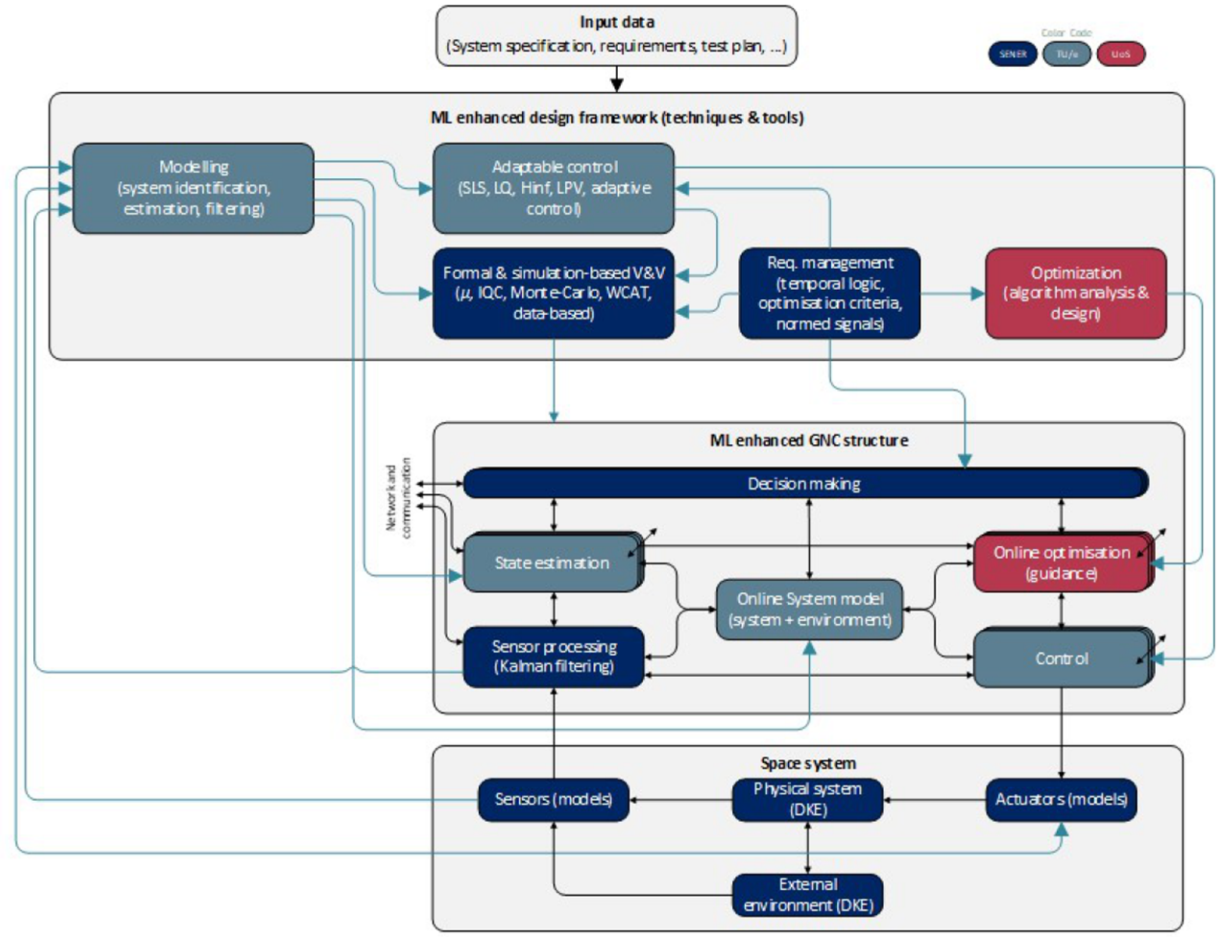
Artificial Intelligence Techniques

for GNC Design, Implementation and Verification



Executive Summary Report

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CHANGES RECORD

Issue.Rev.	Date	Modified by	Section / Paragraph modified	Change implemented
1.0	2023-01-18	Lukas Hewing	All	Initial release

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1 INTRODUCTION

1.1 Objective and Scope

The present Executive Summary Report summarises the findings of the AI4GNC project in a concise manner for a non-expert reader in the field.

