

The probability of total mission success is calculated for mission time, t

$$P^{\text{success}}(t) = \bigcap_{a \in A} S_a(t) \left[\frac{\text{Successful Missions}}{\text{Attempt}} \right]. \quad (11)$$

3.4.8 Step 8: Display results

Finally, results of the AMSE analysis are presented in a human readable form to support decision making. To make the results of the AMSE analysis human readable, the instantaneous hazard rate and survival rate for an individual critical system of interest should be plotted, as well as the probability of total mission success over time. This provides a quick visual check of how the probability of mission success develops over time, as well as providing insight on any task or period of time that may be adversely affecting the probability of mission success. Additionally, it may be helpful to plot system- and hazard-specific values to determine what degraded system health states may be leading to less-than-desired mission success probability that need to be directly addressed. Viewing the results of the analysis in this way allows for easier interpretation of the results, troubleshooting of low-success-probability mission plans, and allows prognostics-enabled decisions to be made by human operators that better consider how system health develops over time.

Similar to Phase 1, the initial setup of Phase 2 can be time-intensive, but after it is set up the first time, it is unlikely to require any additional work be performed and it should be applicable to any model generated in Phase 1.

3.5 Phase 3: Interpretation of results

Phase 3 of the AMSE method consists of interpreting the results of the analysis from Phase 2. This phase is difficult to break into concise steps as it is less procedural, and instead aims to generate mission decision or design insight that is informed by analysis and is model- and mission-specific. However, there are some general guidelines that can be applied to most cases that a practitioner might encounter.

One important metric to observe is the probability of mission success at the beginning of the mission, $P^{\text{success}}(0)$, or the probability of total mission success over the entire span of the mission from beginning to end. This metric is important, because it describes the total probability that a mission will be successful including all tasks, systems, expected environmental conditions, and other health-affecting factors over the entire mission plan. Additionally, it should be noted that $P^{\text{success}}(t)$ at time $t = 0$ is the lowest that it will ever be during a nominal mission, because it includes all of the risk from all of the tasks that are to be completed.

One way to conceptualize $P^{\text{success}}(0)$ is as the probability that a speeding driver will be pulled over by the police during a long trip. At the beginning of the drive, there exist the most opportunities for the driver to be pulled over. However, over the course of the trip, the number of remaining chances to be pulled over decreases, because there is less of a distance left to traverse, and therefore, less of a chance that the speeding driver will be caught.

Additionally, it should be noted that $P^{\text{success}}(t)$ approaches 1 as time remaining in the mission approaches 0. It is important to keep this in mind, especially in high-risk missions that appear to become more successful near the end of the mission. This line of thought constitutes a fallacy in the way the model is viewed as the higher probability of survival near the end can only be achieved, if a low probability of survival is completed near the beginning. Additionally, it is important to understand how a single high-risk mission task could drastically lower all of the mission success estimation before the task is completed. For example, if a mission is conducted where all mission tasks have a 100% probability of success, except for one task that has a 10% chance of success but presents no long-term system health effects, the probability of mission success will be only 10% until after the task is completed.

An important consideration when working with AMSE is properly defining expected and acceptable levels of risk early in the process and realistically considering the consequences of possible outcomes. If a manufacturing process has a 70% chance that each product will pass quality checks, then that may be acceptable in some cases. However, a 70% chance of loss of life is generally unacceptable. Digging into the model and seeing how it responds to a wide variety of foreseeable issues before they come up is advisable, because this will help to inform the decision maker's general attitude and will allow operators to address problems before they arise.

Finally, if uncertain parameters are used in the creation of the model, sensitivity analysis should be performed. This will inform the operator of potential biases and shortcomings their model could have based on assumptions about the performance of individual sub-systems.

4 Case study

A case study is presented in this section of a hypothetical space mission to establish a permanent research settlement on the Martian surface using simple and widely available models. This approach allows for the more direct evaluation of the AMSE methodology as a decision support tool, while using the case study as a framework for the evaluation of AMSE's effectiveness and responsiveness.

The planned mission consists of two crews consisting of four female astronauts each arriving at the same site 26 months apart. The time horizon of the mission begins with the arrival of the first crew, Crew Alpha, and continues up to their departure after 1070 Martian sols. This time horizon was selected, so that the comparatively high-risk activities of ascent and descent from orbit would not affect the

analysis, and the focus can remain on surface operations and the demonstration of AMSE. The second crew, Crew Beta, is also analyzed with AMSE, but the primary focus of the case study is on Crew Alpha.

4.1 Crew composition

Each crew consists of four female astronauts who are all approximately 170 cm tall and range from 60 to 65 kg. The reason behind sending an all-female crew is that it cuts down on the quantity of food necessary to sustain their health and allows for more shared resources such as commonly sized space suits or extravehicular mobility units (EMUs). This idea has been proposed in the past by a variety of individuals including participants in the NASA Hawaii Space Exploration Analog and Simulation (HI-SEAS) test (HI-SEAS Mission 3|Solar System Exploration Research Virtual Institute 2016; Greene and Oremus 2014).

To model human crew survival from a functional perspective, models of the Martian environment and the necessary conditions for human life are developed. Critical information used in the development of the model is presented in Sect. 4.2 through 4.5.

4.2 Human requirements to live in space

Humans operating in space environments requires external life support systems to continue living and to be able to perform work tasks. The major requirements for sustained human survival in space include: temperatures between 4 and 35 °C, 0–0.5% atmospheric carbon dioxide by volume, 35–350 kPa ambient pressure, radiation dose below 15 roentgens per year (Environment of Manned Systems 2016), 2 liters of water per day (Gleick 1996), access to 34 essential nutrients (Nutrition 2016), and a minimum of approximately 1300 kcal per day (Appendix 2 Estimated Calorie Needs per Day, by Age, Sex, and Physical Activity Level-2015–2020 Dietary Guidelines-Health.Gov" 2016).

On Mars, threats to maintaining human life include: exposure to radiation, surface storms, and exposure to the very low atmospheric pressures and temperatures. On the Martian surface, ambient pressures averages 0.6% of Earth sea-level pressure, atmospheric composition consists of over 96% carbon dioxide (Mars Fact Sheet 2016), mean surface temperatures are approximately –63 °C, and raw surface radiation exposure is upwards of 1000 times greater on the surface of Mars than Earth (Plante and Lee 2005).

4.3 Human exploration of Mars and site selection

Current NASA deep space mission planning methodology is heavily reliant on materials acquired at the site

through the process of in situ resource utilization (ISRU) (NASA::S&MS::In Situ Resource Utilization (ISRU) Element 2016). For this reason, NASA has compiled a series of parameters that are ideal for a Mars base site. A decision matrix, compiled by the First Landing Site/Exploration Zone Workshop for Human Missions to the Surface of Mars, lists two primary criteria categories: (1) Scientific Merit and (2) ISRU/Engineering criteria. The engineering criteria consider foundational factors such as water supply and the presence of plant micronutrient minerals that are foundational to a long-term human presence. The optimal ISRU/Engineering selection criteria were used as the primary criteria for site selection.

The principal location risk was deemed to be dust storms. These have typically originated in the southern hemisphere during or around perihelion, and Martian summer (Barnes 1999). Dust storms can reduce visibility over the entire planet, making navigation difficult for astronauts during an extravehicular activity (EVA). Additionally, dust can also compromise solar power generation. Evidence for surface lightning has also been observed, which could affect power systems (Ruf et al. 2009). Dust storms occur at an average rate of 7.1 storms per Martian year (Beish and Recorder 2016), and are generally more intense in the southern hemisphere (Cantor et al. 2002). Thus, the northern hemisphere is preferable for colonization.

The planned Mars mission utilizes solar power (Do et al. 2016). While average insolation is greater at the poles, it is more consistent at the Martian equator. An average insolation of 200 W/m² occurs around the Martian equator. A peri-equatorial site would, therefore, be best for power and agricultural performance.

