Modeling and Optimization of the Design of a Robotic Hydroponic System

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Abstract. The progress of space exploration towards establishing human colonies on extraterrestrial bodies, coupled with the pressing need to address the climate crisis on Earth, underscores the significance of developing sustainable and self-sufficient cultivation techniques. A review of the existing literature reveals that most research in this area has concentrated on the operation and control of robotic hydroponic systems, often applied to off-the-shelf designs. However, by focusing solely on operational aspects, past research may have overlooked opportunities for significant resource savings that could be achieved through structural optimization. We propose in this paper a framework to optimize the structure of an automated Nutrient Film Technique (NFT) hydroponic system to minimize resource consumption (e.g. energy and plant nutrients), mass and volume. The modelling and optimization process employs Multidisciplinary Design Analysis and Optimization (MDAO) techniques to accommodate the diverse range of disciplines involved and the multiple optimization objectives of the system. The proposed framework considers the composition of the crew and computes the optimal structure tailored to meet their dietary requirements, based on the selected optimization objectives. To evaluate the system's performance, our framework incorporates criteria inspired by the innovative Advanced Life Support System Evaluator (ALiSSE), developed by the European Space Agency (ESA), which offers a comprehensive system approach for assessing life support systems. Through rigorous analysis, consistency of the model and optimization is demonstrated, yielding expected results, and affirming the effectiveness of the approach.

Keywords: Hydroponic system, Multidisciplinary Analysis and Optimization (MDAO), ALiSSE criteria, Human spaceflight, Automated cultivation, Life Support Systems, Space Architecture, Precision Agriculture, Robotics

Nomenclature

NFT	=	Nutrient Film Technique
MDAO	=	Multidisciplinary Design Analysis and Optimization

ALiSSE	=	Advanced Life Support System Evaluator
ESA	=	European Space Agency
BLSS	=	Bioregenerative life support systems
LEO	=	Low Earth Orbit
MMEC	=	Modified Energy Cascade Model
TRL	=	Technology Readiness Level
PPFD	=	Photosynthetic Photon Flux Density

1 Introduction

The future colonization of the solar system will necessitate the sustained presence of numerous astronauts across vast distances from Earth, such as on Lunar and Martian outposts. The current approach of resupplying these missions by transporting and storing all necessary resources from Earth will need to evolve into a system that heavily relies on regenerative components. Over the past two decades, bioregenerative life support systems (BLSS)[1] have emerged as the leading strategy to reduce the dependence on continuous resupply from Earth. Higher plants are particularly vital in these systems for being highly effective in producing biomass and regenerating essential consumables [3].

Hence, the challenge of establishing permanent human settlements on extraterrestrial bodies highlights the need for sustainable and self-sufficient cultivation techniques [4]. A review of the existing literature reveals that most research in this area has concentrated on the operation and control of robotic hydroponic systems, often applied to off-the-shelf designs. However, by focusing solely on operational aspects, past research may have overlooked opportunities for significant resource savings that could be achieved through structural optimization, for instance the choice of the size of the hydroponic system. Without an accurate plant growth model, which predicts the time required for plants to grow based on light exposure, it could be either underestimated the number of plants needed—failing to meet the astronauts' dietary needs—or overestimated, leading to an unnecessarily large hydroponic system. This would result in the transportation of excess mass, a critical resource given the high costs associated with launching mass into space. Historically, the cost of launching a payload into low Earth orbit (LEO) has been approximately $10,000 per kilogram [12], with even higher costs for missions to the Moon or Mars.

The goal of this paper is to fill this lack in the literature. Concretely, we select the most suitable cultivation technique, then model the chosen system, and finally develop a framework for optimizing its design. Specifically, we aim to design an automated hydroponic system that can provide astronauts with fresh, nutritious food while optimizing resource use, minimizing mass and volume, and enhancing efficiency.