1.2 Evolution of this Document

The present document is issued for the Final Review (FR) without further issues planned along the project's life. However, the present document might be updated after the Final Review (FR).

1.3 Document structure

This document has the following structure:

- Section 1: INTRODUCTION
- Section 2: PROJECT OVERVIEW
- Section 3: TECHNICAL ACHIEVEMENTS
- Section 4: RECOMMENDATIONS & WAY FORWARD

2 EXECUTIVE SUMMARY

Artificial intelligence (AI) and machine learning (ML) encompass systems that act by sensing, interpreting data, learning, reasoning and deciding the best course of action – and have developed into a transformative force across industries. Smart algorithms are capable of processing previously unimaginable quantities of data and learning algorithms have shown predictions accuracies that far surpass traditional models. Nevertheless, AI technology entails risks and uncertainties that have to be accounted for to enable robust and safe decision-making. It is therefore of paramount importance to perform a critical analysis of the use of AI technologies to plan for the next generation GNC systems. The AI4GNC study contributes to this analysis of the potentials and risks of advanced and ML-based techniques.

The field of potential AI techniques for GNC systems is vast, we focus the study on three directions, namely

- **Bayesian Optimization for Automated GNC Tuning and Worst-Case Analysis**. Bayesian optimization has recently shown enormous success for black-box optimization, for instance for hyperparameters of ML algorithms. It is also a prime technique researched for the automated tuning of complex control system. The study investigates its use for GNC software, including antagonistic optimization for worst-case analysis.

- **Robust optimization-based guidance**. Embedded optimization is posed to become a transformative technology within the GNC discipline, for instance for on-demand guidance profiles or high-level feedback control. Most techniques, however, do not take uncertainties into account when carrying out their optimization, which can be particularly relevant when aiming to use learned models in a safe fashion. The study proposes a novel robust optimal trajectory optimization scheme and investigates its use in GNC systems, including for ML-enhanced models.

- **Data-Driven Model Augmentation**. With the success of AI across industries, data becomes of primal ingredient in recent technological successes and advanced. In the context of GNC systems, the aim is then to make use of flight or simulation data in order improve dynamic models to enabled accurate decision making and increased autonomy. The study investigates the of ML-driven techniques to improve dynamics system models allowing for performance improvements by capturing complex closed-loop behaviour.

The developed techniques are investigated on a scenario considering the landing of a spacecraft under guided parafoil, inspired by the Space Rider mission. This was extended during the study to consider landing in challenging terrain under large spatial wind variations, Figure 2-1 shows an illustration. The considered benchmark consists of a full-scale functional simulator corresponding to current industrial practice, ensuring the real-world applicability of results produced in the study.

The evaluated techniques have shown great potential to increase the capabilities of next-generation GNC systems, in particular in directions of increased performance and autonomy, as well as to streamline and the GNC design process and decrease overall design effort. We detail some outcomes for the respective topics below.