Within these criteria, NASA has listed a few potential landing sites for un-manned missions that exhibit fluvial features and possible hydraulic soil infiltrates for ISRU water reclamation. The list includes the Mawrth Vallis and Nili Fossae sites. Martian surface spectroscopy data suggests that the essential micronutrients and minerals vital to the growth of most plants can be found in Martian soil. For this simulation, it is assumed that all inorganic plant micronutrients are present at the chosen Martian Sites.

4.4 Nutrition requirements

The most important long-term life support risk to humans on any deep space mission is nutrition, because food is the greatest one-time consumable by mass after fuel. Lifting mass out of orbit is extremely costly, thus the total supply of food that can be taken into space is limited. Additionally, the biosphere in which most food is grown is arguably one of the most complicated systems yet documented; artificial replication is very prone to catastrophic cascading failure (MacCallum et al. 2004). Therefore, a high risk of starvation

exists due to food production being prone to failure, and food carrying capacity at launch being extremely limited.

The US Food and Drug Administration defines 34 key macro and micronutrients essential to human survival (Food, Administration, and others 2014). In addition to the daily recommended value (DRV), each macro and micronutrient has an approximate biological half-life. To consolidate this information into a more concise metric, an index of criticality was developed as shown in Eq. (12).

$$\text{Criticality Index} = C_i = \frac{\text{DRV}}{\text{Bio-Halflife}} \left[\frac{\text{g}}{\text{h}} \right]. \quad (12)$$

This ratio inflates for both high-intake requirements and quick biological half-lives, yielding a metric whereby the largest numbers represent the most critical nutrients. Conveniently, this criticality index also indicates which micronutrients are practical to bring from Earth as supplements. This index was used to categorize the nutrients that would be more efficient to produce in situ on Mars. Again, high-mass requirements for some consumables, such as carbohydrates, protein, fat, and other macronutrients, restrict the efficiency of supplying such materials from Earth. All macronutrients, namely carbohydrates, fat, protein, and dietary fiber can only be efficiently produced on site (Do et al. 2016). It was found that the most critical nutrients are carbohydrates, protein, dietary fiber, and fat.

Crops were selected using two criteria: the aforementioned nutrient criticality index, and growing time. Ultimately, potatoes, soybeans, sweet potatoes, wheat, and peanuts were chosen as the primary crops. Various other crops were considered as well for their rich micronutrient production including: cabbage, tomato, bell pepper, spinach, cucumber, kale, garlic, onion, and broccoli. Additionally, it should be noted that several vitamins and minerals are principally animal products and will be assumed to be brought along from launch as dietary supplements. These include cholesterol, vitamin D, vitamin B12, vitamin H (biotin), and iodine.

4.5 Included model systems and resources

In addition to the models of the astronauts, two Martian surface habitat modules, two SEVs, and twelve total space suits are included (6 space suits brought by Alpha Crew and 6 space suits by Beta Crew). The modeled systems are broken down further into sub-systems such as those for power generation, life support, in situ resource utilization, or waste management in the case of the habitats. For instance, the model for the habitat examines PHM relevant data such as the quantity and intensity of physical work performed, power consumption, load on the life support systems, time of exposure to the Martian environment, and accumulated fatigue

Table 1 Crew EVA schedule over a nine-Sol period

Crew member	Sol 1	Sol 2	Sol 3	Sol 4	Sol 5	Sol 6	Sol 7	Sol 8	Sol 9
A	EVA			EVA			EVA		
B	EVA				EVA			EVA	
C		EVA		EVA				EVA	
D		EVA			EVA		EVA		

from the use of the habitat airlock. Another system for which a model was developed is the SEV, which models the hazard rates of wheel failure, battery loss, mechanical fatigue, and general health effects from exposure to the Martian environment. Equations (13) through (16) show the distributions used for the hazard rates for tires, power, mechanical fatigue, and environmental damage. Equation (17) shows how the combined SEV failure hazard rate is found.

$$\lambda_{\text{wheel}} = 6 \cdot \lambda_{\text{wheel}} = \frac{6}{1425} \cdot \left(\frac{t_{\text{driven}}}{1425}\right)^4 e^{-(t_{\text{driven}}/1425)^5} \left[\frac{\text{expected failure}}{\text{hour}}\right] \tag{13}$$

$$\lambda_{\text{power}} = \frac{1}{3600} \cdot \left(\frac{Q_{\text{cycle}}}{3600}\right)^5 e^{-(Q_{\text{cycle}}/3600)^6} \left[\frac{\text{expected failure}}{\text{hour}}\right], \tag{14}$$

$$\lambda_{\text{mech}} = \frac{1}{2425} \cdot \left(\frac{\sum I \cdot t_I}{2425}\right)^3 e^{-(t_{\text{driven}}/2425)^4} \left[\frac{\text{expected failure}}{\text{hour}}\right], \tag{15}$$

$$\lambda_{\text{expo}} = \frac{1}{10,000} \cdot \left(\frac{t_{\text{mission}} - t_{\text{maint}}}{10,000}\right)^4 e^{-(t_{\text{mission}} - t_{\text{maint}}/10000)^5} \left[\frac{\text{expected failure}}{\text{hour}}\right], \tag{16}$$

$$\lambda_{\text{SEV}} = \lambda_{\text{wheel}} + \lambda_{\text{power}} + \lambda_{\text{mech}} + \lambda_{\text{expo}} \left[\frac{\text{expected failure}}{\text{hour}}\right]. \tag{17}$$

The SEV allows for greater mission scientific yield through expanding the range of EVAs, but is not necessary for preserving health, so Weibull distributions are fit to desired failure rate characteristics. These distributions can be replaced with more system-specific PHM models to increase model accuracy in exchange for minimal computational cost. However, for the purposes of the case study—namely to demonstrate AMSE—the models presented above are sufficient. The hazard rate for the SEV’s wheels, λ_{wheel} , is dependent on the time that the SEV is driven on the Martian surface, t_{driven} , and models six wheels designed to last two whole mission lengths before replacement. The SEV’s battery health, λ_{power} , is dependent on the number of battery

charge cycles, Q_{cycle} , with the equivalent cycles of five missions before failure. A larger number of missions before expected failure were used, because replacement of the SEV battery would be more time- and resource-intensive than the replacement of the wheels. The SEV’s general mechanical failure rate, λ_{mech} , is dependent on the intensity at which the SEV is driven, I , and the time driven at intensity, t_I , with two mission cycles at expected intensity before failure. The SEV’s failure from exposure to the Martian environment, λ_{expo} , is dependent on the time that has elapsed since the last general maintenance operation, $t_{\text{mission}} - t_{\text{maint}}$, with the equivalent time between maintenance of 350 Martian sols.

Additionally, a variety of consumable resources are brought, such as food and the supplies necessary to start a farm to generate food and become Earth independent. The crops brought along include soybeans, potatoes, peanuts, wheat, and sweet potatoes. The selection of these crops is informed by previous studies, but new calculations are performed to estimate the volume of each crop to grow including updated nutritional information for crops and metabolic model for caloric intake (Do et al. 2016; Jones 2000). These crops are chosen for their ability to meet DRV for necessary macronutrients and provide a variety in the diet. The crops are grown in a vertical farming unit attached to the Martian habitats. It is assumed that the Martian habitats are deployed before the arrival of the crews and only final verification operations must be performed upon arrival.

