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Dynamic Modeling of Crew Performance for Long-Duration Space Missions

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Crew time is the most valuable and limited resource during long-duration space missions and is directly related to performance

Crew time is one of the most valuable and limited resources during long-duration space missions. Crew time requirements fluctuate depending on variations in crew performance. The limited number of crewmembers, resources, and the myriad of tasks to be performed leave a tight schedule for crewmembers during long-duration space missions. This schedule needs to account for potential interventions (stress events) that may alter predicted performance and thus scheduling. A dynamic crew model using a stochastic Auto Regressive Integrated Moving Average (ARIMA) model of interrupted time series was developed to account for the effects of potential stress events on crew performance. This model aids in estimating crew time requirements for varying mission scenarios and for evaluating stress event effects on crew performance.

Long duration space mission crews will have to perform a myriad of tasks under extreme conditions for exploratory and settlement missions. The primary goal for any mission is the achievement of specific scientific endeavors and the maintenance of a safe crew environment. Stressors such as isolation, confinement, microgravity, extraneous work schedules, and crew heterogeneity are examples of elements that may alter the consistency of motivation, crew performance, and productivity (Connors, Harrison, & Akins, 1985). Crew time is the most valuable and limited resource during long-duration space missions and is directly related to performance. It is thus critical to predict the influence of stressors on crew performance for designing successful mission scenarios.

Static crew time calculations have been used for determining the appropriateness of Advanced Life Support (ALS) subsystems for long-duration space missions. An example of this is the methodology used for Equivalent System Mass (ESM) computation of a Bioregenerative Water Recovery System (BWRS) for a space mission by Levri, Vaccari, and Drysdale (2000). An important aspect of this computation is calculating the crew time associated with this particular technology. This crew time estimate is static in the sense that it assumes steadiness in crew performance and uses a time-averaged crew time estimate. The total crew time available for mission related work ($t_{mission}$) is the time used for maintenance and repair of the BWRS (t_{lss}), subtracted from the total time available for performing work (t_{work}). However, assuming a variable that represents the dynamic nature of crew time would further enhance such calculations.

To aid in furthering the fine-tuning of crew time calculations, a dynamic crew

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model was constructed with the notion that crew productivity is not constant and may vary due to potential stressors present during long-duration space missions. Specifically, the objective of developing such a model was to simulate the effects of physiological and psychological stressors on crew performance and ultimately on crew time requirements for various mission tasks. Crew time is a costly and limited resource for long-duration missions, which can effectively increase mission costs. Only a limited amount of time is available during each day for crewmembers to perform tasks such as life support system maintenance and achieve specific scientific endeavors. This time cannot be amplified unless the number of crewmembers is increased, and the number of crewmembers cannot be increased without the addition of more systems and equipment needed to provide life support for the additional crewmembers. Additional systems and equipment increase the Advanced Life Support System (ALSS) mass, which essentially increases mission costs (Drysdale & Hanford, 1999; Jones, 2001).

The dynamic crew model developed for this study is an adaptation of a previously built model (Stahl, 1996), and incorporates earlier work by Goudarzi and Ting (1999). Stahl's CREW model was designed to predict crew performance during critical times throughout a mission, whereas the Goudarzi and Ting model was an empirical tool developed for examining physical requirements, such as calorie intake and oxygen consumption, based upon habitat conditions and specific human characteristics (e.g., gender, age, and body mass). The dynamic model presented here may be used as a stand-alone application, or may be integrated into a system level model, such as the top-level ALSS model developed by the System Studies and Modeling team that was part of the New Jersey NASA Specialized Center of Research and Training (NJ-NSCORT) project (Rodriguez, 2002).

MODEL DEVELOPMENT METHODOLOGY

Mathematical Framework

The dynamic crew model presented here is based on a stochastic ARIMA (Auto Regressive Integrated Moving Average) model of interrupted time series, which can be used for a broad range of phenomena in the social sciences (McDowall, McCleary, Meidinger, & Hay, 1981). The dynamic crew model investigates whether performance of any crewmember would be significantly compromised at critical times during a mission rather than determining the time-averaged physiological-psychological state of an entire crew.

