A Methodology for Controlling Smart HVAC Systems in Planetary Environments

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1 Background

To explore the Moon and Mars, astronauts need smart habitats that support life in harsh environments and remain operational when vacant. NASA's Habitats Optimized for Missions of Exploration (HOME) is an example of such a habitat, providing inhabitants with a breathable atmosphere, drinking water, and food [9]. HOME relies on data analytics to learn, predict, and optimize logistics and maintenance [10].

Smart HVAC systems are instrumental in these habitats because HVAC systems maintain healthy indoor air quality levels and thermal comfort [4]. What makes these systems smart is their ability to act on observed data. While analyzing information collected by sensors, these HVACS are powered by supervised and unsupervised machine learning models[1] (MLM) [1]. For example, smart HVACs can adjust the power supplies of heating and cooling systems based on collected environmental and room occupancy data, optimizing energy usage [2]. Smart HVACs help consumers save on energy bills as well as increase home value [5].

When designing smart systems for HOME, scientists must translate their experience conducting data analysis for equipment on Earth to the context of space and, more specifically, the systems of these habitats [12]. [12]. However, planetary environments are radically different from Earth's. For example, the Moon's lack of an atmosphere causes extreme temperature fluctuations and increased solar radiation [9,13]. This research approach raises the following questions:

(1) How might an algorithm driven by data collected on Earth handle the constraints of a lunar environment?
(2) How might a smart habitat, trained on data that reflects Earth-like conditions, behave in a lunar environment?

This project intends to answer these questions. To this end, we will develop a mechanism that allows a smart HVAC system trained with historical data on Earth to operate within a lunar environment. After solar energy and lunar temperature MLMs simulate and communicate the constraints of a lunar environment to a smart HVAC system, the HVAC works to maintain a livable temperature.

[1] Supervised machine learning has input and output data while unsupervised machine learning only has input data.

2 Research Objectives

The proposed methodology could be a cornerstone of HOME's environmental control systems. As a study that integrates humanity's knowledge of technology made on Earth with the constraints of a space environment, this project informs how life-support systems are developed in future deep space habitats.

This study seeks to

(1) Develop a supervised MLM framework that allows HVAC systems developed on Earth to operate within a space environment.
(2) Develop a smart control approach for HVAC systems that maximizes thermal comfort under limited energy resources.

3 Methodology

Three MLMs will be developed, forecasting lunar outdoor temperatures, solar energy capture, and indoor temperatures respectively. Because energy is a limited resource in planetary environments, the framework seeks to "budget" energy use. Energy is used only when necessary (i.e. during periods of extremely low or high temperatures).

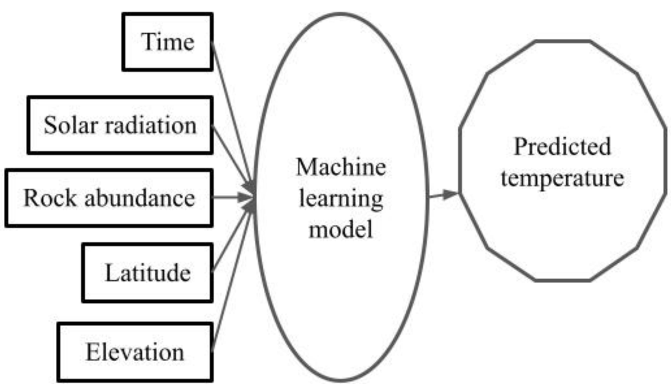

Fig. 1 Input and Output Parameters of the Lunar Weather MLM. *This model forecasts temperatures for the next 24 hours.*

The temperature on the surface of the Moon is correlated to rock abundance, latitude, elevation, and radiation [7,11]. This data will be pulled from the Lunar Reconnaissance Orbiter's instruments: Diviner and Cosmic Ray Telescope for the Effects of Radiation (CRaTER). By training the MLM on the following input data: time, solar radiation, rock abundance, latitude, and elevation, the MLM "learns" to predict outdoor temperatures.