4.6 Mission plan

The plan consists of eight stages. The stages are defined as: (1) Alpha arrival and setup, (2) Starting Farm Alpha, (3) Alpha primary exploration window, (4) Preparation for arrival of Beta, (5) Start Farm Beta, (6) Crew Beta arrival and setup, (7) Cooperative scientific window between Alpha and Beta, and (8) Preparations for departure of crew Alpha. On a typical day, crew members will get 8.6 h allocated for sleep/hygienic activities, 2 h for food preparation and eating, 2 h for exercise, 1 h for farming, and then the remaining time split between intra-vehicular activities (IVA) and extravehicular activities. IVAs refer to any scientific, maintenance, or other task that is performed within the Martian surface habitat module that is not described by another category. EVAs

- Sol 0
 - Crew Alpha Arrives on the Surface
 - Perform EVAs and IVAs to verify critical Martian Surface Habitat functionality
 - Unpack transit vehicle
 - Set up habitat module
- Sol 1-5
 - Perform EVAs to validate external less critical functions
 - Begin Setup for experimentation and
 - Start farm
- Sol 6-130
 - Tend to farm
 - Sol 55: Soybeans mature
 - Sol 67: Wheat mature
 - Sol 75: Potatoes mature
 - Sol 125: Sweet potatoes mature
 - Sol 130: Peanuts mature
 - Sol 130: Self-sufficient food source achieved
 - Perform EVAs on regular schedule
 - Perform IVAs on regular schedule
 - Perform Exercise on regular schedule

Fig. 6 Sols 0 through 615 of the general mission plan

refer to any activities performed in an outside of the habitat while wearing an EMU. This includes tasks that involve the use of the SEVs. EVAs are performed on a rotating nine-sol schedule which can be seen in Table 1. On days where an EVA is performed, it is typically an 8-h EVA. The remaining time of the day is dedicated to IVA.

A segment of the mission plan can be found in Fig. 6; the complete mission plan can be seen in “Appendix 3”.

4.7 AMSE cases

To evaluate AMSE’s ability to inform mission design and decision making through functional modeling, several examples of mission crises that may occur were considered and modeled in AMSE. For the purpose of this demonstration of AMSE, it is assumed that these crises were not previously predicted and analyzed. The primary systems of interest for all crises considered are the astronauts and their survival is considered the metric for mission success. Additionally, loss of crew members has the potential to lead to loss of mechanical systems, as it reduces the crew capability to maintain and repair systems, potentially leading to cascading failure. Due to its high speed, AMSE is primarily useful in supporting decision making in real-time for scenarios that were previously unpredicted or un-modeled.

4.7.1 Inaccurate mission calculations

The first crisis to be considered in the case study is the response to a faulty assumption or calculation performed in the mission planning stage. Previous robotic missions to Mars have been lost due to incorrect calculations (Board 1999). The example considered is that the estimations for time spent performing tasks are inaccurate and as a result, the expected caloric intake necessary is much lower than the real needs of the astronauts.

In this case, the initial estimate for the area to allocate to crops is 35, 40, 85, 65, and 4 m² for soybeans, potatoes, peanuts, wheat, and sweet potatoes respectively, to serve a caloric demand of 2565 kcal per person per day. However, in reality, each astronaut burns 3025 kcal per day in the case study. Crises related to food production and nutrition are of particular interest due to the high impact on mission success and the potentially limited ability to respond due to inability to easily send more food if needed. Additionally, nutrition-based crises provided a good test case for AMSE’s ability to model human survival as part of a PHM problem.

Using only the resources available to them on Mars, Crew Alpha must determine a way to compensate for the discrepancy between their available caloric sources and their actual caloric requirements.

4.7.2 Inability to farm

Due to the criticality of food to the mission success (Weir 2011), a second food inspired case is also considered. In this case, a correct 3025 kcal per day assumption is made during mission planning and enough emergency backup food is planned for triple the time estimated to start the farm and become food self-sufficient (405 sols). However, due to unknown reasons, none of the crops grow and Crew Alpha must wait for Crew Beta to arrive with more food on sol 770. With no ability to generate more food, Crew Alpha must explore options to improve their probability of survival using AMSE to inform their decisions.

4.7.3 Broken arm

The mission plan contains many tasks that must be completed and these tasks are initially distributed to maximize the probability of mission success. However, there are a wide variety of situations that may necessitate a reallocation of tasks, such as the performance of EVAs, to other crew members. This can have potentially dire consequences, because it increases the average caloric load on other astronauts which can lead to nutritional issues as well as increasing the potential exposure to harm, increased wear on assigned EMUs, and increased radiation exposure.

To use this class of problems as an example of AMSE's utility, it is considered that a member of Crew Alpha breaks her arm on sol 771 when she falls from a ladder in the farm. Analysis using AMSE is performed to determine how work should be reassigned to give them the necessary time (approximately 70 sols) for their arm to heal with minimal effects on the mission health. Additionally, to maintain desired scientific yield and continue to perform appropriate maintenance actions on mechanical systems, work must be reassigned to ensure no EVAs are canceled.

5 Results and discussion

For each of the cases described above, an initial round of AMSE is performed for the model of the crisis and then options are explored until an acceptable level of mission success is achieved. Acceptable levels of success include situations in which the total probability of mission success over the entire span of the mission does not go below 95% or a case in which no individual's probability of survival goes below 98% for the mission.

5.1 Inaccurate mission calculations

For the case of inaccurate mission calculations, a mission plan is created that vastly underestimated the quantity of food that is necessary for the survival of the crew. The initial mission plan yields a probability of mission success of 0.5% with the mean probability of survival for each crew member being only 26.6%. The results of the analysis are shown in Fig. 7. Over the length of the mission, the average weight of the astronauts' decreases from 62.50 to 47.99 kg which presents a serious danger from starvation and malnutrition.

Allowing for the possibility that Crew Alpha could use the farm section from Crew Beta's habitat to grow more food, and that Crew Beta can bring along a third farm unit, a solution is found after 1 iteration of AMSE that achieves a probability of mission success of 95.9%. Under this configuration of the mission, 50, 60, 115, 90, and 5 m² are allocated for soybeans, potatoes, peanuts, wheat, and sweet potatoes, respectively. This plan also allows for all planned work to be continued normally without disruption. The results of the analysis are shown in Fig. 8.

5.2 Inability to farm

Similar to the first case, the inability to farm presents a risk from starvation. In this case, only 405-sols worth of rations are brought along to support a 3025 kcal/day diet. Again,

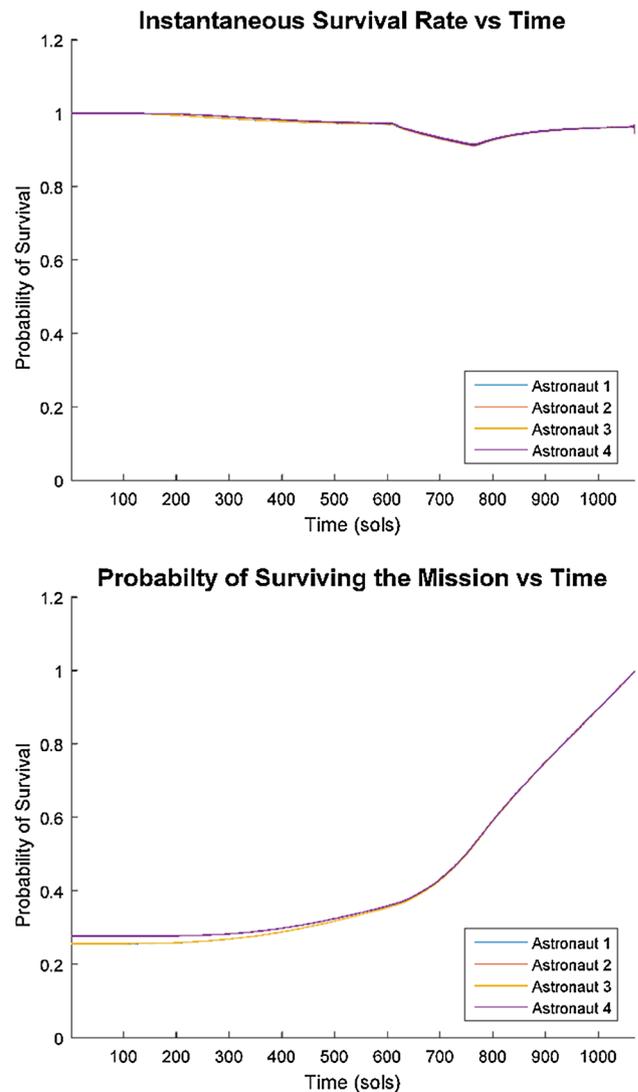


Fig. 7 Inaccurate caloric needs (top) instantaneous survival rate, (bottom) mission success over time

Crew Beta is able to adjust what they bring along to help solve the problem. However, Crew Beta does not arrive until sol 770, well after the point of starvation if no other mitigating actions are taken. The success and survivability plots for this case are presented in Fig. 9.