ARIMA models are statistical models generally used to analyze time series data while assessing the impact of interventions. Such time series may be considered as a realization of a stochastic process. The idea is to observe impacts on a time series due to interventions, which break the series into pre- and post-intervention segments. In an ARIMA model, the current time series observation (Y_t) is partially determined by the previous observation (Y_{t-1}) and so on (See Eq. 1) (McDowall et al., 1981). Following the procedures described by Stahl (1996), the concept of ARIMA modeling was used for this study. However, actual time series data were unavailable for model development. Therefore, it was necessary to choose plausible parameter values (α, ϕ, and θ) for the model, while developing a model structure that can accept "real" input data when they become available. Once the structure was developed, the resulting model was then used for simulating "what if" scenarios, thus investigating its utility.

The general model expression combines the three main ARIMA components (differencing, averaging, and autoregressive components) to determine the relative crew performance while accounting for past trends:

$$Y_i(t) = \alpha_i(t) + \phi_i Y_i(t-1) + \theta_i \alpha_i(t-1) \qquad \text{[Eq. 1]}$$

Where:

$Y_i(t)$	=	*Crew performance relative to optimal performance (=1.0) for crew member i for a given mission at time t,*
α	=	*Random variable with mean μ (= 0) and standard deviation s for the unknown variance in crew performance,*
ϕ	=	*Momentum of $Y_i(t)$,*
θ	=	*Momentum of α.*

In addition to accounting for past trends, an expression that incorporates interventions was added. Interventions are external events that can disturb the flow of a time series (in our model, stress events are the interventions). Impact characteristics such as the duration and intensity of the stress event are accounted for by adding the following expression to the right hand side of Equation 1:

$$\sum_{j=1}^{n} \varepsilon_{ij}^{(tj-t)}\,\omega_{ij} \underset{(\text{for } t < t_j)}{} + \sum_{j=1}^{n} \delta_{ij}^{(t-tj)}\,\omega^*_{ij} \underset{(\text{for } t \geq t_j)}{} \qquad \text{[Eq. 2]}$$

Where:

ε = *Rise rate of stress event j,*

t_j = *Time of occurrence of the j^{th} of n stressor events during the mission,*

δ = *Rise rate of recovery process for event j,*

ω = *Relative intensity of the stress event on Y,*

ω^* = *Relative intensity of the recovery process on Y.*

Equation 2 describes an interruption (event j) through its intensity (ω) and the onset rate (ε), while accounting for the decay (δ) rate of that event. The first summation term in Equation 2 accounts for the onset of a stress event, while the second summation term in the equation is the recovery portion. The recovery process may be quite slow or non-existent. In that case, the second term is zero. A stress event can be a physiological malady such as a cold, having a gradual onset with a recovery lasting several days, or a sudden mechanical failure, that may only affect performance for a few hours.

Therefore, the overall model equation determined by combining Equations 1 and 2 is:

$$Y_i(t) = \alpha_i(t) + \phi_i\, Y_i(t-1) + \theta_i\, \alpha_i(t-1) +$$

$$\sum_{j=1}^{n} \varepsilon_{ij}^{(tj-t)}\,\omega_{ij} \underset{(\text{for } t < t_j)}{} + \sum_{j=1}^{n} \delta_{ij}^{(t-tj)}\,\omega^*_{ij} \underset{(\text{for } t \geq t_j)}{} \qquad \text{[Eq. 3]}$$

Equation 3 is a generalized first-order ARIMA model that also includes the (exponential) onset and decay of *j* interventions (i.e., stress events such as crew illness, emergencies, or mechanical failures). The model determines a single general crew performance factor, $Y_i(t)$, for each of *i* crewmembers that represents his/her performance level. As discussed, the quantitative data to define the intensities, shapes, and durations for the stress onset and recovery functions included in Equation 3 were not available during the development of our model. Similarly, Stahl's (1996) research recovered no data for developing his model. Despite the likelihood that research at NASA collected some of this data, it remained inaccessible for our study. Therefore, qualitative data was used to generate default functions, when needed.

Figure 1 presents examples of two simulated stress-recovery events occurring on the fourth and sixth day of a 10-day period, where it is assumed that the recovery process eventually cancels a stress event (i.e., $\delta = \varepsilon$, and $\omega^* = |\omega|$).

