

Digital Twins and Modelling for Spacecraft Science Operations: Application to Surface Interaction and Sampling on Small Solar-System Bodies

Iosito FODDE^{1,a,*}, Fabio FERRARI^{1,b}, and Franco Bernelli ZAZZERA^{1,c}

¹Department of Aerospace Science and Technology (DAER), Politecnico di Milano, Via La Masa 34, Milan, Italy

^aiosito.fodde@polimi.it, ^bfabio1.ferrari@polimi.it, ^cfranco.bernelli@polimi.it

Keywords: Space Exploration, Digital Twins, Small Solar-System Bodies

Abstract. The increasing number of space exploration missions presents a novel challenge with regards to planning and operations. Current architectures are composed of distinct teams and models performing separate tasks like navigation, planning, and science, which can lead to inefficiencies and delays. This work proposes a Digital Twin (DT) architecture which supports end-to-end mission design, operations, and scientific analysis. The proposed DT combines models of the spacecraft, its scientific payloads, and the target body, linked through a data processing layer that enables continuous monitoring, simulation, and decision support. A case study of a spacecraft exploring an asteroid and interacting with its surface through a lander and sampling arm is presented. This example specifically shows the importance of reduced order models (ROMs) to efficiently predict and interpret surface interactions. This approach highlights the potential of integrated DT architectures to enhance coordination, adaptability, and scientific return in future deep space missions.

Introduction

The number of missions exploring the solar system is increasing rapidly over time, from spacecrafts going to the Jovian system investigating the habitability of its moons, to mission improving our planetary defense capabilities by visiting near earth objects like Didymos and Apophis. These missions are complex, with various instruments that are necessary to meet science objectives, many different subsystems with intricate connections, and large ground teams that must analyse, plan, and operate these missions [7]. While miniaturization has driven down spacecraft manufacturing costs, the operational burden on the ground segment has not scaled down equivalently, in fact, the demands on mission planning and coordination are growing due to increasing number of deep space missions.

Currently, the planning and operation of these missions is performed by separate groups, e.g. hardware design, trajectory planning, navigation analysis, and science investigation groups. During all phases of the mission, decisions made by each group have a large influence on the other and require frequent iterations. This siloed approach leads to inefficiencies and repeated iterations, especially as small design or operational decisions can propagate significantly through the mission's architecture and affect science return. To address this challenge, this work proposes the integration of novel Digital Twin (DT) and modelling methodologies to improve operational efficiency and enhance scientific outcomes across all mission phases, from design to post-mission data analysis. DTs are virtual models of physical processes where data is exchanged (often real-time) to update the state of the virtual model. DTs have already been explored for individual subsystems of spacecrafts, like for example the EPS of Artemis [8]. However, here we propose to have a more holistic view of the mission. Specifically, we envision a DT that encapsulates the spacecraft, its instruments, and the target planetary body. The central objective is not just



engineering health monitoring, but mission science: continuously assessing whether science goals are being met, adapting operations in response to unexpected conditions, and extracting maximum insight from acquired data. In this work we present a general overview of this problem, and give an example related to a spacecraft trying to interact with the surface of a Small Solar-system Body (SSB) like an asteroid or small planetary moon.

Digital Twin

With an increase in computing power, larger numbers of spacecrafts, and more complex space systems the use of DTs in spaceflight has seen an increase in the last decades. Examples can be found for rover operations [10], spacecraft electrical power systems [8], and astronaut training [9]. For a more comprehensive overview, the reader is directed to [6]. There are many different definitions of what exactly a DT is, which also depend on the specific domain in which they are used. In general, there are two key characteristics that are common:

- It is a digital representation of a process/object/system in the physical world.
- There is a bidirectional exchange between the DT and the physical system.

In several cases there is also a (quasi) real-time aspect to the DT, as they are often used in critical processes like structural health monitoring where quick responses are required [5]. Due to the inherent delays present in deep space operations the real-time aspect is not considered for the DTs here.

Figure 1 shows the proposed architecture of the DT for science operations. It mainly consists of two blocks, representing the physical and digital environment. The physical environment consists of both the target objects (e.g. asteroid, moon, planet, etc.) and the spacecraft including all its scientific payloads, sensors, and actuators. The digital block consists of three sub-blocks: the spacecraft model, target model, and data processing blocks. The spacecraft model contains digital representations of the different subsystems and serves two purposes: interpreting incoming data from the physical spacecraft and simulating proposed commands sent from ground. The target block represents the current state of knowledge of the target. It can be used to understand the incoming observations, plan them based on the perceived lack of knowledge, and as a simulation tool for the simulated spacecraft. Finally, the data processing block contains all the decision making logic. It creates commands based on the current state of the spacecraft and target, it then performs predictive simulations using these commands, and finally decides on the actual command sent to the physical spacecraft (either human-in-the-loop or autonomously).

