

Real-Time System Identification for Complex Disturbance Rejection and Versatile Missions

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ABSTRACT

This paper presents two approaches to real-time System Identification (SysID), applied to challenging space use-cases to enable complex disturbance rejection. The first approach consists of a novel Sparse Identification of Nonlinear Dynamics algorithm based on Nonlinear AutoRegressive eXogenous models (NARX-SINDy), using an L_1 -regularised regression to identify the model structure while accounting for real-time, discretization, and observability constraints. The second approach, used as baseline, consists of an Extended Kalman Filter (EKF) assuming narrowband disturbance spectral content. To evaluate these approaches, two industrial use-cases are considered. The first involves nonlinear propellant sloshing during orbit control manoeuvres, and the second involves solar array drive mechanism (SADM) behaviour in the presence of backlash and nonlinear stiffness effects. In both cases, the disturbance spectral content is close to the controller bandwidth, where it is not possible to increase the controller gain without compromising performance and robustness. Performance is assessed using real flight data from Airbus' fleet and representative simulation campaigns. The NARX-SINDy method outperforms the EKF when the disturbance deviates from the narrowband approximation, or when significant time-varying effects are present, and it enables active disturbance rejection on both use-cases. Implementation feasibility is verified using a processor in the loop test based on a space-grade LEON4 processor.

1 Introduction

The growing ambition of space missions leads to complex, composite spacecraft that are often subjected to nonlinear and uncertain dynamics. Conceptual and preliminary design phases may struggle to accurately anticipate such effects since they are inherently tied to detailed components. This can lead to excessive caution and conservatism during early sizing and architecture definition activities, in order to avoid threatening mission feasibility if such effects were to be discovered later in the design process. Consequently, this drives up the cost. This trade-off advocates for increasing the versatility of the Attitude & Orbit Control System (AOCS), and Guidance, Navigation and Control (GNC) algorithms with respect to complex disturbance sources and unmodelled dynamics, where the ability to accurately identify and predict disturbances plays a key role.

System Identification (SysID) has a long history and tradition in systems and control engineering that started back in the 1950s. Since then, a vast amount of research and development has been conducted to further advance this field [1], [2], [3], [4], even more nowadays with the recent advances in data-driven control and identification [5], [6], [7], as well as in machine- and deep-learning [8], resulting in a wealth of ideas, concepts, theories, algorithms, and use cases. In general terms, SysID deals with the problem of building and learning dynamical systems (mathematical) models based on data and it is useful when models would be overly difficult

or impossible to obtain due the complex nature of the physics of the underlying process to be studied [5]. SysID is based upon input and output measurement data collected either experimentally or during operation of the underlying process, and most often to derive and refine a plant model's knowledge, and as preliminary step for controller synthesis and/or simulator setup activities, which are often iterative and time-consuming.

In the scope of the design of future high-accuracy space missions, and with the limitations of ground testing or physical modeling principles, it is possible that nonlinear dynamics encountered during the operation in space, such as propellant sloshing or complex interactions in a drive mechanism, may not be captured (see Figure 1). Furthermore, the associated disturbances might be close to the loop bandwidth, where it is often not possible to further increase the static controller gains. In this context, real-time SysID methods can play an important role in further improving the performance of the AOCS loop. Various approaches are discussed in the literature, e.g., neural networks [8], [9], [10], or the Unscented Kalman Filter [11]. Machine learning and neural network-based methods are generally incompatible with current hardware capabilities, while Kalman-filter-based approaches focus on parameter estimation to refine existing physical models. Both approaches often assume knowledge of internal states, an assumption which is not realistic for most applications. In [12] a more efficient, black-box SysID technique based on nonlinear autoregressive models is considered, but its implementation still requires a GPU which is not available for real-time use on most missions. Combining real-time SysID of arbitrary unknown dynamic effects with a subsequent augmentation of the spacecraft's AOCS/GNC bears high potential for future mission design but has not yet been considered.

