Digital twin and physics informed machine learning for rover motion simulation

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Abstract

Predicting the motion of rovers on regolith is key for unmanned extraterrestrial exploration to ensure their safety while traversing new terrains and for the successful completion of scientific tasks on Lunar surface. Some terramechanics studies tackle this problem looking at the interactions between wheels and deformable soil made of regolith. Although those techniques provide very accurate results, the computation loads are too heavy to be used in the rovers' real-time decision-making process. This study aims to reduce the running time of the simulation model while keeping very accurate predictions. To this purpose, Physics Informed Machine Learning (PIML) was identified as a promising architecture as it can capture physical knowledge using ordinary differential equations (ODE) and improve the final solution using data driven machine learning (ML). Additionally, this technique requires significantly less training data which is very useful in the context of space exploration. The architecture proposed in this paper is composed of two components. The first component consists of an ODE to simulate the physical behavior of the rover. Although not accurate, the ODE predicts the position of the rover simplifying the problem to a rigid body on a rigid slope with a constant friction coefficient. Applying the net forces, this yields to a rough estimation of the positions using analytically solvable ODEs. A neural network is then added as a second component which is trained to compensate the differences between the solutions of the simplified ODE and the ground truth data given by an accurate, but slow, terramechanics simulation engine. By combining the ODE with a neural network, we demonstrate that the PIML can reduce an error of 60m (ODEs only) to 20cm while drastically reducing the running time. The outputs of the PIML are indeed generated in 400ms where it takes more than 90min with traditional methods to produce the ground truth data with which those outputs are compared. This research represents a significant advancement in robotic modelling, simulation and prediction methodologies, offering a robust framework that combines foundational physics principles with data driven machine learning for optimized digital twin techniques. By bridging the gap between accuracy and efficiency, this approach holds great promise for optimizing robotic operations in lunar extraterrestrial environments and autonomous decision making.

Keywords: Physics Informed Machine Learning (PIML), digital twins, rover motion prediction, Terramechanics, Lunar exploration

Acronyms/Abbreviations

AI: Artificial Intelligence,
PIML: Physics Informed Machine Learning
ODEs: Ordinary Differential Equations
PDEs: Partial Differential Equations
NN: Neural Network
ML: Machine Learning
CADRE: Cooperative Autonomous Distributed Robotic Exploration
VIPER: Volatiles Investigating Polar Exploration Rover
SLIM: Smart Lander for Investigating Moon
SCM: Soil Contact Model
CRM: Continuous Representation Model
DEM: Discrete Element Model
HLS: Human Landing System

1. Introduction

Going back to the Moon to better understand planetary processes, conduct science in situ and pave the way to further space exploration have gained more and more interest worldwide. They are all part of the seven science goals identified by the Artemis III science definition team [1]. These drove several missions in the United States such as Odysseus from Intuitive Machines [2] that recently landed in February 2024 but also upcoming ones such as the Cooperative Autonomous Distributed Robotic Exploration (CADRE) [3,4] or the Volatiles Investigating Polar Exploration Rover (VIPER) [5,6] planned to be launched in 2024. This interest has been shared by many other countries that have recently successfully put landers on the Moon such as India with Chandrayaan-3's lander [7,8] in August 2023 and Japan with the Smart Lander for Investigating Moon (SLIM) in January 2024 [9,10].

Another main objective of NASA Artemis missions is to build a base camp on the surface of the Moon [11]. Many different concepts have been explored such as inflatable structures [12], giant regolith 3D printers [13], using the natural protection of lava tubes [14], or even reusing the SpaceX Human Landing System (HLS) once decommissioned [15]. Despite being very different concepts they all have one thing in common – they all require to use robots that will have to be able to drive autonomously on Moon and accomplish complex tasks in a very harsh environment.

With the growing interest for the Moon and the necessity to send more robots there, appears the need to thoroughly test them before sending them to the Moon. However physically replicating the Moon environment on Earth is a very hard task to do on a very large scale for many reasons. To cite only a few, the much lower gravity, the absence of atmosphere, the very different property of its soil, the regolith, are all hard aspects to reproduce accurately on Earth. Hence, the importance to develop virtual accurate test environment.