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[1] These systems are designed to (a) revitalize the atmosphere by producing oxygen and removing carbon dioxide, (b) purify water, and (c) most importantly, supply fresh, edible food such as vegetables. Higher plants are particularly vital in these systems for being highly effective in producing biomass and regenerating essential consumables [3].

Importantly, we developed a comprehensive modeling of the hydroponic system, which includes accounting for the crew's dietary needs, plant behavior (using the modified energy cascade model), the system's structure, energy, and resource consumption aspects. In addition, our approach integrates hydroponic system modeling with the optimization process. To achieve this, we employ a Multidisciplinary Design Analysis and Optimization (MDAO) approach, guided by multiple objectives inspired by ALiSSE criteria [7]. This allows us to determine, for example, the optimal amount of light or the best plant arrangement. One might argue that also on Earth similar optimization efforts are made, such as in greenhouse design, however the optimal solutions for Earth do not coincide with the optimal solutions for space, one example is the different value of mass in space and on Earth. Through this framework, we can design an optimal hydroponic system tailored specifically for space missions, thus conserving critical resources.

Moreover, this framework can also be used to evaluate existing hydroponic systems and suggest potential improvements. Future work could involve comparing off-the-shelf hydroponic systems used in other studies to quantify the efficiency gains achieved through our optimization framework. This study goes beyond conventional hydroponic system design by optimizing the system with multiple objectives and integrating various disciplines into the model. Collectively, these aspects contribute to advancing knowledge in the field and underscore the importance of this research.

This paper is organized as follows. Section 2 provides a brief review of indoor agriculture and hydroponic techniques, including the method used to select the most suitable technique for the project. Section 3 discusses the optimization problem and the methods employed. Section 4 details the model of the hydroponic system. Section 5 presents the preliminary results of the optimization problem. Finally, conclusions and future research directions are presented in Section 6 and 7.

2 Indoor agriculture and hydroponic techniques selection

This research is supported by an extensive literature review, enabling informed decision-making and the development of effective cultivation systems. The initial critical decision was identifying the most suitable cultivation technique for our study. We evaluated several cultivation methods, including soil-based agriculture, hydroponics, aquaponics, and aeroponics. Within the realm of hydroponics, we specifically considered techniques such as Nutrient Film Technique (NFT), the Kratky Method, Flow & Ebb, Drip Hydroponics, Wick Hydroponics, and Deep-Water Culture (DWC). To guide this selection process, we developed a qualitative optimization method that allows for the comparison of these various techniques against specific criteria.

The qualitative optimization involved creating two matrices (Fig. 1 and 2) to compare various plant cultivation methods and hydroponic techniques. These matrices provided a comprehensive visual comparison, facilitating the identification of the most suitable technique for the project.

Regarding the comparison between the different methods of plant cultivation, from its matrix – Fig. 1 –, it is evident that hydroponics and aquaponics exhibit a more balanced performance in comparison to soil-based and aeroponic methods. These two techniques do not exhibit excessively high values in the criteria to be maximized nor in the criteria to be minimized. In fact, hydroponics and aquaponics are the optimal parameters for the minimax (red), and the maximin (blue). In detail: these operators optimize the worst-case criterion [9]. Aquaponics offers the advantage of incorporating a protein source into astronauts' diet but has a lower TRL, hence a lower level of reliability [5]. Reliability and safety considerations are also encompassed in the ALiSSE criteria, the selection criteria. Furthermore, given the contextual constraints of the application, where maintenance or repairs from Earth are not feasible due to long distances, it is prudent to minimize risks. Thus, for the project, a conservative approach of designing a hydroponic system was chosen. The comparison of different hydroponic techniques – Fig. 2 - was instead limited due to scarce and contradictory literature, consequently it's recommended the future involvement of a specialist to complete the matrix. Despite the incomplete matrix, valuable insights were gained. For example, the Ebb and Flow technique is likely to be excluded due to its unfavorable characteristics, while the Nutrient Film Technique (NFT) emerged as a promising candidate, also because supported by a significant portion of available literature. Consequently, NFT was selected for further modeling.