As shown, the most significant impact of the stress events occurs on days 4 and 6. However, in the case of both stress events, performance starts to drop some time prior, as determined by the rise rate (ε) associated with each stress event. The dashed line is an example of a stress event that starts to affect crew performance slowly ($\varepsilon = 0.5$, $\omega = -0.6$). For example, a lack of proper nutrition may start to affect performance gradually, whereas a mechanical failure, where the crew has to allot additional time for fixing the subsystem, may affect relative performance more rapidly as shown by the solid line ($\varepsilon = 0.01$, $\omega = -0.9$). It should be noted that performance decreases are used as a proxy for increased crew time requirement.

The recovery events for both examples in Figure 1 mirror the rise rates and intensities of their onset events. However, the recovery events may also vary depending on the stressor type and the crewmembers' response to it (e.g., a crewmember may come down with food poisoning within a few hours but take several days to fully recover). Therefore, there may be instances where performance may drop in a short time (e.g., a day) but the recovery characteristics could be different and last longer (e.g., 5 days) or vice versa. Such an example is shown in Figure 2 ($\varepsilon = 0.01$, $\omega = -0.9$, $\delta = 0.9$, $\omega^* = 0.3$).

For this study, the stochastic component in Equation 3 (i.e., the two α terms) was interpreted as an approximation for all the random effects on crew performance, for example, variance in sleep patterns, or the variability in resistance to various stressors for individual crewmembers at different times. Since α is different for each crewmember and each time step (day), crew performance will vary among individuals even for identical initial conditions and stress-recovery events.

For the purpose of this study, it was assumed that a value of $Y_i(t) = 1$ corresponds to optimal crew per-

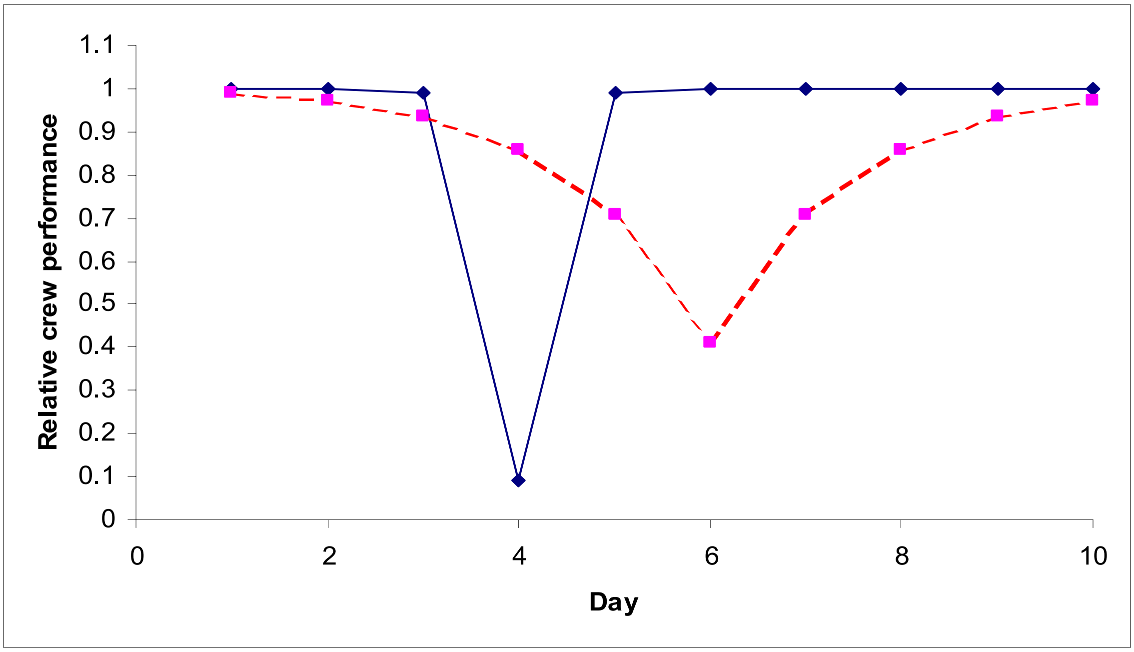

Figure 1. Example of two stress-recovery events, each for a single crewmember - one with a rapid onset and recovery occurring on day 4, and one with a gradual onset and recovery occurring on day 6.