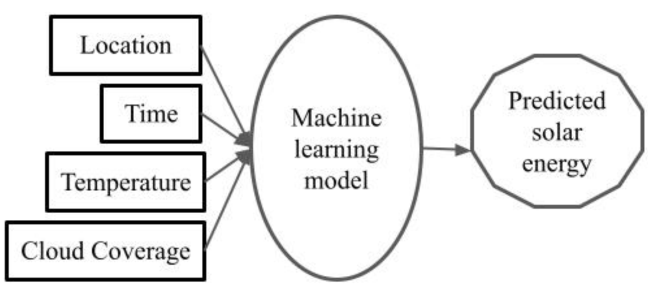

Fig. 2 Input and Output Parameters of the Solar Energy MLM. *Location includes latitude, longitude, and elevation. The MLM forecasts solar energy output for the next 24 hours.*

A recent study proved that certain weather and location data could predict the power output of solar panels on Earth [8]. We will use the study's dataset to build a model that predicts energy generation from lunar solar panels. By training the MLM on the following input data: location, time, temperature, and cloud coverage, the MLM “learns” to predict how much solar energy is generated.

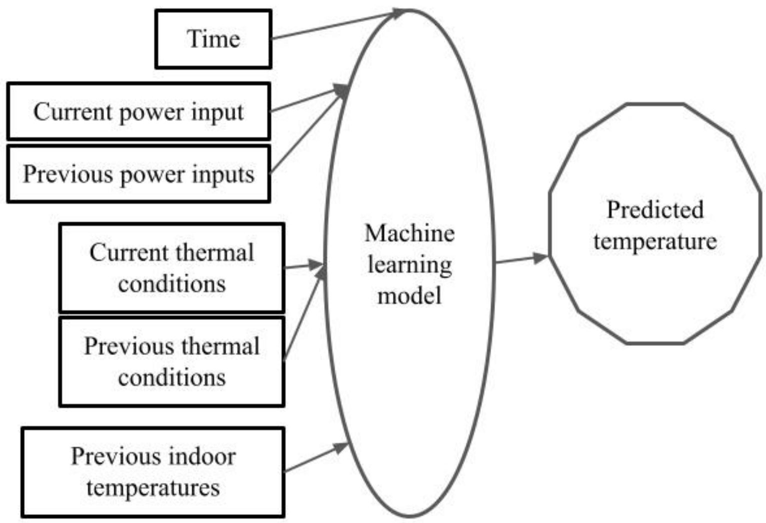

Fig. 3 Input and Output Parameters of the HVAC System MLM. *Thermal conditions include electricity availability[2], thermal load[3], solar radiation, and outdoor temperature.*

Recent research proposed that the HVAC system shown in Figure 3 could accurately predict indoor room temperature [6]. This study builds on that paper; we aim to get access to the data used by the authors to develop our own MLM and validate the model’s efficiency and accuracy. By training the MLM on the following input data: time, power, and thermal conditions, the model “learns” to predict indoor temperature

Each MLM follows a supervised learning approach because the correct output is known. To select the most optimal supervised learning algorithm, each MLM will implement algorithms from the programming language R’s Regression Training package as this package can handle the study’s continuous data[4]. The model’s accuracy, specifically its Root Mean Square Error (RMSE), will serve as a performance metric. The model will use the algorithm that produces the lowest RMSE.

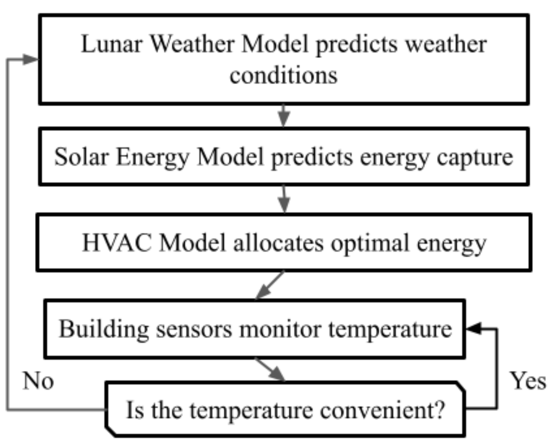

Fig. 4 Working principle of novel methodology. *Information simulating the lunar environment is passed into each MLM.*

The framework is designed to balance short-term thermal comfort with long-term energy availability. To prevent extreme lunar temperature fluctuations from affecting habitat temperatures, solar energy is used whenever the outside temperature reaches its peak or trough. The control algorithm is successful when a livable temperature is achieved for all 24 hours.

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[2] Electricity availability is measured because solar energy cannot be generated at night.
[3] Thermal Load is the amount of heat energy required to add or remove to maintain the desired room temperature
[4] Continuous data is described as data that can take any numerical value

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