Roles of Human and Robotic Agents Toward Operating a Smart Space Habitat

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To construct and operate a deep space habitat, for example, on Mars, is an ambitious goal but bound to happen for future space exploration. Such a mission represents a grand challenge that will require the application of the highest technologies we have. Countless questions are to be answered. One of the most relevant questions is what roles humans and robots would play to maintain and operate a long term space habitat. There may not be a decisive answer to this question in the short term, depending on the critical technologies involved in human life support and robotic autonomy. However, by initially quantitatively comparing the needs and capabilities of a human and a robot for designated mission tasks, evidence may be found to support later strategy and to drive research in new directions in automation, robotics, and human-machine interaction. Here we propose a methodology to perform such a study. In this paper, two independent parallel scenarios are formed to develop an approach to compare mission success with, in one case a human agent (HA), and in the second case a robot agent (RA). In each scenario, the HA and RA are scheduled appropriately to carry out a series of tasks to maintain the space habitat in a safe and functional state. The tasks include the repair of certain subsystems in terms of reacting to emergencies. Models are developed to capture the resources and common daily activities of HA and RA, e.g., sleeping of HA, recharging of RA. Stochastic simulations are performed for each scenario. The habitat mission is to perform research. Thus, to evaluate the actual performance of the HA and RA, we have included an independent human scientist in the study. The science research hours generate by the human scientist is the metric utilized to compare the performance of the agents against the modified equivalent system mass.

Nomenclature

BB	=	building block
CDCM	=	control-oriented dynamic computational model
HA	=	human agent
HM	=	health management
HS	=	human scientist
M-ESM	=	a modified version of equivalent system mass
RA	=	robot agent
SRH	=	science research hours

I. Introduction

From interstellar probes to moon landings, from the international space station (ISS) to future extraterrestrial habitats, the exploration of deep space must evolve. The roadmap of exploration does include an ambitious plan involving the construction and operation of a permanent habitat on Mars. This mission represents an engineering grand challenge that will require the application of the highest technological capabilities. However, there are questions and concerns

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over the delegation of tasks and the confidence level that crew will have on the ability of robotic and/or autonomous agents to successfully complete various necessary objectives.

The complementary roles of robot and human is a long-standing debated topic in several realms. Specifically, in deep space exploration, the rationale for both sides remains solid. Advocates of sending human crews to space argue that humans bring intelligence, a capacity to learn, adaptability to mission constraints, not to mention the habitation of another planet in the future. Countering opinions focus on the outrageous costs in terms of resource requirements and design redundancy to support humans during a long-term space mission. Regardless of the complexity of the proposed question and difficulty in answering this question, comparing a robot and human in a deep space mission naturally forms a problem that is worthwhile to seek an answer. To approach this, we turn to the idea of a comparative study which is normally used to compare two or more design options.[1-3] For this preliminary comparison study, though we hardly believe the choice between human and robot is mutually exclusive. It is expected that the two will be working in collaboration in this future landscape. Tools have been developed in the past to perform such comparative studies.[4] However, one of the main limitations is the lack of considering the dynamics and uncertainties present in an evolving system. To contribute towards this point, the Resilient Extraterrestrial Habitats institute has developed such a framework, called the control-oriented dynamic computational model (CDCM)[5,6] that supports the formulation of meaningful comparative studies and will serve as the framework for performing this study.

Here we carry out a preliminary comparison study to model and subsequently examine the benefits and costs of a human and a robot when attending to a smart space habitat. Here the performance comparison is limited mainly to physical activities completed by the two types of agents and the time and resources to support those agents to do these physical activities. The physical activities included at this point in the work are simplified activities and performed with agents utilizing simplified resources, but will be expanded to be more realistic later. To explain the rationale for performing this study, it is practical to compare, for example, truck and human for moving an object from one place to the other given different scenarios. For a long distance (1 mile), a truck certainly is the better choice. However, for a short distance (1 meter, from a room to the neighboring room), it would be reasonable to use a human. Following this logic, in this initial study we do not yet consider cognitive abilities, like planning, on-site decision making, etc. of the agents in a space mission environment, rather at this time we focus on the physical capability they can output.

More importantly, our aim is not to draw conclusions about whether to use a human or robot in a space habitat environment. Certainly the intelligence and capacity for exploration brought by human is essential in these missions, and cannot be replaced by a robot for the foreseeable future (and perhaps it never should). Even as greater automation becomes within reach in deep space exploration, the intelligence of human agent will still play an essential role in decisions. Rather, with this work we aspire to shed light on whether the physical capabilities of human and robots can be compared through modeling and simulated scenarios, and what is the physical performance level to aim for in future robotics? These conclusions can help focus future investments in research and development in the right directions, with a knowledge of highly possible and plausible achievement in the end.

In this work, we aim to develop an approach that may help address these questions. We construct models of both the human agent (HA) and robot agent (RA) by defining a subset of their inputs and outputs. Modeling details are currently simplified somewhat to align with the scope and purpose of this work. Yet, the models include essential features of both agents, including agent status, how agents perform tasks, resources required, etc. Therefore, we propose an illustrative example to perform the comparison study by plugging the agent models into a space habitat scenario, with other subsystems, like the structure, interacting with agents. To maintain the functionality of the habitat, agents are requested to perform certain tasks. We run long-term simulations of random scenarios to generate realizations. Using the outcomes of the ensemble of stochastic scenarios, we generate metrics on the habitat level for evaluating the performance and functionality. For this study, success is measured by assessing and quantifying the science/research output of the habitat. Our metrics are designed to evaluate two quantities, first the cost side using a modified version of equivalent system mass (M-ESM), and second the benefit using the amount of science hours which is generated by a research scientist agent. By comparing the cost and benefit, discussion and conclusions can be drawn from the study.

The remaining sections of this paper are organized as follows. Section II explains the details of the approach, mainly focusing on the modeling of HA and RA. In Section III, an illustrative example is constructed to perform the proposed comparison study with the developed models. In the end, the conclusions are given in Section IV.