Fig. 1. Comparison chart of different indoor agriculture techniques

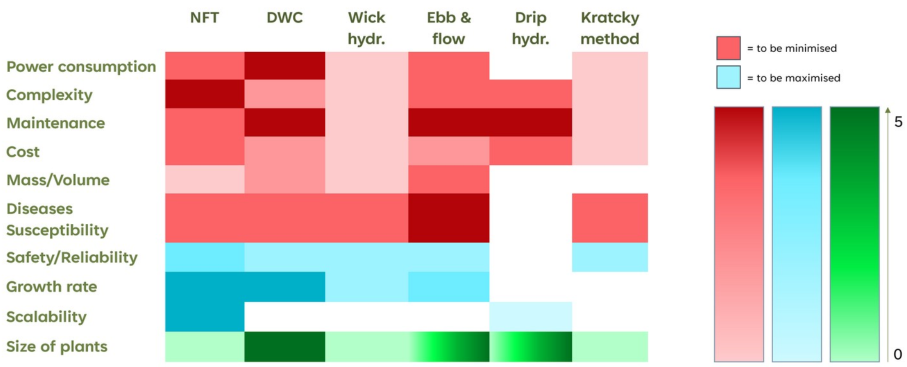

Fig. 2. Comparison chart of different hydroponics techniques

The Nutrient Film Technique (NFT) is a widely utilized hydroponic method that promotes plant growth by maintaining a thin film of nutrient solution around the roots without the use of a substrate [10]. In this process, the nutrient solution is consistently distributed at the higher end of a channel, flowing downwards at a regulated pace, due to the channels slope, ensuring the roots remain soaked in the solution. The lower end of the trough permits the drainage of the solution, bringing the cycle to completion [11].

3 Methods

To optimize the hydroponic system's design, an analytical model of the system needs to be developed. This model encompasses all the subsystems that constitute the hydroponic system, their interconnections and the evaluation criteria, which was inspired by ALiSSE criteria (mass, energy, efficiency, risk to human, reliability, crew time, sustainability, and life cycle cost) [7]. The process begins with the creation of a simplified and approximate model, which is subsequently refined through iterations to capture the intricacies of the actual system.

The optimization phase consists of qualitative optimization, as we mentioned before, and quantitative optimization. Quantitative optimization was conducted using the OpenMDAO framework for numerical optimization. Given the significant impact of the hydroponic system's shape on volume computation, we assumed an NFT hydroponic system composed of inclined parallelepiped pipes. The goal was to determine the optimal number of pipes, their height, and the number of plants per pipe in both length and width dimensions, among other variables.

When doing multi-objective optimization in OpenMDAO, it is strongly recommended performing multiple single-objective optimizations instead of using a multi-objective optimizer. This is because multi-objective optimizers often have difficulties finding the best designs, whereas single-objective optimizers (especially gradient-based ones) can more efficiently search the design space [1].

The simplest method for multi-objective optimization is the weighted sum approach, which combines multiple objective functions by summing them with assigned weights. In our optimization scenario, the objective function is defined as:

$$obj = w_e \frac{energy}{energy_{ref}} + w_V \frac{V_{material}}{V_{material_{ref}}} + w_n \frac{nutrients}{nutrients_{ref}} \quad (1)$$

Here, *energy*, $V_{material}$ and *nutrients* represent the three objectives being optimized, and w_e, w_V and w_n are the weighting factors for each objective function, with their sum equal to 1. The objective functions are normalized to ensure equal contribution to the overall optimization, and the weights are adjusted to prioritize specific objectives as necessary.

It's worth noting that OpenMDAO does not handle discrete variables directly; it only deals with continuous variables [1]. Therefore, we integrate OpenMDAO with continuous relaxation—a method that interprets combinatorial or discrete problems in a continuous manner.