Given these challenges, it is crucial to develop virtual environments for testing all equipment and rovers intended for lunar missions. A first version of such a virtual environment, VIRCLE, was developed using the Omniverse platform. For this test bed to be truly effective, it must not only reproduce the unique properties of the lunar environment with high accuracy but also meticulously simulate all the properties of the equipment to be tested, particularly rovers, such as mechanical, electronic, communications, etc. All those elements constituting rovers' digital twins of the highest importance to increases the of mission safety and success.

While VIRCLE tackles many challenges, this work focuses on the terramechanics aspect of rover motion on lunar regolith. Specifically, it aims to accurately simulate the interactions between rover wheels and regolith to predict the rover's position at each time step in real time. Precise simulation of these interactions is key to ensure that rovers are well-designed to traverse the expected terrain, follow planned paths without flipping over on a too steep slope or becoming stuck in regolith. This would indeed lead to mission termination, as it tragically happened to Spirit and Opportunity on Mars, despite a highly successful mission.

The very unique properties of Moon regolith lead to various challenges, including a higher slip ratio for rovers that is difficult to predict. However, several terramechanics groups have addressed this issue in multi-body dynamics studies. Software like Chrono can achieve very high accuracy in simulating these interactions. However, these simulations are very long to run.

This work aims to explore if it is possible to reach similar accuracy in real time using Artificial Intelligence (AI), and more specifically Physics Informed Machine Learning (PIML).

2. Material and methods

2.1 Ground truth data

A Physics Informed Machine Learning model still requires some data to be trained on. This could be taken from all the data gathered by all the sensors in the rovers during their missions or when they are tested on regolith simulant. However, such real data gathered by sensors usually necessitate some preprocessing, denoising and cleansing before being usable to train model. Besides, this limits the available data to the scenarios that have been tested or seen during the missions.

Using a simulation engine, provided it has a good accuracy, enables us to control the complexity of the environment and use specific scenarios. This is what Chrono Engine developed by the Simulation Based Engineering Lab at the University of Wisconsin provides. It is a physics-based modelling and simulation infrastructure based on a platform-independent open-source design implemented in C++. It is capable of simulating wheeled and tracked vehicles and robots operating on deformable terrains and fluid solid interaction phenomena. This Engine provides three modes of simulation that provide more and more accurate predictions, at the expense of computation speed: Soil Contact Model (SCM), Continuous Representation Model (CRM) and Discrete Element Model (DEM).

Chrono Engine was thoroughly tested against measured data observed during the tests of the rover Viper on regolith simulant on a test bed at NASA Glenn Research Center. The predicted behavior of the rover on regolith simulant being strongly aligned with the one that was measured during the test, we decided to use this Engine to generate our ground truth data for the study. Although Chrono is highly accurate, its simulations are computationally intensive, running hundreds to thousands of times slower than real-time. This makes it challenging to use for real-time decision-making. This study aims at investigating ways to get results with similar accuracy in a faster way. To this end, a PIML model was trained on data generated by Chrono in order to determine whether it could predict the rover's position with similar accuracy in a much faster way, enabling real-time decision-making applications.

2.2 Physics Informed Machine Learning

Physics-informed Machine Learning is a set of different approaches combining traditional machine learning with knowledge encompassed in Ordinary Differential Equations (ODEs), and more generally, Partial Differential Equations (PDEs). By integrating physical laws directly into the learning process, PIML ensures that the models not only learn from the data but also follows physical principles. This makes PIML particularly effective for complex systems where purely data-driven models might struggle due to limited or noisy data.

In the context of simulating the motion of rovers on regolith, PIML offers a promising solution. The interaction between the rover's wheels and the regolith is a complex phenomenon governed by principles of terramechanics, which can be challenging to model accurately with purely data-driven methods.

PIML encompasses multiple approaches such as Physics Informed Neural Network proposed by Raissi et al. (2019) but also residual modelling offering a promising solution by learning the discrepancies between simplified physical models and observed data. Here a first attempt was explored by using residual modelling and only analytically solvable equations to describe the problem in order to keep the inference of the prediction as close as possible to real time. However, ODEs cannot fully describe very complex physical behaviours such as the motion of a rover on regolith, which would require more complex models such as Bekker and Wong [45]. Therefore, the residual modelling approach uses an additional neural network (NN) to learn the differences (residual) between the simple solutions of the ODEs and the ground truth data. By doing so, it reduces the overall error between the predictions of the PIML model (Physics equations + NN) and the ground truth data.