II. Approach

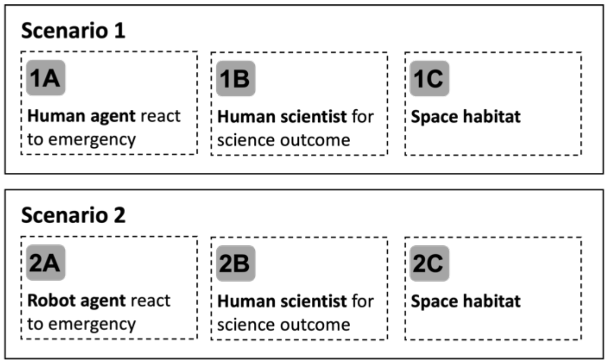


Figure 1. Approach overview

An overview of the approach is provided in Figure 1. In each row a scenario is considered in which an HA or an RA is assigned to maintain a smart space habitat, as a preliminary design for conducting the proposed comparison study. We compose these two scenarios to perform a comparison of the agents. Scenario 1 includes an HA to perform tasks, whereas scenario 2 includes an RA to perform the same tasks.

Each scenario is divided into three parts. First, starting with scenario 1, it is divided into 1A, 1B and 1C. 1A is the agent which is designed to react to emergencies. In scenario 1, the HA takes on this role. The term emergency here indicates incidents that happen on an irregular period and threaten the smooth operation of the habitat. For example, this incident may be structural damage of the habitat caused by a micrometeorite strike. Because micrometeorite strike occur on an irregular period, they may lead to an emergency that is different from routine tasks that require periodic attention. In this preliminary study we are neglecting other tasks for the HA, such as maintenance and will include more tasks as we expand the study. Meanwhile, we have included an independent human scientist (HS) that is tasked with research (box 1B) through which the science outcome produced is used for evaluating the performance at the system-level. The HS must stop their work when there is an emergency. This is only an assumption for the purpose of this study. For 1C we have a smart space habitat configured for the HA and HS to play their roles. Similarly, scenario 2 has one major difference compared to scenario 1. In scenario 2 the RA, 2A, is responsible for responding to emergency tasks. And for 2B and 2C, the settings are exactly the same as 1B and 1C. The overall picture of how the HA or RA performs in these preliminary designed scenarios are evaluated in terms of benefit and cost. The choice of the metrics and their details will be explained in Section II-D. Then, based on the values and distribution of those metrics, conclusions will be drawn.

Each agent is modeled using the CDCM framework by defining what we call building blocks (BB). Each BB is meant to capture items relating to one specific aspect of the agent. We define multiple states within each BB. Each state can only have one value at each simulation time step. BBs are modeled following a systematic hierarchy, from BB, to states, and to values. Note that some BBs share the same name with the states under its hierarchy. To avoid confusion, all BB are denoted with a name containing BB, other terms either as states or their values, unless it is a common usage. For example, the term "environment" just represents the surroundings. In this work, we consider the time length as 10 years, and simulation time step is 1 hour.

In the remainder of this section, we will describe the models used in the approach, the modeling of these agents and how they interact with the habitat subsystems, and the metrics we adopt to evaluate their performances.

A. Human agent modeling

The HA model is developed to capture fundamental input-output behavior of a human when in a space habitat, as shown in Figure 2. This model includes six building blocks (BBs). Those inputs are Resources BB, Task input of Task BB, and Environment BB. The outputs are Status BB, Task output of Task BB, and Agent health BB. The modeling details of each BB are listed below.

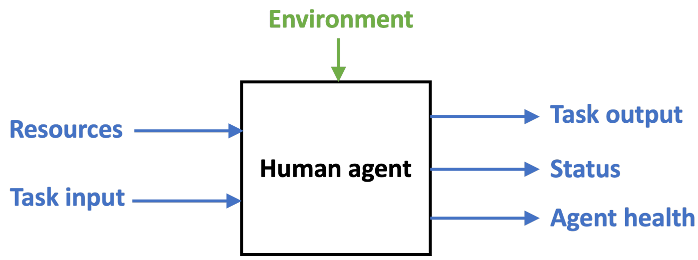


Figure 2. Input-output of HA

Environment BB

In the Environment BB, we model the factors from inside of the space habitat which we call internal environment that can cast influence upon the condition of HA. In this work, we simply consider the temperature of the internal environment as the ambient temperature, $e_{Temp}(t)$, where t is the variable for the simulation time. Time starts from t = 0, and is updated at each time step. The initial value of the ambient temperature for each simulation is modeled as a uniformly distributed random number taken from the safe temperature interval. The specific values are listed in Section III. Then, $e_{Temp}(t)$, has a 50% probability it will increase by 1% of the value during the previous time step, and another 50% probability it will drop by 1%. Thus, R is $U(0,1)$ and

$$e_{Temp}(t) = \begin{cases} e_{Temp}(t-1) * 1.01, \text{if } R \geq 0.5 \\ e_{Temp}(t-1) * 0.99, \text{otherwise} \end{cases} \tag{1}$$

Also, the ambient temperature does not change to emergencies and is not affected by other subsystems in this study. The temperature's effect on the HA will be discussed later in Health BB.

Resources BB

In Resources BB, we define the resources that are the basic requirement for supporting life for the HA. The resources are physical materials that have mass and volume, although we do not include resources relating to mental health.

Three parameters are defined to describe the amount of the corresponding resources that are consumed by HA in a time step. These are

a) Oxygen, this is to describe the mass of oxygen consumed by HA in a time step.
b) Water, this is to describe the mass of water consumed by HA in a time step.
c) Food, this is to describe the mass of food consumed by HA in a time step.