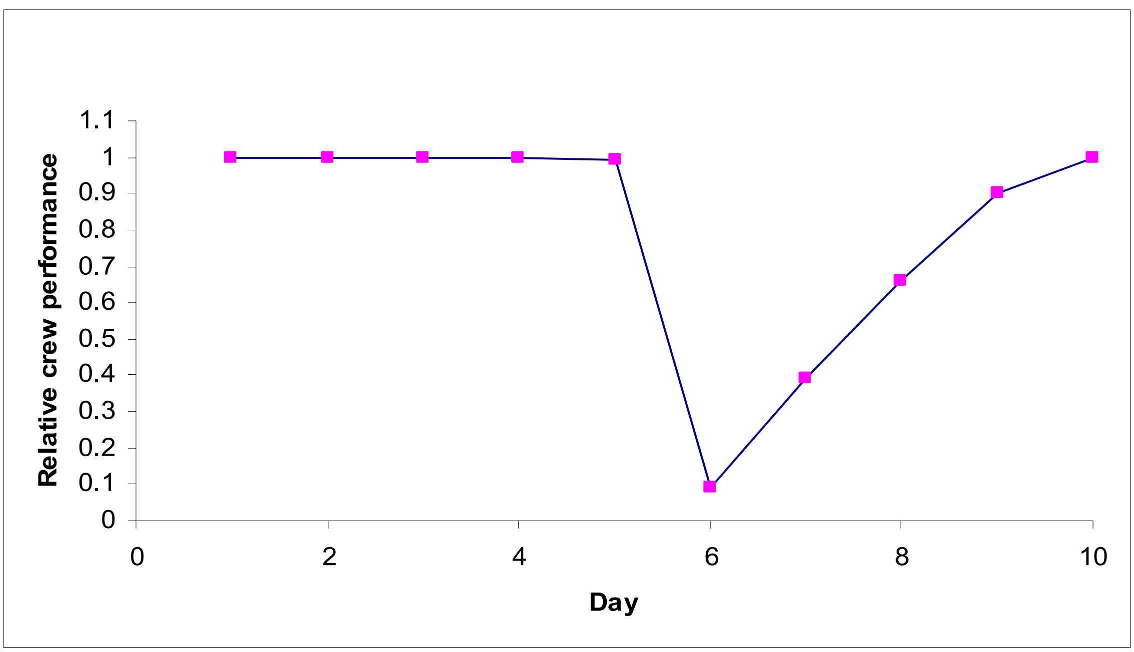

Figure 2. Example of a stress-recovery event for a single crewmember - with a rapid onset and gradual recovery occurring on day 6.

formance (performance at 100%), with tasks being completed successfully within the planned time schedule. As a result of the random variable α, $Y_i(t)$ will fluctuate around 1, even without stress-recovery events. If the intention is to account only for performance decrements, the overall crew performance can be assumed to not exceed 1.0 (i.e., overall relative crew performance = Min [1.0, $Y_i(t)$]). However, the random term in the model often causes performance to exceed 100% (i.e., implying that more work than scheduled was completed). In such cases, we did not penalize performance (truncate it to 100%) and carried the effects of a "good" day (a day where performance exceeds 100%) via the term $Y_i(t-1)$, into the next day.

Energy Deficiency Stress

Certain stressors can be directly linked to reduced food intake caused by factors such as loss of appetite, fatigue, or illness. In such cases, stress events were linked to the Goudarzi and Ting (1999) model by coupling crew performance to reduced food intake, and comparing it to "normal" energy consumption required to perform a task. This model includes calculations of oxygen consumption and carbon dioxide production, energy expenditure, heat and waste loads, and nutritional analyses.

The energy expenditure is calculated based on a set of functions that relate crew characteristics to activity schedules over a 24-hr period. Using the energy expenditure and the amount of energy intake through food, an energy deficiency (where more energy is expended than consumed due to a lack of appetite, limited food supply, etc.) or surplus (where more energy is consumed than used, due to excess food consumption or a light work schedule) is determined. Specifically, energy deficiencies are linked to the dynamic crew model where they are seen as stress events. This process allows for a direct estimate of decreases in relative performance and related increases in crew time requirements for variations in energy expenditure.