The individual spacecraft and target model blocks do not necessarily present novel ideas. Engineers have already implemented models and digital twins of the spacecraft itself during previous missions [8] and scientists have done the same for the target of interests of individual or combined missions [1]. The main novelty of the proposed architecture is to combine the different blocks into a single architecture and use the data processing block to monitor the system as a whole, perform scientific interpretation of the data, and plan the next steps. The advantages of this approach is the fact no long iterations between the different teams and their separate models/DTs are necessary, decreasing the turnaround time and making the mission more flexible to new observations. It also ensures that any unexpected events and faults in the spacecraft are propagated throughout the whole system, directly observing the consequences.

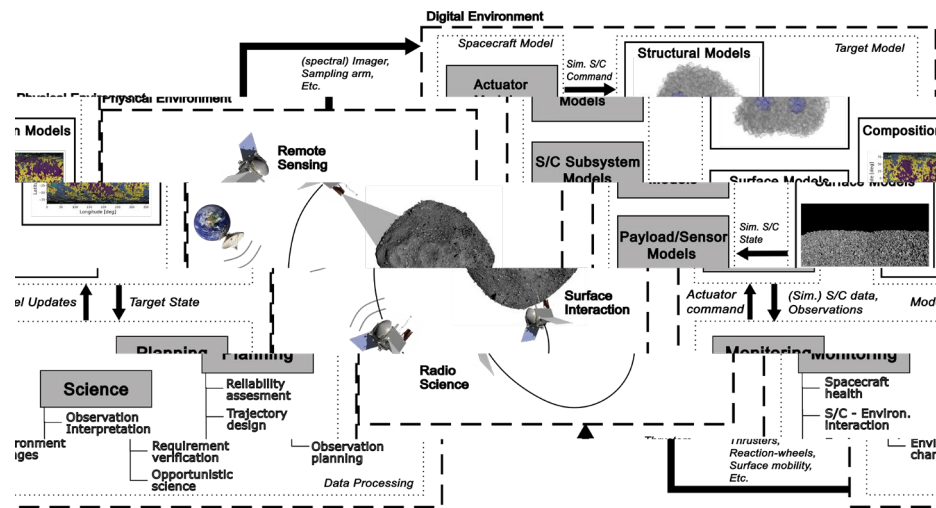


Figure 1 Schematical representation of the Digital Twin for space exploration and science

The main complexity of this architecture lies in the efficient modeling of the systems and efficiently using the sensors and instruments available on the spacecraft. For example, a large number of Small Solar System Bodies (SSBs) are thought to have a large amount of granular material, also known as regolith, and boulders on their surface. The interactions between the individual regolith particles, the boulders, and the spacecraft itself are governed by complex contact forces and are hard to model on Earth due to the low-gravity environment on these SSBs. Modeling SSBs thus requires complex discrete element models (DEMs), which have a high computational burden. Running many DEM simulations for interpreting continuously the novel observations and performing statistical predictions can take several days to weeks [4], thus reacting to these new observations becomes infeasible. Hence, reduced order models (ROMs) are needed that can be more efficiently used inside the DT. The focus for the following will be on how to generate these ROMs and how they can be used inside the DT framework. 3

Case Study: SSB landing and sampling

Many missions have attempted, or are planning to attempt, interactions with the surface of a SSB. For example, NASA's OSIRIS-Rex successfully obtained a sample from the asteroid Bennu using its TAGSAM robotic arm, while JAXA's Martian Moons eXploration (MMX) will deploy a rover on the surface of the Martian moon Phobos. One of the main difficulties for these missions is the uncertainty related to the surface properties of SSBs. These properties are related to, for example, their size distribution, strength, contact parameters, and density. Determining these parameters not only serves to reduce the risk of an interaction, but also to improve our scientific knowledge as these parameters can tell us about the formation and evolution of these SSBs.