To determine appropriate values for the above parameters to be used in the simulation, we refer to published data about the actual usage of these resources in past space missions. Here we consider that the HA consumes a constant volume of these resources at each time step during the simulations when the relevant state is engaged, so food consumption only happens during the HA's "Eating" state. For oxygen, data are provided for the typical steady-state values for the oxygen being consumed when in a vehicle environment, with a lower value as 0.518, nominal value as 0.818, upper value as 5.67 kg/CM-D (crew member – day), where the nominal value is used here. Thus, $r_{HA,Oxygen}(t) = 0.818/24 = 0.034$ kg/h.[7] For water, data are provided for the typical steady-state water usage rates for various missions.[7] Thus, we take $r_{HA,Water}(t) = 9.82/24 = 0.41$ kg/h. For food, similarly, a 10-day menu for short-term missions is provided,[7] for each day, the mass of the food provided to a single crew member is given. At this point, we do not distinguish the varying consumption between different meals: breakfast, lunch and dinner. All three meals are considered to be equally distributed in terms of mass. The food is measured before cooked or, in another sense, after dehydration. Following this example, we use the mean value of the mass of meals in the 10-day menu as the food consumption, $r_{HA,Food}(t) = 0.51$ kg/meal-h or kg/h.

Task BB: Task input and Task output

Task BBs include Task input which is the task requirement assigned to HA from a health management (HM) subsystem, and the Task output. In these BBs, we define the possible states relating to when the HA is at "Working" status (which is when they perform tasks), and how these states are used to describe the "Working" process. The Task BB is irrelevant to the specific task content. The difference is reflected in choosing varying numerical values of the following states based on specific task, instead of modeling the process differently. An example of choosing numerical values will be shown in Section III.

The parameters in this BB are:

a) Task speed, $t_{HA,Speed}(t)$, to describe the workload that the human agent finishes in a time period, specifically, one time step during simulation.

b) Task success probability, $t_{HA,Probability}(t)$, to describe the chance of success of task performance given by HA in each time step.

c) Task progress, $t_{HA,Progress}(t)$, which is the main output from the HA to other subsystems. Its value is a number ranging from 0 to 1, representing the percentage work that is finished for a given task.

Task speed and Task success are defined as probabilities, and these are affected by the health state of the HA, $h_{HA}(t)$, which will discussed in Health BB. To capture the effect of the health of the agent on its task performance, $h_{HA}(t)$ is multiplied by their default values.

The updating of task progress, $t_{HA,progress}(t)$, is described by

$$t_{HA,Progress}(t) = \begin{cases} \min\left(1, t_{HA,Progress}(t-1) + t_{HA,Speed}(t)\right), \text{if } R \geq t_{HA,Probability}(t) \wedge t_{HA,Input}(t) \neq \text{Empty} \\ t_{HA,Progress}(t-1), \text{otherwise} \end{cases} \quad (2)$$

where R is a uniformly distributed random variable, $U(0,1)$. When R is larger than or equal to $t_{HA,Probability}(t)$, and meanwhile Task input, $t_{HA,Input}(t)$, is not "Empty", the task progress is able to progress at this time step, and the output, $t_{HA,progress}$(t), is equal to the progress at the previous time step plus the amount of the progress which is denoted by $t_{HA,Speed}(t)$. min(~,1) is to guarantee $t_{HA,Progress}$(t) does not exceed 100%. Otherwise, when R is smaller than $t_{HA,Probability}(t)$, the task progress remains the same as in the last time step. The values for $t_{HA,Speed}(t)$, and $t_{HA,Probability}(t)$ will be chosen and discussed in Section III.

Status BB

Here, we define Status BB to describe the possible states of the HA. Each status is the condition when HA is conducting the corresponding activity. These possible states include all of the activities of the HA that we consider in this study. Some activities happen on a regular basis, thus we call them time-based activities. And others happen irregularly and only when there is a need, which we call event-based activities. We define two states, Status for all activities and Default Status to distinguish time-based activities from event-based activities. Herein, the values of Default Status form a subset of Status.

First, we introduce the possible values of Status. These are listed in Table 1.

Table 1 Values of Status for HA

Values of status	Description	Occurrence
Sleeping	This is to describe when HA is sleeping.	It occupies 8 of every 24 hours, from 23:00 to 7:00.
Eating	This is to describe when HA is eating (meal).	3 times every 24 hours. Each meal takes 1 hour.
Exercising	This is to describe when HA is exercising.	Of every 24 hours, this occurs from 19:00 to 22:00.
Working	This is to describe when HA is working. As explained in Figure 1, HA is designated to only emergency tasks. Here, this status happens in a randomized manner based on the occurrence of emergency-related tasks.	This happens depending on the emergency.
Idle	This is to describe when HA is not allocated to an activity.	This happens during all times not in the above.

Next, we have the values of Default Status, $s_{HA,Default}(t)$, being defined as {Sleeping, Eating, Exercise, Idle}. They share the same definition as which of Status in the above. The update of $s_{HA,Default}(t)$ at time being is as,

$$s_{HA,Default}(t) = \begin{cases} \text{“Sleeping”}, \text{if } 16 < t\%24 \leq 24 \\ \text{“Eating”}, \text{if } 0 < t\%24 \leq 1 \vee 4 < t\%24 \leq 5 \vee 10 < t\%24 \leq 11 \\ \text{“Exercising”}, \text{if } 12 < t\%24 \leq 15 \\ \text{“Idle”}, \text{otherwise} \end{cases} \quad (3)$$

Then, the update of Status, $s_{HA}(t)$ is as,

$$s_{HA}(t) = \begin{cases} \text{"Working"}, \text{if } t_{HA,Input}(t) \neq \text{Empty} \\ s_{HA,Default}(t), \text{otherwise} \end{cases} \quad (4)$$

where $t_{HA,Input}(t)$ is the Task input state from Task BB, which will be discussed in Task BB. When it is not "Empty", it indicates there is a task requirement given to HA. Otherwise, $s_{HA}(t)$ just equals to $s_{HA,Default}(t)$.

Agent health BB

The agent health of HA is modeled here as a concept that is not as same as the word "health" in our daily use. Here, we use health to describe the state of the agent related to its capability to perform tasks. If the health is at its maximum value, the HA is able to output the best performance when it is reacting to a task. And when the health state decreases below that value, its performance will drop.