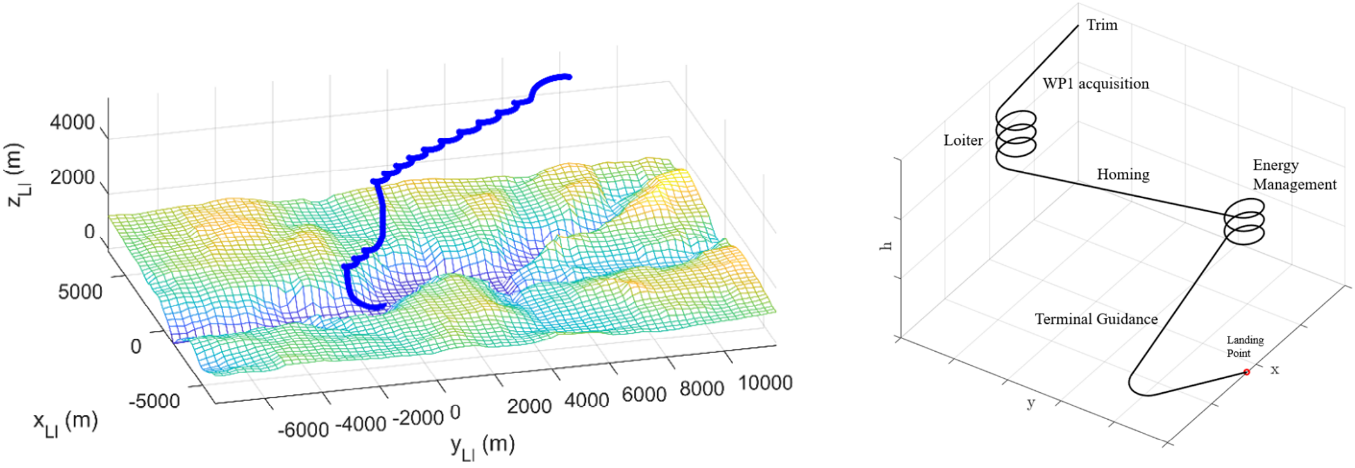


Figure 2-1 Illustration of the Benchmark mission inspired by the Space Rider. The right plot shows the relevant phases of the descent & landing considered in this study as a Benchmark GNC problem. The left plot shows a simulation shot of a trajectory in the extended scenario – landing in Yosemite Valley under the influence of spatial winds. Note the drift due to winds in the realized trajectory with respect to the plan on the right which is computed in wind-compensated coordinates.

2.1 Bayesian Optimization & Temporal Logic

The goal of the investigation into *Bayesian optimization* (BO) for GNC tuning was to showcase the use of automated exploration of parameters of GNC systems such as to *(a)* improve the performance of the resulting GNC software, and *(b)* gain engineering insights into complex parameter dependencies -- all the while automating the process and thereby reducing engineering effort and trading it off with computation power and large-scale simulations. The study had several features differentiating it from previous investigations and tools on global optimization more commonly used, for instance,

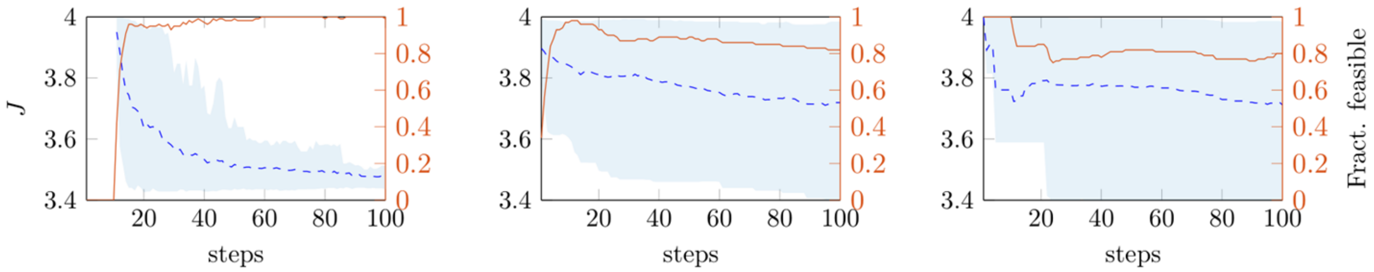
- **Noisy simulations/function evaluations:** Bayesian optimization is particularly suited to deal with such noisy optimizations/simulations as are typical established MC campaigns.
- **Temporal Logic Constraints:** Constraints in a global optimization tool can be used to optimize performance while ensuring that some other requirements are not violated for the considered optimizer. Such constraints often directly relate to requirements, which can typically be precisely and relatively easily expressed as *temporal logic* (TL) expressions.
- **Interpretability & Engineering Insights:** A final focus of the development was to create a tool that provides engineering insights over the parameter landscape. Aspects of this are found in plotting functionality of resulting surrogate Gaussian process models, as well as the interpretability of optimized hyperparameters of such models; large kernel lengthscales indicate that the corresponding feature has little influence on the outcome; the estimated noise levels or computed likelihoods give an indication of whether the data can be explained well by the selected features.