If no action is taken, then the probability of mission success is effectively 0% due to the astronauts starving to death around sol 450¹.

The first option that investigated involves rationing the food to evenly split portions across all 770 sols, which while still insufficient in total calories, at least keeps the food from running out. However, it is found that just rationing the food

¹ This assumes no self-sacrifice or other extreme solutions.

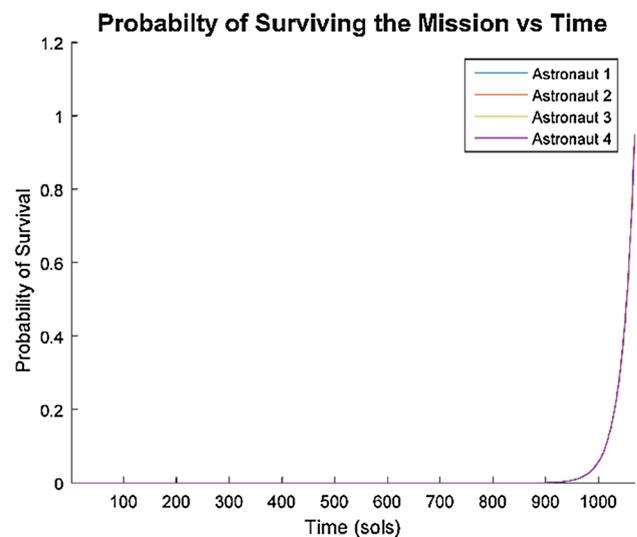
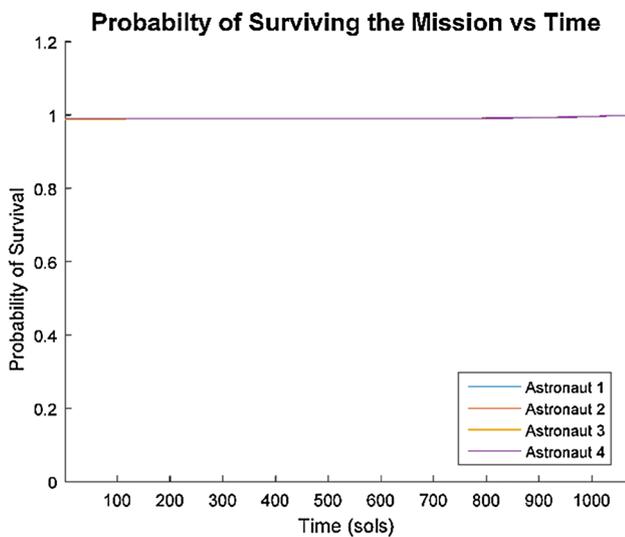
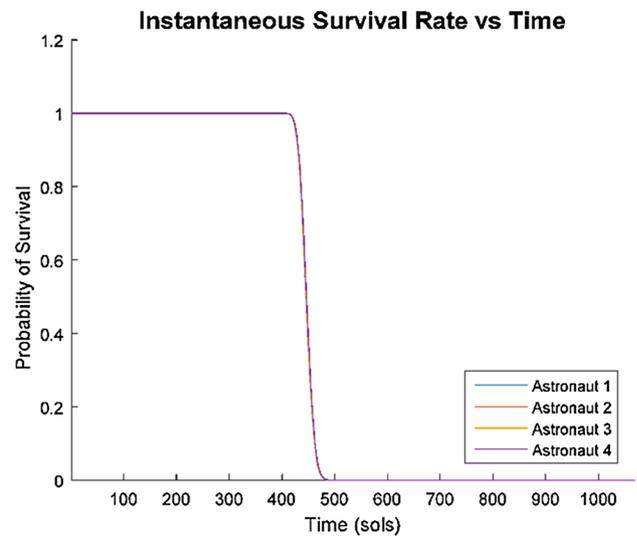
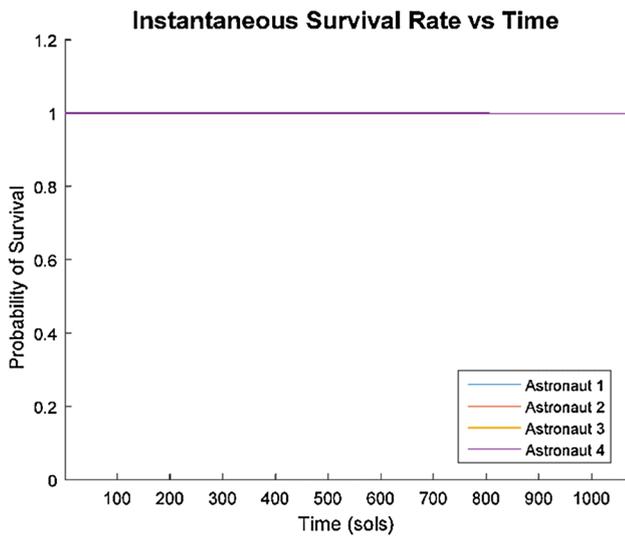


Fig. 8 Inaccurate caloric needs with larger farm (top) instantaneous survival rate, (bottom) mission success over time

Fig. 9 Inability to farm (top) instantaneous survival rate, (bottom) mission success over time

leads to loss of crew due to starvation sooner due to them being malnourished earlier on by dramatically reducing intake of calories, but not reducing their need caloric usage. The associated plots can be found in Fig. 10.

AMSE is performed again, and again the reserve of food is rationed to extend available food as long as possible, but all EVAs and exercise are canceled, and the rest/sleep period is extended from 8.6 h per day to 16.6 h per day. While this approach completely halts any planned scientific endeavors, it is enough to keep from dramatic weight loss, and the probability of mission success (defined as keeping the astronauts alive) increases to 92.99% with a mean individual survival probability of 98.2%. This is considered a sufficient solution given the constraints of the problem. The associated plots for this mission plan can be found in Fig. 11.

One potential consequence of this strategy is that the crew's ability to respond to additional crises is severely limited, and taking any actions could potentially lead to starvation. This is compounded by the canceled EVAs and reduced IVAs, which has numerous effects on the health of physical systems that require scheduled maintenance. For example, when the EVAs are canceled, the SEVs are likely to accumulate damage from ordinary Martian weather leading to reduced system health and a higher probability of system loss. While the SEVs are not critical to mission survival and their failure does not affect mission success, the potential scientific yield of the mission is limited after rescue by Crew Beta is limited by their loss.

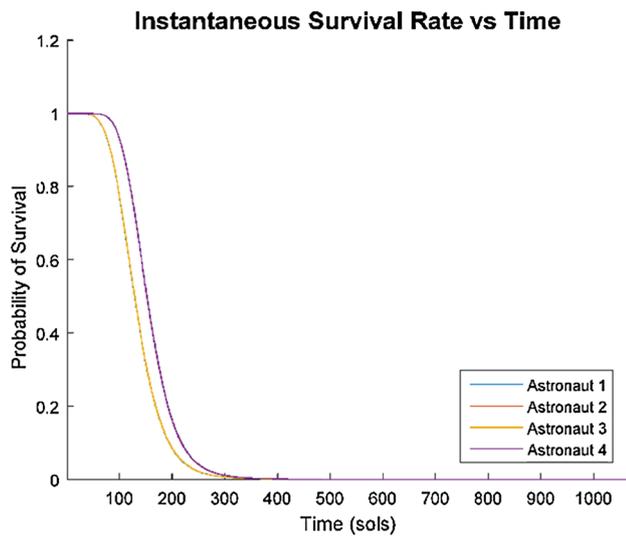


Fig. 10 Inability to farm with rationing (top) instantaneous survival rate, (bottom) mission success over time

5.3 Broken arm

The broken arm problem investigates what occurs if someone becomes temporarily incapacitated. In this case, astronaut A of Crew Alpha is unable to perform EVAs for 70 sols beginning on sol 771. EVAs are required to be performed by two astronauts at a time in the mission plan to improve EVA safety. However, if EVAs are canceled, scheduled system maintenance tasks and scientific opportunities are reduced. To keep up scientific yield, the EVA schedule is temporarily revised to the one shown in Table 2.

