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HI-SEAS habitat energy requirements and forecasting

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ABSTRACT

Travel to other planetary bodies represents a major challenge to resource management. Previous manned exploration missions of long duration have been resupplied with food, water, and air as required. Manned missions to other planetary bodies will have durations of years with little to no possibility of resupply. Consequently, monitoring and forecasting resource consumption are mission-critical capabilities. The Hawaii Space Exploration Analog and Simulation, a long-duration planetary analog simulation, has recently completed its fifth long-term isolation mission conducted to assess the energy, food, and water needs of a six-person long-term planetary mission. This study presents a novel method for forecasting energy consumption, which incorporates the emotional state of the habitat crew. Gathered data show inhabitants in small environments can be influenced considerably by the actions of a single member. This can result in dramatic changes in consumption that could cause forecasting models to deviate to the point of total failure. Previous work found that inclusion of the daily activities and the psychological states of the crew allows for higher accuracy in long-duration forecasts. Currently, psychological assessments in the form of a Positive and Negative Affect Schedule and a generalized artificial neural modulation method are used to incorporate emotional response into machine learning forecast methods. Using these techniques and developments, a large-scale smart habitat control and forecasting system is proposed that will monitor, control, and forecast HI-SEAS habitat resources for future HI-SEAS missions. This new system requires the incorporation of psychological and physiological data of the crew, together with information on their activities and schedules.

1. Introduction

NASA has designated a number of red flag problems that must be solved prior to extending manned missions deeper into the solar system, with crew performance and cohesion being major concerns during long periods of isolation. The HFBP has funded a number of campaigns (i.e., NNX11AE53G, NNX13AM78G, and NNX15ANO5G) in the form of HI-SEAS to investigate crew composition and cohesion over long durations (i.e., eight months or longer) in an isolated and confined environment. The details of the Hi-SEAS missions are listed in Table 1.

NASA has used analog experiments for planetary exploration studies such as the Haughton Mars Project (HMP), Aquarius/NEEMO, Human Exploration Research Analog (HERA), and within some Antarctic Stations over the years. Analog missions are useful for testing situations that may occur during real exploration missions to Mars and the experimental setup is a important part of spaceflight research [1].

Previous studies dealing with team risk and performance have included the Team Performance Task/Price of Cooperation test, continuous monitoring of face-to-face interactions with sociometric badges, mitigation of the effects of isolation using immersive 3D virtual reality interactions with the crew's family and friends, measurement of emotional and effective states using automated analysis of multiple forms of textual communications provided by crew members to identify relevant and effective teamwork behaviors, and multiple stress and cognitive monitoring studies [2].

Crew selection is studied as part of the development of a model for crew composition. The level of autonomy is varied throughout each mission, with low crew operational autonomy during the first and last two months of the mission and high crew autonomy during the middle months. This study constituted opportunistic research focused on energy consumption during mission simulations, conducted in addition to the funded principal psychological and teamwork studies.

Abbreviations: HI-SEAS, Hawaii Space Exploration Analog and Simulation; PANAS, Positive and Negative Affect Schedule; NASA, National Aeronautical Space Agency; HFBP, Human Factors and Behavioral Performance; DSE, Disruptive Significant Event; ANN, Artificial Neural Network; M1 … M5, Mission One … Mission Five; S2S, Sequence to Sequence; LSTM, Long Short Term Memory; RNN, Recurrent Neural Network

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Table 1
HI-SEAS mission dates, durations, and crew compositions. Mission 1 (M1) through Mission 5 (M5).

Mission	Start	End	#Days	Male/Female
M1	4/12/13	8/12/13	120	3/3
M2	3/26/14	7/26/14	120	3/3[a]
M3	10/7/14	6/17/15	240	3/3
M4	8/28/15	8/28/16	365	3/3
M5	1/19/17	9/19/17	240	4/2

[a] M2 reduced to M/F of 2/3 four weeks into experiment.