For illustration purposes, only energy deficiencies were considered, and the effects of surpluses in energy, which could translate to stored energy and possibly weight gain, were not accounted for. It was assumed that the astronauts consumed up to their daily maximum allowable nutritional limit.

Energy expenditures over a 24-hr period were calculated using equations extrapolated from data provided by the Advanced Life Support Program Requirements Definition and Design Considerations (RDDC) document (Lang & Lin, 1998). The energy balance was computed by comparing energy expenditure to the available energy content for the three main food ingredients (proteins, carbohydrates, and lipids). The available energy content was calculated using estimated energy contents in the main food ingredients (KJ/g) multiplied by the amount consumed by each crewmember (g).

Model Implementation

The developed model has three main structural parts. The first part allows for user input. Here, initial information for each crewmember is specified. Crewmember characteristics such as age, weight, and gender are detailed by the user. Additionally, stress events are either specified or randomly selected using a random number generator. The information from this first part then feeds into the second (empirical) and third (ARIMA) portions of the model.

The empirical section of the model employs the user-defined information and allows for either a user-defined crew activity level and nutritional intake, or calculates the crew activity level and nutritional intake using a random number generator. Using this information, energy deficiencies or surpluses are calculated. Deficiencies are regarded as stressors and used as inputs for the third part of the model, the ARIMA portion. This portion is where the overall crew performance is calculated. In addition to the energy deficiency, the stress events (previously mentioned as user-defined or randomly generated) are utilized here to track performance variations.

MODEL APPLICATIONS

Martian Surface Mission Case Scenario

The utility of the model is demonstrated with a simulation based on the recommendations described in the Mars Reference Mission Document (MRMD; Hoffman & Kaplan, 1997) for a Martian surface mission scenario. The proposed crew size for this 600-day Martian surface mission is eight with an undetermined gender and age composition. However, based on the gender distribution of active astronauts, a breakdown of 79% male and 21% female was used (6 male and 2 female crewmembers) (Gibson, 2002). The ages and body weights were chosen randomly within the following ranges; age: 18-50 years, weight: 65-73 kg.

The activity schedule outlined for the 600-day Martian surface mission in the MRMD was used as a guide for this simulation. The assumed activity level of the crew during the Mars surface mission scenario was derived from the "Mars Surface Mission Time Allocation" table in the MRMD and was interpreted using several assumptions. The assumptions made were related to task designation. The objective was to take each assignment and decide whether it would fit into one of four major activity categories: 1) sleep (sleeping and sleep preparation), 2) light work (hygiene, cleaning, communication, planning, documentation, reporting, analysis, meetings, and health care), 3) medium work (recreation, exercise, system shut down, and departure preparation), and 4) heavy work (system monitoring, inspection, calibration, repair, maintenance, extra vehicular activities [EVAs]).

The recommended nutritional intake for astronauts is 0.8 g/kg of body mass per day of protein, 5 g/kg of body mass per day of carbohydrates, and 1 g/kg of body mass per day of lipids (Eckart, 1994). This recommendations is very similar to the one by Larson and Pranke (2000): approximately 0.8 g/d per kg of body mass of protein, 350 g/d per person of carbohydrates, and 77-103 g/d per person of lipids. For each crewmember, an availability range for each food ingredient was identified: the model randomly picked a number within the recommended range for each day as the presumed intake. The reason for setting a range in the model and randomly selecting the actual intake from this range is to simulate the effect of random eating habits. An example of this would be a crewmember's wish not to eat a certain type of food. The ranges of the main food ingredient intake used for each crewmember were 95-105% of Eckart's (1994) recommended rates for carbohydrates, lipids, and protein consumption. The advantage to using body mass-dependent rates for calculating energy input is that indirectly, a distinction between female and male food intake is made via the common gender differences in body mass.

In addition to stress events from nutritional deficiencies, additional stress events were introduced for each crewmember. We assumed one randomly occurring stress event within each 10-day period. Therefore, each crewmember experienced 60 stress events over the course of a 600-day mission. Two types of simulations were performed; one with only random stress events, and one with both random and nutritional stress events.