2.1.1 Results Produced

The produced can be roughly grouped into three distinct categories: *(1)* proof of concepts and algorithm performance analysis on simple examples presented as part of the tradeoff analysis in D3-A [AD6], *(2)* application to the benchmark problem for the baseline in D5 [AD12] and novel GNC developed within the project in D6 [AD13], and, finally, *(3)* the application in antagonistic optimization for worst-case-analysis in D7 [AD15].

(1) The *GncTuner* toolbox performed well and showed little dependency on its exact parameterization, e.g. selection of kernel or acquisition functions. In addition, it was demonstrated that constraints complicate the optimization task, but that the BO algorithm can effectively optimize also in this case including with temporal logic specifications. These have been shown to effectively avoid chattering behavior in controller switching for the inverted pendulum, following from a natural high-level description of this requirement.

The results have been reported in an associated conference publication [1].



(a) Bayesian Optimization (b) Random (c) Surrogate optimization

Figure 2-2 Mass-Spring-Damper constrained results for different algorithms. Blue dashed line is the average over different optimization runs of the resulting performance of the optimizer, with shaded 10% and 90% quantiles, while the solid red line represents the fraction of respective optimizers leading to constraint satisfaction.

(2) The tuning results on the benchmark example demonstrate the applicability of the BO on challenging real-world examples. All necessary requirements to be considered in the tuning could be expressed as *temporal logic* expressions and were directly included in the optimization as a constraint in the form of the robustness degree. The *GncTuner* tool was further used to tune cost function parameters of the optimization-based guidance which is a typical manual tuning task. Here the tool was successfully used to inform the hand-tuning decision, in particular significantly improving on the original tuning of the constraint penalty parameters.

It was demonstrated that it IS a highly useful tool in the design and exploration of typically hard to choose parameterizations. Care, however, needs to be taken in the design of these optimization problems in order to ensure the validity of the found optimizers, i.e. it needs to be ensured that the optimization is well-posed and decidable within a reasonable amount of simulation experiments.

Early results have been reported in the aforementioned conference publication [1].

(3) Finally, the *GncTuner* tool was successfully used to carry out a worst-case analysis in two formulations. The first is ANantagonistic optimization, that is, uncertain parameters are optimized such as to yield the worst-possible outcome. The second is powered by constrained Bayesian optimization and aims to find a robustness radius, i.e. the radius within which a certain level of

performance can be maintained. The *GncTuner* performed well in these tasks, again showing its strength in noisy simulations.

2.2 Robust optimization-based guidance

The second major technical development in the AI4GNC is to fuse methods from robust control engineering and optimization-based trajectory planning to take robustness into account on a higher level within the overall GNC architecture. To address these tasks, we have developed a new method called *robust Differential Dynamic Programming* (robust DDP). The algorithm provides solutions for the robust trajectory optimization problem of nonlinear systems expressed in the fashion of the usual M-Δ structure through an iterative procedure. The algorithm then makes use of sequential linearizations to solve the robust trajectory optimization problem, requiring the solution of a sequence of small semi-definite programs (SDPs). As an outcome, robust DDP generates an optimized reference trajectory as well as a time-varying linear feedback gain to track the reference. The baseline algorithm was extended in two directions

1. **Dual robust DDP:** An issue of the primal robust DDP formulation is that it only supports uncertain disturbances (like uncertain wind) and not model uncertainties. This issue was addressed during the preliminary design phase by establishing a *dual formulation* of robust DDP.

2. **Primal robust DDP with accelerated solver for online optimization:** As a final algorithmic development, the numerical performance of Robust DDP was addressed and successfully improved as reported in D6 [AD13] including a *custom solver* dealing with linear matrix inequality constraints.

A CDC conference paper outlining the some of the material has been developed during the project [2].