In this work, the agent health is currently designed to focus on the ambient temperature of the habitat. This value then reflects the health of the agent under the influence of the internal environment (Environment BB) through ambient temperature. h_{HA} is expressed as, $h_{HA}(t) = h_{HA,Temp}(t)$. In reality, ambient temperature can cause a wide range of physical impacts. For instance, it can cause physical discomfort, mental discomfort, and increased fatigue level of HA. Instead of all possible aspects that can be listed, the influence of ambient temperature on the HA health is represented here as the capability of performing tasks following the logic as we explained in Task BB.

Herein, a state is defined as ambient Temperature Health ($h_{HA,Temp}$), representing the influence of ambient temperature. The value ranges of $h_{HA,Temp}$ is 0 to 1. We define three values for this state, an optimal point, a lower value and an upper value (hereafter, these are $p_{T,o}$, $p_{T,l}$ and $p_{T,u}$ for temperature). At the optimal point, HA is naturally believed to have the maximum health. The HA will increasingly decrease its health state when the ambient temperature moves away from the optimal point in either the lower or higher direction. Thus, the model of $h_{HA,Temp}$ reflects the influence on health, induced by the difference between the actual value and the optimal point.

We need to choose appropriate values for these ranges of $h_{HA,Temp}$. Anderson, et al. (2018) use the assumption for temperature in typical steady vehicle atmosphere as having a lower point as 291 K, a nominal point as 296 K, and an upper point as 300 K (or $p_{T,o}$ as 21, $p_{T,l}$ as 18 and $p_{T,u}$ as 27 °C).[7] Thus, in this study, we set $h_{HA,Temp}$ to be 95% (or 0.95) at $p_{T,l}$ and $p_{T,u}$, and to be 100% (or 1) at $p_{T,o}$. We write both sides as a sigmoid function[8] by plugging in the above conditions as follows

$$h_{HA,Temp}(t) := h_{HA,Temp}\left(e_{Temp}(t)\right) = \begin{cases} \dfrac{1}{1+e^{-2.35e_{Temp}(t)+39.39}}, \text{if } 18 \le e_{Temp}(t) \le 21 \\ \dfrac{1}{1+e^{1.18e_{Temp}(t)-34.69}}, \text{if } 21 < e_{Temp}(t) \le 27 \\ 0.95, \text{otherwise} \end{cases} \quad (5)$$

The plot of $h_{HA,Temp}(t)$ is shown in Figure 3.

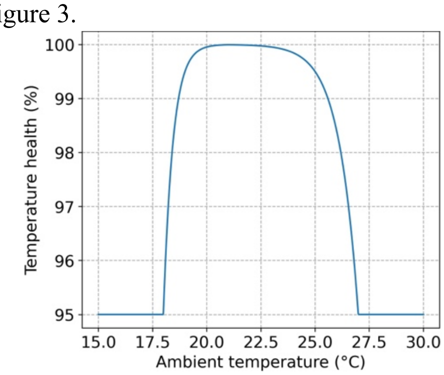


Figure 3. Temperature health over ambient temperature

Outside of $p_{T,l}$ or $p_{T,u}$, we set the values of $h_{HA,Temp}$ to stay at 0.95, as we only consider the situation where ambient temperature is within this range.

Ambient temperature, in this study, affects task speed, task success probability and that eventually it will respond to emergencies so this is why it is included currently, and for later study other factors will also be included as well.

Updating the states

To reflect the transitions among the states, the states must be updated during simulation from the current time step to the next time step. The updating process for HA is shown in Figure 4 to accommodate interdependencies that between different BBs, like, $h_{HA}(t)$ affects Task BB. Updating follows the process shown where the BBs are updated following this order. No variables are passed between BBs to annotate the order of the updates. As shown in the figure, we update (i) Status BB, of $s_{HA,Default}(t)$ and $s_{HA}(t)$, then (ii) Health BB, of $h_{HA}(t)$, then (iii), mainly $t_{HA,Progress}(t)$ of Task BB, in the end, $r_{HA,Oxygen}(t)$, $r_{HA,Water}(t)$, $r_{HA,Food}(t)$ of Resources BB.

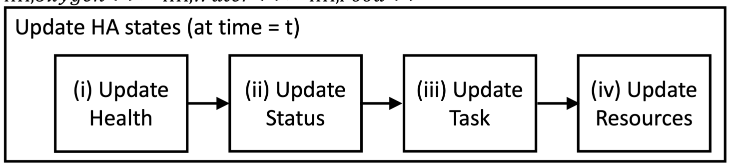


Figure 4. Flow chart for updating the HA states

B. Robot agent modeling

As a parallel model to the HA, we also model the robot agent, RA. The RA has similar BBs as HA, although for BBs with same names, the details of modeling are different at some level. In this section, we describe only those points that are different, and where the modeling details are the same, they are only briefly covered.

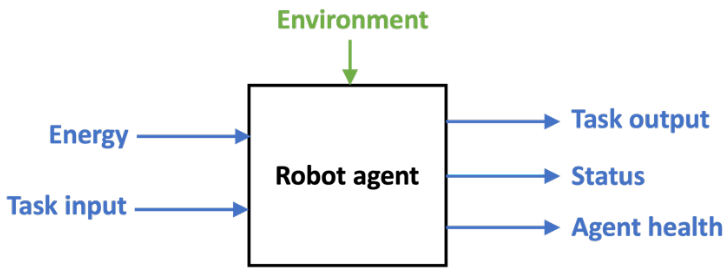


Figure 5. Input-output of RA

Environment BB

As mentioned at the beginning of Section II, we are simulating a case where HS always exists. That model is a subclass of HA and inherits the Environment BB from the HA. As discussed in Agent health BB of HA, we are considering an ambient temperature range which is safe for HA, which in reality is also a safe zone for RA. Herein, the modeling of Environment BB of RA is skipped in this study.

Energy BB

In Energy BB, we track the energy drawn by the RA from the habitat. This behavior only happens when RA is to a "Charging" activity, determined by $s_{RA,Status}(t)$ defined below. The amount of energy is the charging power, $h_{RA,ChargingPower}(t)$, multiplied by the charging time.