The final step involves validation, which may employ multiple methods to ensure the accuracy and reliability of our model and optimization problem. The first validation method involves verifying that the optimization problem consistently yields the expected logical results. As a second validation approach, we propose implementing the framework with genetic algorithms [8] or PyCSP3, a Python library designed for creating models of combinatorial constrained problems in a declarative manner [6]. This validation step aims to ensure that the results obtained using genetic algorithms or PyCSP3 align with those obtained using OpenMDAO. The latter validation methods are left for future work.

4 Model

A numerical model can be decomposed into a series of smaller computations that are chained together by passing variables from one to the next. In OpenMDAO, all these numerical calculations are performed inside a component, which represents the smallest unit of computational work the framework understands. Furthermore, given that the computations are distributed across multiple components, it becomes necessary to organize and establish data transfer between them. For this purpose, Groups are employed, which serve as containers for constructing intricate model hierarchies [1].

Within the studied model, four main groups are identified: *Crew*, *Automation*, *Structure*, and *Plant* which collectively form the Hydroponic System.

The *Crew* group takes as input the number of female (n_F) and male (n_M) crew members. Leveraging their respective daily caloric needs, the module computes the total daily consumed number of plants, considering the calories per plant.

The *Automation* group is dedicated to calculating the energy consumed by the various machines employed in the hydroponic system, including the robotic arm, water pump, LEDs, and sensors. For the sake of simplicity, the energy calculation is performed as a linear combination of the movement of the robotic arm, the operation of the water pumps, and the usage of the LEDs (PPFD) and sensors. Specifically addressing the water pump operation, we model it as directly proportional to the water flow within the hydroponic system, that depends on the inclination and length of the pipes.

The *Structure* group focuses on the hydroponic system's volume and mass considerations. The main variables of the *Structure* group, which are also the most important design variables, are the number of pipes (n_{pipes}), along with parameters such as the number of plants per length (n_x) and width (n_y) of each pipe, and the height of the pipes (*h*), as illustrated in Fig. 3. This group then undertakes the computation of crucial parameters, including the total number of spaces available for plants, the volume of material required for constructing the channels, and the total surface and volume occupied by the hydroponic system.

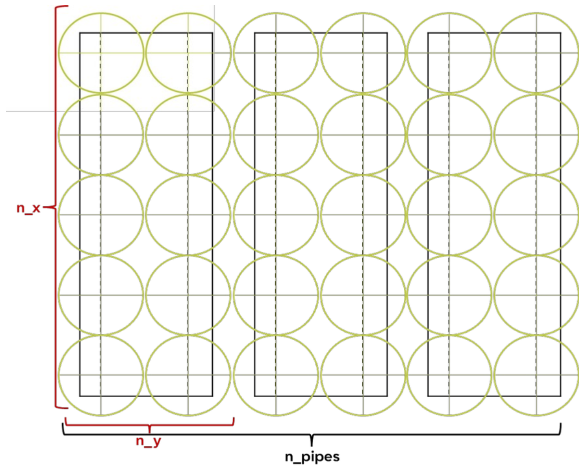

Fig. 3. Model of the hydroponic system structure

The *Plant* group focuses on plant growth and health considerations. It is responsible for calculating the growth time of the plants and consequently the total number of plants present simultaneously in the hydroponic system. Constraints can be introduced within this component, such as maintaining water and nutrient intake within a range that ensures plant health.

To model plant behavior, we adopt a simplified version of the modified MEC (MMEC) model algorithm [3], with the following assumptions:

- For most crops, the carbon use efficiency over 24 hours (CUE24) remains constant. Similarly, in our model, we assume CUE24 to be constant.
- t > t_A, hence $A = A_{max}$, where t_A is the time of canopy closure and *A* is the fraction of photosynthetic photon flux density absorbed by the canopy.
- Canopy Quantum Yield (CQY) is usually defined as a time-dependent function. We assume it to be constant, equal to an average value, taking a value slightly greater than CQY_{min} found in literature.
- Final mass and surface of the plant were found experimentally and with a process of trial and error. Specifically, the ratio of the mass to the surface was adjusted to achieve the same growth time for the lettuce under equal inputs (e.g., PPFD = 200 $\mu mol_{photons} / s\, m^2$ as per NASA's Life Support Baseline Values [2].