2.2.1 Results Produced

A series of numerical studies have been carried out. This includes a *Comparison Study* benchmarking against existing comparable algorithm as well as *Benchmark Results* on the functional simulator. In all cases, the robust DDP formulation have shown exceptional success, as is illustrated in Table 2-1, showing significantly enhanced performance for both a nominal and robust DDP formulation over the existing baseline solution.

Table 2-1 Landing accuracy statistics of robust DDP, nominal DDP and the baseline guidance of the SENER simulator. The statistics are computed for a landing scenario with a 1D wind field and different intensities of the wind uncertainty.}

algorithm	wind error	90% quantiles	mean accuracy	median accuracy
Baseline	$0\mathrm{m/s}$	27.8517	27.5154	16.1469
Baseline	$\frac{2.5}{3}\mathrm{m/s}$	39.9353	34.9835	17.594
Baseline	$\frac{5}{3}\mathrm{m/s}$	97.5034	59.1223 (39.3975)	21.4595
Baseline	$\frac{7.5}{3}\mathrm{m/s}$	185.8093	108.3531	26.7415
DDP	$0\mathrm{m/s}$	24.7212	20.2993	11.7073
DDP	$\frac{2.5}{3}\mathrm{m/s}$	38.3248	28.8612	14.4037
DDP	$\frac{5}{3}\mathrm{m/s}$	82.8809	52.1305	20.4581
DDP	$\frac{7.5}{3}\mathrm{m/s}$	145.9398	94.1244	27.9901
robust DDP	$0\mathrm{m/s}$	21.4472	19.8503	11.6286
robust DDP	$\frac{2.5}{3}\mathrm{m/s}$	24.3172	21.7991	12.7784
robust DDP	$\frac{5}{3}\mathrm{m/s}$	49.698	38.3896	16.2578
robust DDP	$\frac{7.5}{3}\mathrm{m/s}$	127.2579	80.0665	22.0501

On top of that, the utilization of robust DDP with ML-enhanced dynamics models for the parafoil was investigated. This was done using Gaussian process (GP) regression, which allows to use uncertainty estimate of the learning task to be used as the robustness description in the robust DDP. (Note that such an uncertainty encourages the optimization algorithm to not leave the data distribution on which the model has been generated.) Here, the GP augmentation improved the performance of the guidance significantly effectively exploiting the learning behavior together with its uncertainty description. **Figure 2-3** shows an illustration of the learning GP dynamics.