This leads to no significant reduction in the probability of mission success, with a probability of success of 95.9%. The resulting associated plots can be seen in Fig. 12.

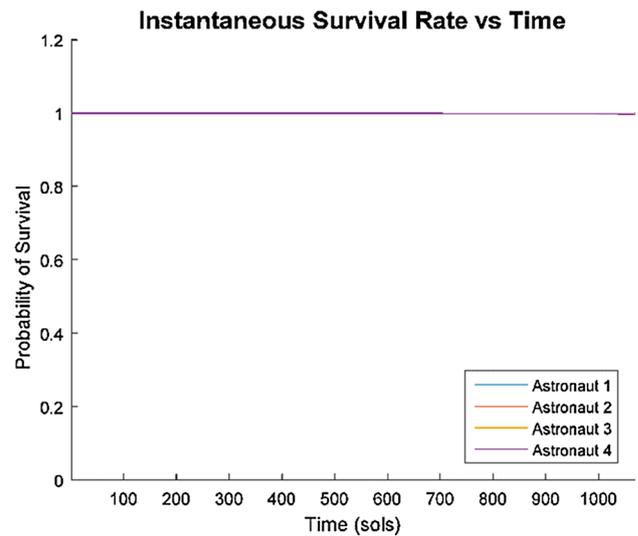


Fig. 11 Inability to farm with extra rest (top) instantaneous survival rate, (bottom) mission success over time

While this adjustment in task planning does not seem to have a significant influence on the probability of mission success, it does have some effects on the individual astronauts that may result in potential consequences. For example, over the course of the mission, astronauts B, C, and D end up being exposed to an additional 0.2 mSV of radiation, which is equivalent to receiving two chest X-rays.

For this case, we considered the astronaut completely incapacitated for the purpose of EVA's, but their other work assignments remained the same.

5.4 Discussion of results

In the cases presented above, AMSE is used to make risk-informed space mission control decisions. In each case,

Table 2 Revised EVA nine-Sol Schedule

Crew member	Sol 1	Sol 2	Sol 3	Sol 4	Sol 5	Sol 6	Sol 7	Sol 8	Sol 9
A									
B	EVA				EVA		EVA	EVA	
C	EVA	EVA		EVA				EVA	
D		EVA		EVA	EVA		EVA		

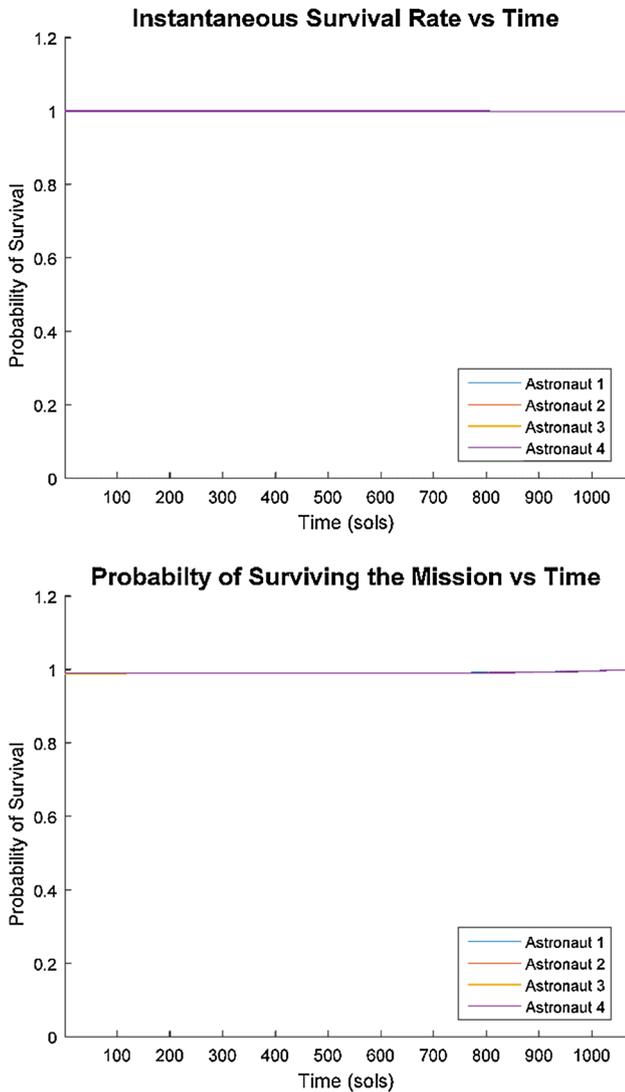


Fig. 12 Broken arm with revised EVA schedule (top) instantaneous survival rate, (bottom) mission success over time

the mission model is reconfigured within several minutes and analysis can be run in under 80 s. This allows for rapid response to mission crises. The selected crises for the case study were relatively simple with fairly apparent solutions, but each selected case was representative of a different class of space mission crisis that may be encountered. The selection of simple cases was intentional to focus on the

demonstration of the AMSE as a method for risk-informed space mission decision making.

In the initial investigation of the risk-informed space mission model used for this study, it was found that the probability of mission success was very highly dependent on nutrition of the astronauts, and that maintaining a healthy astronaut and a productive mission would be a difficult balancing act. Additionally, if the quantity of work is increased, even temporarily, the caloric load can be thrown greatly out of balance. On Earth, this would not be a significant problem, because more food can be acquired, but on Mars, additional food could take several years to arrive as flight times are highly dependent upon launch windows. This observation was part of the inspiration for having multiple cases that focused on food-related crises.

The uniqueness of AMSE in providing a decision support tool that uses real-time system health information to help mission operations managers in rapidly developing unanticipated scenarios positions AMSE to be a useful addition to space missions. The underlying system models that provide risk analysis capability are directly modified by PHM information from the physical systems. In the case of the case study, the systems are simulated; however, we have conducted initial testing on a PHM testbed platform with promising results.

While the case study focused on crises that were relatively easy to avert, the AMSE method is capable of handling much more complicated system failure scenarios. The limiting factor of the AMSE method's ability to model and analyze a mission is the availability of computational resources and the resolution of the developed mission model.

5.5 Generalization of the method

While the presented case study focuses on space mission control decisions, the AMSE method can be used to make decisions for the design and management of a wide variety of systems. As demonstrated in the case study, AMSE can be used to model traditional engineering systems, such as electrical and mechanical systems; however, AMSE has been demonstrated to handle less traditional biological systems and environmental systems.

One concept that is important to understand when it comes to generalizing AMSE to problems outside of space

mission risk assessment is the concept of missions and mission success. While in the demonstrated case study, a very traditional definition of mission is used, a mission is any series of tasks that are necessary for the completion of a goal, dependent on the state of systems for completion, and chronologically ordered. One example of this could be the design and production of a chair. This model could include human designers, computer systems, tools for manufacture, human craftspeople, and could even extend to transit systems for delivery. The objective that defines success for this system is delivery of the correct number of chairs to a buyer (though secondary conditions of human safety could also be considered). A nested super system model of the entire process could be developed, and tasks could be defined that account for everything that must be done in production. AMSE could then be used to explore potential problems in production, as well as used in crises to determine potential solutions to problems as they arise, while maintaining a long-term big picture view of success.

6 Conclusion and future work

Active mission success estimation (AMSE) is a method for the modeling and analysis of space missions for the purpose of risk analysis and informed decision making based on real-time PHM information. The bulk of the AMSE method consists of three phases. The first phase of AMSE is modeling. In this phase, a functional model of the mission containing PHM information is developed using a nested super systems approach to represent multiple interacting mission components. In addition to the functional model of the system, a mission plan is developed that contains a list of all tasks to be performed over the course of the mission. The tasks are represented by task modules, which contain quantitative information and mathematical models necessary to analyze the effect of the task on the health of systems within the mission framework. The second phase of AMSE, analysis, utilizes the functional model of the system and the mission plan to perform calculations to determine the probability of mission success over time. This phase is highly dependent on analysis of the system health models developed in Phase 1. The third and final phase of AMSE involves the interpretation of the results of the analysis to inform mission control decisions.