Task BB: Task input and Task output

As with the HA, we define three states relating to how RA performs tasks. These are all related to the "working" status of the RA, and describe the quality of the "working" process as in the HA. These are Task speed, $t_{HA,Speed}$, Task success probability, $t_{RA,Probability}$, and task progress, $t_{RA,Progress}$. The definitions for the states and the update are identical to the HA, and are not discussed again here.

Status BB

Here, we define Status BB to describe all the possible states of the RA. That is, this reflects the type of activity that the RA is conducting. None of these activities are triggered based on time, and they are all event-based activities.

First, we introduce the possible values of Status, $s_{RA,Status}(t)$. These are

a) Charging: this describes when RA is at "Charging" activity. To power the activities of RA, a battery is included as a component of RA. The battery requires charging to input and store power, and it outputs power for supporting the activities of RA. Clearly the need for charging the battery depends on the actual usage of the power stored in the battery.
b) Working: this describes when RA is "Working" activity, same as which of HA.
c) Idle: this describes when RA is at no other activities.

Updating of $s_{RA,Status}(t)$ is coupled with the modeling of "Charging" activity, as discussed next.

Health BB

The RA requires a battery charged with sufficient amount of power, and thus the health of the RA is dependent on its charge. Each activity the RA performs consumes power from the battery. When the energy stored in the battery goes lower than a threshold, the RA moves to a "Charging" activity. The logic governing charging is included here.

Here, we explain the parameters relating to health, which is in this case "Charging". These are

a) Battery capacity, this parameter is to describe the max amount of energy that can be stored by the battery.
b) Charging power, this parameter is to describe the amount of energy input to the battery when the RA is in "Charging" Status.
c) Working power, this parameter is to describe the amount of energy that consumed by the RA when it is in "Working" Status.
d) Standby power, this parameter is to describe the amount of energy that consumed by the RA when RA is in "Idle" Status.
e) Charging threshold, this parameter describes the energy threshold for RA to switch to "Charging" Status.

and state,

a) Battery charge, $h_{RA,Charge}(t)$, this state is to describe the amount of energy that is stored in the battery.

The update of the states in Status BB and Health BB proceeds as follows. To start, we decide whether battery requires charging, by comparing $h_{RA,Charge}(t)$ to the threshold, $h_{RA,Charge,Th}(t)$. If not, the RA is ready for performing tasks if there is a Task input, $t_{RA,Input}(t)$. (1) We set the charg indicator, $h_{RA,Charging,I}$, to False, indicating that RA is not at "Charging". (2) Then, if $t_{RA,Input}(t)$ is not "Empty", $s_{RA,Status}(t)$ is set to "Working", and the amount of working power, $h_{RA,WorkingPower}(t)/h_{RA,Capacity}(t)$, is subtracted from $h_{RA,Charge}(t)$. Besides that, (3) RA is at "Idle", and the appropriate amount of standby power is consumed, $h_{RA,StandbyPower}(t)/h_{RA,Capacity}(t)$. (4) Then, it transitions to the case where RA requires charging. $h_{RA,Charging,I}$, the charging indicator, is set to True, and $s_{RA,Status}(t)$ is set to "Charging". $h_{RA,Charge}(t)$ adds the amount of energy according to the charging power, $h_{RA,ChargingPower}(t)/h_{RA,Capacity}(t)$. To guarantee that once charging happens, the battery will be charged to its maximum, $h_{RA,Charge,Th}(t)$ is temporarily set to 1. (5) In the end, when $h_{RA,Charge}(t)$ reaches 100%, $h_{RA,Charge,Th}(t)$ is back to the default value.

Updating the states

The states of HS are updated according to the order of the BBs shown in Figure 6. The only difference to note compared to the HA is that the battery concept is used, as explained in Health BB. We must combine updates to the Status BB and Health BB.

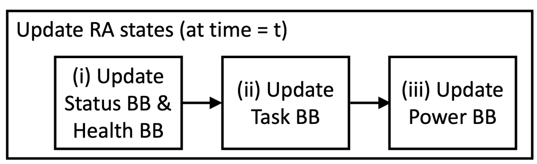


Figure 6. Flow chart of updating RA states

C. Human scientist modeling

The human scientist (HS) is modeled based on the human agent to capture the resources needed and time spent in each activity. Most of the modeling details remain the same, except that for the task module the HS performs research and generates research outcomes that is measured in hours. In this section, we will only talk about Task BB.

Task: Task input and Task output

In this preliminary study we assume that the HS does not do any repair or maintenance tasks. The HS is dedicated to science. The activity is denoted as "Working" Status in the model. Task BB of HS is modeled in the same way as which of the other two agents. Besides R being a random variable and use its relative relationship to $t_{RA,rate}(t)$, we determine the science outcome to be successful generated or not, and concurrently, we also consider the value of Task input, $t_{HA,Input}(t)$, to HA or RA. When $t_{HA,Input}(t)$ is "Empty", it indicates there is no emergency in the habitat, and the HS is able to generate science hours. Otherwise, the HS is not able to do research.

D. Metrics

Cost and benefit are used to compare the two agents in the next section. Two metrics are used, as follows

Table 2 Summary of the values used for M-ESM calculation.