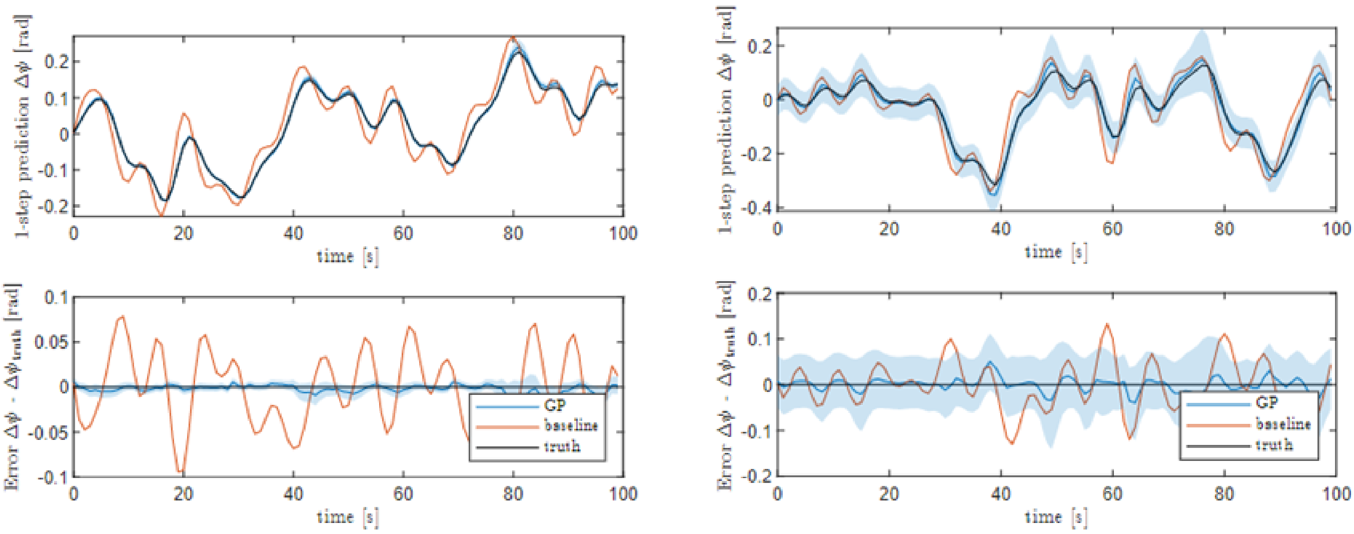


Figure 2-3 Example of validation results of GP training under additional wind disturbances and without. Shown are 1-step ahead prediction error of baseline and GP-augmented system. The shaded blue area shows the 2-σ uncertainty bounds.

2.3 Data-Driven Model Augmentation

The third major technical development in the AI4GNC project was to use data – from high-fidelity simulations or flight data – to improve by machine learning techniques the models that describe the flight dynamics. The key idea within the proposed approach is to combine an existing model of the system with static or dynamic nonlinear mappings in the form of *artificial neural networks* (ANNs). The envisioned outcome is then a flexible ML-based grey-box identification framework which can later be used for analysis and control. the following aspects were treated in this study

1. **State-of-the-art LPV identification and control** The LPV framework combines linear time-invariant (LTI) theory with surrogate models to tackle modelling of, control design for, and analysis of complex nonlinear systems.

2. **Dynamic and static ANNs** One of the key elements in this study is to use machine learning tools to improve on current GNC capabilities. We used universal approximators in terms of ANNs, both static and dynamic structures, to complete baseline dynamic models in terms of augmentation.

3. **Model-augmentation framework** A learning-based model-augmentation approach was developed to combine both aspects, which is included in deepSI[1], a software for ANN-based model learning.

2.3.1 Results Produced

A large quantity of results have been accomplished to demonstrate the efficiency of the proposed tools, which can be grouped as (1) Demonstration of state-of-the-art LPV techniques on the Control Moment Gyroscope (CMG), (2) Demonstration of the model-augmentation capabilities on the GPRV, (3) Towards the integration of model-augmentation-based models in the guidance algorithms.

(1) State-of-the-art LPV techniques have been shown to achieve highly accurate models and high-performance control of a complex system such as a control moment gyroscope.

(2) The model-augmentation capabilities have been demonstrated on a parafoil system using a linear fractional representation (LFR) form of an ANN – this is referred to as the SUBNET approach. Some of these results are described in an associated CDC conference publication [3]. Related results are found in an associated master thesis [4] and conference publication [5].

(3) The model-augmentation has been applied to learn the closed-loop behaviour of the parafoil system, which can then be used to enhance (model-based) guidance accuracies. It has been demonstrated that locally, the model can be augmented well using linear techniques, while ANN-based augmentation increases the domain of validity.

2.4 Recommendations & Conclusion

The AI4GNC project has shown the significant potential of some exemplary ML-based or enhanced techniques, providing strong evidence that also in the field of GNC they can become a transformative technology. A key hurdle towards more widespread adoption of ML-based and advanced techniques may then lie less in the specific techniques considered, but rather in the clear demonstrations of potentials in terms of performance increases or cost reduction that can be realized with these techniques. In the considered Benchmark study significant performance improvements were demonstrated, which, however required serious engineering effort such that the performance-complexity tradeoff is not always obvious.

It has been demonstrated during the project that, while certainly much work is still required, the challenges to be overcome to introduce the techniques in a modern GNC discipline are far from insurmountable. In fact, with the increasing relevance of complex computation on board, as well as the direct use of data during GNC system design, a gradual adoption of these and related methods is already well underway. The results of this study serve to further accelerate these developments by increasing the fluency of GNC engineers in these highly promising techniques and demonstrating the attainability of their potential.