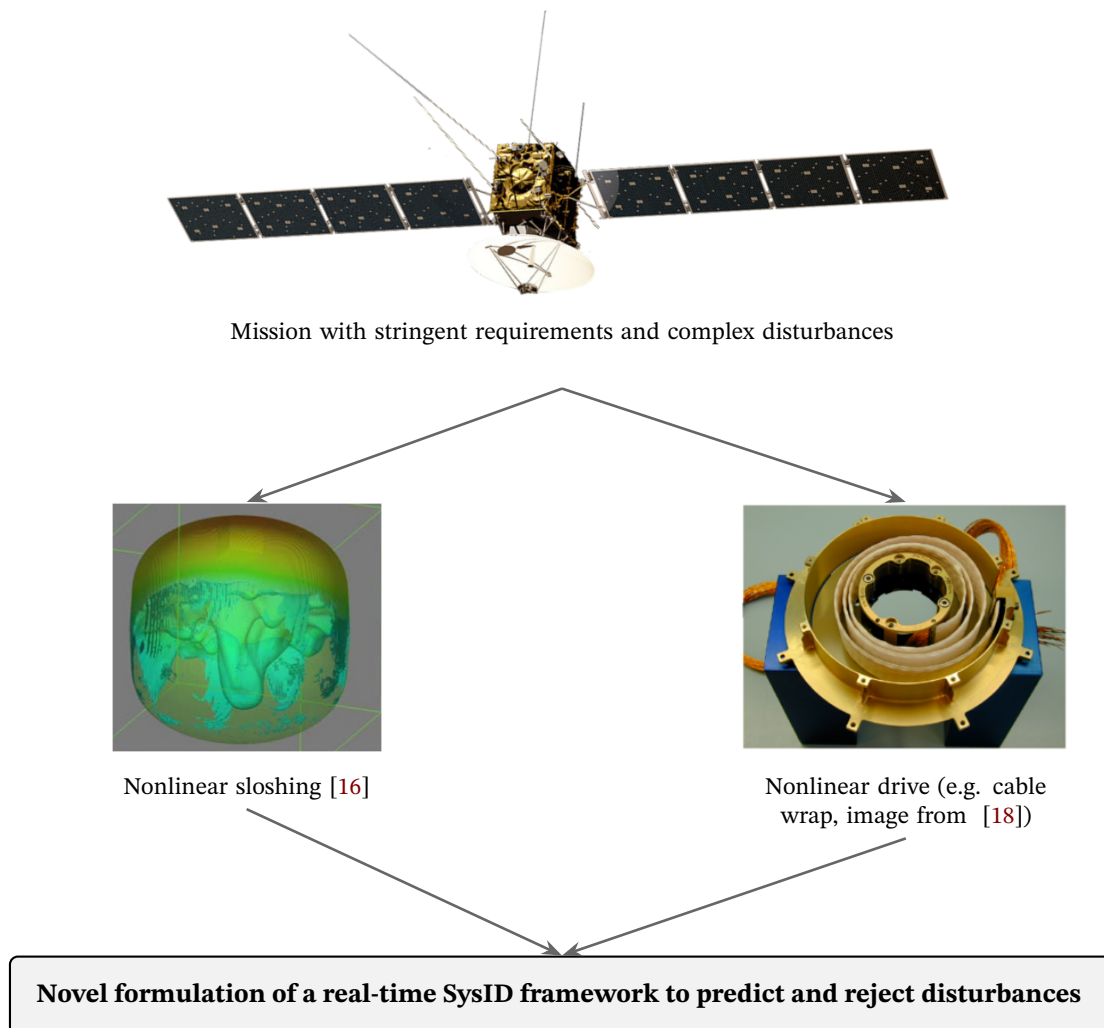


Figure 1 Overview of promising use-cases for real-time SysID

The main contribution of this paper is therefore twofold: the formulation of a novel, generic and discrete-time Sparse Identification of Nonlinear Dynamics (SINDy) algorithm addressing two distinct space industrial use-cases, and its subsequent use within a disturbance rejection algorithm to achieve pointing performance improvement in challenging missions. This novel formulation differs significantly from the original SINDy in two respects. First, it is directly synthesised in discrete time to enable real-time operation within the AOCS loop. Second, it is able to address cases where the inner states of the dynamics are not directly measurable. Model structure is based on Nonlinear AutoRegressive eXogenous (NARX), hence the name NARX-SINDy for the novel method discussed in this paper. The identified nonlinear model derives from a sparse $L1$ -regularized regression; then, it can be propagated within an Extended Kalman Filter (EKF) in an automated, real-time compatible way.

Furthermore, the real-time approaches presented in this work only rely on operational timelines and do not require any dedicated excitation, which maximises the mission availability and drastically reduce the implementation complexity. In this context, an extensive validation process has been set up, considering not only data generated from representative simulators but also real flight data from Airbus' fleet. In addition, the added value of the novel SINDy-based algorithm is illustrated by benchmarking it against a baseline standalone EKF based on initial model knowledge.

As introduced in Figure 1, two use-cases are considered, namely propellant sloshing during orbit control manoeuvres of a geostationary spacecraft, and nonlinear disturbance induced by a solar array drive mechanism on a science mission. Both use cases have in common a disturbance spectral content close to the controller bandwidth, in a region where increasing rejection from a static controller could not be made without compromising on performance or robustness. Nonlinear dynamic models, cross-validated against flight data, are also derived in this work.

The remainder of this paper is structured as follows. Section 2 provides the theoretical background and methodology regarding the novel SINDy-based formulation, factoring in the constraints applicable to the real-time application in a spacecraft, and describes the strategy regarding the use of SysID to perform disturbance rejection. Section 3 covers the use-cases modelling within representative simulators. Section 4 presents the specific implementation the surveyed SysID algorithms and provide the results of their application on flight data as well as simulated data, in open- and closed-loop configurations. The outcomes of the processor-in-the-loop (PIL) implementation of the algorithms are also presented to showcase their real-time applicability. Section 5 provides the conclusion of this paper.

2 Operational System Identification Approaches

The main motivation of this work lies in the current difficulty to reject complex disturbances with traditional robust control techniques, due to their time-varying nature or/and proximity to the desired bandwidth. Challenging use-cases in this regard are formulated further in Section 3. To achieve such disturbance rejection, two building blocks are needed (see Figure 2: (I) a real-time system identification algorithm able to provide knowledge of the dynamics to the on-board software and (II) a rejection scheme exploiting this knowledge to enhance the pointing performance. Both blocks are operated during *operational* sequences. Section 2.1 provides an overview of the novel SysID algorithm tailored for practical space use-cases, inspired by the original SINDy formulation. Section 2.2 introduces the design of the Extended Kalman Filter used either in a standalone way (as a baseline method) or as an augmentation to NARX-SINDy. Section 2.3 then provides insights on how closed loop rejection is achieved.

2.1 Methodology for Sparse Identification of Nonlinear Dynamics

The initial SINDy formulation was proposed in [13] following the concept of parsimonious modeling by including an $L1$ -regularization term in a regression problem. However, until recently, subsequent work was limited to continuous time application and required measurements of all system states, which is not applicable to a wide range of engineering problems. In this work, a more general input-output based formalism for discrete-time systems is discussed, by imposing a NARX-structure (*Nonlinear AutoRegressive Models with eXogenous Inputs*)[15] on the identified models. The resulting NARX-SINDy design is presented below (see [14] for more details).

As introduced above, the first challenge to operational identification is the exclusive reliance on available on-board observables. In most space applications, including the considered use-cases in this paper, the AOCS architecture does not allow to measure internal disturbance states. To circumvent this issue, we propose to consider

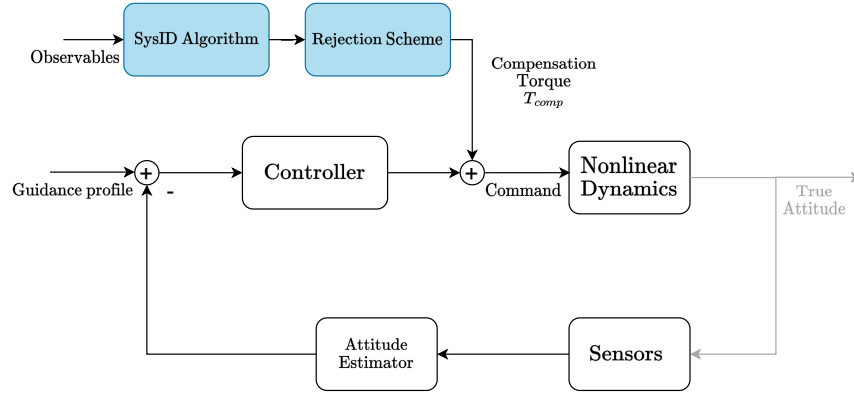


Figure 2 Augmented AOCS loop enabled by SysID

the disturbing torque acting on the spacecraft τ_d , which is the result of the dynamics targeted by SysID. This torque is not measured, but can be reconstructed as follows:

$$\tau_d = J\dot{\omega} + \omega \times (J\omega) - \tau_c. \quad (1)$$

In this equation, the term $\omega \times (J\omega)$ can be neglected due to small angular rates. The spacecraft inertia matrix J and commanded torque τ_c are known and the angular acceleration $\dot{\omega}$, which is usually not measured, can be retrieved from angular rate measurements and lowpass filtering to mitigate noise amplification issues. Other disturbance sources are neglected over the timeline, which is a fair assumption in the considered use cases.

We consider a discrete-time input-output NARX-model with time step k defined as

$$\tau_d(k+r) = f(\tau_d(k+r-1), \dots, \tau_d(k), \mathbf{u}(k)) \quad (2)$$

The degree r must be predefined using engineering judgment based on a fundamental physical understanding of the problem. The nonlinear equation for each output is identified individually, but can depend on input vector $\mathbf{u}(k)$ as well as previous values of all outputs, e.g., for the body frame x-axis

$$\tau_{d,x}(k+r) = f_x(\tau_d(k+r-1), \dots, \tau_d(k), \mathbf{u}(k)). \quad (3)$$

For the sake of brevity, the following explanation is limited to the approximation of f_x with a degree of $r = 2$. The general process is illustrated in Figure 3. At first, the relevant quantities based on *measurements and processing* are defined and then sampled in time for a manoeuvre. To ensure diverse training data and thus prevent model over fitting, multiple data sets can be combined by column-wise stacking the samples. A set of *basis functions* f_i is defined, which depend only on known inputs and outputs. The outputs include the current value as well as up to the last r previous time steps. Typical choices are monomials, trigonometric or exponential functions. Each basis function is then evaluated at each input and output sequence for the entire time series to construct the *data matrix* F . Similarly, the *output vector* Y is constructed with the selected quantity.