3. Theory and calculation

The first application of this study is to estimate the position of a rover, with the same characteristics as Viper, going over a slope covered with regolith and limited to two dimensions. The PIML model is trained with the ground truth data generated by Chrono simulating the motion of Viper going over such a slope with different inclinations. The trained model is then used to predict the position of this rover at any time step for a new inclination of the slope that has not been seen by the model during training.

As this study is limited to 2D and the rover is considered, and set in Chrono, as a rigid body, estimating the position of only one wheel is enough. Here below is the schematics of this wheel on a slope with the difference forces applied to it to derive the ODEs applying Newton's second law.

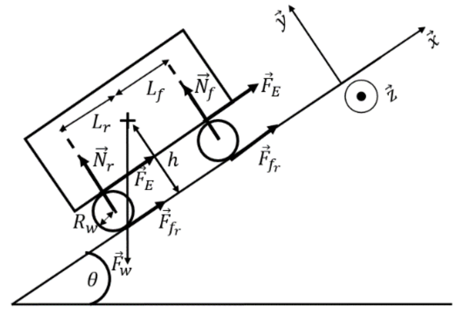


Fig. 1. Representation of a rover going up a slope

Where θ is the inclination of the slope (in degree)
τ is the torque applied on the wheel
μk is the friction coefficient of the regolith

Applying Newton's second, this leads to the following equations applied to the rear wheel:

$$m\frac{d^2x_{Phys}}{dt^2} = -mg\left[\frac{L_r + h * \sin(\theta)}{L}\right]sin(\theta) + \mu_k mg\left[\frac{L_r cos(\theta) + h\sin(\theta)}{L}\right] + \frac{\tau}{R_w} \quad (1)$$

$$y_{Phys} = R_w \quad (2)$$

Those equations constitute the Physics foundation of the Physics Informed Machine Learning model. The solutions can be obtained analytically which ensures inferences in real time very but does not capture enough complexity to accurately simulate the motion of rovers on regolith. Therefore, a neural network is used to learn how to reduce the discrepancies between the output of the ODEs (Xphys, Yphys) and the ground truth generated by Chrono (Xsimu, Ysimu) on a given slope. This NN is training following the architecture described below:

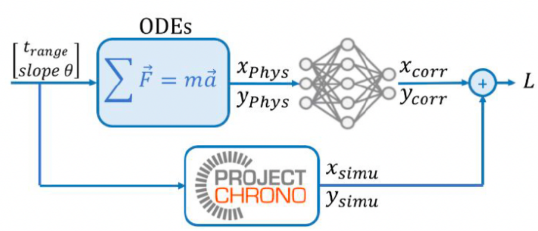


Figure 17: Architecture of the Physics Informed Machine Learning model

where:

$$\begin{aligned} x_{\text{corr}} &= x_{\text{Phys}} + \Delta x_{\text{NN}} \\ y_{\text{corr}} &= y_{\text{Phys}} + \Delta y_{\text{NN}} \end{aligned} \quad (3)$$

Given this architecture, the loss function of the neural network is the difference between the predicted position by the ODEs and the output of Chrono Engine written as follows:

$$L = \frac{1}{N} \sum \left[(x_{\text{simu}} - x_{\text{corr}})^2 + (y_{\text{simu}} - y_{\text{corr}})^2 \right] \quad (4)$$

As a first application, a simple NN with five dense layers (30, 120, 500, 50, 2) and Relu activation functions is tested as a fully connected NN.

4. Results and discussion

To train the NN of the PIML, Chrono Engine is used to generate all the datasets (training, validation and test). Several simulations are run on Chrono making Viper drive over a slope of regolith with different inclinations for 10s. The 2D position of the front wheel is recorded every 0.5ms generating 20k data points per slope. Each of these simulations, performed in 3D, taking 90min on Chrono with an NVIDIA Quadro RTX 3000 GPU.

Starting to train with a very limited number of scenarios simulated with different slopes, the training and validation sets were separated as follows: one data point every 4 on each slope is removed from the training set and saved for the validation set. This way the first three points are used for the training and the fourth for validation. Therefore, a total of 15k data points are used for training and 5k data points for validation per simulated slope.

Once the NN is trained on different slopes with different inclinations, two main analyses have been conducted. The first one testing the capability of the model to accurately predict the motion of the same rover, in 2D, on a different slope and in real time. The second one testing the possibility of simulating the motion of a rover with new characteristics such as a very different mass.