[1] github.com/GerbenBeintema/deepSI

3 REFERENCES

3.1 Applicable Documents (ADs)

The following documents, listed in order of precedence, contain normative information applicable to the activity.

Table 3-1. Applicable Documents list.

[AD1] DOC50C0015-1030 AI4GNC Detailed Proposal, 2020.

[AD2] ESA-TECSAG-SOW-019234 Statement of Work – Artificial Intelligence Techniques for GNC Design, Implementation and Verification, 2020.

[AD3] AI4GNC-SEN-TN-01 Literature Review. Technical report, SENER Aeroespacial, June 2021.

[AD4] AI4GNC-SEN-TN-02 Benchmark Mission Definition, Framework Definition, Study Cases. Technical report, SENER Aeroespacial, June 2021.

[AD5] AI4GNC-SEN-TN-03 Comparative & Trade-off Analyses (D3): Summary. Technical report, SENER Aeroespacial, October 2021.

[AD6] AI4GNC-SEN-TN-04 Comparative & Trade-off Analyses (D3): A – GNC Autotuning. Technical report, SENER Aeroespacial, October 2021.

[AD7] AI4GNC-SEN-TN-05 Comparative & Trade-off Analyses (D3): B – Online Optimization. Technical report, SENER Aeroespacial, October 2021.

[AD8] AI4GNC-SEN-TN-06 Comparative & Trade-off Analyses (D3): C – LPV Identifaction & Control. Technical report, SENER Aeroespacial, October 2021.

[AD9] AI4GNC-SEN-TN-07 Framework & AI GNC Systems Justification Files - AI Techniques for Control part A – GNC Autotuning (D4). Technical report, SENER Aeroespacial, October 2022.

[AD10] AI4GNC-SEN-TN-08 Framework & AI GNC Systems Justification Files - AI Techniques for Control part B – Online Optimization (D4). Technical report, SENER Aeroespacial, October 2022.

[AD11] AI4GNC-SEN-TN-09 Framework & System Justification Files (D4): C – LPV Identifaction & Control. Technical report, SENER Aeroespacial, October 2022.

[AD12] AI4GNC-SEN-TN-10 Framework & AI GNC Systems Justification Files - AI Techniques for Control Study Cases & Test Plan (D5). Technical report, SENER Aeroespacial, October 2022.

[AD13] AI4GNC-SEN-TN-11 AI4GNC Framework & Benchmark Detailed Design (D6). Technical report, SENER Aeroespacial, October 2022.

[AD14] AI4GNC-SEN-TN-12 Software User Manual (SW-UM). Technical report, SENER Aeroespacial, October 2022.

[AD15] AI4GNC-SEN-TN-13 Benchmark AI4GNC System & Framework - Test Plan Execution Validation (D7). Technical report, SENER Aeroespacial, October 2022.

[AD16] AI4GNC-SEN-TN-14 Study Synthesis, Way Forward, and Maturation Plan (D8). Technical report, SENER Aeroespacial, October 2022.

3.2 Informative Documents (RDs)

The following documents can be consulted as they contain all other information used as reference to carry out the project.

Table 3-2. Reference Document List.

[1] R. Polonio, C. Ardura, V. Preda, and L. Hewing, "Bayesian optimization with temporal logic constraints for automated GNC tuning," in European Conference for Aeronautics and Space Sciences (EUCASS), 2022.

[2] D. Gramlich, C. W. Scherer, and C. Ebenbauer, "Robust differential dynamic programming," in IEEE Conference on Decision and Control (CDC), 2022

[3] C. Verhoek, G. I. Beintema, S. Haesaert, M. Schoukens, and R. Tóth, "Deep-learning-based identification of LPV models for nonlinear systems," in IEEE Conference on Decision and Control (CDC), 2022

[4] M. de Lange, "Linear parameter-varying control for the atmospheric flight of a parafoil guided return vehicle," Master's thesis, Eindhoven University of Technology, 2022

[5] M. de Lange, C. Verhoek, V. Preda, and R. Tóth, "LPV modeling of the atmospheric flight dynamics of a generic parafoil return vehicle," in IFAC World Congress, 2022