The nonlinear functions is approximated via a linear combination of the basis functions, i.e.,

$$f_x(\tau_d, \mathbf{u}) = \sum_{i=1}^{n_b} b_i f_i(\tau_d, \mathbf{u}). \quad (4)$$

The coefficients b are calculated using an $L1$ -regularized least square regression, i.e., sparse regression. It means that the model complexity is reduced by minimizing the number of nonzero coefficients without significant decrease of model accuracy, following the concept of parsimonious modeling [13]. The regression problem is defined as

$$\min_b ||Fb - Y||_2^2 + \lambda ||b||_1, \quad (5)$$

where λ is the sparsity parameter to tune the tradeoff between the regularization term and the least squares fit.

Note, that for the regression the data matrix F and output vector Y must be columnwise normalized to ensure that each aspect is equally penalized by the regularization. The normalization must be reverted on the obtained coefficients before the final approximation $\hat{f}_x$ is determined according to (4).

This presented algorithm is easy to tune, with only two relevant parameters. One is the sparsity parameter λ , the other a zeroing threshold parameter ε to reject insignificant terms in $\mathbf{b}$. A detailed and more general derivation of the proposed method is provided in [14].

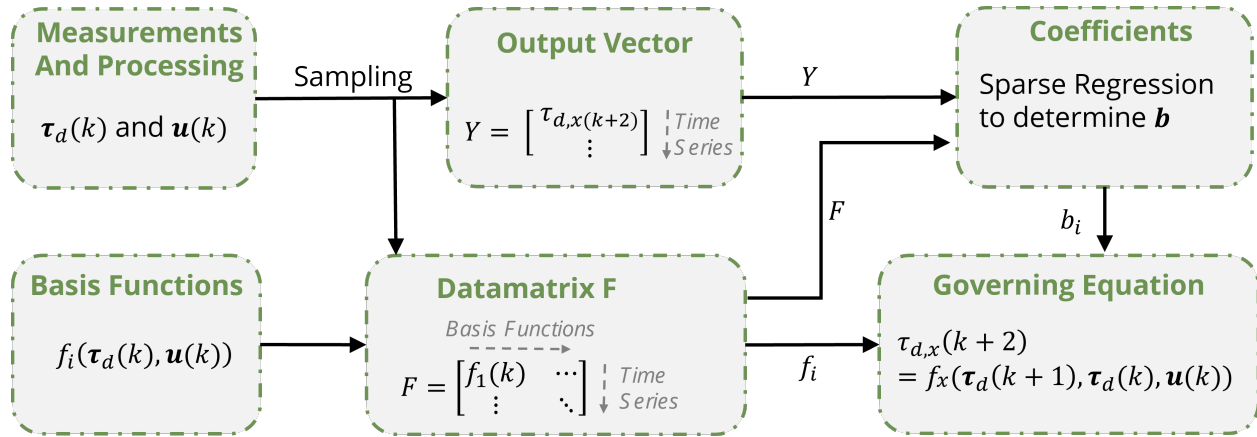


Figure 3 Illustration of NARX-SINDy Setup

2.2 On-board estimation using EKF

The Extended Kalman Filter (EKF) can be used for recursive nonlinear state and parameter estimation. It is a well-established method for academic and industrial applications alike and is discussed in detail in various literature, e.g., [15]. In this work, the EKF has been used to pursue two goals: (1) to provide a baseline method and comparison point with respect to NARX-SINDy, and (2) as an option to augment the SINDy-identified equations (used to perform the state propagation step) with innovation and update steps. In the former case, the dynamic equations arise from a predefined model. In the latter case, they are directly obtained from the system identification results.

2.3 Closed-loop rejection

A rejection algorithm based on the SysID inputs has been implemented to demonstrate feasibility of its added value to the AOCS-loop. The general configuration in Figure 2 is augmented with a more specific implementation and shown in Figure 4. The identification of the nonlinear equations occur in an offline training step, i.e., the process discussed in Section 2.1 is performed without an active rejection scheme. The resulting equations are then included in the scheme to enable online propagation of the identified disturbances. The input are on-board available observables, e.g. estimates, commands, inertia matrices. The *pre-processing* covers filtering so as to, for example, focus on a frequency band of interest. A *post-processing* step can be included to, for instance, negate the phase offset introduced by the pre-processing step (e.g. using a lead filter).

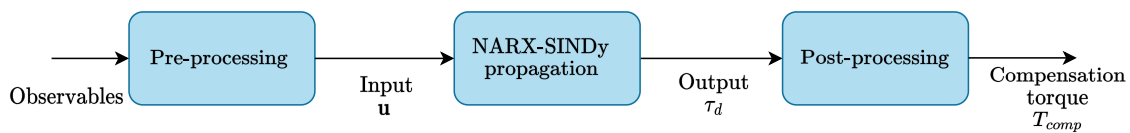


Figure 4 Focus on the compensation torque generation

3 Use cases

This Section introduces both use-cases and deals with their modeling aspects, applicable to the construction of representative simulators. Although flight data is available to build benchmarks, such simulators are used for assessment of the algorithms in closed-loop as well as to perform performance and robustness analyses through Monte-Carlo simulations.

3.1 Nonlinear Sloshing

Propellant sloshing is always a source of concern during development of missions equipped with chemical propulsion. Cost pressure incentivizes a simple propulsion subsystem architecture, with a single large capacity tank covering all the mission needs. However, this approach still raises feasibility issues for missions with stringent pointing requirements such as optical missions: proper sloshing rejection by robust control is not always possible due to the proximity of the disturbance with the typical bandwidth frequency. In parallel, several recent experiments [16], as well as the consideration of flight data from operational missions, have enabled improvement in the level of confidence in sloshing modeling. As such, the problem of sloshing identification and rejection, in the scope of successive station keeping manoeuvres using a bi-propellant architecture (see Figure 5), is investigated in this Section.

Abramson's and Dodge's work [17] allows to evidence equivalent mechanical models for sloshing under specific applicability conditions. Such conditions are based on the Bond number (Bo), expressing the ratio between the acceleration-induced efforts and the capillary-induced ones:

$$Bo = \frac{\rho F h R}{m \sigma} \quad (6)$$

where ρ is the fluid density, σ the fluid surface tension, γ the tank acceleration, F the thrust force, m the satellite mass, h the tank half-height along the thrust direction, and R the tank characteristic radius. The numerical application leads to $Bo = 23$ and $Bo = 52$, which are both over the usual threshold of 10, associated to the acceleration-dominated behaviour modelled using an equivalent pendulum model.

Figure 5 illustrates the spacecraft layout, with thrusters T1 to T3 creating a thrust about the Y_{sat} axis. Tank accommodation (centers along the Z_{sat} axis) is such that the initial fluid acceleration, natively associated to a transient force about Y_{sat} , induces a transient torque about the X_{sat} axis, as depicted in Figure 6.

Specific notations are adopted in this Section to prevent ambiguity. Let $\mathbf{v}_{Mx/y}$ (resp. $\mathbf{a}_{Mx/y}$) be the linear rate (resp. acceleration) of the point M attached to body x with respect to body y , and let $\omega_{x/y}$ (resp. $\dot{\omega}_{x/y}$) be the angular rate (resp. acceleration) of body x with respect to body y . Let p_i be a sloshing pendulum ($i \in 1, n$, with n the number of tanks), located by its attachment point O_i and its point mass (Q_i, m_i). Let I be an inertial frame.