The AMSE method is shown to be an effective tool for risk-informed PHM-driven decision making using analysis conducted on functional models representing real systems.

This is demonstrated through the evaluation of three potential crises that could occur during a space mission.

Through the case study, AMSE shows its ability to be rapidly reconfigured in highly detailed ways.

6.1 Future work

AMSE is a promising tool for risk-informed mission risk analysis and decision making, but is currently limited in its user-friendliness and lacks any form of GUI or developed UI and instead relies on the user to make changes to the code performing the analysis. While this is doable, it is a non-ideal implementation and it vastly reduces the ability for AMSE to be used by new people. Therefore, development of a GUI for the AMSE code to be run through is given a high priority.

Another area for improvement on AMSE is in the sourcing of functional models which include PHM data and health modeling. Currently, models must be developed for each system that is to be included in the nested super systems framework. However, a database or design repository could be developed of common models for use in AMSE. This would enable the more rapid creation of mission model and improved configurability speeds by allowing for more rapid interchanging of systems or sub-systems.

A final avenue of interest for future investigation is the use of AMSE with an Artificial Intelligence (AI) to enable autonomous decision making under risk. For the case study presented in this paper, a human was able to try multiple solutions to the problem scenarios relatively quickly, however, as the problems get bigger and more complex, they could become impossible for a human to manage. However, if an autonomous decision maker was developed that could efficiently use AMSE to respond to crises and find multiple potential solutions, we could vastly reduce the time needed to find a solution to a problem. Developing better methods for autonomous decision making in hazardous and unknown environments could have applications in a wide variety of fields including, self-driving cars, home robotics, national security, and space exploration.

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Appendix 1

Task	Duration (sec)	Systems used	System health factors		Resources used	Quantity
Sleeping	30,960	Habitat module	Time inhabited	30,960 (s)	Calories burned	$\sim 8.5 \text{ (kcal/kg)} \times$ Astronaut weight (kg)
			Physical intensity	0.5/10		
Eat food	7200	Habitat module	Time inhabited	7200 (s)	Calories burned	$\sim 2.8 \text{ (kcal/kg)} \times$ Astronaut Weight (kg)
			Physical intensity	1.0/10	Food eaten	3025 (kcal) Gained
Exercise	7200	Habitat module	Time inhabited	7200 (s)	Calories burned	$\sim 17.4 \text{ (kcal/kg)} \times$ Astronaut weight (kg)
			Physical intensity	9.5/10		
Maintain farm	3600	Farm module	Time inhabited	3600 (s)	Calories burned	$\sim 4.4 \text{ (kcal/kg)} \times$ Astronaut Weight (kg)
			Physical intensity	4.5/10	Water used	$\sim 20 \text{ (L/m}^2 \text{ of Crops}$ Being Grown)
					Food produced	$\sim 8.4 \text{ (kg/day)}$ At full production
EVA	28,800	Air lock	Uses	2	Calories burned	$\sim 25 \text{ (kcal/kg)} \times$ Astronaut weight (kg)
		EMU	Time inhabited	28,800 (s)		
			Physical intensity	3.0/10		
		SEV	Time inhabited	3600 (s)		
			Physical intensity	1.7/10		
IVA	10,800	Habitat module	Time inhabited	10,800 (s)	Calories burned	$\sim 5 \text{ (kcal/kg)} \times$ Astronaut weight (kg)
			Physical intensity	1.3/10		

Appendix 2

Sol	Hour	Radiation	Temperature	Starvation	Exhaustion	Injury
0	8.6	1.53E-06	5.09E-80	7.48E-12	9.87E-10	1.00E-09
0	9.6	1.53E-06	6.02E-10	1.25E-08	1.37E-07	8.00E-06
0	13.6	1.53E-06	1.32E-37	1.56E-08	2.33E-07	7.20E-06
0	15.6	1.53E-06	3.63E-19	1.64E-08	1.74E-06	1.00E-08
0	19.6	1.53E-06	1.32E-37	2.04E-08	4.50E-06	7.20E-06
0	24.6	1.53E-06	2.19E-28	1.24E-08	2.67E-05	1.00E-08
1	33.2	1.53E-06	5.09E-80	8.49E-12	9.87E-10	1.00E-09
1	36.2	1.53E-06	6.02E-10	7.96E-09	1.37E-07	1.00E-05
1	37.2	1.53E-06	6.02E-10	8.51E-09	2.33E-07	1.00E-05
1	38.2	1.53E-06	6.02E-10	9.10E-09	3.91E-07	1.00E-05
1	39.2	1.53E-06	6.02E-10	9.73E-09	6.49E-07	1.00E-05
1	40.2	1.53E-06	6.02E-10	1.04E-08	1.07E-06	1.00E-05
1	41.2	1.53E-06	6.02E-10	1.11E-08	1.74E-06	1.00E-05
1	42.2	1.53E-06	6.02E-10	1.19E-08	2.81E-06	1.00E-05
1	43.2	1.53E-06	6.02E-10	1.27E-08	4.50E-06	1.00E-05
1	47.2	1.53E-06	1.32E-37	1.41E-08	7.12E-06	1.00E-08
1	49.2	1.53E-06	3.63E-19	1.82E-08	4.07E-05	2.00E-05
2	57.8	1.53E-06	5.09E-80	1.38E-11	9.87E-10	1.00E-09
2	60.8	1.53E-06	6.02E-10	1.17E-08	1.37E-07	1.00E-05
2	61.8	1.53E-06	6.02E-10	1.25E-08	2.33E-07	1.00E-05
2	62.8	1.53E-06	6.02E-10	1.33E-08	3.91E-07	1.00E-05

Sol	Hour	Radiation	Temperature	Starvation	Exhaustion	Injury
2	63.8	1.53E-06	6.02E-10	1.42E-08	6.49E-07	1.00E-05
2	64.8	1.53E-06	6.02E-10	1.52E-08	1.07E-06	1.00E-05
2	65.8	1.53E-06	6.02E-10	1.62E-08	1.74E-06	1.00E-05
2	66.8	1.53E-06	6.02E-10	1.73E-08	2.81E-06	1.00E-05
2	67.8	1.53E-06	6.02E-10	1.85E-08	4.50E-06	1.00E-05
2	71.8	1.53E-06	1.32E-37	2.05E-08	7.12E-06	1.00E-08
2	73.8	1.53E-06	3.63E-19	2.64E-08	4.07E-05	2.00E-05

Appendix 3

Mission Plan

- Sol-770
 - Crew Alpha Equipment Arrives on Planet
- Sol 0
 - Crew Alpha Arrives on the Surface
 - Perform EVAs and IVAs to verify critical Martian Surface Habitat functionality
 - Unpack transit vehicle
 - Set up habitat module
- Sol 1–5
 - Perform EVAs to validate external less critical functions
 - Begin Setup for experimentation and
 - Start farm
- Sol 6-130
 - Tend to farm
 - Sol 55: Soybeans mature
 - Sol 67: Wheat mature
 - Sol 75: Potatoes mature
 - Sol 125: Sweet potatoes mature
 - Sol 130: Peanuts mature
 - Sol 130: Self-sufficient food source achieved
 - Perform EVAs on regular schedule
 - Perform IVAs on regular schedule
 - Perform Exercise on regular schedule
- Sol 131–615
 - Perform EVAs on regular schedule
 - Perform IVAs on regular schedule
 - Perform Exercise on regular schedule
- Sol 616–620
 - Begin verification of Beta Martian Surface Habitat during EVAs
 - Perform IVAs on regular schedule
 - Perform Exercise on regular schedule
- Sol 621–769
 - Sol 621
 - Begin Farm Beta
 - Tend to Farm Beta
 - Sol 671: Soybeans mature
 - Sol 688: Wheat mature
 - Sol 696: Potatoes mature
 - Sol 746: Sweet potatoes mature
 - Sol 751: Peanuts mature
 - Sol 751: Self-sufficient food source achieved
 - Perform EVAs on regular schedule
 - Perform IVAs on regular schedule
 - Perform Exercise on regular schedule
- Sol 770
 - Crew Beta Arrives on surface
 - Perform EVAs and IVAs to verify critical habitat functionality
 - Unpack transit vehicle
 - Set up habitat module
- Sol 771–775
 - Crew Alpha
 - Perform EVAs on regular schedule
 - Perform IVAs on regular schedule
 - Perform Exercise on regular schedule
 - Crew Beta
 - Perform EVAs to validate external less critical functions
 - Begin Setup for experimentation and