The energy consumption in the habitat is the focus of the research presented here as human travel to other planetary bodies will have duration of years, with little to no possibility of resupply. Consequently, the monitoring and forecasting of resource consumption is a mission critical capability. The actions of a single crew member can heavily influence small environments and throw forecasting models to the point of total failure. Understanding how the energy is utilized and if the energy can be forecasted are crucial to the success of these mars mission. The research presented in the following sections examine energy consumption and forecasting improvements through the incorporation of the emotional state of the crew. Subsequent sections suggest to increase HI-SEAS simulation fidelity through the application of a virtual water tank, and outfitting the crew with biometric feedback sensors.

1.1. HI-SEAS habitat

The HI-SEAS habitat is a 36-foot diameter dome that has two levels (Fig. 1). The main floor consists of a work area, kitchen, dining room, laboratory, and bathroom with a shower. It is attached to an 8-foot square airlock that is connected to a 20-foot sea container. This area contains the washer, dryer, and the networking/telemetry room. The first floor area of 933-square feet has a useable area of 878-square feet [3].

1.1.1. Power resources

Fig. 2 shows a simplified schematic of the habitat power system. Power is provided by a 10-kW solar array, hydrogen fuel cell, and a propane generator. Fig. 2 shows how power from each source enters the habitat, is converted from DC to AC (if applicable), and then sent to the habitat power loads on the outlets.

When battery power is low and there is insufficient solar generation, the propane generator is activated. The hydrogen generator switches on automatically should the battery levels become too low in the evening. The propane generator is started manually by the crew.

A 10-kW solar array is located to the south of the habitat and it is visible from the lab window. The monocrystalline silicon wafer modules generate 275 W at maximum power. During the day, the solar array charges the batteries (see Fig. 3) and the habitat operates on this battery power overnight. The solar array generally starts charging the batteries at around 08:00 local time (LT) and it stops charging at around 16:30 LT, although there are seasonal and weather-related variations. On cloudy days, the solar panels are unable to charge the battery bank fully [3].

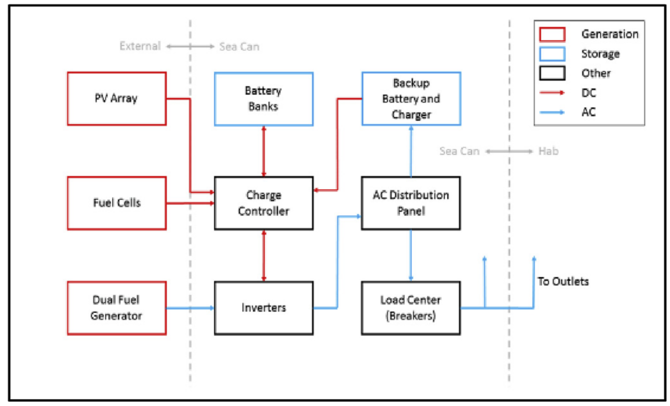

Fig. 2. Simplified schematic of habitat power system. Credit: Alex Velhner, Blue Planet Research Ltd. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Fig. 3. HI-SEAS battery bank. Photo credit: Ansley Barnard.

The propane generator shown in Fig. 4 is used strictly as a backup generator. The habitat stores energy in three Sony battery banks, up to 28.5 kWh (Fig. 2). The DC current from the batteries passes through an inverter and it is converted to AC for use at the habitat outlets. Generally, the batteries are charged from the PV array during the day, and the batteries will reach full charge by late morning or early afternoon. With full sun, 80% of the batteries can be charged by 16:00 LT, and the habitat will normally have sufficient power to operate until sunrise the following day. Smart power management by the crew can extend the

Fig. 1. HI-SEAS habitat with 10-kW solar array and solar water heater with tank. Photo credit: Ansley Barnard.

Fig. 4. HI-SEAS habitat propane-fueled backup generator. Photo credit: Ansley Barnard.

Fig. 5. HI-SEAS external water tanks containing 3785 L (1000 gallon) of water. Photo credit: Ansley Barnard.

duration of battery power availability [3].

1.1.2. Water resources

Hot water for the habitat is provided by a solar water heater, which heats water contained in 150 gal. insulated tank. Hot water is available to the crew well after sunset. This is a passive system and it requires no maintenance from the crew engineer. There are also two external water tanks seen in Fig. 5 of 1000 gal. (3785 L) that are refilled by habitat support teams when required.