For this test case, a Hayabusa-2 like mission is used where first a lander is placed on the surface and afterwards a sampling maneuver is performed. In this case, the DT architecture can help in interpreting the data from different instruments and the initial landing to inform the sampling strategy. First, the simulation setup is performed using a DEM code called GRAINS (more information regarding this code can be found in [2]). The surface conditions are first determined by observations from the optical and thermal imagers, which can obtain particle size and shape distributions (PSDs). Using these observations and the results from the radio science instrument to determine the local gravity level, the surface is created inside the DEM by generating a set of particles using the determined PSD and letting it settle under the local gravity level. This model can be continuously updated by new measurements of the imagers and/or the radio science

experiment. Once the surfaces are created, objects representing the lander and sampler can be incorporated, see Figures 2a and 2b.

As discussed before, a ROM of the surface interaction needs to be generated to perform statistically relevant reliability assessments and parameter estimation. This is achieved using a data-driven approach where a small number of DEM simulations are used to fit a ROM that can be more efficiently used. This ROM is created by a non-intrusive polynomial chaos method, which samples the initial conditions and system parameters in an optimal way, and takes the input-output relationship of these sample simulations to create a fit based on a family of orthogonal polynomials that represent the prior distribution of the input variables. A more detailed description of this method is given in [3].

It was found that the generated ROM for the landing has a maximum error of around 5 percent. Using this model, a reliability assessment was made for a hypothetical landing scenario on Didymos, show in Figure 2c. After the actual landing is performed, a Markov Chain Monte Carlo (MCMC) method was used to determine the contact parameters of the surface material. The MCMC method required 50000 samples to achieve an acceptable accuracy, using the original full order DEM model would take around 14.26 years to run. With the ROM this was reduced to around 6 minutes (excluding the one time cost of generating the ROM, requiring around 12 hours). This info can then be used for the sampling maneuver to derive a more robust maneuver. Similarly to before, after the sampling maneuver an MCMC method was performed to have a final estimate of the surface parameters, which are shown in Figure 2d.

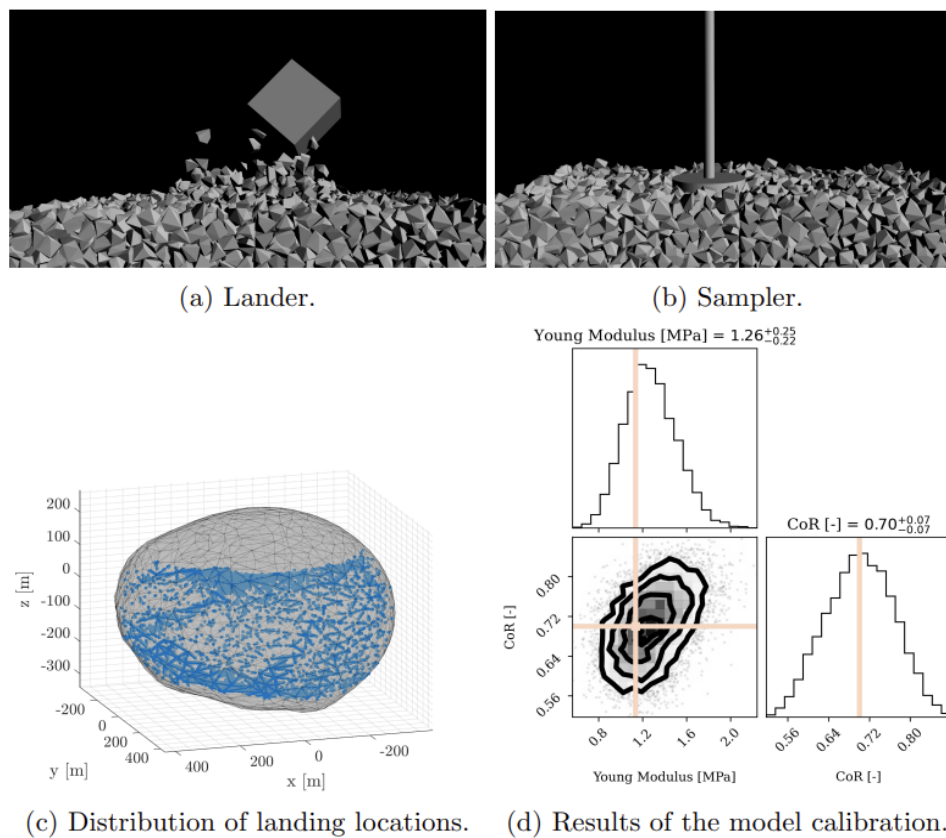


Figure 2 Results for the test case of the landing and sampling of a SSB.