The acceleration of a pendulum attachment point can be written as:

$$\mathbf{a}_{O_i p_i / I} = \mathbf{a}_{O_i sat / I} = \frac{\mathbf{F}}{m_{sat}} + \dot{\omega}_{sat / I} \times \mathbf{GO}_i + \underbrace{\omega_{sat / I} \times (\omega_{sat / I} \times \mathbf{GO}_i)}_{\text{neglected}} \quad (7)$$

where m_{sat} is the spacecraft wet mass. As we consider an attitude stabilization problem according to the scheme of Figure 5, small angular rates are expected and the quadratic term in $\omega_{sat / I}$ can be neglected. The pendulum acceleration is then written as:

$$\mathbf{a}_{Q_i p_i / I} = \mathbf{a}_{O_i p_i / I} + \dot{\omega}_{p_i / I} \times \mathbf{O}_i \mathbf{Q}_i + \underbrace{\omega_{p_i / I} \times (\omega_{p_i / I} \times \mathbf{O}_i \mathbf{Q}_i)}_{\text{neglected}} \quad (8)$$

The translational equilibrium of each pendulum can now be written, noting $\mathbf{R}_{IO_i}$ as the interface torque between the tank pendulum and the spacecraft body:

$$\mathbf{R}_{IO_i} = m_i \mathbf{a}_{Q_i p_i / I} = \frac{\mathbf{F} m_i}{m_{sat}} + m_i \dot{\omega}_{p_i / I} \times \mathbf{O}_i \mathbf{Q}_i + m_i \dot{\omega}_{sat / I} \times \mathbf{GO}_i \quad (9)$$

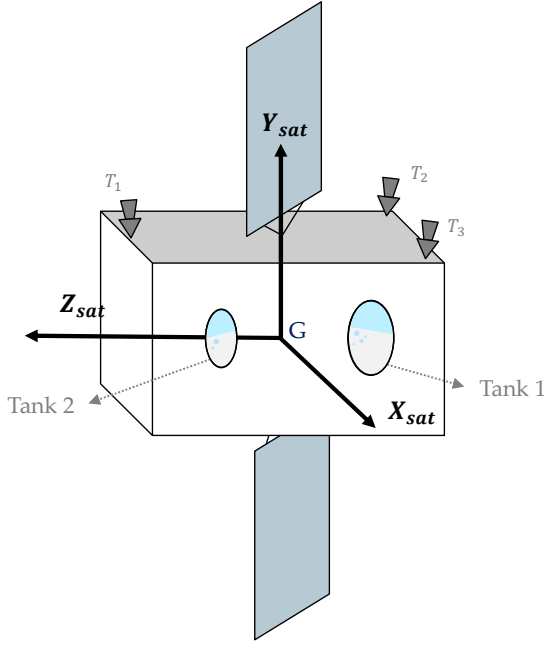


Figure 5 Considered spacecraft

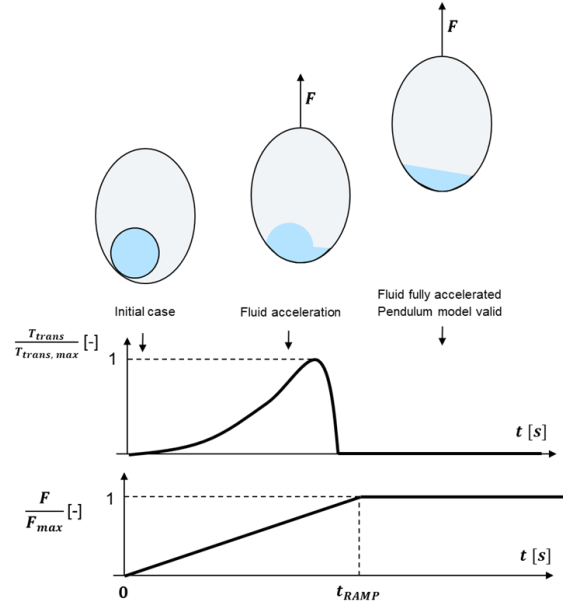


Figure 6 Initial fluid transient due to acceleration

The rotational equilibrium of the central body at the centre of mass is written as:

$$\tau_{rw} + \sum_{i=1}^n \mathbf{R}_{lO_i} \times \mathbf{O}_i \mathbf{G} = J_{sat} \dot{\omega}_{sat/I} \quad (10)$$

where J_{sat} is the spacecraft inertia matrix and τ_{rw} is the reaction wheel torque. Other contributors (such as non-sloshing disturbing torques) are neglected in this analysis. Finally, one can write the rotational equilibrium for each pendulum at the centre of mass $\mathbf{Q}_i$, $\mathbf{R}_{lO_i}$ being the only applied force on the pendulum:

$$\mathbf{R}_{lO_i} \times \mathbf{O}_i \mathbf{Q}_i = 0, \forall i \in 1 \dots n \quad (11)$$

$$\left(\frac{\mathbf{F} m_i}{m_{sat}} + m_i \dot{\omega}_{p_i/I} \times \mathbf{O}_i \mathbf{Q}_i + m_i \dot{\omega}_{sat/I} \times \mathbf{G} \mathbf{O}_i \right) \times \mathbf{O}_i \mathbf{Q}_i = 0, \forall i \in 1 \dots n \quad (12)$$

Equations (9), (10) and (12) form a system of nonlinear differential equations which can be resolved numerically to find the spacecraft and pendulum rotational kinematics ($\omega_{sat/I}$, $\omega_{p_i/I}$), and consists in the dynamics core of the representative use case simulator. The transient torque profile affecting the beginning of the timeline, as illustrated in Figure 6, has been directly deduced from available flight data and adds a time-varying component to the identification problem.

3.2 Nonlinear SADM

This use-case focuses on an optical mission associated with stringent pointing requirements. The presence of large solar arrays is a potential risk of disturbance due to the SADM rotation during the acquisition phases, justifying the need of specific mitigation actions. A particular case of SADM, featuring a cable wrap to transmit power in parallel with the usual components (stepper motor, bearings, and gearbox), is considered in this paper. This configuration is able to generate a specific nonlinear disturbance pattern which may hinder the mission feasibility, as seen in the Relative Pointing Error (RPE) spectral content in Figure 7.

- in one rotation direction, the cable wraps itself and exerts a torque opposed to the commanded motion. This can cause low-frequency bouncing within the motor deadzone;

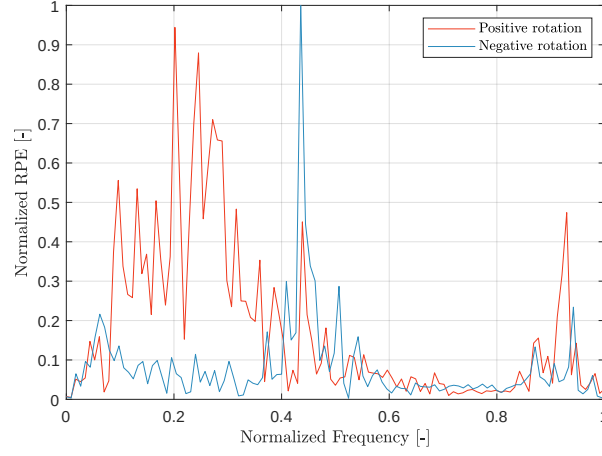


Figure 7 Differentiated SADM behaviour: FFT of the RPE over 1 s

- in the other direction, the cable unwraps itself and the resistive torque is less significant. The contact between the rotor shaft and the solar array mobile part is maintained and the SADM behaves linearly.