1.1.3. Sensors and telemetry

The habitat system is fitted with a sensor telemetry routing system. A ControlByWeb X-310 web interface is utilized to control and collect sensor information and to distribute it to a remote location. The X-319 is an Ethernet I/O module with four digital inputs that allow support for up to four temperature and humidity sensors. Sensors are interfaced by the web and they can be controlled externally. Using this technology, the habitat is enabled for monitoring and logging of the power supply using a customized web-based control page. Software allows graphical visualization of the telemetry data, as well as its extraction into CSV files for statistical analysis.

Sensors are located in a variety of sites within the habitat. All power consumption is routed through the X-310 module via circuit breakers. The circuits are specific to the laundry room, downstairs washroom and laboratory, upstairs rooms and bathrooms, living room, dining room, and kitchen. Power used in any of these areas can be monitored separately. A CO_2 sensor was placed in the dining area of the dome. Temperature sensors are placed in the dining Room, one of the bedrooms, and the telemetry room. The main water tank has a laser level sensor, and the Planetary Power Generator computer is able to monitor and track power generation and distribution on its own [2].

2. Resource consumption

Energy and water consumption are monitored during the analog missions, and these data provide a picture of the likely resource requirements during exploration or colonization missions of other planetary bodies. Mars missions could last for as long as 2.5 years with no potential for resupply [2]. A no resupply restriction, consumption must be monitored, controlled, and forecasted with a high degree of accuracy. This study considered data on crew consumption rates obtained from current and previous HI-SEAS missions to construct predictor models. These models were designed to predict crew consumption rates and to allow for changes in crew schedules and behavior. Utilizing machine learning, the habitat water and appliance usage was modeled based on the frequency and power consumption of each system. This information will assist in the production of high-accuracy forecasts of consumption rates of future long-duration HI-SEAS missions.

Table 2
HI-SEAS total mission consumption in habitat areas in KWH.

(KWH)	M1	M2	M3	M4	M5
Living room	4129	524	2243	4037	2557
Lab and bath	847	221	6463	10663	7819
Washer/dryer	642	95	28	48	37
Kitchen	3544	990	3732	4478	3582
2nd Floor	392	969	3460	5967	2228
Heater	329	230	511	1034	840
Total	9887	5043	16437	26230	15219

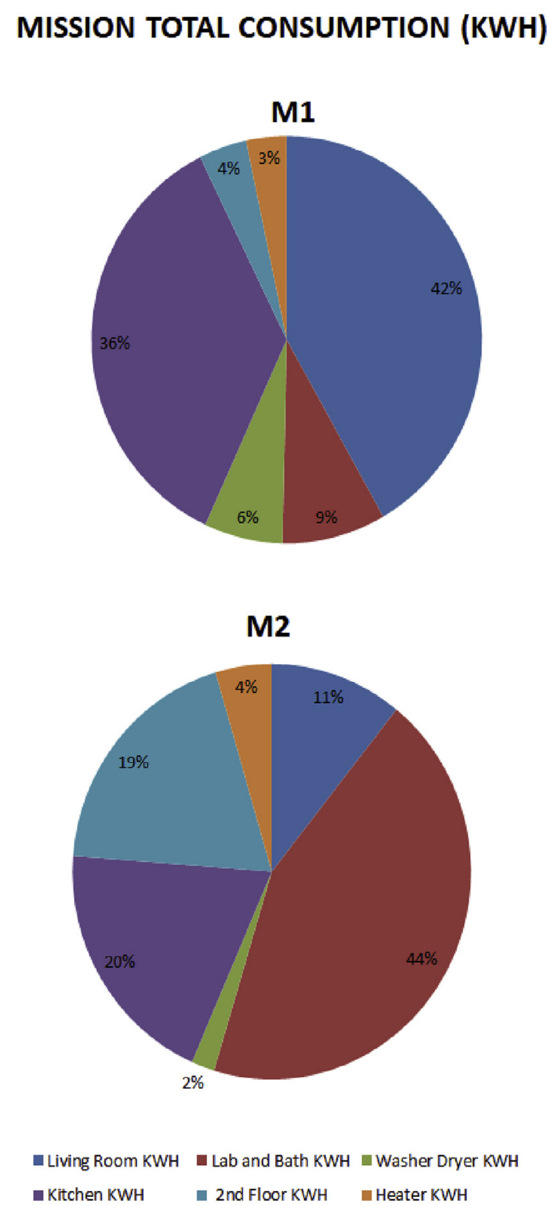

Fig. 6. Total power consumption (KWH) from both 120-day missions. The major difference in kitchen power is attributable to a food study conducted during M1. During M2, the crew conserved energy diligently.