4.1 Predictions on novel slopes

The NN was trained here on the datasets generated by 12 scenarios with 12 different slopes, from 20° to 32° by increment of 1° and leaving one slope for testing. This results in a training of 180k data points, validation on 60k data points and test on 20k data points on a new slope the NN was not trained on.

Below are the results of the model trained on scenarios with slopes from 20° to 32° (excluding 28°). This model is evaluated on a slope with an inclination of 28° and 12-time steps are presented. Each time step representing the ground truth position (Chrono in green) of the rover's rear wheel going up the slope. Additionally, the estimated position the rover by the Physics equations (ODEs in blue) and the ones corrected by the PIML (PIML in orange) are plotted.

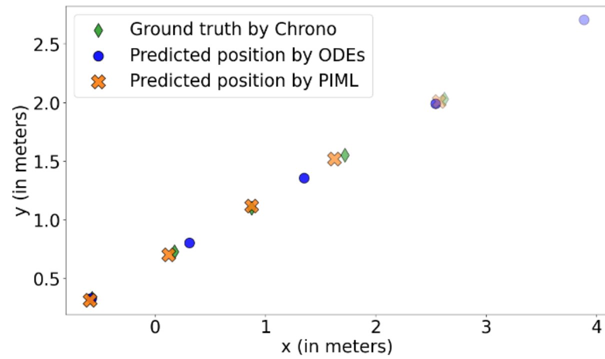


Fig. 2. Position (x,y) of the rear wheel of a rover going over a 28° slope with regolith simulated in Chrono Engine (ground truth), predicted using ODEs only and predicted using Physics Informed ML. Training performed on slopes [20.0, 32.0, 1.0] \ {28.0}.

Looking at the distances between the last predicted position and its associated ground truth data, the neural network plays a significant role in reducing the error induced by the simple ODEs that cannot capture all the complex physical interaction of regolith with the rover's wheels. Indeed, the ODEs output an error of 1.9m in positioning, where the neural network reduces it to 6.1cm.

By plotting the distance covered by the rover over time the action of the neural network to correct the predicted position of the rover is clear.

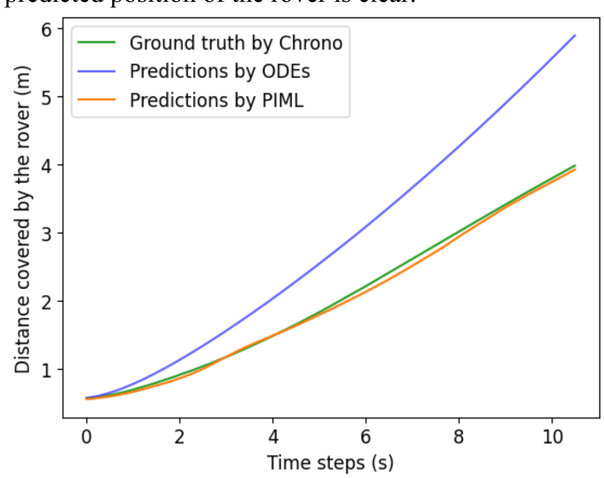
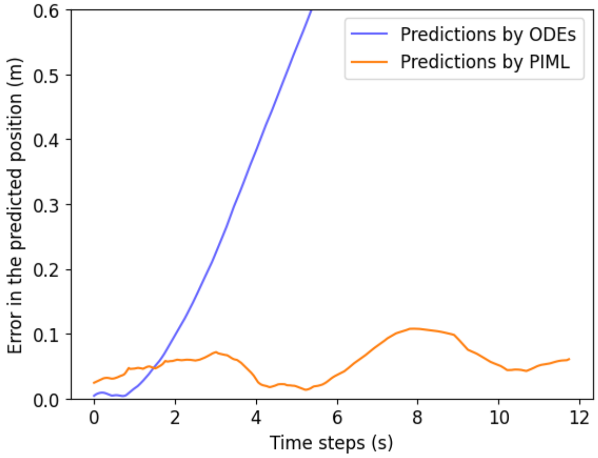


Fig. 3. Distance covered by the rover over time on regolith simulated in Chrono Engine, predicted using ODEs only and predicted using Physics Informed ML. Training performed on slopes [20.0, 32.0, 1.0] \ {28.0}.