	Mass (kg)	Volume (m^3)	Factor for Volume (kg/m^3)	Power (kW)	Factor for power (kg/kW)	Cooling (kW)	Factor for cooling (kg/kW)	Crewtime or robot time (CM-h/y)	Duration of mission (y)	Factor for crewtime or robot time (kg/CM-h)
Scenario 1										
HA – agent[7,10]	90	3.42	9.16							
HA – oxygen[7,11]	6.77*$r_{HA,O}$	0.004*$r_{HA,O}$	9.16							
HA – water[7,12]	1.032*$r_{HA,W}$	0.011*$r_{HA,W}$	9.16							
HA – food[7]	1.17*$r_{HA,F}$	0.0027*$r_{HA,F}$	9.16							
HS – agent[7,10]	90	3.42	9.16							
HS – oxygen[7,11]	6.77*$r_{HS,O}$	0.0045*$r_{HS,O}$	9.16							
HS – water[7,12]	1.032*$r_{HS,W}$	0.011*$r_{HS,W}$	9.16							
HS – food[7]	1.17*$r_{HS,F}$	0.0027*$r_{HS,F}$	9.16							
Structure[7]								c_{HA}	10	1.50
Scenario 2										
RA[7,13]	272	0.60	9.16							
HS – agent[7,10]	90	3.42	9.16							
HS – oxygen[7,11]	6.77*$r_{HS,O}$	0.0045*$r_{HS,O}$	9.16							
HS – water[7,12]	1.032*$r_{HS,W}$	0.011*$r_{HS,W}$	9.16							
HS – food[7]	1.17*$r_{HS,F}$	0.0027*$r_{HS,F}$	9.16							
Structure[7]								c_{RA}	10	1.50

a) Cost: A modified equivalent system mass (M-ESM) is chosen as the metric for denoting the cost of each scenario. It is computed based on the agents themselves and subsystems (currently only the structure subsystem, serving as the subsystem that generates task requirement, and later it will expand to other subsystems) that interact with the agents. M-ESM is calculated following the equations[9] which considers mass, volume, crew time, power needs, cooling needs. Note that the specific values are difficult to obtain, so in some cases assumptions are used and are noted where that occurs. The values we use for modeling and, in turn, calculating M-ESM are summarized in Table 2. These values are divided into those relevant to scenario 1 and those for scenario 2. In scenario 1, we start with the calculations for HA, including the mass and volume of the agent. We assume the resources are shipped from the Earth, such as oxygen, water and food. As the resources being consumed accumulate over time, the numerical values in Table 2 correspond to oxygen, water and food are as per kg of the consumed resources. To obtain the total mass and volume for the consumed resources over the whole simulation, we multiply by the amount of the consumed resources, denoted by $r_{HA,O}$ for oxygen, $r_{HA,W}$ for water, and $r_{HA,F}$ for food to the values. We are currently not including the subsystems required for processing the resources, such as tanks, pumps, food preparation, etc. Also, the power subsystem is not included in this study currently. So, power term and cooling term are not included in the calculation of M-ESM. The procedure used for the HS is similar. Additionally, we include values for the structural subsystem because a Task input to HA is generated, herein, crewtime, c_{HA}, for performing the task is considered. The same logic is followed for scenario 2 and will not be discussed in detail. The citations used for obtaining the values are provided in the table. Specifically, the Factor for Volume is chosen as 9.16, and the Factor for crewtime is as 1.50, because the calculation relates to the Moon[7].

b) Benefit: One of the primary goals for deep space missions is to "support scientific research".[14] Towards this direction, we use science research hours (SRH) as the metric for measurement of the benefit of a given scenario. SRH is the accumulated time that the HS works on research, or simply is in the "Working" state. This value is mainly governed by the Task BB of HS in Section II.

III. Illustrative example

Next we provide an illustrative example on the developed approach to preliminarily address the question posed about the roles of human and robotic agents. To recap, note that the purpose is comparing the physical capabilities of HA and RA when they are maintaining and operating a space habitat. The two scenarios shown in Figure 1 are simulated independently each for 100 realizations. The randomness is introduced through the occurrence of a micrometeorite strike event. Then we record and evaluate the outcomes for each agent. Each case is run to consider the habitat located on Moon.

Other subsystems of the habitat are explained below. Both scenarios include the same habitat details. After building scenario 1 and scenario 2, we run simulation of the whole system which contains the habitat, agents, etc, and their interactions. Details for setting up the simulation, and the outcomes and the related discussions are explained in the remaining of this section.

A. Modeling agents and a smart space habitat

To focus on the agent modeling, we simplify the modeling of the other subsystems of the habitat. The habitat includes the following:

a) Structural subsystem. In this subsystem, we describe the structure of the habitat. In this work, this model only considers a state that generates damage condition of the structure which solely caused by random event of a micrometeorite strike. Here, we simply use a Bernoulli distribution to describe the time of occurrence of the damage caused by a micrometeorite strike.

$$D_{Struct,I}(t) \sim B(p = \alpha\%) \tag{6}$$

where, $\alpha\%$ is the probability of the structure being damaged and causing a task in a given time step. For performing this task, the corresponding task speed and task success probability of HA and RA are chosen as 30% and 0.9 for HA, 20% and 0.8 for RA.[15]

b) Health management subsystem. In this subsystem, we describe how the Task inputs and Task outputs are managed. To simplify, a Task input is directly assigned to the agent when structure subsystem is under emergency condition, or as depicted, micrometeorite strike. And a Task output is the task progress from HA or RA.

c) Internal environment subsystem. In this subsystem, we describe the internal environment in terms of the ambient temperature, $e_{Temp}(t)$. To simplify, we consider the initial value of $e_{Temp}(t)$ are randomly generated for given internals during each time step. Here, we set the range to be from the lower temperature in typical steady vehicle atmosphere to the higher temperature (18 to 27 °C).[7] Then, it updates follows the equation in Section II Environment BB.

The models of the habitat and the agents are built with CDCM framework.[5,6] As explained in Section I, this tool is a modular framework allows the user to build and executes a space habitat model and is able to simulate various design choices to draw evidence for supporting early stages of design.