Having a combined DT of the spacecraft, the sampling arm, and the surface of the SSB will help in planning this operation, tracking the successful execution of this maneuver, and interpret

the data for scientific purposes. The main difficulty here is the complexity of these types of simulations (requiring discrete element models (DEM) to simulate the motion of the surface particles, the spacecraft, and their interaction), and efficiently using the sensors and instruments available on the spacecraft. For both real-time tracking and post-processing the spacecraft data, reduced order models are needed that can be more efficiently run.

Conclusions

Here it was discussed how concepts from digital twins (DT) can be used in deep space missions, specifically looking at science operations. This DT serves multiple roles: (1) it supports pre-arrival parametric analysis, enabling assessment of operational feasibility and risk under different conditions; (2) it facilitates real-time mission support by quickly evaluating the implications of sensor data; and (3) it enables inverse modeling, where in-situ measurements are used to infer target properties, advancing scientific understanding of the Solar system. Concluding, this work highlights the potential of Digital Twin architectures to improve science operations for planetary missions. By integrating spacecraft dynamics, instrumentation, and environmental interaction into one model, decision-making can happen more efficiently, mission performance is optimised, and scientific return is maximised. Our SSB surface interaction case study gives an example of how this approach can be practically applied, from pre-mission design through to data interpretation, in one of the most complex and uncertain operational scenarios in planetary exploration.

Acknowledgments

This work was carried out within the Space It Up! project funded by the Italian Space Agency (ASI) and the Italian Ministry of University and Research (MUR) under contract No. 2024-5-E.0, CUP No. I53D24000060005.

References

- [1] P. Bauer, T. Hoefler, B. Stevens, and W. Hazeleger. Digital twins of Earth and the computing challenge of human interaction. *Nature Computational Science* 2024 4:3, 4(3):154-157, 3 2024. <https://doi.org/10.1038/s43588-024-00599-3>
- [2] F. Ferrari, M. Lavagna, and E. Blazquez. A parallel-GPU code for asteroid aggregation problems with angular particles. *Monthly Notices of the Royal Astronomical Society*, 492(1):749-761, 2 2020. <https://doi.org/10.1093/mnras/stz3458>
- [3] I. Fodde, L. F. Civati, A. Cremasco, and F. Ferrari. Modelling and Estimation of Spacecraft Interactions with the Surface of Small Solar System Bodies. Submitted, 2025.
- [4] I. Fodde and F. Ferrari. Dynamical modelling of rubble pile asteroids using data-driven techniques. *Astronomy & Astrophysics*, 695:A30, 3 2025. <https://doi.org/10.1051/0004-6361/202452432>
- [5] S. Hassani and U. Dackermann. A Systematic Review of Optimization Algorithms for Structural Health Monitoring and Optimal Sensor Placement. *Sensors* 2023, Vol. 23, Page 3293, 23(6):3293, 3 2023. <https://doi.org/10.3390/s23063293>
- [6] W. Liu, M. Wu, G. Wan, and M. Xu. Digital Twin of Space Environment: Development, Challenges, Applications, and Future Outlook. *Remote Sensing* 2024, Vol. 16, Page 3023, 16(16):3023, 8 2024. <https://doi.org/10.3390/rs16163023>
- [7] P. Michel, M. K"uppers, A. C. Bagatin, B. Carry, S. Charnoz, and others. The ESA Hera Mission: Detailed Characterization of the DART Impact Outcome and of the Binary Asteroid (65803) Didymos. *The Planetary Science Journal*, 3(7):160, 7 2022.

- [8] G. J. Pierce, J. D. Heeren, and T. R. Hill. Orion SysML Model, Digital Twin, and Lessons Learned for Artemis I. INCOSE International Symposium, 33(1):290-304, 7 2023. <https://doi.org/10.1002/iis2.13022>
- [9] O. Piñal and A. Arguelles. Mixed reality and digital twins for astronaut training. Acta Astronautica, 219:376-391, 6 2024. <https://doi.org/10.1016/j.actaastro.2024.01.034>
- [10] L. Pinello, L. Brancato, M. Giglio, F. Cadini, and G. F. De Luca. Enhancing Planetary Exploration through Digital Twins: A Tool for Virtual Prototyping and HUMS Design. Aerospace 2024, Vol. 11, Page 73, 11(1):73, 1 2024. <https://doi.org/10.3390/aerospace11010073>