Finally, by plotting the error in distance between the ground truth position and the predicted positions by ODEs only and by PIML two pieces of information can be drawn.



Firstly, it is clear that the error using PIML is much lower than the error using ODEs. Additionally, it is worth noticing that the error using PIML doesn't keep increasing but also goes down, as it is not the case using the ODEs only.

Finally, the main incentive for using PIML was to reduce the running time for associated simulations. While Chrono Engine takes about 90 min to provide the ground truth, the PIML ran the prediction in 120ms with an NVIDIA Quadro RTX 3000 GPU, which demonstrates the efficiency of this architecture to reduce the running time and think of real-time use for decision making. However, one needs to keep in mind that the runtime comparison cannot be a direct comparison as Chrono Engine gives a 3D simulation and outputs more information than just the 2D positions of one wheel.

As this study is conducted in a more global work of building digital twins and virtual environment testbed, another aspect was looked at in this research. A virtual testbed will have to be able to handle many different rovers and it would be very impractical if to simulate the interaction of the regolith and the wheels of each rovers, a new model would require to be trained. Therefore, we also studied here if the trained PIML could be used to predict the motion of another rover with different characteristics. As a first exploration of this ability to adapt to a change in rovers' characteristics, the PIML model already trained in this section is used to predict the motion of the same rover but with a mass twice as much as the one used for the training.

4.2 Predictions with new rover mass

In this section, the training dataset is not changed and the PIML model is not retrained. Only the input of the Physics equations is changed to reflect the changes of mass of the rover by doubling the mass and the torque. Another test set is generated using Chrono and changing only the mass of the rover from 430kg to 860kg. The pre-trained PIML model is used to predict the motion of this 860kg rover on a slope of 28°. The results are plotted in the following sketch and compared with the ground truth generated by Chrono.

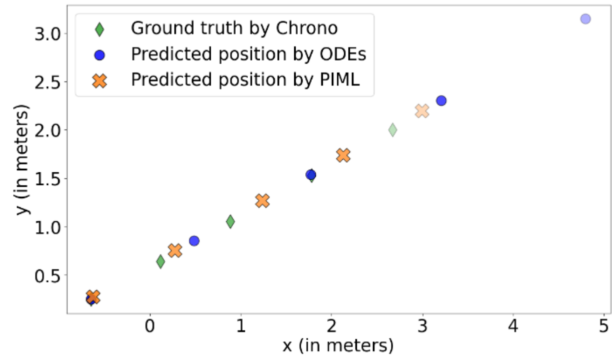


Fig. 4. Position (x,y) of the rear wheel of a 860kg rover going over a 28° slope with regolith without retraining the PIML. Comparison with the simulation by Chrono Engine changing the rover's mass to 860kg.

The results here are pretty similar to the ones previously displayed without mass adaptation. The NN is capable of efficiently correct the predictions of the ODEs and get predictions very close to the ground truth provided by Chrono. These results demonstrate the robustness of the PIML to mass adaptation without necessitating to retrain the NN.

5. Conclusions

This study proposes a Physics Informed Machine Learning architecture based on analytically solvable equations and a trained NN to attempt to predict the motion of rovers on the Moon in real time. Trained on a few scenarios, the NN proved to be able to efficiently correct the error made by the ODEs and predict the overall position of the rover with high accuracy with errors between 1 to 10 cm for this application. Additionally, as this architecture also relies on Physics equations, it requires less data to train than fully data driven methods and it is shown to be robust to some changes in the physical characteristics of the rover, such as its mass, without necessitating any retraining of the NN. Finally, the main advantage of this hybrid method is its ability of running predictions much faster than finite elements methods, in a couple of 100ms. This very low running time, close to real time, while maintaining a high accuracy is very promising to enable real time decision making for rovers on the ground. This could for instance enable them to make decisions whether to go over certain slopes given the output of a real time simulation.