Figure 8 represents the monodimensional modelling of the considered spacecraft (along Y axis). The central body is divided in two identical parts (B_m and B_p), linked together in torsion by a spring (stiffness k) and damper (viscous coefficient c), modelling flexibility and energy dissipation within the central body. The degrees of freedom of this system are:

- the central bodies' angles θ_{B_m} and θ_{B_p} ;
- the solar array angles with respect to their respective central body θ_{Y_m} and θ_{Y_p} .

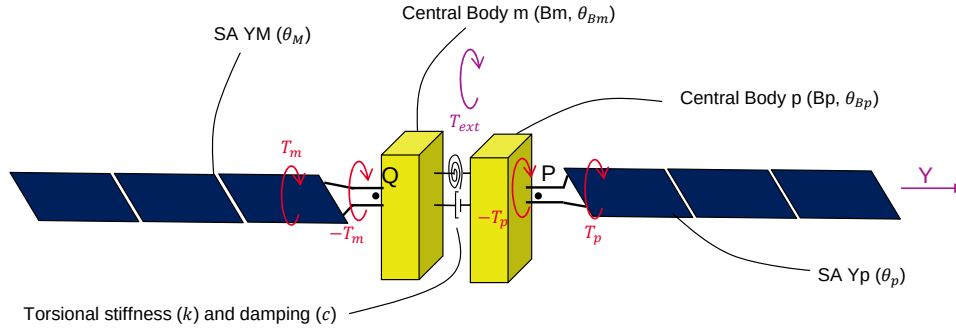


Figure 8 1D representation of the spacecraft dynamics

The dynamic equilibrium equations of the spacecraft along Y, neglecting the cross-axis terms, are written as follows:

$$T_{ext}/2 - T_{mm} - k(\theta_{B_m} - \theta_{B_p}) - c(\dot{\theta}_{B_m} - \dot{\theta}_{B_p}) = J_y^B/2 \ddot{\theta}_{B_m} \quad (13a)$$

$$T_{ext}/2 - T_{mp} - k(\theta_{B_p} - \theta_{B_m}) - c(\dot{\theta}_{B_p} - \dot{\theta}_{B_m}) = J_y^B/2 \ddot{\theta}_{B_p} \quad (13b)$$

In this equation, T_{ext} is the applied torque (only the RW torque is considered in this case), T_{mm} and T_{mp} the motor interface torques (defined below), and J_y^B is the pitch moment of inertia of the central body.

The dynamic equilibrium of the flexible arrays, of modal participation matrix $[\mathbf{L}]$ and pitch inertia J_y^{SA} , are written as:

$$T_{mm} = J_y^{SA}(\ddot{\theta}_{B_m} + \ddot{\theta}_{Y_m}) + [\mathbf{L}]^T \ddot{\eta}_m \quad (14a)$$

$$T_{mp} = J_y^{SA}(\ddot{\theta}_{Bp} + \ddot{\theta}_{Yp}) + [\mathbf{L}]^T \ddot{\eta}_p \quad (14b)$$

The equations coupling the rigid degree of freedom of each solar array to their modal coordinates are written as:

$$\ddot{\eta}_m + [2\xi\omega_0]\dot{\eta}_m + [\omega_0^2]\eta_m + [\mathbf{L}](\ddot{\theta}_{Bm} + \ddot{\theta}_{Ym}) = \mathbf{0} \quad (15a)$$

$$\ddot{\eta}_p + [2\xi\omega_0]\dot{\eta}_p + [\omega_0^2]\eta_p + [\mathbf{L}](\ddot{\theta}_{Bp} + \ddot{\theta}_{Yp}) = \mathbf{0} \quad (15b)$$

where $[2\xi\omega_0] = \text{diag}(2\xi_k\omega_k)$, $[\omega_0^2] = \text{diag}(\omega_k^2)$, $k \in \{1 \dots N\}$, N being the number of modes characterized by an eigenpulsation ω_k and damping ratio ξ_k . Equations (13a) to (15b) form a system of differential equations to solve in the representative simulator.

The remaining task is to express the motor torque, T_{mi} (with $i \in \{m, p\}$). This torque can be written as:

$$T_{mi} = -K_{\text{sadm}}\mathcal{B}(\delta\theta) + T_{\text{cable}} + T_{\text{fric}} \quad (16)$$

In this equation, K_{sadm} is the equivalent stiffness of the SADM (seen from the output shaft), T_{cable} is the cable wrap torque and T_{fric} is the Dahl friction torque. $\mathcal{B}(\delta\theta)$ represents the backlash nonlinear characteristic function, described as follows:

$$\mathcal{B}(\delta\theta) = \begin{cases} \delta\theta - b & \text{if } \delta\theta \geq b \\ 0 & \text{if } -b \leq \delta\theta \leq b \\ \delta\theta + b & \text{if } \delta\theta \leq -b \end{cases} \quad (17)$$

where b is the backlash half width, and the angle offset $\delta\theta$ represents the deviation with respect to the expected motor position in absence of load torque:

$$\delta\theta = \theta_{Yi} - \theta_{ci} - \theta_{\text{dist}} \quad (18)$$

where θ_{ci} is the commanded angle, and $\theta_{\text{dist}} = \frac{T_{\text{cog}} - T_{\text{harmonic}}}{K_{\text{sadm}}}$, considering the motor endogenous torques T_{harmonic} the harmonic torque (modeling gear teeth imperfections) and T_{cog} the cogging torque (modeling interactions between the rotor permanent magnets and the ferromagnetic circuits). Both are modelled as spatial harmonics of the true SA angle θ_{Yi} .

The cable wrap torque is at the heart of the identification problem. Following past observations [18], we propose to model it by an affine torque model depending on the rotation direction (with parametric slopes $m_{\pm}$ and offsets $T_{0\pm}$):

$$T_{\text{cable}} = \begin{cases} T_{0+} + m_{+}\theta_{Yi} & \text{if } \dot{\theta}_{Yi} \geq 0 \\ T_{0-} + m_{-}\theta_{Yi} & \text{if } \dot{\theta}_{Yi} < 0 \end{cases} \quad (19)$$

While very simple, this model allows the description of the distinct behaviours exposed at the beginning of this Section.

4 Implementation and Results

This section presents the results of the system identification and disturbance rejection approaches described in Section 2, on the operational use-cases introduced in Section 3.

Section 4.1 provides insights on how the generic designs presented in Section 2 can be particularized to the use-cases. Section 4.2 provides system identification results on flight data (without active rejection). Then, Section 4.3 showcases closed-loop results and Section 4.4 provides additional comparisons by providing Monte-Carlo campaign outputs. Section 4.5 concludes this part with the outcomes of the processor in the loop (PIL) test, demonstrating feasibility of real-time operation of these concepts.