Under these assumptions, the hourly crop growth rate (HWCGR), hence the total time

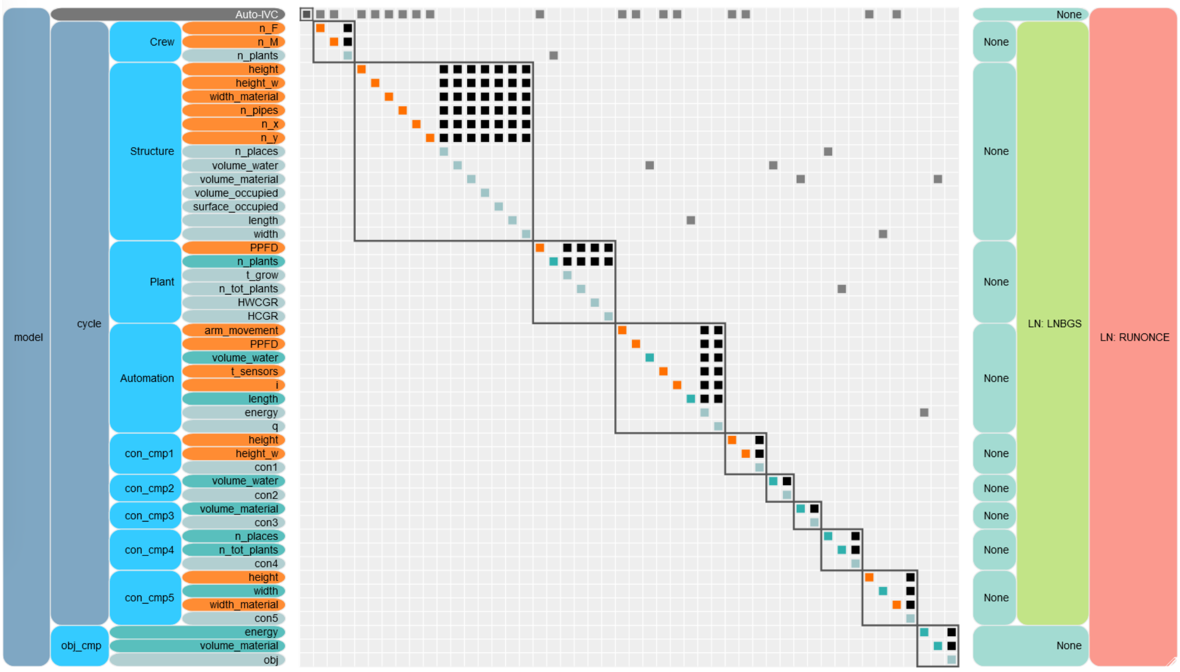

Fig. 4. N2 diagram of the hydroponic system model

5 Results

We present an analysis of the obtained results to showcase the effectiveness of our developed framework. It's important to note that these results should be viewed as general trends, specific to the selected plant (lettuce), constraints, and objectives. In addition, in this project's early stages, our focus was primarily on establishing the model's structure rather than refining the parameters to accurately reflect real-world conditions, hence the values presented for illustrative purposes and are based on arbitrary choices. The primary aim of the framework is to identify the optimal structure of the hydroponic system based on user-defined scenarios, making the framework itself the main outcome of the research.

We define a set of weights and we compare results obtained using the consequent objective function outlined in Section Methods. In all analyses, we consider w_n=0, given that the model for nutrient consumption has not yet been implemented. The main design variables affecting the optimization problem include PPFD, inclination, height, $width_{material}$, n_x, n_y, and n_{pipes}, which subsequently impact the length and width.

When considering w_e=1, that corresponds to minimizing energy consumption, it's logical to minimize PPFD, arm and sensor utilization time, and flow rate, hence maximizing pipe length and minimizing inclination. However, reducing PPFD increases growth time and the total number of plants, leading to increased volumes. Our results align with these expectations, as shown in Fig. 5.