2.1. Power consumption

Power consumption within the habitat for each of the missions (M1 through M5) are tabulated and analyzed for comparison. Table 2 shows the total amount of power used in KWH over the duration of the mission. Table 2 does not scale the missions due to their different length, so refer to Table 1 to account for the different lengths of each mission.

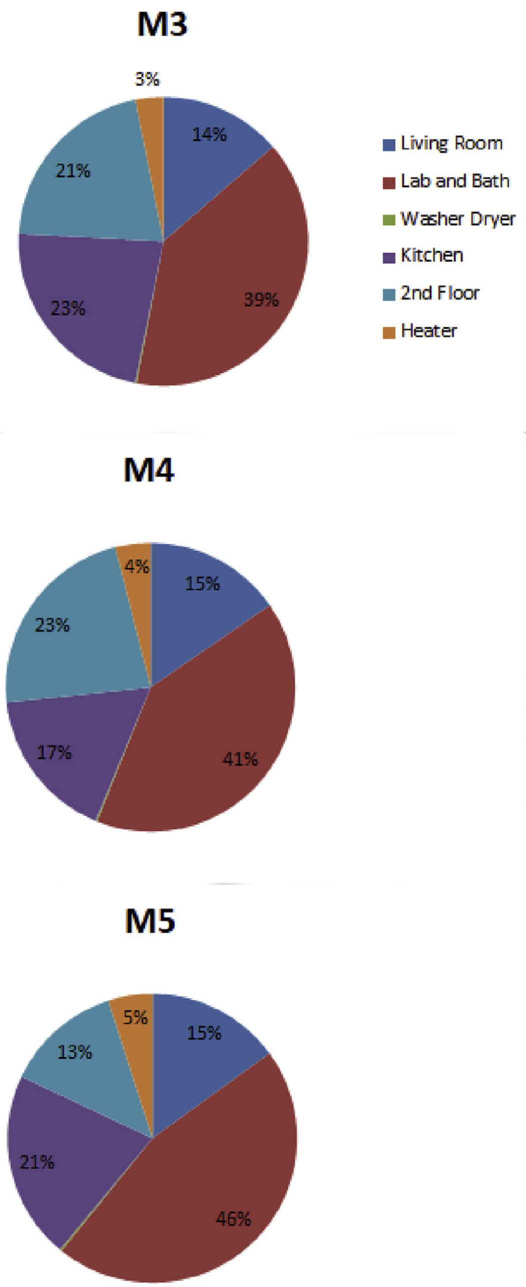

Fig. 7. Total power consumption (KWH) during M3–M5. Distribution of power usage within the habitat remained consistent with low variation throughout all three missions.

Power consumption within the different areas of the habitat for the first two missions (M1 and M2) are shown in Fig. 6. The total power used over both missions show a major difference between the kitchen power and is attributed to a food study being conducted in M1.

Additionally, M1 and M2 used space heaters in the living room area making it difficult to compare to subsequent missions. The other areas within the habitat show proportional usage between each mission.

The distribution of power consumption for M3 through M5 are shown in Fig. 7 which importantly show a consistent power usage distribution in the habitat, which an important result as this indicates that the power usage is easily comparable between the three missions.

Table 3
HI-SEAS mission water consumption rates.

Mission[a]	Daily	Weekly	Monthly	Total
M2	53.4	449	1617	8088
M3	59.3	580	2240	15675
M4	61.7	299	1227	15256
M5	56.5	406	1659	14228

[a] Mission 1 (M1) data excluded because of major differences in water infrastructure between simulations. All values in gallons.

2.2. Water consumption

Total water consumption during all five missions varied greatly. M1 had abnormally high water consumption because of the use of flushing toilets and a 500 gallon water tank, which made it difficult to compare with the other missions; therefore, it was removed from the study. All subsequent missions used composting toilets and had water tanks with double the capacity (i.e., 1000 gallons). The total water usage for each mission is shown in Table 3.