4.1 SysID implementation

Baseline EKF implementation For the use-cases, the baseline standalone EKF has been derived considering as state equations the rigid central body dynamics of (1) and a simple second-order linear differential equation in the disturbance angular momentum h_d , i.e.

$$\dot{h}_d + 2\xi\omega_0\dot{h}_d + \omega_0^2 h_d = \alpha\omega \quad (20)$$

where the damping ratio ξ and eigenpulsation ω_0 are parameters estimated by the EKF, and α is a coupling factor considered null in this work. In other works, this baseline EKF attempts at estimating a pseudo-harmonic disturbance with possibly variable frequency and amplitude.

NARX-SINDy implementation For both use-cases, it is proposed to consider the following reconstructed state vector $\mathbf{x}(k)$. A degree r of 2 has been deemed sufficient for this analysis.

$$\mathbf{x}(k) = \begin{pmatrix} \tau_d(k) \\ \tau_d(k+1) \end{pmatrix} \quad (21)$$

For the sloshing use-case, the NARX-SINDy input vector $\mathbf{u}(k)$ is built as follows:

$$\mathbf{u}(k) = \begin{pmatrix} t(k) \\ \tau_c(k) \\ S_c(k) \\ q(k) \end{pmatrix} \quad (22)$$

where $t(k)$ is the elapsed time since the beginning of the manoeuvre, $\tau_c(k)$ is the commanded torque, $S_c(k) = \Delta T \sum_{i=0}^k \tau_c(i)$ is the integral of the commanded torque signal sampled at ΔT , and $q(k) = 1 - f(k)$, $f(k) = \frac{F(k)}{F_{max}}$ being the normalized thrust norm. The presence of S_c in the input vector helps to capture the oscillatory behaviour along the Y_{sat} axis, whereas $t(k)$ and $q(k)$ help to capture the transient effects.

For the nonlinear SADM use-case, the retained inputs vector is the following:

$$\mathbf{u}(k) = \begin{pmatrix} \omega(k) \\ \tau_c(k) \end{pmatrix} \quad (23)$$

where $\omega(k)$ is the spacecraft angular rate, and $\tau_c(k)$ is the commanded torque, both along the considered Y axis of Figure 8.

Another interesting asset of NARX-SINDy lies in its tuning simplicity: only two parameters (the sparsity coefficient λ and the zeroing threshold ε) have to be tuned, leading to straightforward tuning activities. The retained values were ($\lambda = 0.02, \varepsilon = 10^{-4}$) for the sloshing use-case, and ($\lambda = 10^{-4}, \varepsilon = 5 \cdot 10^{-4}$) for the nonlinear SADM use-case.

On the other hand, the EKF presents a significant number of tuning parameters (measurement noise covariance, four terms related to process noise covariance, the initial guess for the disturbance pulsation and the four state covariance initial guesses). Identifying the most accurate set of parameters can be challenging, and sensitivity analyses were made to extract the best set of parameters.

Operational SysID concept with NARX-SINDy The NARX-SINDy *training* identifies governing equations based on past manoeuvres. For the sloshing use-case, data from five previous station keeping manoeuvres was considered, whereas for the nonlinear SADM use-case, data was collected from three prior SADM rotation sequences.

Closed loop concept The pre-processing step applied on the NARX-SINDy propagation inputs (see Figure 4) consists of a 4th-order Butterworth lowpass filter. This allows extraction of the relevant (low frequency) disturbance content, e.g. below 0.2 Hz for the nonlinear SADM use-case according to Figure 7, and reduction of noise levels. The post-processing step is designed accordingly and consists of a 4th order lead filter whose purpose is to compensate for the phase shift caused by the lowpass filter.

4.2 System Identification using flight data

Results of sloshing identification based on flight data are provided in Figure 9a for X_{sat} and Y_{sat} axes. The third axis is not represented as it is irrelevant regarding sloshing effects. This showcases very promising results regarding operational system identification using NARX-SINDy, which slightly outperforms the EKF in terms of Normalized Root Mean Square Error (NRMSE). The bi-propellant architecture causes nonlinear and dual oscillations which are better captured by NARX-SINDy due to the versatility offered by the library of basis functions.

Figure 9b exposes the reconstruction of the pitch disturbance torque for the nonlinear SADM use-case. Again, the SINDy-based algorithm outperforms the EKF as it allows better tracking of the irregular torque oscillations. As such, the single harmonic EKF design presented in Section 4.1 presents clear limitations, although it was still deemed more promising than a physics-based EKF formulation, attempting full state and parameter estimation of the drive train quantities (as in (13a) to (15b)), which is hardly tractable for embedded applications.

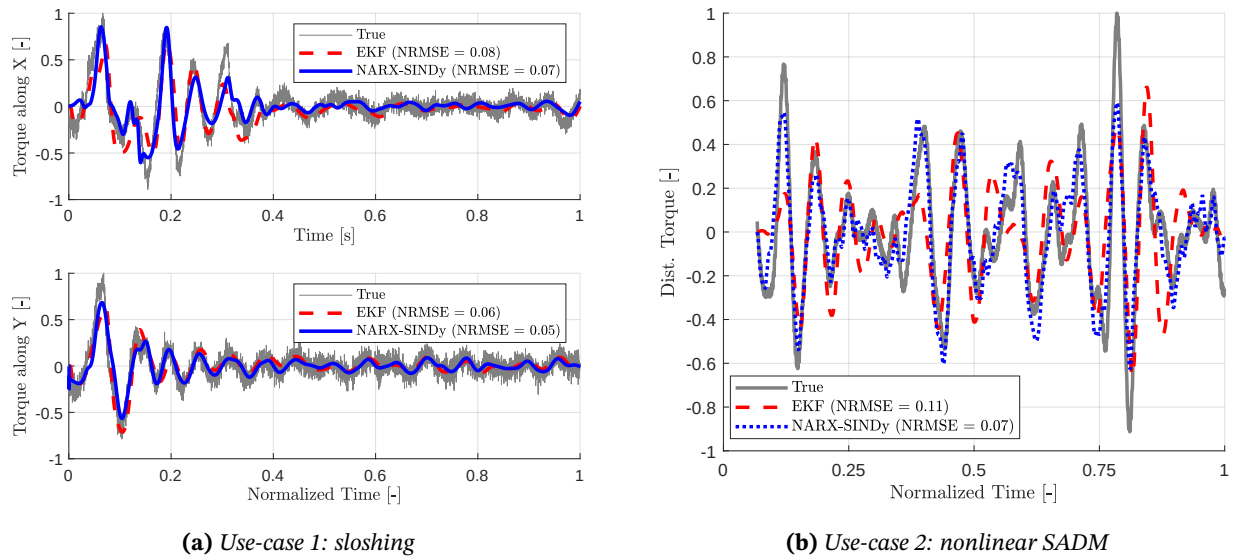


Figure 9 Identified disturbance torque from flight data (normalized)

4.3 Closed-Loop Disturbance Rejection

As pre-recorded flight data do not allow closed-loop assessments, representative use-case simulators were used to evaluate the potential of closed loop rejection using SysID, and relying on the operational concept exposed in Section 4.1.

Figure 10 illustrates the Absolute Performance Error (APE) during an orbit control manoeuvre for the sloshing use-case. In all three represented cases, a robust controller is running in the background of the AOCS loop as per Figure 2. It is seen that the baseline EKF provides outstanding rejection capabilities, whereas NARX-SINDy (also augmented by an EKF) allows a partial reduction of the maximal APE value.