Whereas when considering w_e=0, it corresponds to minimizing material volume. In the pursuit of minimizing material volume, it becomes imperative to reduce the number of plants simultaneously present in the system. This necessitates minimizing plant growth time thus maximizing PPFD.

When considering values of w_e between 0 and 1, a trade-off exists between minimizing energy consumption and material volume. Certain variables are unaffected by the global objective and are minimized independently to reduce energy and material volume. However, variables like PPFD and n_x require a trade-off, with PPFD needing to be minimized to reduce energy consumption but maximized to minimize material volume.

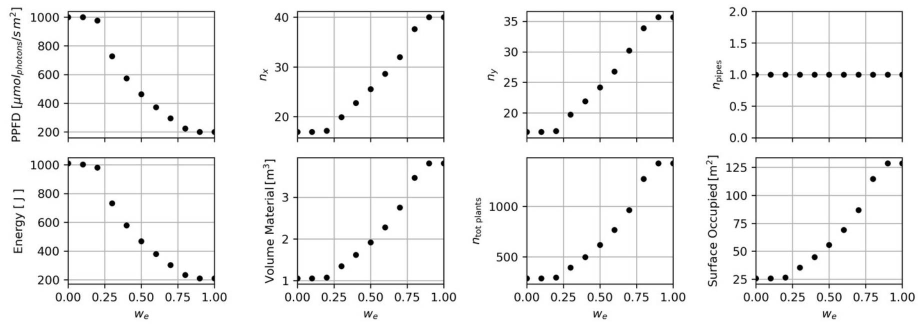

Fig. 5. Results considering different objectives. The values are for illustrative purposes and are based on arbitrary choices.

Furthermore, we can analyze the behavior of the two terms of the objective function, (energy and material volume). From Fig. 6 we can observe that all our solutions are at the Pareto front, hence they are optimal.

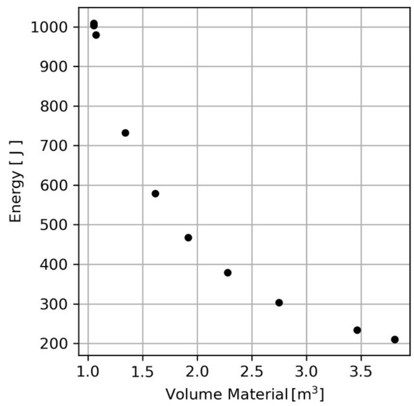

Fig. 6. Pareto front. The values are for illustrative purposes and are based on arbitrary choices.

Another intriguing observation gleaned from the results is that the optimal pipe configuration varies based on disparity between plant space and root space requirements. Results show that a single pipe is optimal when plant space is similar to root space, while multiple pipes are preferred when the difference is significant, as illustrated in Table 1.

Another significant aspect worth noting is the influence of continuous relaxation on the optimization process. Following the optimization performed with continuous relaxation, there is a need to revert to discrete variables, which requires rounding up all obtained input variables to ensure compliance with dietary requirements. However, this can result in outputs exceeding the desired values by a significant margin, as evident in Table 1. While this ensures compliance with constraints, it can be overly conservative. One potential approach to address this issue is selectively rounding up only specific output variables to achieve outputs closer to the constraints. However, this process can not be automated and must be performed by the user.

Table 1. Results considering different inputs.