3. Forecasting energy use with crew emotional state

The HI-SEAS crews are presented with a battery of daily psychological surveys and social experiments. Data used in this research project were derived from the PANAS [7]. At the end of each day, each member of the crew is presented with a questionnaire that comprises 20 different words, and they are asked to rate by how much they believe each emotion applies to them. Negative words include guilty, hostile, and irritable, while words associated with positive emotions include proud, strong, and active [8].

The emotions are rated between 1 meaning “not at all” and 5 meaning “very much.” For non-clinical experiments, the PANAS is considered a reliable measure of a population [9].

In this research, we defined a Disruptive Significant Event (DSE) as any type of event that causes a major disruption of HI-SEAS crew routines and activities. Each DSE was taken from the crew commander's daily report and categorized into events that range from power failures to water resupply. Research in Ref. [3] showed that the psychological state of the crew has an effect on resource consumption rates. DSE have minor to catastrophic effects on time series forecasting models. Thus, consideration of DSE and psychological states could improve time series forecasts [10].

To incorporate DSE into crew data HI-SEAS research provided this study with a measure of the crews’ emotions through the PANAS results, as discussed in Sec. 3., which comprised the emotional ratio score and the relative daily change in that ratio score. as seen in Fig. 8. Since forecasting models are often Neural Networks and human emotion is the neural modulation of synaptic responses [11], it was shown in Ref. [3] that the incorporation of the emotional PANAS score into a Artificial Neural Network (ANN) improved the performance of the energy forecasting models [12].

The PANAS score has direct effect on neural modulation and its probability by incorporating it into existing neurons in an ANN through the modification of the activation function. Within an ANN, this has the effect of externally altering the weights of the network to enforce a new type of behavior that is independent and external to training [13].

As seen in Ref. [3], altering the activation function is done to reflect the general changes seen in the probability distribution according to the PANAS score. A threshold value determines whether the neuron will fire. To alter the probability density, we can alter the shape of the activation function.

Forecasts for M3 were run on an Sequence to Sequence (S2S) Long Short Term Memory (LSTM) Recurrent Neural Network (RNN). The S2S LSTM-RNN model is constructed for weekly forecasts using a sliding memory window each hour for 168 h for the entire 30 week simulation.

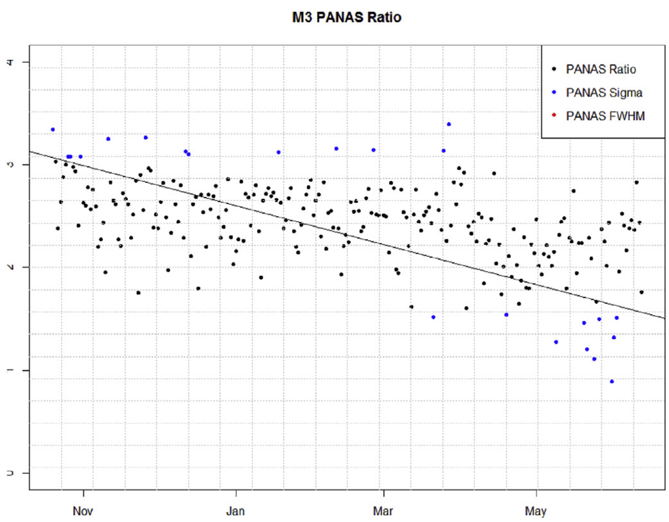

Fig. 8. M3 PANAS Ratio showing the PANAS Ratio, PANAS Sigma, and PANAS FWHM. median = 2.45, Max. = 3.39, X-Intercept = 107.8 [3].

Details of S2S LSTM-RNN are complex and readers are encouraged to examine references [4–6] for further details.

Forecasting models run in Ref. [4] showed that forecasts improved significantly with the incorporation of the crew's emotional state through the PANAS score. Fig. 9 shows that forecasts without emotional state showed a mean error of 14.13% while forecasts that incorporate the crew PANAS score had a mean error of 5.39% as seen in Fig 10. This shows that the crew mood correlates strongly the PANAS score. It is hypothesized that more accurate measures of the crew's mental and physical state will enable greater accuracy in forecasts, and is recommended as a way to improve HI-SEAS simulation fidelity.