Figure 11 shows the Relative Pointing Error (RPE) over 1 second during the operational timeline of the SADM use-case. The EKF results are not displayed as no satisfactory tuning of the baseline method, leading to an improvement of the RPE, was found during the study. However, NARX-SINDy brings clear benefits as a 30% improvement of the indicator is achieved, meeting the requirement in the early phases of the study.

The fact that the EKF performs well on the sloshing use-case can be explained by the fact that its state equations, leading to damped oscillatory disturbance as expressed in (20), are very close to the actual sloshing physics: exploitation of the prior knowledge on this use-case played a key role. On the other hand, such approach was not possible to implement on the nonlinear SADM use-case, due to the complexity of the physics (interaction of a flexible mode within a deadzone, also coupled with the nonlinear torque characteristic of the cable wrap). In this context, the more potent NARX-SINDy method brings significant benefits regarding disturbance mitigation.

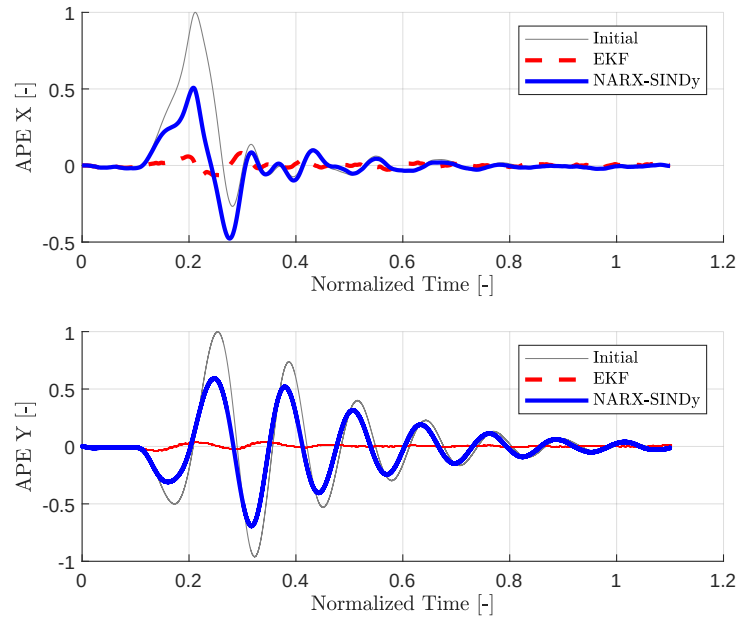


Figure 10 APE improvement on the sloshing use-case

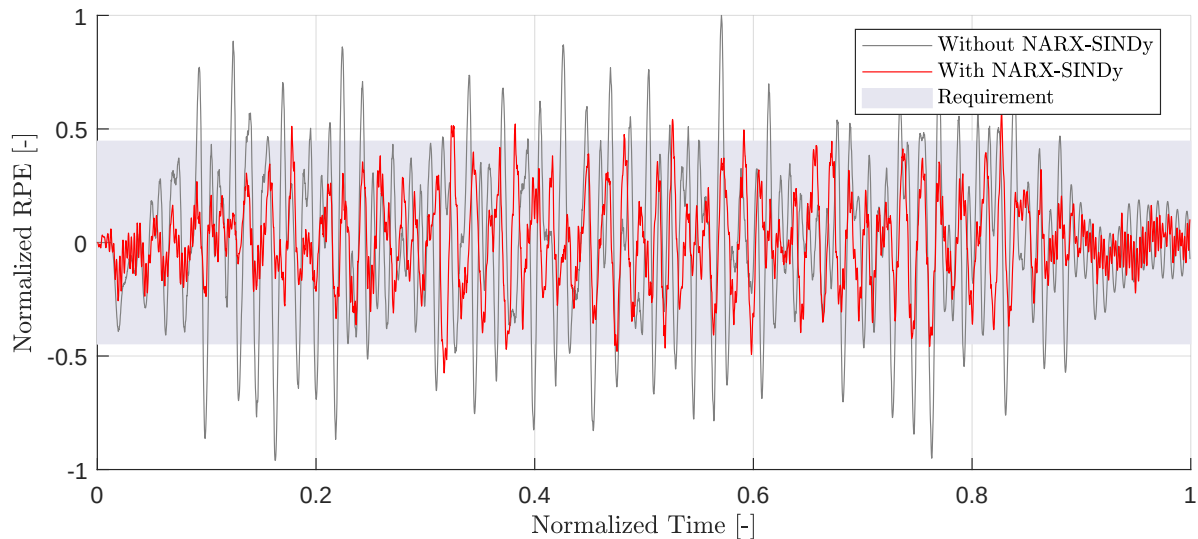


Figure 11 RPE improvement on the SADM use-case

4.4 Validation Campaign

In the end, extensive Monte-Carlo campaigns were made to assess the robustness of the algorithms to varying parameters, such as vehicle properties (mass, centering and inertia), and disturbance properties. Variability in the initial fluid / SADM positions was also considered.

Figure 12 showcases the NRMSE distribution, as a torque reconstruction indicator, focusing again on X_{sat} and Y_{sat} axes. This confirms a trend, fully consistent with the observations made on flight data, that NARX-SINDy slightly outperforms the standalone EKF in terms of open-loop dynamics identification.

Figure 13 illustrates that NARX-SINDy is able to consistently decrease the RPE on the nonlinear SADM use case, meeting the required value at 95 % of the distribution, over the whole mission envelope.

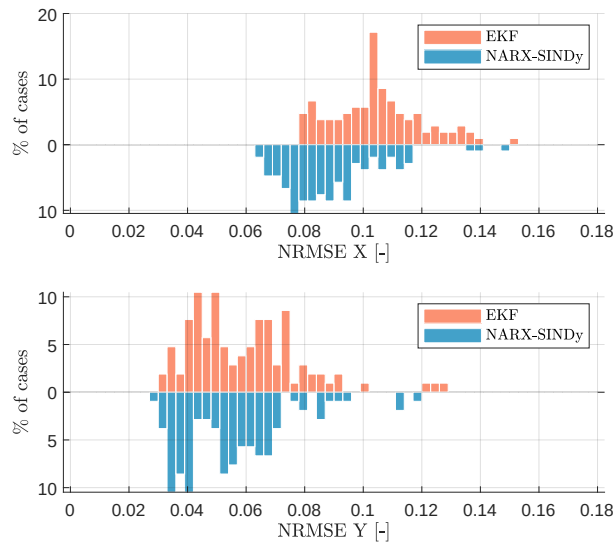


Figure 12 Slushing torque identification: NRMSE distribution

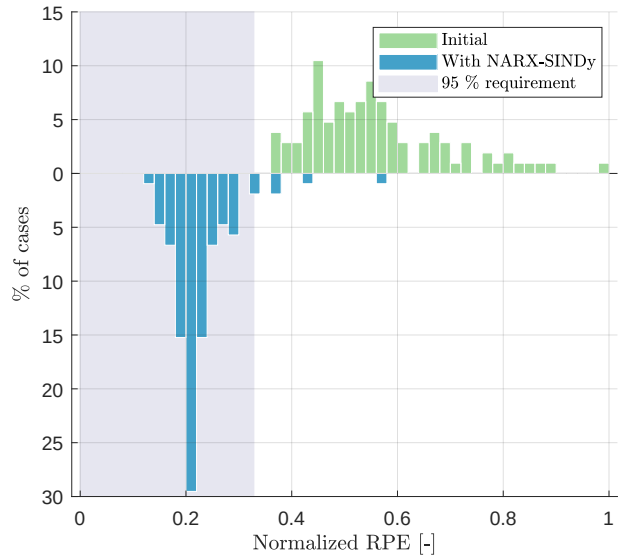


Figure 13 SADM torque rejection: RPE distribution

4.5 Processor-in-the-Loop Test

A Processor in the loop (PIL) test has been performed to assess the execution time of the SINDy-based system identification algorithms on a representative space-grade processor. Other AOCS algorithms, such as attitude estimator and controller, sensor measurements processing, are not included in this assessment. This test relies on the GR740 device [19], which is a radiation-resistant system-on-chip that integrates a fault-tolerant quad-core LEON4 SPARC V8 processor (only one core is considered in the test), and is part of the ESA's roadmap for standard microprocessor components.