Inputs	Continuous Outputs	Discrete Outputs
$plant_x$ = 0.3 m	n_{pipes} = 1	n_{pipes} = 1
$plant_y$ = 0.3 m	n_x = 16.90	n_x = 17
$roots_x$ = 0.1 m	n_y = 16.90	n_y = 17
$roots_y$ = 0.1 m	n_{places} = 285.68	n_{places} = 289
$plant_x$ = 3 m	n_{pipes} = 36.95	n_{pipes} = 37
$plant_y$ = 3 m	n_x = 2.75	n_x = 3
$roots_x$ = 0.1 m	n_y = 2.75	n_y = 3
$roots_y$ = 0.1 m	n_{places} = 285.85	n_{places} = 333

6 Conclusions

In this paper, we have developed a comprehensive framework aimed at optimizing the design of hydroponic systems for space missions, addressing a critical gap in the existing literature, which has largely focused on operational control rather than structural optimization. This framework integrates advanced modeling of plant behavior (MMEC), resource consumption, and system structure, utilizing a Multidisciplinary Design Analysis and Optimization (MDAO) leveraging NASA's OpenMDAO framework together with continuous relaxation.

Notably, the framework has demonstrated its efficacy through the consistent generation of reliable results. However, certain limitations persist, such as the necessity for precise tuning of problem parameters for successful optimization and the overly conservative approach stemming from the use of continuous relaxation in OpenMDAO.

The successful development of this dedicated framework for optimizing hydroponic systems represents a significant advancement in space exploration missions. In addition, the framework also holds promise for evaluating and improving existing hydroponic systems, with the potential for significant resource. Future research should focus on comparing off-the-shelf designs with our optimized framework to quantify these efficiency gains and further refine the model.

7 Perspectives

To ensure the continuous improvement and evolution of hydroponic systems for space exploration, several intriguing avenues for future research and development merit exploration.

Firstly, it is important to address the limitations of the current framework. One approach could involve implementing the framework in PyCPS3 and/or utilizing genetic algorithms, which can handle discrete variables. This expansion could not only address current limitations but also serve as a validation method for the framework's effectiveness.

Secondly, there is a need to extend the modeling capabilities of the framework to incorporate additional criteria from ALiSSE standards, such as human risk, reliability, crew time, sustainability, and life cycle cost.

Thirdly, there's an opportunity to explore different shapes and configurations of hydroponic systems beyond the current rectangular design. This could involve investigating alternative pipe shapes and dispositions, optimizing the distribution of photosynthetic photon flux density (PPFD), and studying the integration of different plant types to identify an optimal plant variety combination for the hydroponic system.

Fourthly, validating the analytical model of the hydroponic system through adaptation to a real hydroponic system, such as the one available at InnovSpace at ISAE-Supaero, would provide valuable insights. This real-world test bed could confirm the efficacy of the framework and provide opportunities for refining model parameters using experimental data, particularly regarding energy consumption. Indeed, in this project's early stages, our focus was primarily on establishing the model's structure rather than refining the parameters to accurately reflect real-world conditions. In future phases, these parameters should be updated, or external users may adjust them to fit specific scenarios, particularly if they have access to experimental data that we lacked.

Finally, exploring the adaptation of the hydroponic system to aquaponics is an intriguing future possibility. Aquaponics combines hydroponics and aquaculture and offers a resilient food production system for space exploration. However, hydroponics will initially be prioritized for its reliability, with the option to transition to aquaponics in later colonization phases while maintaining the ability to revert to hydroponics if needed for safety reasons.

Acknowledgments

The authors would like to thank Dr. Lucie Poulet for the support regarding plant and ALiSSE modeling, and Dr. Lucas Baraton regarding MDAO.

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Appendix

The complete set of code implemented for this research project is available on the GitLab page of ISAE-Supaero.

The code comprises three main types of files:

- *Disciplines_with_MMEC*: Python file that contains all the components of the hydroponic model.
- *Hydr_with_MMEC*: Python file that implements the groups and the problem.
- *input_with_MMEC*: YAML file that contains the input data, including the constant parameters of the problem.

Furthermore, the repository includes generated N2 diagrams and XDSM diagrams that provide visual representations of the problem.

Interested readers can access the code repository by visiting the following link: https://gitlab.isae-supaero.fr/alice/nanostar/hydroponic-group/2022-2024_rp_marina_mileni/-/tree/master/RP/openMDAO/Code/reports/Hydr.