B. Simulation setup

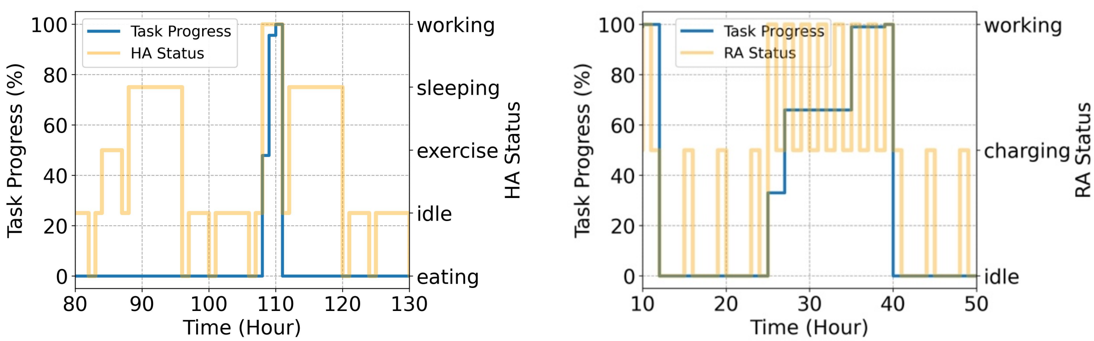
Using the previous agent models and habitat models, simulations are performed. One simulation begins at $t = t_{start}$ and runs to $t = t_{end}$ of one of the scenarios as depicted in Figure 1. Each run has just one configuration of the whole system, either RA or HA. In this example, we use t_{start} as 0 days (and hours) and t_{end} as 10 years, and the time step is 1 hour. To consider uncertainties, we perform 100 runs independently for scenario 1 and scenario 2.

For each run, the agent, HA or RA, is assigned to perform repair tasks. The task requirement is randomly generated from the structure subsystem. Currently, we consider the repair needs of the structure subsystem. The task is to repair structure damage caused the micrometeorite strike. The task requirement is generated by regarding to the indicator, $D_{Struct,I}(t)$. When $D_{Struct,I}(t)$ is sampled to be 1, with a probability of $\alpha\%$, there is a task requirement in the current time step. Otherwise, the task requirement is empty when $D_{Struct,I}(t)$ is 0. If an in-process task is not complete, the task requirement remains to be repair SDMS until the task progress is 100%. Also, we simplify that when the structure is under damage influence (a repair task is ongoing), there cannot be another damage happened to the structure.

C. Outcomes

To further explain the simulation process, we show the time history of one run in Figure 7. In the figure, we present the updates of the agents in both the scenarios. The most core states to output task progress, $t_{HA,Progress}(t)$ is picked to be main shown in Figure 7(a). As explained in the modeling details in Section II-A, default activities, including "Eating", "Sleeping", etc. take more priority than task performance (this is because we only consider the task requirements that can be performed without taking default "Eating", "Sleeping" of HA, for a more realistic situation where "Eating", "Sleeping" can be possibly skipped for reacting to emergencies will be studied later) , therefore, it observes that when HA is at one of these activities, $t_{HA,Progress}(t)$ holds in the same level and continue to progress when HA is free from them, and being available to work. This is ongoing until $t_{HA,Progress}(t)$ reaches 100%, then HA is able to be at "Idle" other than to be at default status. After the current task is finished by HA, $t_{HA,Progress}(t)$ is set to 0%, it just indicates the previous task is finished and ready for next task.

As a comparison, the progress of RA also depends on its status where its battery charge level plays a key role. As it shows in Figure 7(b), each status of RA is companied with a corresponding consumption of power from the battery. When the battery holds an amount of power less than threshold, it moves to a "Charging" status, and the task progress has to stop until the battery is fully charged. The reason that RA goes to "Charging" frequently between "Working" is mainly determined by the configuration of the robot we chose as a reference, which is Spot robot by Boston Dynamics.[13] Based on the specifications, the typical runtime of the robot is documented as 90 minutes due to the battery capacity, working power consumption, etc. In later studies, we will consider a variety of configurations, for example, a wired RA which is always powered, etc. Meanwhile, the time required by RA to finish the same task is higher than which of HA, due to the effect of task speed and task success probability together.



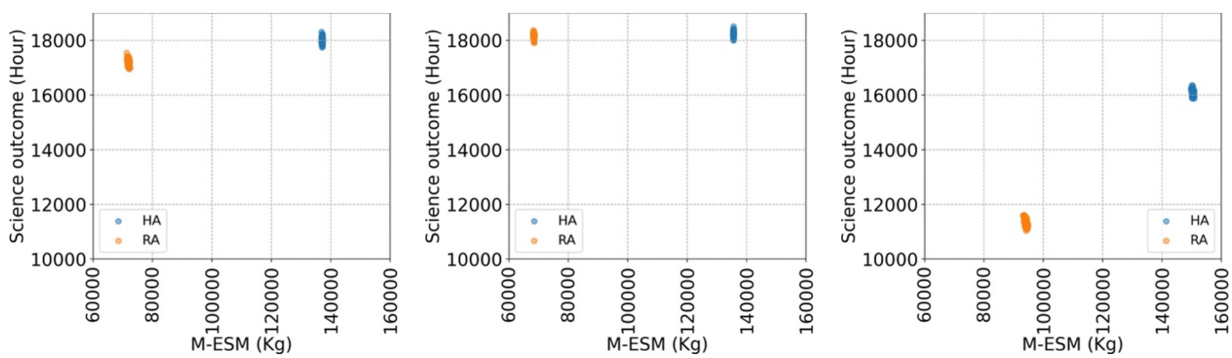
(a) Verification of HA in scenario 1 (b) Verification of RA in scenario 2

Figure 7. Verification of human agent and robot agent in one realization

After observing the verification of how HA or RA update their states in one example run, we show the overall outcomes in Figure 8. In Figure 8(a), we demonstrate the case where $\alpha\%$ is picked as 0.4% (3 micrometeorite strikes in one month), the chance that task requirement is generated from structure subsystem. The results of each of the two agents naturally forms two distributions. The results for scenario 1 with HA is shown in a blue color and falls in the upper right corner, while the results for scenario 2 with RA are shown in an orange color and fall in the left side of the figure. Clearly the HA has a larger cost (M-ESM), due to the required resources to support HA, while it also results in more science hours. Both metrics decrease for RA.