The retained use case for this test is the slushing one, which is expected to bear the most computational challenges due to the three-axis identification. The operational scenario (manoeuvre spacing) is such that the NARX-SINDy model training can be spread over a 2 h time interval. Results are shown in Table 1 for the NARX-SINDy training phase and Table 2 for the estimation tasks executed synchronously at AOCS frequency (8 Hz).

Functionality	Execution time	CPU load if distributed over 2 h
NARX-SINDy training	380 s	5 %

Table 1 NARX-SINDy training execution time

It is seen that the developed components are compatible with an on-board application (less than 5 % of CPU time as per the requirements). While the online compensation part shall be executed on-board, the training, which

Functionality	Execution time	CPU load
NARX-SINDy preprocessing	16 μ s	0.01 %
NARX-SINDy propagation	898 μ s	0.7 %
EKF update	80 μ s	0.06 %
TOTAL SysID + estimation	990 μs	0.8 %

Table 2 NARX-SINDy onboard execution time

is also the most time-consuming task, could either be performed on ground or on board. However, assessing its ability to be executed on board is interesting in an attempt to further enable mission autonomy.

5 Conclusion and Outlook

5.1 Conclusion

A generic real-time operational system identification approach with a focus on industrial space systems has been presented. It accounts for the limited resources available on-board, while promoting intuitive setups and interpretable results. It is based on an $L1$ -regularized least square regression with a predefined set of versatile library functions, which allows its application to a wide range of problem formulations. This results in a novel formulation of a Sparse identification of Nonlinear Dynamics algorithm based on Nonlinear AutoRegressive eXogenous models, denoted NARX-SINDy, which was applied to two realistic use-cases derived from actual flight data. Results showed not only that the method successfully identified the unknown dynamics, but also that the identified results added value to the existing control laws, increasing their performance. When disturbance state equations can be concisely derived from physics, as for the sloshing use-case, a standalone EKF-based disturbance rejection approach remains relevant for active rejection, although this approach quickly becomes intractable for more complex disturbances such as those associated with the SADMs, where NARX-SINDy is clearly superior. A Processor-in-the-loop (PIL) campaign demonstrated the compatibility of NARX-SINDy with space applications. With the capability to identify unknown dynamics in-flight and augment the AOCS/GNC, the presented method plays an important role in enabling new design practices and operational scenarios for future missions.

5.2 Outlook

One outlook derived from this work on real-time SysID is to develop robust time-varying guidance and control algorithms for other challenging space applications (e.g. in-orbit servicing and assembly), supported by analytical, model-based, and predictive dynamical models. This includes deriving nonlinear, multivariable physical models and complementary data-driven or surrogate predictive models with uncertainty bounds, suitable for online motion planning, trajectory optimisation, SysID, and parameter estimation. Demonstration through realistic numerical simulations for other challenging autonomous operations such as rendezvous, docking, refilling, capture, attitude and pose stabilisation, and assembly is the current outlook to continue developing this work, in the context of Airbus Defence and Space roadmap to achieve more autonomous AOCS/GNC solutions.

We seek to also assess areas for improvement related to the system identification and the active disturbance rejection scheme, by providing additional stability and robustness guarantees, by considering alternative error metrics in the fit to better capture time-varying effects, and by performing reduced- and full-scale verification and validation in a relevant environment, to further increase the TRL.

Acknowledgement

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References

- [1] R.E. Maine and K.W. Iliff, "Identification of Dynamic Systems, Theory and Formulation". *NASA RP-1138*, 1985.
- [2] R. Isermann and M. Muenchhof, *Identification of Dynamic Systems: An Introduction with Applications*, Springer, 2011.
- [3] L. Ljung, *System Identification: Theory for the User*, Second Edition. Prentice Hall, 2012.
- [4] L. Ljung and T. Glad, *Modeling and Identification of Dynamic Systems*, Prentice Hall, 2016.
- [5] S.L. Brunton and J. N. Kutz, *Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control*, Second Edition. Cambridge University Press, 2022.
- [6] G. Pillonetto et al., *Regularized System Identification: Learning Dynamic Models from Data*. Springer (Open Access), 2022.
- [7] I. Markovsky et al., "Data-Driven Control Based on the Behavioral Approach: From Theory to Applications in Power Systems". *IEEE Control Systems Magazine*, vol. 43, no. 5, 2023.
- [8] G. Pillonetto et al., "Deep networks for system identification: a Survey". *Automatica* 171, C, 2025.
- [9] Y. Bao et. al. "Identification of State-space Linear Parameter-varying Models Using Artificial Neural Networks". *IFAC-PapersOnLine*. 2020
- [10] A. Perez-Munoz et. al. "Feasibility of Deep Reinforcement Learning for the real-time attitude control of a satellite system". *Journal of Systems Architecture*. 2025
- [11] O. Christidi-Loumpasefski et. al. "Towards onboard identification of space systems". *International Symposium on Artificial Intelligence, Robotics and Automation in Space 2022*.
- [12] M. Marques Soudré et. al. "A novel GPU-based approach for embedded NARMAX/FROLS system identification". *Mechanical Systems and Signal Processing*, Volume 211, 2024.
- [13] S. Brunton et al.: "Discovering governing equations from data by sparse identification of nonlinear dynamical systems", *Proceedings of the National Academy of Science*, 2016.
- [14] E. Burgin et al. "Identification of Non-linear Sloshing Dynamics using Operational Manoeuvres". *IFAC-Online*, 2026.
- [15] S.A. Billings, I.J. Leontaritis: "Parameter estimation techniques for nonlinear systems". *IFAC-Proceedings*, 1982.
- [16] R. Pierre, R. Roumiguié, J.Mignot, "Fluid dynamic in space experiment". *10th International ESA conference on Guidance, Navigation and Control Systems*, 2017.
- [17] F.T. Dodge, *The New "Dynamic Behavior of Liquids in Moving Containers"*. SouthWest Research Institute, San Antonio, Texas, 2000.
- [18] P.-A. Maüsli, G. Feusier, V. Gass, "Rotating electrical joints with continuous metallic connections". *European Space Mechanisms And Tribology Symposium (ESMATS)*, San Sebastian, 2003.
- [19] Hjorth, M. and Åberg, M. and Wessman, N.-J and Andersson, Jan and Chevallier, R. and Forsyth, R. and Weigand, R. and Fossati, L. , "GR740: RAD-Hard quad-core Leon 4ft system-on-chip", 2015.