4. Discussion

Given that crew energy consumption is influenced by both emotions and external events, it should be possible to increase the fidelity of the HI-SEAS simulation through modifications of the experimental procedures. Crew consumption is heavily influenced by water resupplies,

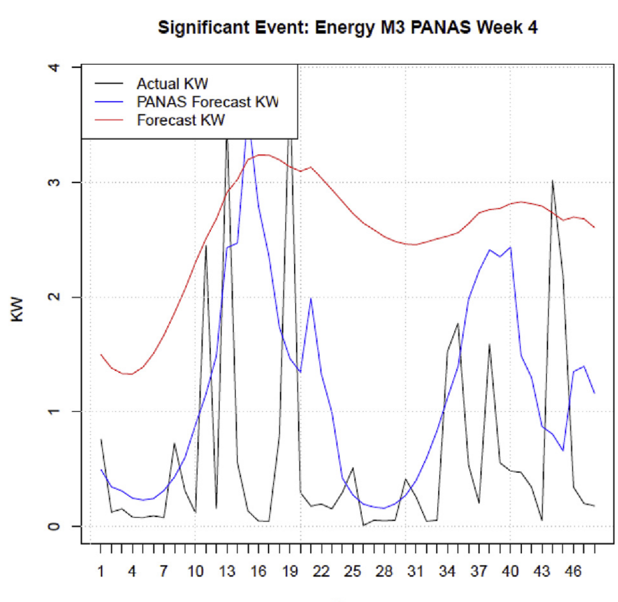

Fig. 9. The standard S2S LSTM-RNN model (red line) and the PANAS LSTM-RNN forecast (blue line) show a strong forecast performance difference compared to measured data (black line) [3].

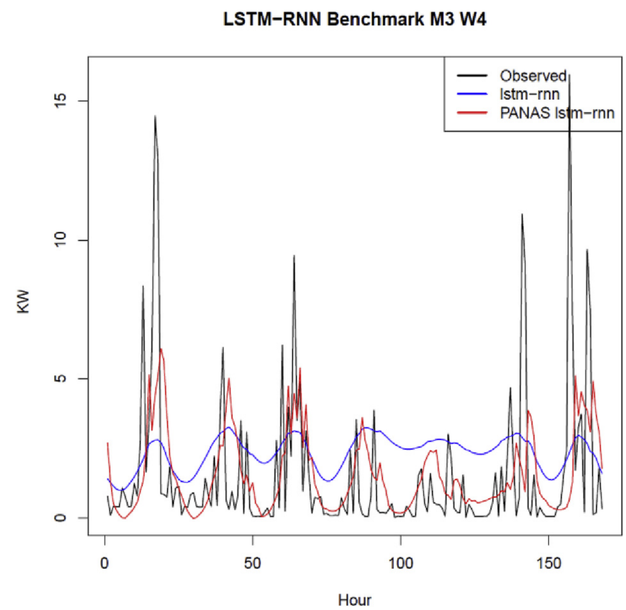

Fig. 10. Example of a forecasting failure due to the occurrence of a DSE correlated to an emotional change in the crew [3].

which are not realistic on a real mission; therefore, it is proposed to create a virtual water tank for the crew to monitor. Additionally, crews adapt their behaviors regarding power consumption based on the power available from the solar panels. Efforts to reduce power consumption during various levels of power production have been undertaken by the crews. However, this was done without full knowledge of the actual power production or recognition of those appliances that would have overall negative effects on energy resources. Two modifications to the simulation are proposed to improve fidelity.

4.1. Virtual water tank

Data from previous crews have shown very strong correlation between changes in crew behavior and water resupply. Leading up to the resupply, crews begin to restrict water usage. Upon water delivery, there is an explosion in activity with crews doing laundry and taking showers. The water resupply creates an inadvertent out-of-sim situation that should be rectified to increase the fidelity of HI-SEAS. Here, we propose presenting future crews with a virtual water tank that they could monitor and use without any indication of resupply. Meanwhile, mission support could monitor the real water tanks and schedule the refills.