RESULTS AND DISCUSSION

Simulation Results

The average relative performance for each crewmember of an eight-member crew experiencing only random stress events over a 600-day simulation period is presented in Table 1. The average relative performance for each crewmember experiencing both random and nutritional stress events is presented in Table 2.

Table 1: Average Relative Crew Performances of an Eight-Member Crew (Six Male, Two Female) Over a 600-Day Martian Surface Mission Simulation for Crewmembers Experiencing Only Random Stress Events.

Crewmember	C 1	C 2	C 3	C 4	C 5	C 6	C 7	C 8
Average Relative Performance	0.941	0.926	0.903	0.920	0.904	0.855	0.785	0.792

Table 2: Average Relative Crew Performances of an Eight-Member Crew (Six Male, Two Female) Over a 600-Day Martian Surface Mission Simulation for Crewmembers Experiencing Both Random and Nutritional Stress Events.

Crewmember	C 1	C 2	C 3	C 4	C 5	C 6	C 7	C 8
Average Relative Performance	0.759	0.721	0.659	0.906	0.686	0.775	0.721	0.727

The results in Table 1 show that the average crew performance of eight crewmembers experiencing only random stress events was 0.878. The variability which exists among the performance of all crewmembers is not attributed to the number of stress events affecting them (all were faced with 60 events with the same characteristics) or the age difference between them (all were in the 31-60 year age range). Therefore, the variation in average relative performance of the crewmembers is simply due to the random variability factor α, coupled with the difference in timing of the stress events among crewmembers. Table 2 shows a lower average relative performance of the eight crewmembers: 0.744. This is due to the additional hardship (stress events) experienced by the crew due to nutritional deficiencies (Goudarzi, 2003).

Evaluations of Different Crew Sizes

The model was employed to illustrate how it may examine the most favorable crew size based on the average relative performance and performance variability (standard deviation). The daily average relative performances and standard deviation for a four-, six-, and eight-person crew were calculated. For comparison purposes, the age of all crewmembers was set at 35 years, while the gender breakdowns were selected randomly by the model. The nutritional intake was set to be a function of weight with a plus or minus 5% randomness to simulate intake variability. Similarly, the schedules were set up randomly to schedule amounts of sleep, light, medium and heavy work. As one would expect during "real" missions, each of these variables changed daily during the simulation, producing unique performance numbers for each day. Tables 3 and 4 show the average results of these simulations (each simulation was repeated 10 times to address the idea of randomness in the model) for a 600-day Martian surface simulation.

Table 3: Calculated Average Relative Performances and Standard Deviations for 4, 6 And 8 Person Crews.

Crew Size	4 – person	6 – person	8 – person
Average Relative Performance	0.852	0.847	0.840
Standard Deviation	0.087	0.086	0.079

Four-, six-, and eight-person crews resulted in very similar average relative performances. As the crew size gets larger, the standard deviations slightly decrease (stability increases). Intuitively, this makes sense, because if one or two crewmembers are stressed on a given day, other crewmembers that are not affected by that stress event could take on activities that could not be completed by the stressed crewmembers. An example would be a mechanical failure. In such an event, if there were only four crewmembers and two of them had to tend to the problem, only two people would be left to complete the remaining activities. On the other hand, if there were eight crewmembers, there would be six crewmembers to make up for the loss in overall performance. Larger crews seem to indicate stability. However, it is important to acknowledge the fact that there should be a cap or limitation on the number of crewmembers. At some point, a larger crew size will not be cost effective for a mission. Larger crews would require more supplies, more radiation shielding, more life support systems, and more crew time needed to maintain the additional life support systems. Not to mention the additional psychological and social factors (such as crowding and interpersonal conflicts) that need to be accounted for in a larger crew size.