- Sols 776–1050
 - Crew Alpha
 - Perform EVAs on regular schedule
 - Perform IVAs on regular schedule
 - Perform Exercise on regular schedule
 - Crew Beta
 - Perform EVAs on regular schedule
 - Perform IVAs on regular schedule
 - Perform Exercise on regular schedule
- Sols 1051–1069
 - Crew Alpha
 - Begin Prep for departure
 - Wrap up experiments
 - Perform EVAs to hand off tasks to Beta
 - Prepare habitat Alpha for vacancy
 - Will be used by Crew Gamma
 - Crew Beta
 - Perform EVAs on regular schedule
 - Perform IVAs on regular schedule
 - Perform Exercise on regular schedule
- Sol 1070
 - Crew Alpha Departs from Martian Surface
 - End AMSE analysis
- Sol 1540
 - Crew Gamma arrives and moves into habitat Alpha

References

- Appendix 2. Estimated Calorie Needs per Day, by Age, Sex, and Physical Activity Level-2015–2020 Dietary Guidelines-Health. Gov (2016). <http://health.gov/dietaryguidelines/2015/guidelines/appendix-2/>. Accessed Apr 5 2016
- Balaban E, Narasimhan S, Daigle M, Roychoudhury I, Sweet A, Bond C, Gorospe G (2013) Development of a mobile robot test platform and methods for validation of prognostics-enabled decision making algorithms. *Int J Prognostics Health Manag* 4:1–19
- Barnes JR (1999) Initiation and Spread of Martian Dust Storms. In: The fifth international conference on Mars, 1:6011. <http://adsabs.harvard.edu/abs/1999fcm.conf.6011B>
- Beish J, Former ALPO Senior Mars Recorder (2016) A trend analysis for predicting dust storms on Mars. <http://www.alpo-astronomy.org/jbeish/MetTrendDust.htm>. Accessed Apr 5 2016
- Blanchard BS, Fabrycky WJ (1990) *Systems Engineering and analysis*, vol 4. Prentice Hall Englewood Cliffs, New Jersey
- Board Mars Climate Orbiter Mishap Investigation (1999) *Mars Climate Orbiter Mishap Investigation Board: Phase I Report*. Jet Propulsion Laboratory
- Bohm MR, Stone RB, Szykman S (2005) Enhancing virtual product representations for advanced design repository systems. *J Comput Inf Sci Eng* 5(4):360–372
- O'Halloran B, Papakonstantinou N, Van Bossuyt DL (2015) Modeling of function failure propagation across uncoupled systems. In: *Reliability and maintainability symposium (RAMS), 2015 Annual*. IEEE, pp 1–6
- Bryant CR, Stone RB, McAdams DA, Kurtoglu T, Campbell MI et al (2005) Concept generation from the functional basis of design. In: *ICED 05: 15th International conference on engineering design: engineering design and the global economy, 1702*. Engineers Australia
- Cantor B, Malin M, Edgett KS (2002) Multiyear Mars Orbiter Camera (MOC) observations of repeated Martian weather phenomena during the Northern Summer Season. *J Geophys Res Planets* (1991–2012) 107(E3):3–11
- Daigle M, Roychoudhury I, Narasimhan S, Saha S, Saha B, Goebel K (2011) Investigating the effect of damage progression model choice on prognostics performance. In: *Proceedings of the annual conference of the Prognostics and Health Management Society*
- Do S, Owens A, Ho K, Schreiner S, de Weck O (2016) An independent assessment of the technical feasibility of the Mars One Mission Plan—updated analysis. *Acta Astronaut* 120(March):192–228. <https://doi.org/10.1016/j.actaastro.2015.11.025>
- Environment of Manned Systems (2016). <http://history.nasa.gov/conghand/mannedev.htm>. Accessed Apr 5 2016
- Food D, Administration et al (2014) *Guidance for industry: a food labeling guide* (14. Appendix F: calculate the percent daily value for the appropriate nutrients
- Friedenthal S, Moore A, Steiner R (2014) *A practical guide to SysML: the systems modeling language*. Morgan Kaufmann
- Frost SA, Goebel K, Obrecht L (2013) Integrating structural health management with contingency control for wind turbines. *IJPHM Special Issue on Wind Turbine PHM (Color)*, p 11
- Gao L, Liu S, Dougal RA (2002) Dynamic lithium-ion battery model for system simulation. *IEEE Trans Compon Packag Technol* 25(3):495
- Gleick PH (1996) Basic water requirements for human activities: meeting basic needs. *Water Int* 21(2):83–92
- Goddard RH (1920) A method of reaching extreme altitudes. *Nature* 105(August):809–811. <https://doi.org/10.1038/105809a0>
- Goebel K, Saha B, Saxena A, Celaya JR, Christophersen JP (2008) Prognostics in battery health management. *IEEE Instrum Meas Mag* 11(4):33
- Greene K, Oremus W (2014) An all-female mission to Mars Slate. http://www.slate.com/articles/health_and_science/space/_20/2014/10/manned_mission_to_mars_female_astronauts_are_cheaper_to_launch_into_outer.html?wpsrc=sh_all_dt_tw_top. Accessed Oct 19 2014
- Herr N, Nicod J-M, Varnier C (2014) Prognostic decision making to extend a platform useful life under service constraint. In: *Prognostics and Health Management (PHM), 2014 IEEE conference on* IEEE, pp 1–11
- Hirtz J, Stone RB, McAdams DA, Szykman S, Wood KL (2002) A functional basis for engineering design: reconciling and evolving previous efforts. *Res Eng Des* 13(2):65–82
- HI-SEAS Mission 3 | Solar System Exploration Research Virtual Institute (2016). <http://sservi.nasa.gov/articles/hi-seas-mission-3/>. Accessed Apr 4 2016
- Hutcheson RS, McAdams DA, Stone RB, Tumer IY (2006) A function-based methodology for analyzing critical events. In: *ASME*