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References

[1] artemis-iii-science-definition-report-12042020c.pdf, (n.d.). https://www.nasa.gov/wp-content/uploads/2015/01/artemis-iii-science-definition-report-12042020c.pdf (accessed July 6, 2024).
[2] IM-1, Intuitive Mach. (n.d.). https://www.intuitivemachines.com/im-1 (accessed July 6, 2024).
[3] J.-P. de la Croix, F. Rossi, R. Brockers, D. Aguilar, K. Albee, E. Boroson, A. Cauligi, J. Delaune, R. Hewitt, D. Kogan, G. Lim, B. Morrell, Y. Nakka, V. Nguyen, P. Proença, G. Rabideau, J. Russino, M.S. da Silva, G. Zohar, S. Comandur, Multi-Agent Autonomy for Space Exploration on the CADRE Lunar Technology Demonstration, in: 2024 IEEE Aerosp. Conf., 2024: pp. 1–14. https://doi.org/10.1109/AERO58975.2024.10521425.
[4] https://www.jpl.nasa.gov, CADRE, NASA Jet Propuls. Lab. JPL (n.d.). https://www.jpl.nasa.gov/missions/cadre (accessed July 6, 2024).
[5] K.E. Smith, A. Colaprete, D.S.S. Lim, D. Andrews, The VIPER Mission, a Resource-Mapping Mission on Another Celestial Body, (2022). https://ntrs.nasa.gov/citations/20220005327 (accessed July 6, 2024).
[6] VIPER - NASA Science, (n.d.). https://science.nasa.gov/mission/viper/ (accessed July 6, 2024).
[7] K.D. Prasad, D. Misra, Amitabh, M. Bhatt, G. Ambily, S. Sathyan, N. Srivastava, A. Bhardwaj, Chandrayaan-3 Alternate Landing Site: Pre-Landing Characterisation, (2023). https://doi.org/10.48550/arXiv.2308.10712.
[8] Chandrayaan-3 Details, (n.d.). https://www.isro.gov.in/Chandrayaan3_Details.html (accessed July 6, 2024).
[9] J. Haruyama, S. Sawai, T. Mizuno, T. Yoshimitsu, S. Fukuda, I. Nakatani, Exploration of Lunar Holes, Possible Skylights of Underlying Lava Tubes, by Smart Lander for Investigating Moon (SLIM), Trans. Jpn. Soc. Aeronaut. Space Sci. Aerosp. Technol. Jpn. 10 (2012) Pk_7-Pk_10. https://doi.org/10.2322/tastj.10.Pk_7.
[10] JAXA | SLIM Special Site, JAXA Jpn. Aerosp. Explor. Agency (n.d.). https://global.jaxa.jp/countdown/slim_special_site.html (accessed July 6, 2024).
[11] Lunar Living: NASA’s Artemis Base Camp Concept – Artemis, (2020). https://blogs.nasa.gov/artemis/2020/10/28/lunar-living-nasas-artemis-base-camp-concept/ (accessed July 7, 2024).
[12] Inflatable Moon base, (n.d.). https://www.esa.int/ESA_Multimedia/Images/2020/09/Inflatable_Moon_base (accessed July 7, 2024).
[13] ICON To Develop Lunar Surface Construction System With $57.2 Million…, ICON (n.d.). https://www.iconbuild.com/newsroom/icon-to-develop-lunar-surface-construction-system-with-57-2-million-nasa-award (accessed July 7, 2024).
[14] R.P. Martin, H. Benaroya, Pressurized lunar lava tubes for habitation, Acta Astronaut. 204 (2023) 157–174. https://doi.org/10.1016/j.actaastro.2022.12.013.
[15] A. Abdin, S. Amberger, E. Apollonio, G.B. de Fourtou, K. Bolmgren, G. Ciocca, M. Ekal, A. Garcia, A. Godeanu, D. Irrera, L.C.L. Lidgard, G. Lorini, S. Monat, J. Montenegro, A. Oleary, O. Onn, L. Pauzie, C. Pouwels, A. Sokolowski, Z. Tian, A. Za, Solutions for construction of a lunar base: A proposal to use the spacex starship as a permanent habitat, in: 2021. https://hal.science/hal-04318110 (accessed July 7, 2024).
[16] Artemis I - NASA, (n.d.). https://www.nasa.gov/mission/artemis-i/ (accessed July 6, 2024).
[17] E. Chow, T. Lu, K. Payumo, G.B. de Fourou, E. Sadler, N.E. Janvisloo, J. Carrillo, B. Li, B. Hubler, O. Littlejohn, V. Hernandez-Cruz, S. Torrellas, Collaborative Moonwalkers, in: 2024 IEEE Aerosp. Conf., 2024: pp. 1–15. https://doi.org/10.1109/AERO58975.2024.10521103.