We consider the same problem when the value of $\alpha\%$ is changed to 0.04% and 4% (0.3 and 30 micrometeorite strikes in one month) resulting in decreased or increased work for the agents. The results are shown in Figures 8(b) and (c). Naturally, the case where $\alpha\%$ is 0.04% generates an increased amount of science due to the less frequent repair tasks. Thus, it is obvious that when the probability of an emergency is reduced significantly, the benefits (i.e., the SRH in scenario 2) of the RA are approaching those of the HA. The HA requires a higher M-ESM with respect to the RA in Figure 8(b). Of course, the chance for emergencies triggered by natural events, like micrometeorite strikes, to happen is hardly able to vary drastically. The set of task requirements that the agents will need to perform, however, depends on the robustness of the other subsystems in the habitat. Take the space habitat in this section as an example. If the structure subsystem has a low possibility of being damaged under a given level of micrometeorite strike, the simulation results in Figure 8(b) are obtained. This indicates that the development of improved technologies for designing and constructing other subsystems, will influence the comparison between the HA and RA. In Figure 8(c) where $\alpha\%$ increases to 4%, we observe that SRH facilitated by both HA and RA drops. In the same time, the M-ESM of RA and HA both increase, and the amount of increase by RA exceeds HA. This behavior is due to the long time length of the mission in simulations, causing the crew time term in M-ESM to contribute more to the calculations. Although a 4% probability of a micrometeorite strike is not likely, we could still extrapolate this outcome to consider that with a different but frequent emergency, the HA would outperform the RA in terms of SRH (the larger the better) by an obvious advantage. Such extensions of the models to more tasks will be considered as this preliminary study evolves.

It also worth mentioning, in all three results, each group of results forms a similar arrangement from upper left to lower right direction. This is because the uncertainties mainly are due to the occurrence of emergencies or task requirements. Herein, as more frequent tasks are needed, more cost is generated, in terms of crew time, resources for the HA and HS during the missions which are used in M-ESM calculation, and the meantime, less science is produced, as the space habitat is more frequently under emergency condition which stops all research of the HS. Also, the difference in the two agents is much more obvious as in Figure 8(b), and less obvious in the other results. This is because occurrence of the task requirement is only reflected in M-ESM calculation through the crew time term. When the agents both spend less time performing tasks, M-ESM is dominated by items that are irrelevant to task requirements or performance conditions, for instance, the mass and volume of the agents, etc.



(a) Outcomes of $\alpha\%$: 0.4% (b) Outcomes of $\alpha\%$: 0.04% (c) Outcomes of $\alpha\%$: 4%

Figure 8. Overall outcomes of simulation over 10 years

Typically we do not count robot agents time in an identical way as we count human agents crew time. In the above results we do include RA time in the robot time terms of the structure subsystem in scenario 2. As long as the RAs are able to perform tasks, it is recommended for them to do so. To examine this, we alter the robot time factor for scenario 2 by multiplying the robot time term by 0.2, as an example. We simulate the above case where $\alpha\%$ is chosen as 0.4%, with other settings being the same. The outcomes are shown in Figure 9. Here the M-ESM of scenario 2 drops from around 72000 kg to around 68000 kg. To pick a proper value for the robot time factor of RA does influence any decision that may be related, as the cost in terms of M-ESM could be over designed in such a case. Another observation is that the difference between the results is reduced due this change. It is easy to comprehend that by doing so, the numerical contribution of robot time toward the M-ESM calculation is dropping.

This indicates even with robot technologies providing a lower task speed and task success probability with respect to human, it would still be reasonable to engage robot in certain level of task assignments. This is indicated by that in a relatively realistic emergency frequency (0.4%), robot result in a lower SRH outcomes, in return, it requires also a less M-ESM cost than HA. How to balance between strategies that give low cost, low benefit and high cost, high benefit requires consideration of the specific mission setting and impact in a long run. Furthermore, different comparison conclusions can be given with different emergency frequencies. Like, with a much less emergency happening, robot could maintain the low level of M-ESM cost but providing a close level of SRH to human. However, based on the consumption and agent modelling in this study, RA is not comparable to HA when emergency frequency increases. This result does not necessarily apply to any other type of configuration of robots or comparisons of the agents in other scenarios. As we expand this study we will look into this further.

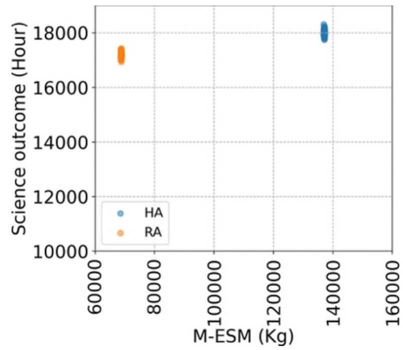


Figure 9. Outcomes with tuning the robot time factor for RA ($\alpha\%$: 0.4%)

IV. Conclusions

In the near future, deep space exploration is a must do direction for bringing innumerable values to human society. Along the path, the complementary roles of human agents or/and robot agents for performing tasks are a piece of the puzzle. Although there are roles to play for both robotic agents and humans in these scenarios, engaging robots for some of the tasks is certain to happen and will grow over time. Towards that goal, this work is proposing a methodology to answer some preliminary questions such as, how to compare the physical performance of human and robot, what are the cost and benefit for using either of the agent for a particular task under a defined scenario? We design numerical models using an input/output approach that capture the basic resources and products of the agents. Then, we construct an illustrative example by putting the agent models in a smart space habitat environment, simulate the stochastic scenario a large number of times, and evaluate the outcomes. Comparison of the agents is based on the research hours and a modified version of the equivalent system mass. This methodology is being expanded for future studies to compare human or robot in the deep space missions. We aim to expand the models of the agents and the habitat to include more randomness and more complex tasks. We anticipate that that this work will highlight likely areas for future development and needs of robotics technologies.

The challenge this problem lies in the fact that there are numerous details and influencing factors that can be considered. Here, we perform an initial study that provides a balance between considering the key tasks and major resources. Our main objective in this study is to propose a methodology to approach this problem. In future work, we will focus on adding more complexity to the models of the agents and of the habitat. Additionally, more random events and randomness in the resources used will be included. Thus, while the same framework can be used, we will expand the modeling details of the agents, connections between different BB of the agents, more subsystems of the space habitat and interactions between them and the agents.

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