- 2006 international design engineering technical conferences and computers and information in engineering conference. American Society of Mechanical Engineers, pp 1193–1204
- Jensen DC, Tumer IY, Kurtoglu T (2008) Modeling the propagation of failures in software driven hardware systems to enable risk-informed design. In: ASME 2008 international mechanical engineering congress and exposition. American Society of Mechanical Engineers, pp 283–293. <http://proceedings.asmedigitalcollection.asme.org/proceeding.aspx?articleid=1645006>
- Jensen DC, Tumer IY, Kurtoglu T (2009) Flow state logic (FSL) for analysis of failure propagation in early design. In: ASME 2009 International design engineering technical conferences and computers and information in engineering conference
- Jones H (2000) Matching crew diet and crop food production in BIO-Plex. No. 2000-01-2397. SAE Technical Paper
- Keller K, Swearingen K, Sheahan J, Bailey M, Dunsdon J, Wojtek Przytula K, Jordan B (2006) Aircraft electrical power systems prognostics and health management. In: 2006 IEEE conference on aerospace. IEEE, p 12
- Kumamoto H, Henley EJ (1996) Probabilistic risk assessment and management for engineers and scientists, 2nd edn. IEEE Press, Chicago
- Kurtoglu T, Tumer IY (2007) Ftip: a framework for early assessment of functional failures in complex systems. In: The International conference on engineering design, ICED, vol 7
- Kurtoglu T, Campbell MI, Bryant CR, Stone RB, McAdams DA et al (2005) Deriving a component basis for computational functional synthesis. In: ICED 05: 15th international conference on engineering design: engineering design and the global economy, 1687. Engineers Australia
- Kurtoglu T, Tumer IY, Jensen DC (2010) A functional failure reasoning methodology for evaluation of conceptual system architectures. *Res Eng Des* 21(4):209–234
- Lucero B, Viswanathan VK, Linsey JS, Turner CJ (2014) Identifying critical functions for use across engineering design domains. *J Mech Des* 136(12):121101
- MacCallum T, Poynter J, Bearden D (2004) Lessons learned from biosphere 2: when viewed as a ground simulation/analog for long duration human space exploration and settlement. In: International conference on environmental systems
- Mars Fact Sheet (2016). <http://nssdc.gsfc.nasa.gov/planetary/factsheet/marsfact.html>. Accessed Apr 5 2016
- Mimlitz Z, Short AR, Van Bossuyt DL (2016) Towards risk-informed operation of autonomous vehicles to increase resilience in unknown and dangerous environments. In: ASME 2016 international design engineering technical conferences and computers and information in engineering conference
- Modarres M, Kaminskiy M, Krivtsov V (2011) Reliability engineering and risk analysis: a practical guide. CRC Press
- Mohaghegh Z, Kazemi R, Mosleh A (2009) Incorporating organizational factors into probabilistic risk assessment (PRA) of complex socio-technical systems: a hybrid technique formalization. *Reliab Eng Syst Saf* 94(5):1000–1018
- NASA::S&MS::In Situ Resource Utilization (ISRU) Element (2016). <http://isru.msfc.nasa.gov/>. Accessed Apr 5 2016
- Nassif SR, Strojwas AJ, Director SW (1986) A methodology for worst-case analysis of integrated circuits. *Comput Aided Des Integr Circuits Syst IEEE Trans* 5(1):104–113
- Nathalie HERR, Nicod J-M, Varnier C (2016) Prognostics-based scheduling to extend a distributed platform production horizon under service constraint: model, complexity and resolution. <https://hal.archives-ouvertes.fr/hal-01005443/>. Accessed Apr 16 2016
- Nutrition, Center for Food Safety and Applied (2016) Labeling and nutrition—guidance for industry: a food labeling guide (14. Appendix F: Calculate the Percent Daily Value for the Appropriate Nutrients). WebContent. <http://www.fda.gov/Food/GuidanceRegulation/GuidanceDocumentsRegulatoryInformation/Labeling/Nutrition/ucm064928.htm>. Accessed Apr 5 2016
- O'Halloran BM, Papakonstantinou N, Van Bossuyt DL (2015) Modeling of function failure propagation across uncoupled systems. In Reliability and maintainability symposium (RAMS), 2015 Annual. IEEE, pp 1–6
- Pecht M (2008) Prognostics and health management of electronics. Wiley
- Pinto CA, Garvey PR (2012) Advanced risk analysis in engineering enterprise systems. CRC Press, Boca Raton
- Plante J, Lee B (2005) Environmental conditions for space flight hardware: a survey. <http://ntrs.nasa.gov/search.jsp?R=20060013394>. Accessed 4 Apr 2016
- Ramp IJ, Van Bossuyt DL (2014) Toward an automated model-based geometric method of representing function failure propagation across uncoupled systems. In: ASME 2014 International mechanical engineering congress and exposition, V011T14A007–V011T14A007. American Society of Mechanical Engineers
- Ruf C, Renno NO, Kok JF, Bandelier E, Sander MJ, Gross S, Skjerve L, Cantor B (2009) Emission of non-thermal microwave radiation by a Martian dust storm. *Geophys Res Lett*. <https://doi.org/10.1029/2009GL038715/full>
- Saha B, Goebel K (2007) Battery Data Set, NASA Ames Prognostics Data Repository. NASA Ames, Moffett Field, CA, USA [Online]. <http://ti.arc.nasa.gov/project/prognostic-data-repository>. Accessed 15 Apr 2016
- Saha B, Goebel K (2009) Modeling li-ion battery capacity depletion in a particle filtering framework. In: Proceedings of the annual conference of the prognostics and health management society, pp 2909–2924
- Saha B, Goebel K, Poll S, Christophersen J (2009) Prognostics methods for battery health monitoring using a Bayesian framework. *IEEE Trans Instrum Meas* 58(2):291–296
- Saha B, Koshimoto E, Quach CC, Hogge EF, Strom TH, Hill BL, Vazquez SL, Goebel K (2011) Battery health management system for electric UAVs. In: 2011 IEEE conference on aerospace. IEEE, pp 1–9
- Saha B, Quach CC, Goebel K (2012) Optimizing battery life for electric UAVs using a bayesian framework. In: 2012 IEEE conference on aerospace. IEEE, pp 1–7
- Sheppard JW, Kaufman MA, Wilmering TJ (2014) IEEE standards for prognostics and health management
- Short AR, Van Bossuyt DL (2015) Risk attitude informed route planning in a simulated planetary rover. In: ASME 2015 international design engineering technical conferences and computers and information in engineering conference, V01BT02A048–V01BT02A048. American Society of Mechanical Engineers
- Short AR, Van Bossuyt DL et al (2015) Rerouting failure flows using logic blocks in functional models for improved system robustness: failure flow decision functions. In: DS 80-6 proceedings of the 20th international conference on engineering design (ICED 15) Vol 6: design methods and tools-part 2, Milan, Italy, pp 27–30
- Short AR, Mimlitz, Van Bossuyt (2016) Autonomous system design and controls design for operations in high risk environments. In: ASME 2016 international design engineering technical conferences and computers and information in engineering conference
- Short AR, Lai AD, Van Bossuyt DL (2017) Conceptual design of sacrificial sub-systems: failure flow decision functions. *Res Eng Des*:1–16
- Stone RB, Wood KL (2000) Development of a functional basis for design. *J Mech Des* 122(4):359–370
- Stone RB, Tumer IY, Van Wie M (2005) The function-failure design method. *J Mech Des* 127(3):397–407
- Sweet A, Gorospe G, Daigle M, Celaya JR, Balaban E, Roychoudhury I, Narasimhan S (2014) Demonstration of prognostics-enabled

- decision making algorithms on a hardware mobile robot test platform
- Upadhyay SK (2010) Common failure distributions. Wiley Encyclopedia of operations research and management science
- Van Bossuyt DL, Hoyle C (2012) Risk attitudes in risk-based design: considering risk attitude using utility theory in risk-based design. *Artif Intell Eng Des Anal Manuf*. <https://doi.org/10.1017/S0890060412000261>
- Van Bossuyt DL, Dong A (2013) On measuring engineering risk attitudes. *J Mech Des*. <https://doi.org/10.1115/1.4025118>
- Van Bossuyt DL, Tumer IY, Wall SD (2013) A case for trading risk in complex conceptual design trade studies. *Res Eng Des* 24(3):259–275
- Weir A (2011) *The Martian*. Crown Publishing Group, USA
- Wertz JR, Everett DF, Puschell JJ (2011) Risk and reliability. In: *Space mission engineering: the new SMAD*. Microcosm Press, USA
- Widodo A, Shim M-C, Caesarendra W, Yang B-S (2011) Intelligent prognostics for battery health monitoring based on sample entropy. *Expert Syst Appl* 38(9):11763–11769
- Xing Y, Williard N, Tsui K-L, Pecht M (2011) A comparative review of prognostics-based reliability methods for lithium batteries. In: *Prognostics and system health management conference (PHM-Shenzhen)*. IEEE, pp 1–6
- Ye Y (1997) Worst-case analysis. *Interior point algorithms: theory analysis*, pp 147–177
- Zhang G, Isom J (2011) Gearbox vibration source separation by integration of time synchronous averaged signals. In: *Annual conference of the prognostics and health management society*