Small crew sizes may not be ideal for a long-duration mission, such as a Mars mission, either. Not only are many different skills and expertise levels needed, but also the amount of work required for maintaining life support systems and performing scientific endeavors will require more human participation. During a Mars analogue mission (Mars Desert Research Station – MDRS Crew 8), the crew reported a decrease of team performance when a six-person crew was reduced to five (Fisher, 2002), due to the unexpected premature departure of a crewmember. In addition to specific expertise loss, this report indicates that during the normal three-person EVAs, there were not enough people at the operations base (habitat) tending to daily duties. Thus, the crew was forced to reduce the frequency of their EVAs in order to maintain the life support systems. Hence, their scientific endeavors and primary mission objectives were compromised by loss of a crewmember and her specific skills. In the end, a balance between crew performance and mission goals will have to be struck, and it will be up to the mission designers to carefully determine the optimum crew size.

The example presented here shows that the optimum crew size can be determined using such a simulation tool. But the results presented above only show the operational integrity of the model with some basic initial assumptions and little available data from "real life" space missions. More true performance measurements are required to further increase the integrity of the equations used in the model.

An interesting discovery made during these simulations was that when the random gender generator produced a larger number of female crewmembers in an eight-person crew, generally the average relative performance increased, while the standard deviation decreased. Table 4 shows calculated values for the average relative performances and standard deviations for eight person crews with increasing numbers of female crewmembers.

Table 4: Calculated Average Relative Performance And Standard Deviation For Varying Gender Breakdowns For An Eight-Person Crew.

Crew Composition	25% Female	50% Female	75% Female
Average Relative Performance	0.801	0.840	0.904
Standard Deviation	0.114	0.078	0.047

The increase in average relative performance due to an increasing number of female crewmembers can be attributed to the equations used to describe nutritional stress. Other than differences in body weight, which are accounted for in the food consumption equations, no other gender specific relationships were used in the model. However, the data used to determine the energy expenditure calculations (Lang & Lin, 1998) shows that males of the same body weight spend more resting energy than females. Hence, females would need less energy to do the same amount of work. Thus, the amount of food intake is not only weight but also gender specific. Because in the model no distinction in food intake was made based on gender, it depicts females as experiencing less nutritional stress than males. Also, the differences in physical strength that may favor males on Earth are no longer applicable in microgravity environments. Therefore, one has to account for other factors such as motor and cognitive skills, dexterity, disease resistance, and radiation responses, to decide on optimum crew gender compositions. Data and equations to account for these factors would be needed to accurately simulate their effects. Including this data in future simulations will help identify knowledge gaps or ambiguities that can hinder comprehensive efforts of whole systems studies modeling.

Presently, the model performs simple calculations of crew performance based on a few crew characteristics. The performance of each crewmember is evaluated independent of other crewmembers. It would be interesting, once more real life data is available, to also incorporate the effect of one crewmember's performance on the other crewmembers. For example, it is possible that if one crewmember panics due to a stress event, it could have a negative impact on the other crewmembers and this could decrease the overall crew performance. Mathematically, this could be modeled by making the stress event parameters for a given crewmember (i.e., ε, δ, ω and ω^*) dependent on the performance of one or more other crewmembers.

The dynamic crew model provides a useful tool for performance measurements and mission planning. However, while developing this model, a lack of space mission human performance data was encountered, and, even when such data were collected, it was not always accessible to us. Therefore, the results presented in this study are not comparable with other findings and are for concept illustration only. The availability of more of the collected data would help make our model a better mission-planning tool. With the use of real life data, it may be possible to evaluate many different crew compositions including varying age ranges and genders. In addition, the estimates of crew time requirements to perform different tasks would be more accurate. Once all these data are available, the developed simulation model may be incorporated into a larger systems model such as the "Dynamic Object Oriented Top Level ALSS Model" (Rodriguez, 2002), where the different Advanced Life Support System subcomponents are combined (biomass production, food processing and nutrition, waste processing and resource recovery, and the crew). The crew model would then allow for a dynamic assessment of crew performance and crew time requirements as opposed to the static assumptions currently made in most top level ALSS models. Such dynamic crew performance estimates could account for scenarios where one ALSS subsystem takes up more than the allotted crew time due to performance decrements. An example scenario would be one where mission designers need to account for remaining time of tending to a waste management subsystem if more than the allotted time were used to tend to a biomass production unit. Such improved top-level ALSS models could better account for crew performance and time variations and select technologies that require less crew time, resulting in reduced mass and ultimately lower mission costs.

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