The virtual tank will be much smaller, i.e., 1.5 times the average daily water usage by the crew. The crew will be told the virtual tank has a water generator with a variable generating rate, e.g., 1 gallon per hour, which could be varied as required. The levels of the real water tanks and the virtual tank will be interlinked in such a way that the virtual generation rate will slow as the real water tank levels get lower, ensuring the crew will not drain the tanks before resupply. The virtual tank is 50 gallons. The rate is governed by the estimated number of days left in the real tanks, such that it will never drop below one day's supply of water. The water in the virtual tank can be calculated as in Eqs. (1)–(3):

$$W_h(l) = l/1000 * W_{ave} \tag{1}$$

$$W_{rate} = (W_{hours} - 24)/24 \tag{2}$$

$$V_l(h) = V_{(l-1)} + W_{rate} * h <= 50 \tag{3}$$

here, in Eq. (1), W_h is the number of water hours given by the current level l , divided by the average usage per day in gallons. In Eq. (2), the

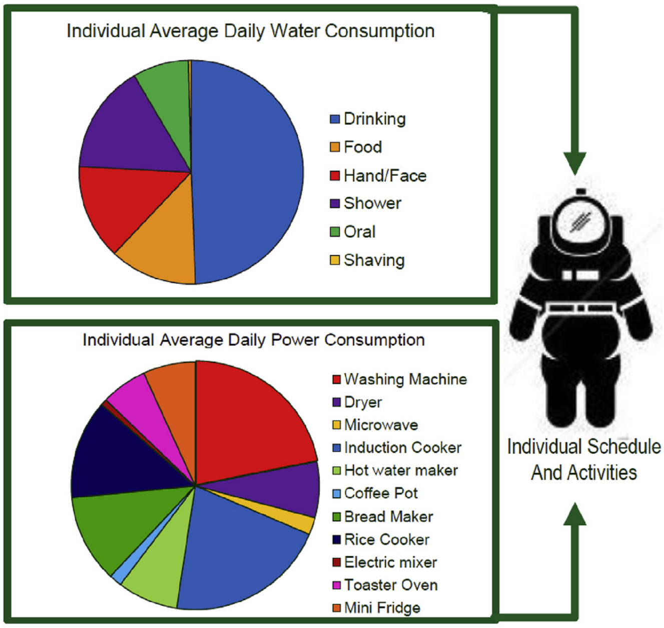

Fig. 11. Diagram depicting the variety of activities that the crew can plan ahead of time and the impacts of those activities on resources [3].

water production rate W_{rate} is set by the results of Eq. (1) by subtracting the number of water hours by one day and dividing by 24 h. This ensures the water production rate will slow as the water level approaches the average of one day's water usage. This ensures the virtual tank will not have water when the real water tanks are empty. The water hours of the virtual tank are then calculated using Eq. (3) by taking the previous virtual tank level $V_{(l-1)}$ and adding the water production rate over the number of hours.

4.2. Modeling crew individually

The crew's schedules and personal activities are uploaded to the simulation on a daily basis. Fig. 11 shows the variety of activities that the crew can plan ahead of time and the impacts of those activities on resources. This allows the simulation to adapt for changes in activities. The crew consumption simulation model will be implemented in the habitat to log crew activities. The crew will be able to change their intentions and inform the computer with ease. The crew simulation model will be combined with methods for monitoring and identifying appliances. The combination of these two models will be the foundation of the forecasting model, which will be the next stage of development.

5. Conclusion

This study considered the electrical consumption in the kitchen of the HI-SEAS habitat and psychological data of the crew in relation to the proposal of a smart habitat control and forecasting system. The next steps will be to incorporate all areas of consumption within the habitat, including water. The neural modulation method is an analogy for emotion that uses the PANAS score as a neural enhancer/inhibitor, which has shown encouraging results. The neural modulation method does not show that the results directly simulate emotional response and is limited due to the PANAS score being such a broad measure. Body sensors could provide data indicating the level of activity of each member of the crew, which could be incorporated into predictions of the daily needs of the crew. Once the system has been expanded into the entire habitat, it could be adapted for all the habitat and planetary colony systems. A large-scale intelligent control system could be developed to monitor and guide the crew in its activities, and to forecast resource requirements over the course of a mission as a next step in this research.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at doi:10.1016/j.actaastro.2019.05.049.

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